SAMPLE PROPOSAL #1

Improving Police-Community Relations with a Social-Psychological Intervention for Reducing Racial Bias in Policing

Author: Calvin K. Lai

At almost any point of contact between police officers and Black Americans, one can see evidence of unequal treatment. Police officers are more likely to stop, question, arrest, injure, or kill Black people than White people (Glaser, 2015). *Implicit or hidden biases* have been identified as a psychological mechanism underlying these inequities in police decision making and behavior (Spencer, Charbonneau, & Glaser, 2016). Unconscious or spontaneous mental associations cause police officers to perceive Black people as more dangerous than is warranted. For instance, a controlled laboratory experiment found that police recruits are more likely to shoot unarmed Black men than unarmed White men in ambiguous situations (Ma et al., 2013).

These racial inequities were thrust into the nation's awareness following the 2014 police shooting of Michael Brown –an unarmed Black teenager – in Ferguson, Missouri. This incident (and others like it) disrupted the public trust in law enforcement and led to the rise of the "Black Lives Matter" movement. By the next year, the percentage of Americans who had "a lot" of confidence in the police reached a nadir at 52% (Jones, 2015). This lack of faith was especially notable among Black Americans, of whom only 30% had "a lot" of confidence in the police (Norman, 2017).

Recognizing this loss of trust as a crisis, law enforcement agencies across the United States have stepped up their efforts to reduce racial inequities with bias training programs (President's Task Force on 21st Century Policing, 2015). A recent survey of 155 police departments in large metropolitan areas indicates that 69% have some form of implicit bias training program (CBS News, 2019). Despite these widespread efforts, bias training programs have not been evaluated empirically and are not informed by psychological research on bias reduction or lasting behavior change (James, 2017). There is a real risk that training programs undertaken with the best intentions may be ineffective or create only fleeting reductions in bias (Lai & Banaji, 2019). Given all that is at stake in police-civilian interactions, there is a *critical need* to develop and test psychologically-informed interventions tailored for racial bias in policing.

The proposed research will be the first large-scale randomized controlled trial (RCT) to examine the effectiveness of *any* training program specifically designed to reduce racial biases in policing (Paluck & Green, 2009). We will develop and test a program to train police officers to interact with citizens in a more racially equitable manner. The program will draw on social-psychological research on interventions to address racial bias (Lai, Hoffman, & Nosek, 2013; Lai et al., 2016; Paluck & Green, 2009) and effective behavior change (Frey & Rogers, 2014; Miller, Dannals, & Zlatev, 2017) to create lasting changes in how officers interact with citizens. We will determine efficacy from the perspectives of officers' self-reports, community perceptions, and administrative data. This proposal was formulated on the basis of preliminary studies finding that a similar day-long training increased knowledge about racial bias, reduced officer bias in simulated scenarios, and increased intentions to use empirically-supported strategies to address bias in everyday life.

Review of Relevant Literature: **Implicit or hidden biases in policing.** The perception that police officers regularly discriminate against Black people is justified by the data. For example, officers are more likely to stop Black drivers for unjustified reasons than White drivers in the first place (Pierson et al., 2019). When stopped, evidence from video-recorded traffic stops finds that officers afford less respect toward Black drivers than their White peers (Voigt et al., 2017).

When speaking to Black drivers, officers are more likely to use informal language (e.g., “man” vs. “sir”), use harsher legal terms (e.g., “arrest” vs. “registration”), and are less likely to explain the reasons for their actions (e.g., “I’m doing this because...”).

Implicit assumptions about the criminality of Black individuals by virtue of their race underlie these inequalities. In one study (Eberhardt, Goff, Purdie, & Davies, 2004), police officers were subliminally shown images related to crime. These subliminal presentations of crime-related images led to faster identification of Black faces rather than White faces, suggesting that thoughts of crime lead to thoughts of Black people. A follow-up study by the same authors found evidence that thoughts of Black people lead to thoughts of crime, as well. Officers were much faster to identify images of weapons when those images were preceded by subliminal images of Black rather than White faces. These findings indicate a reciprocal relationship between Blackness and criminality within the minds of police officers: crime begets Blackness, and Blackness begets crime.

Racial inequities in perceived criminality extend to police use of force. Officers are 3.6 times as likely to use physical force against Black people than against White people (Goff, Lloyd, Geller, Raphael, & Glaser, 2016). Use-of-force decisions are not merely attributable to differences in crime rates or otherwise-dangerous behavior. Even when controlling for many other factors related to use of force, police use greater force on non-White suspects (Terrill & Mastrofski, 2002).

Implicit biases are implicated in the most extreme expression of police force: critical life-or-death decisions to shoot criminal suspects. In one series of studies (Correll, Park, Judd, & Wittenbrink, 2002), subjects participate in a simulation where they observe images of White and Black men. Some of the men are armed with guns, while others are unarmed. Participants are instructed to press a button to “shoot” (if the man is holding a gun) or press another button to “don’t shoot” (if the man is not holding a gun). Police officers who participate in this simulation are more likely to mistakenly shoot unarmed Black men than unarmed White men when they are fatigued (Ma et al., 2013) or regularly interact with minority gang members as part of duties (Sim, Correll, & Sadler, 2013).

Review of Relevant Literature: **Bias training programs.** There have been no peer-reviewed studies examining the efficacy of a bias training program in reducing racial biases among police officers. However, there have been several RCTs of bias reduction training in educational and organizational settings that inform how to develop an effective program for reducing racial biases in policing (Carnes et al., 2015; Forscher, Mitamura, Dix, Cox, & Devine, 2017; Moss-Racusin et al., 2014). These interventions emphasize two critical prerequisites for bias reduction that we will incorporate into our proposed training program:

Prerequisite 1: Awareness of hidden biases. As awareness of bias is a prerequisite for making efforts to reduce biased behavior (Monteith, 1993), trainees should be made aware of how discrimination can affect daily behavior.

Prerequisite 2: Motivation to address hidden biases. Knowledge of unintentional bias may lead to reduced feelings of accountability for addressing bias (Daumeyer, Onyeador, Brown, & Richeson, 2019). To address this issue, effective trainings motivate trainees to think of bias reduction as a “habit” that can be worked on over time (Devine, Forscher, Austin, & Cox, 2012)

The interventions also emphasize two consistently effective strategies that we will adapt for our proposed training program:

Strategy 1: See people as individuals rather than as groups. Efforts to reduce stereotyping often involve seeing people as individuals (Forscher et al., 2017). This can be accomplished through actively taking the perspective of others (Galinsky & Moskowitz, 2000; Galinsky, Ku, & Wang, 2005), noticing stereotypic thoughts and replacing them with non-stereotypic thoughts (Monteith, 1993), or thinking of how other people are unique individuals rather than representatives of their groups (Fiske & Neuberg, 1990).

Strategy 2: Create opportunities for intergroup contact. Over seventy years of research have shown that positive contact with outgroup members can powerfully reduce prejudice and discrimination (Pettigrew & Tropp, 2006). For example, White police officers in the 1950's who had Black co-workers were less likely to later object to taking orders from Black officers or teaming up with Black partners (Kephart, 1957). Similarly, patrol officers who had regular contact with non-criminal minority community members are less likely to mistakenly shoot an unarmed Black man in a simulation than special unit officers who primarily engaged with minority gang members (Sim et al., 2013). Encouraging trainees to actively seek positive contact with members of the community can reduce inequities in policing (Spencer et al., 2016) and is the basis of community-oriented policing strategies (Kessler, 1999).

Review of Relevant Literature: **Community perceptions of bias in policing.** Community trust is a crucial component of effective policing. When citizens trust police, they are more likely to follow the law, cooperate with police, and support policies that empower police (Sunshine & Tyler, 2003). However, trust in police is rare for departments working with communities of color. Surveys find that a majority of Americans believe police departments are racist, and Black Americans are especially likely to believe that they will experience unjust treatment by police (Tyler & Huo, 2002; Weitzer & Tuch, 2006). These concerns manifest in daily interactions.

Black people are more likely to feel nervous or scared when interacting with a police officer than White people (Najdowski, Bottoms, & Goff, 2015). In turn, officers may interpret nervousness or fear as evidence of suspiciousness, leading to unjustified stops and questioning (Najdowski, 2011). These unjustified stops then lead to diminished trust in the police (Tyler, Fagan, & Geller, 2014). One potential approach to break this vicious cycle is changing police behavior – to be more equitable, fair, and respectful.

A procedural justice approach to policing provides one avenue for cultivating community trust, and is increasingly incorporated into police education within the United States (Eberhardt, 2016). The core principles of procedural justice involve (Tyler, 2004):

- Being *fair* by applying the law impartially to all community members
- Treating community members with *respect*
- Giving *voice* to community members by listening to community members' views
- Being *trustworthy* by acting out a sense of benevolence for the community

Procedural justice approaches are effective for building trust within communities generally and may be uniquely effective for communities of color where trust in police is in short supply. Our proposed training program will incorporate two evidence-based strategies for police stops that adapt procedural justice approaches with a focus on curbing hidden biases.

Strategy 3: Justify the stop. When an officer relies on intuition when making a stop, they are especially likely to rely on stereotypes and stop Black people at higher rates (Glaser, 2015; Spencer et al., 2016). A simple intervention can curtail unjustified stops: before initiating a stop, ask officers to justify to themselves why a stop is necessary and consider whether the stop would be justifiable to others. Establishing a personal sense of accountability increases impartiality and reduces discrimination (Axt & Lai, 2019; Lerner & Tetlock, 1999; Uhlmann & Cohen, 2005).

Strategy 4: Sell the stop. It is not enough to stop citizens fairly; citizens must also perceive the stop to be fair as well. To do so, officers must "sell the stop" by explaining why a citizen was stopped, linking the stop to broader concerns about public safety, and listening to citizens' concerns about the stop (Lachman, La Vigne, & Matthews, 2012; Tyler & Fagan, 2012). This approach incorporates all four principles of procedural justice: fairness, respect, giving voice, and being trustworthy.

Table 1. Evidence-based strategies for addressing racial bias in policing.

Strategy	**Description**	**Rationale**
Perspective-Taking	Actively take the perspective of a citizen you are interacting with.	Perspective-taking reduces stereotyping & fosters social bonds.[1]
Contact	Seek opportunities to know people in your patrol as individuals.	Contact with people outside of one's group is a powerful approach to reducing discrimination.[2]
Justify the Stop	Explain to yourself why a stop is necessary and consider whether the stop would be justifiable to others.	Giving officers a sense of accountability reduces bias in decision-making.[3]
Sell the Stop	Explain to a citizen why they are being stopped. Emphasize how the stop benefits public safety.	Citizens who believe that police are acting fairly are more likely to help officers in reducing crime.[4]

Note. See *Review of Relevant Literature* for detailed descriptions of these strategies.
[1] Galinsky & Moskowitz, 2000; Galinsky et al., 2005. [2] Pettigrew & Tropp, 2006.
[3] Axt & Lai, 2019; Lerner & Tetlock, 1999; Uhlmann & Cohen, 2005. [4] Lachman et al., 2012; Tyler & Fagan, 2012.

Research aim. My team will develop and experimentally test a program to train police officers to interact with citizens in a more racially equitable manner. The program will draw on social-psychological research to create lasting changes in how officers interact with citizens. We will train officers to employ evidence-based practices in perspective-taking, having positive contact with community members, initiating police stops, and explaining stops to citizens (See Table 1). All four strategies have a strong record of efficacy in the general population and are tailored to officers' work practices. To make the learning "stick", the program will take a habit-building approach that incorporates an intensive initial session and six brief practice sessions.

Preliminary studies. This proposal builds on a **large-scale study** that we are currently conducting with the Anti-Defamation League (ADL), a nonprofit that trains approximately 15,000 law enforcement professionals annually on bias-related issues. We are testing the effects of a training program on 2,000 police officers in the United States.[1] This day-long training introduces practices designed to enhance officers' ability to manage the impact of hidden biases in their work. In this study, we are administering surveys to officers before and after the training to understand whether officers endorse what they learned about racial biases and whether they report using the practices designed to manage the impact of racial biases. Before this large-scale study, we conducted a **pilot study** in four cities using pre-post designs. We found that a pilot version of that training increased knowledge about racial bias, reduced officer bias in simulated scenarios, and increased intentions to use empirically-supported strategies to address bias in everyday life.

Funding from the Russell Sage Foundation would support a cluster randomized controlled trial (RCT) to expand on the encouraging results from the preliminary studies. The RCT will assess the impact of a new training program that improves on the large-scale program referenced above with innovations in social-psychological approaches to bias reduction and behavior change (Lai et al., 2013; Miller et al., 2017). Crucially, we will assess a broad set of key

[1] To preserve the confidentiality of police departments undergoing training and evaluation, no cities are named in this proposal.

psychological and behavioral outcomes: (1) officers' reports of their own behavior, (2) community perceptions of officers, and (3) administrative data.

Examining efficacy across three types of criteria will allow us to triangulate aspects of the intervention that are effective from the varying perspectives of police, the citizens impacted by police behavior, and administrative data on crime and citizen complaints against police. Many possible patterns could emerge. In the best-case scenario, the training program will improve outcomes across all three criteria. However, it is easy to imagine alternate scenarios. For example, officers may show change in self-reported behavior and administrative data, but community members may not perceive these changes. Or, officers may be unaware of their own behavior change, but community perceptions and administrative outcomes suggest otherwise.

RESEARCH DESIGN

This study will be conducted with the ADL, with whom we have a strong ongoing partnership. ADL will assist with recruiting police departments and delivering the training program.

Participants. Police officer participants will be 1,620 patrol officers belonging to 200 police beats in a metropolitan area (or areas) in the United States. These officers will participate in the survey as part of their regular work activities. This sample allows for 80% power to detect an effect of .20 as calculated in WebPower (Zhang & Yuan, 2018).

We will recruit 1,500 community members through a telephone survey using a geographically stratified random sampling strategy that reflects the racial and age demographics of the metropolitan area (or areas), with people of color being oversampled. We plan on collecting this data under a longitudinal panel design but may employ a repeated cross-sectional design if participant retention is expected to be difficult in the local context (e.g., low initial participation rates, high probability of selective attrition). The community sample also allows for 80% power to detect an effect of .20 as calculated in WebPower (Zhang & Yuan, 2018).

Training program. We will construct a new day-long program that improves on past programs by combining effective elements of ADL's current training with other evidence-based bias reduction interventions (Carnes et al., 2015; Devine et al., 2012; Moss-Racusin et al., 2016) and techniques for creating long-lasting behavior change (Frey & Rogers, 2014). In an initial training, expert facilitators from ADL will educate officers on how subtle or implicit biases affect officers' interactions with citizens. This education will frame successful behavior change as a habit that must be developed over time through practice.

Next, participants will be trained on four evidence-based strategies to practice over the following two months (See Table 1 for a summary and *Review of Relevant Literature* for detailed descriptions). After the initial training, officers will complete six brief follow-up training sessions on their phones or computers. Officers will practice strategies with challenging exercises that stress active engagement and have been shown to enhance learning (e.g., applying a strategy to a novel scenario; Bjork & Bjork, 2011). Follow-up trainings will be spaced out after the initial training to maximize memory consolidation (Hintzman, 1974) and increase the likelihood that officers will apply the lessons to their daily practices (Eberhardt, 2016): 1, 3, 7, 12, 18, and 26 days.

Procedure. In a baseline assessment, officers will report on their personal demographics and beliefs about racial biases in policing. Then, 202 police beats (i.e., distinct areas where officers patrol) matched on crime rates and racial composition within the metropolitan area (or areas) will be randomly assigned to participate in the training program or a control condition in which they receive no training. Officers in treatment beats will participate in the training program, completing an initial day-long training session and six brief follow-up sessions. All officers will take surveys four times after the initial training sessions have been completed: 8 days after, 30 days after, 3 months after, and 6 months after.

Community members will be assessed before the training begins, 30 days after, 3 months after, and 6 months after. This schedule allows us to track the duration of intervention effects – be it a week, a month, or longer. These longer-term evaluations will complement our preliminary studies, which focused on shorter-term impacts over two months. See the Appendix for a draft of all survey materials.

Officer self-report. Officers will complete one pre-training baseline assessment about demographics, contact with minority group members, and beliefs about racial inequities in policing. Officers in both treatment and control conditions will also complete four assessment sessions after the training program is administered: after 8 days, 30 days, 3 months, and 6 months. These sessions will assess beliefs about the existence of racial bias in policing, motivations to address bias in policing, and self-reported use of the evidence-based strategies.

Beliefs about the existence of racial bias in policing. Assessment of knowledge and understanding of key concepts will be tailored to the concepts covered in the training program. Examples of questions that will be included for assessing knowledge of bias include 7-point Likert-style questions asking about agreement/disagreement to statements such as "Everyone, including me, has biases toward other people", "Subtle or implicit biases influence my decision making about other people" and "Whether I am aware of it or not, I use a person's race or ethnicity to form an impression of the kind of person they are." (adapted from Perry, Murphy, & Dovidio, 2015).

Motivations to address bias in policing. To assess motivation to address bias, we will examine officers' perceptions that bias can be changed (example item: Agreement to the statement "People have a certain amount of bias toward other people and they can't really change that"; Carr, Dweck, & Pauker, 2012), worry about acting biased, and motivation to apply the evidence-based strategies.

Self-reported use of evidence-based strategies. Participants will report on the use of strategies to manage the impact of implicit bias. They will be asked about how many times they have used each of the four strategies in the past week along with their perceptions of the strategies' feasibility and effectiveness (adapted from Devine et al., 2012).

Community perceptions. Community perceptions will be assessed once before the training and three times after (30 days, 3 months, 6 months). In all time-points, we will assess general perceptions of police, perceptions of racial bias in local policing, and experiences with local police to understand how community perceptions respond to changes in police behavior.

General perceptions of police. To assess general perceptions of police, we will adapt the well-validated Perceptions of Police Scale (Nadal & Davidoff, 2015) to perceptions of police within one's own community. Examples of questions that will be included include 5-point Likert-style questions asking about agreement/disagreement to statements such as "The police in your community are trustworthy", "Police officers care about the community", and "The police in your community usually give an honest explanation for their decisions."

Perceptions of racial bias in local policing. To assess perceptions of racial bias in local policing, we will adapt a scale from Tyler and Wakslak (2004). Questions will be asked on a 5-point scale from "Not at all" to "A great deal" and include questions such as "How much do police in your community consider a person's race when deciding which cars to stop for possible traffic violations?" and "How much do police in your community consider a person's race when deciding which people to stop and question on the street?"

Experiences with local police. Using scales from Oliveira and Murphy (2015) and Rosenbaum and colleagues (2005), we will ask about contact with police and perceived treatment by police. These questions ask about direct contact with police, knowledge of others who have had contact with police, the overall positivity or negativity of those experiences, and perceptions of whether the police were professional and fair.

Administrative indicators. Administrative indicators will include racial inequities in stops, searches, and use of force 3 months, 6 months, and 1 year after training. We will also assess the total number of citizen complaints against officers in a beat and racial differences in citizen complaints (i.e., how often White vs. Black citizens report officers). If the training is effective, then all five administrative indicators should decrease.

Qualitative interviews. To provide additional context to the survey findings, we will conduct semi-structured interviews about reactions to the training over the phone or Skype with patrol officers and their managers after the training program is completed. We will have separate questions for participants that attended the training program and participants that manage attendees of the MIB training program. We expect that we will reach saturation between 10-25 participants. We will audiotape and transcribe verbatim each interview (Creswell, 2003) and conduct a thematic analysis of the text data to develop broader conclusions about participants' responses.

Analysis plan. To examine how officers change over time in response to the training program, we will conduct multilevel models examining how the three outcome variables (i.e., racial bias in policing, motivations to address bias in policing, and self-reported use of the evidence-based strategies) are predicted by beat treatment condition, timepoint, and their interaction with random intercepts for each subject. We will also conduct follow-up analyses examining potential moderators of treatment effects (e.g., perceived efficacy and motivation to use strategies, officer race, compliance with training program, individual strategy use).

To examine how community perceptions change over time, we will conduct multilevel models examining how the three outcome variables (i.e., general perceptions of police, perceptions of racial bias in local policing, and experiences with local police) are predicted by beat treatment condition, timepoint, and their interaction with random intercepts for each subject. We will also conduct follow-up analyses examining potential moderators of treatment effects (e.g., participant race, participant age).

To examine how administrative indicators change over time, we will conduct linear regression models examining how the five outcome variables (i.e., racial inequities in stops, racial inequities in searches, racial inequities in use of force, total number of citizen complaints, and racial inequities in citizen complaints) for each beat are predicted by beat treatment condition, timepoint, and their interaction.

Statement on transparency and reproducibility. Dr. Lai has publicly posted the materials for every paper that he has published as a lead author and pre-registered every study he has led since 2012. This proposed work will continue to prioritize open and reproducible research practices. This will include (1) posting all study materials so methods can be directly replicated, (2) posting all final data (in unidentifiable form) and analysis scripts so that others can reproduce our analyses, (3) pre-registering analysis plans to reduce "researcher degrees of freedom" (Simmons, Nelson, & Simonsohn, 2011), and (4) sharing all pre-prints publicly on preprint servers so that public and scientific community stakeholders can freely access them. Materials, data, analysis, scripts, and pre-registrations will all be stored at Open Science Framework (https://osf.io). Preprints will be hosted at PsyArXiv (https://psyarxiv.com/), a preprint service hosted by the Open Science Framework.

LIKELY CONTRIBUTIONS

Advancing the objectives of the Russell Sage Foundation. This project aligns with RSF's Decision Making and Human Behavior in Context initiative, in particular:

Biases and Misperceptions: This project will focus on hidden racial biases in policing. Collecting officer and community outcomes will also help develop an understanding of how officers and community members perceive (or misperceive) each other.

Motivations and Incentives: The training program seeks to cultivate officers' motivations and values so that they feel empowered to address racial biases and motivated to implement the strategies we will teach them. As part of our assessment strategy, we will track how motivations to address racial bias are increased, reduced, or maintained in the months following the training program.

Habits and Behavior Change: The proposed intervention incorporates many of the latest innovations in habit-building and behavior change to create long-lasting changes in how officers interact with the citizens they are duty-bound to protect and serve.

Potential impact. As the first large-scale RCT to examine the effectiveness of a training program specifically designed to reduce racial biases in policing (Paluck & Green, 2009), this study is well-poised to have broader impacts on policing and policy-making. If it is effective, the training will dramatically impact how officers interact with citizens, particularly citizens of color. That reduction of racial bias in policing could be coupled with improvements in community perceptions of police and police-community relations. The training will also affect what communities ask of their police departments and how policymakers address racial disparities in policing. If the training is effective, then there may be greater investment in bias training. If bias training is ineffective, then greater investment into alternative strategies would be preferable (e.g., body cameras, programs focused on building trust between police officers and the community).

PROJECT WORK-PLAN

Work on the project will begin immediately with a focus on adapting the procedure to the local context over four months. Data collection of baseline characteristics, the training program and follow-up assessments will take place over ten months. After survey data collection, we will obtain administrative data, clean and analyze data from the three sources, and write up the findings for academic publication. See Table 2 for specific dates.

Table 2. Project Timeline.

	Jan. - Mar.	**Apr. - Jun.**	**July - Sept.**	**Oct. - Dec.**
2019	N/A	N/A	N/A	Tailor procedure for local context
2020	Finalize study design & materials	Baseline assessment	Training prog.; 8 & 30 day assessment	3-month assessment
2021	6-month assessment	Obtain admin. data; clean data	Analyze data & write publication	Write publication

RESEARCH TEAM QUALIFICATIONS & RESPONSIBILITIES

Our team is led by Dr. Calvin Lai, an assistant professor of Psychological & Brain Sciences at Washington University in St. Louis. His laboratory studies interventions to address implicit bias and its impact on behavior (https://calvinklai.wordpress.com/research/). He studies prejudice and discrimination with a focus on developing interventions to mitigate their pernicious effects. Dr. Lai has published in journals such as *Science*, *Journal of Personality & Social Psychology*, *Perspectives on Psychological Science*, and *Journal of Experimental Psychology: General.* He was named a Rising Star by the Association for Psychological Science in 2017. Dr. Lai completed his post-doctoral training at Harvard University and his PhD in Social Psychology from the University of Virginia.

Experience with evaluation of implicit bias training programs. Since 2011, Dr. Lai has given 33 implicit bias education workshops to diversity leaders at the White House and at organizations such as the Association of Corporate Counsel, the Department of Housing and Urban Development, the Environmental Defense Fund, and Harvard Business School. The structure of these workshops is similar to the MIB training program: (1) Raise awareness of the existence of implicit biases, (2) Demonstrate the relevance of implicit biases (and related concepts) to work practices, and (3) Improve the capacity for and use of strategies to mitigate the impacts of implicit bias. Internal evaluation of these workshops using quasi-experimental designs and a natural experiment found that the workshops have beneficial long-term effects.

Dr. Lai has given 48 academic presentations on implicit bias, covering topics such as interventions to reduce implicit bias, the relationship between implicit bias and behavior, and strategies to prevent discrimination. He has also advised on the development and evaluation of an exhibit on implicit bias at the National Underground Railroad Freedom Center and served on an external blue-ribbon panel evaluating progress on diversity and inclusion issues at Amherst College.

In his academic research, Dr. Lai has conducted many large-scale studies evaluating the efficacy of interventions to reduce implicit or hidden biases (e.g., Axt & Lai, 2019; Forscher*[2], Lai*, et al., 2019; Lai et al., 2014a, 2014b, 2016). He has also published reviews evaluating the evidence for interventions to address implicit bias and its impacts on behavior (Lai et al., 2013; Lai & Banaji, in press). These reviews find that implicit bias is difficult to change directly in the long-term, but breaking the link between implicit bias and behavior with action-oriented interventions is consistently effective.

Experience with designing and administering evaluations of programs in the field. Dr. Lai's large-scale studies on implicit bias interventions have involved coordinating data collection at 18 universities simultaneously. This work required management skills at scale and an awareness of the issues that arise in large-scale field data collection. He has also taken a graduate course on Field Experiments and is familiar with the unique methodological and statistical issues that arise when testing interventions in the field (e.g., quasi-experimental designs, attrition, noncompliance, intent-to-treat, spillover). In addition to collecting data on police officers, he has collected field data from populations such as: attendees in diversity education workshops, surgeons, football fans, and K-12 students.

Familiarity working with law enforcement. Beyond his experiences leading studies of law enforcement with the Anti-Defamation League, Dr. Lai has conducted research examining police officers' implicit associations, beliefs, and attitudes about race in a police academy and in police departments in Los Angeles, Las Vegas, and Houston with the Center for Policing Equity

[2] Co-lead-authors.

(http://policingequity.org/). He has informally advised police officers and educators on implicit bias education, including trainers at the Department of Justice. He has also attended citizen-police workshops to gain working knowledge about everyday practices at police departments.

Jaclyn Lisnek, Research Assistant. Jaclyn Lisnek is a lab manager (Research Technician I) at Washington University in St. Louis. She graduated from Indiana University with majors in Psychology and Gender Studies, a minor in nonprofit management, and a thesis on community perceptions of policing. As part of her undergraduate research, she assisted Dr. Mary Murphy at Indiana University in an intervention to better the dynamics between White teachers and minority students in Chicago. Jaclyn Lisnek has assisted in the data collection of multiple large-scale field studies, including the preliminary studies described above.

REPORTING OF STUDY FINDINGS

Dissemination of findings to the public and relevant stakeholders. Dr. Lai is the Director of Research at Project Implicit, a non-profit whose mission is to educate the public about hidden biases with a site that receives millions of visitors per year (implicit.harvard.edu). Our team will use this website to promote a series of accessible articles, data visualizations, and blog posts about the link between implicit attitudes and behavior that will highlight the proposed work. Dr. Lai will write summaries of our proposed research for media outlets (past example: an article for *The Conversation* that was picked up by 20+ outlets including Time & Newsweek), and respond to media interviews about our research (past examples include *New York Times, Washington Post, Boston Globe, The Atlantic, BBC, National Public Radio, The Wall Street Journal, The Huffington Post*). Dr. Lai will also give talks to organizations focused on policing or communities of color about applying our scientific evidence (e.g., National Association of

Police Organizations (NAPO), National Association for the Advancement of Colored People (NAACP); past example: speaking at the White House about implicit bias).

Dissemination of findings within the scientific community. To broaden the reach and application of our findings, we will target scientific outlets that will tap into distinct audiences interested in biases within policing. We will submit our findings to journals with broad readership (e.g., *Science*, *PNAS*, *Nature Human Behavior*) and specialized journals (e.g., *Psychological Science*, *Journal of Personality and Social Psychology*, *Criminal Justice and Behavior*). We will present this research at conferences such as *Society for Personality and Social Psychology*, *Association for Psychological Science*, and *American Society of Criminology*. We will also present the research at other universities. Within the past three years, Dr. Lai has given invited talks at universities such as Harvard University, MIT, University of Toronto, McGill University, Tufts University, University of Illinois at Urbana-Champaign, and the University of Michigan.

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* Co-lead authors.

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SAMPLE PROPOSAL #2

Linking Electronic Health Records and In-depth Interviews to Uncover Barriers to Social Mobility and Health in a Declining Coal Mining Community

Statement of the Problem and its Importance

This research is situated at the nexus of poverty, social mobility, and health among low-income, racially diverse women in rural Pennsylvania. Poor health is a barrier to social mobility, and marginalized populations are both more likely both to experience poor health and to receive inadequate medical care. Yet the relationship between economic disadvantage and health is complex, and our awareness of the mechanisms that drive health attitudes and behaviors in poor communities is inadequate. Our research design is uniquely suited to uncover the mechanisms through which social inequalities of class, race, and gender shape women's health experiences and behaviors on the one hand, and how these experiences and behaviors compound poverty and reduce social mobility on the other (Murray 2006). Conducting this research is crucial to improving the physical and emotional well-being of poor women in poor communities.

While research in the social sciences documents disadvantaged people's health care challenges, this existing scholarship usually provides only the individual's perspective on their health and health care and may not be a reliable source of health data (e.g., healthcare utilization, medication prescribing and use, or diagnoses). In studies based only on medical health care data, in contrast, the voice of the patient is often missing, especially among marginalized groups, leaving the pathways through which social inequality and health experiences and outcomes interact unknown. Our research rectifies these omissions by developing an innovative mixed methods approach that links electronic health record (EHR) data from Central Health System, an integrated health system, with consented patients' own accounts of their experiences, worldviews, struggles, and obstacles to social, physical, emotional, and economic well-being.

Our study builds on previously funded research which links in-depth interviews with low-income white women to their electronic health record (EHR) data. Our data collection takes place in the anthracite coal region of Northeastern Pennsylvania, specifically in the rural counties of Schuylkill and Northumberland. Since the 1960s, mining jobs have been replaced by service jobs in education, health care, and retail that are largely non-union, pay low wages, and offer few benefits. Only 16% of the area's population holds a college degree in comparison to 20% at both the state and national level. The region reports an overall 14% poverty rate (American Community Survey 2012–2016). While Pennsylvania has historically been an overwhelmingly white state, with a minority of African-Americans in major cities, rural Pennsylvania is growing increasingly more ethnically and racially diverse (see, for example, Milofsky 2008). Over the last decade, rising housing costs, poverty, and crime have pushed black and Latino people out of urban economies and into the coal region, challenging long-standing boundaries of urban and rural, race and place. The counties of our research focus have a documented hyper-increase in the Latino population since the turn of the new century, increasing by 216% in Schuylkill from 2000 to 2014 and 177% in Northumberland during the same period (Pew Research Center 2014). These counties rank among the lowest in health indicators including poor physical and mental health days, as well as health behaviors such as teen births, preventable hospital stays, and incidences of violent crimes and injury deaths (Robert Wood Johnson 2019). Central Health System Health Center classifies both counties as "high-need communities" based on various socio-economic indicators, including income, educational attainment, insurance coverage, and English language barriers (Baker Tilly 2018).

Initial execution of this research (Stage 1, completed) resulted in interviews with 40 white rural women, 13 conducted in 2017–18 and 27 conducted in summer 2019. The qualitative interviews probed respondents on their life histories, socioeconomic background, health concerns, and previous medical treatments. We linked these respondents' life history narratives to their individual EHRs, which contain their medical and treatment histories, including diagnoses, medications, treatment plans, and laboratory and test results. Stage 1 focused on developing a new methodology for integrating interview and EHR data. Our interdisciplinary team established new data-sharing protocols for merging data while maintaining participant confidentiality (see Appendix A) and novel approaches for analysis with a dataset that includes both interview and EHR data.

For Stage 2, we propose to apply these newly developed methods to a larger and more diverse dataset, to include the addition of 40 non-white participants and incorporation of free-text physician notes, as described below. Making novel connections across two under-utilized and rarely-accessible data sources — in-depth interviews and medical record data — we will uncover the economic, social, and cultural barriers that drive physical and psychological distress among white, black, and Latina low-income women, as narrated by the women themselves, while also situating these accounts within medical diagnoses, treatment plans, and physician's notes. This expanded effort using our refined methods with a larger, more diverse sample is key to understanding the pathways through which both economic and racial inequality impact health — and health impacts social mobility — with the goals of identifying and reducing structural barriers to opportunity and well-being in disadvantaged communities.

Principal Research Questions

1. What are the mechanisms, emerging from rural women's narratives of their experiences and behaviors, through which economic disadvantage and racial identity impact physical and emotional well-being?

    a. How do these mechanisms vary by race and ethnicity?
2. What kinds of discrepancies exist between the formal medical record and patient narratives in terms of sources of poor health, diagnoses, and necessary treatment plans?
    a. How do these discrepancies vary by race and ethnicity?
3. How do experiences within the healthcare system itself shape women's everyday approaches to their own health and well-being, as narrated by women themselves?
    a. How do these experiences vary by race and ethnicity?
4. Can we identify possible patterns in diagnoses, prescribing of medications, and creation of treatment plans in the electronic health records that might either promote or hinder participants' ability to achieve economic and social well-being?
    a. Are there differences by race and ethnicity?

Contribution to Existing Literature

Our project brings together research from sociology, economics, public health, and political science. Sociological studies of working-class Americans in rural settings have documented how stigma, isolation, and lack of effective mental healthcare and substance abuse treatment strengthen barriers to social mobility such as unemployment and low wages (Duncan 2015; Fitchen 1995) and contribute to the persistence of multigenerational poverty. Recent research has proposed that the disappearance of stable, good-paying blue-collar jobs has led to a culture of hopelessness among white Americans without a college degree, leading to rising mortality rates from "deaths of despair" (Case and Deaton 2015, 2017). These life expectancy losses have been particularly dramatic for white women with less than a college degree (Cherlin 2018).

While the specific mechanisms driving up deaths of despair are unknown, economists Case and Deaton (2015 and 2017) propose that working-class white people are turning to unhealthy coping mechanisms such as opioids, alcohol, suicide, and food (Harper et al., 2017) to manage economic and social dislocation. Lending support to this hypothesis, sociological studies have documented that since the 1970s, rural working-class whites have become detached from mainstream institutions like work, marriage, religion, and politics, resulting in multi-generational poverty, vulnerability, and extreme isolation (Carr and Kefalas 2010; Duncan 2015; Gest 2016; Cramer 2016; Wuthnow 2018; Monnat and Brown 2017; Silva 2019). Yet little research has been done on the specific pathways that connect economic decline to psychological health; on the ways in which "despair" manifests biologically and behaviorally at the individual level; or on how whiteness interacts with economic and social distress at the level of individual narrative to produce unhealthy coping mechanisms (Brown and Tucker-Seeley 2018; Mezuk et al., 2013). Furthermore, we need more data on how the experience of poor health such as pain or depression may in turn affect people's ability to escape poverty (Krueger 2017).

Case and Deaton's research "unexpectedly positioned working-class Whites as the new face of disadvantage" (Brown and Tucker-Seeley 2018), spurring a flurry of media attention on working-class white Americans left behind in rural America. Yet the increased focus on the rural white working class tends to obscure two important trends: the increasing racial and ethnic diversity and the geographical flux in non-metropolitan areas (Lichter 2012; Lichter and Ziliak 2017). In the national context, nine out of 10 rural places experienced increases in diversity between 1990 and 2010, with racial and ethnic minorities moving to whiter areas, and white young adults moving to more diverse urban areas (Lee at al 2014). Today, twenty-one percent of rural America is Latino or non-white, and minorities accounted for over 80% of population increases from 2000 to 2010 (Johnson 2017). Scholars are uncertain whether newly-arrived ethnic and racial minorities will find increased opportunities for safety, work, community, and mobility in rural places in contrast to their previous places of residence (Carr, Lichter, and Kefalas; Jensen 2006; Weber et al., 2017), or whether hope will "turn sour" (Kefalas 2000;

Marrow 2017), compounding blocked opportunity, stigma, and social exclusion for the next generation (Eason 2017). Furthermore, past research has established that, despite higher risks of financial strain, stress exposure, morbidity, and mortality relative to whites, black and Hispanic people report lower rates of stress, anxiety, and depression — key indicators of despair — underlining the need for more research on the interplay between racial identity, structural barriers to mobility, and personal narratives of coping (Krueger 2017).

By using newly refined methods for examining the medical records in tandem with in-depth interviews of working-class white women and women of color in Pennsylvania coal country, our research design will provide novel insights into the relationship between poverty, racism, and mental and physical health in the 21st century. Our analysis will capture official medical diagnoses, healthcare utilization, medication usage, and treatment adherence through the EHR while simultaneously documenting the structural constraints such as poverty, racism, economic and social instability, and interpersonal or societal violence from interview transcripts. We will also witness and document how patients' experiences with medical institutions shape women's attitudes and behaviors about health.

Principal Research Objectives

1: We will interview 40 non-white female respondents, adding respondents and diversity to our qualitative dataset and allowing analyses that include race or/and ethnicity.

2: We will link Central Health System EHR data with patient interview data using our newly developed data-sharing protocol and data analysis techniques. We will continue to carefully examine patients' understanding of their diagnoses and required treatment against Central Health System records on diagnoses, treatment, and outcomes to document emergent patterns, especially regarding race or/and ethnicity.

3: We will focus on uncovering the barriers that drive gaps between formal health care and expected v. actual patient outcomes such as the often invisible reasons underlying missed appointments and not following a doctor's advice. Race or/and ethnicity will be key variables in our analysis.

4. We will trace how interactions with medical institutions shape participants' own understandings of health, well-being, and trust, focusing on how these interactions affect their ability to escape poverty and achieve upward mobility.

Research Methodology

We will continue our innovative mixed-methods research approach, relying on Central Health System EHR data and semi-structured interviews with economically disadvantaged women. The 40 white women we have already interviewed were recruited through the connections and relationships that Dr. Silva established while conducting fieldwork for her recent book *We're Still Here: Pain and Politics in the Heart of America.* We will add 40 black and/or Latina women to this sample. We chose to aim for a total sample size of 80, which is small enough to capture the depth of meaning and the vividness of the data (Lareau and Rao 2016) while large enough to establish patterns, look for cases that challenge our theoretical presumptions, and draw robust comparisons between the different groups (DeLuca et al., 2016; Ali and Cohen 2016).

We will continue to integrate electronic health record data with consented patients' own accounts of their experiences, worldviews, struggles, and obstacles to care. The interviews aim to uncover patients' accounts of past medical issues, current medical issues, interactions with GHS, and existing diagnoses; their understanding of required treatment and barriers to compliance; their experiences of stress and economic deprivation; patients' social support systems; and their sense of self-efficacy and trust. Our analysis approach of the semi-structured interviews will employ open coding, in which we read each interview line by line to identify salient themes (See Appendix B for interview guide). We will then link EHR, including physician's notes, to interviews of patients' experiences of health care and their own understandings of their diagnoses and required care.

Central Health System is a health system that serves more than four million primary care patients across Pennsylvania and New Jersey. As one of the earliest adopters of the EHR system — and due to the low out-migration rate within this specific geographic area — Central Health System provides longitudinal health data like few others, capturing information on medical diagnoses and practices that inequality scholars rarely have access to. EHRs — capture in digital form — all inpatient, outpatient, and emergency department encounters, as well as diagnoses, laboratory tests, procedures, doctors' orders, medications, and other information that would be obtained from the clinical encounter (Swartz 2011). Central Health System's primary service area consists of a number of U. S. Department of Health and Human Services Health Resources and Services Administration-designated medically underserved areas (MUAs), including communities in Schuylkill and Northumberland counties. The Central Health System Family Plan is contracted with the Department of Human Services (DHS) to offer coverage to eligible Medical Assistance recipients living in 22 Pennsylvania counties. The Central Health System Clinic service area average household income ($60,378) is 15.3% lower than the US ($71,320);

13.1% have household income less than $15,000/year. The catchment area is one of the oldest and sickest in the nation in terms of multiple comorbidities.

To date, interviews with 40 white women have been completed. We propose to interview 40 women who identify as black and/or Latina and combine those data with the sample of white respondents. We will employ purposeful sampling, selecting cases that provide rich information on diagnoses of obesity and diabetes, reported smoking and drinking behavior, prescription history, and adherence to appointments. Each participant will have an EHR from Central Health System. (See Appendix B for interview guide.)

During the interview process, Drs. Silva and Durden and the research assistants obtain IRB consent from the study participants to access retrospective EHR data. Dr. Hirsch will provide a data pull request to Central Health System's Department of Biomedical and Translational Informatics for the EHR data using the name and date of birth of the consented individuals in the qualitative cohort. The following data elements will be extracted on all consented participants from the date of their first recorded encounter until December 31, 2016:

- Health system utilization: (1) Rates/counts of outpatient, inpatient, emergency department, and urgent care encounters; (2) rates/counts of prescription medication orders by indication and pharmacy class; (3) rates/counts of procedures.
- Health status: (1) Charlson Comorbidity Index — a widely used method of predicting mortality by classifying/weighting comorbid conditions; (2) status of intermediate risk factors for cardiovascular disease and diabetes such as glucose control, blood pressure, cholesterol, body mass index.
- Measure adherence: (1) Rates/counts of no-shows to scheduled appointments; (2) medication adherence as measured by rate of prescription fills (GHP data) for ordered

prescriptions (EHR) among individuals who both receive GC care and are GHP members.

- We will review and code free-text notes documented during the visit to identify themes not typically available in discrete data fields, including concerns regarding medication adherence, patient-reported stress, and social support.

In addition to these discrete data elements, Dr. Hirsch will request free-text physician notes from the EHR for each respondent, as these notes may contain details regarding patient experiences discussed during clinical visits that are not generally recorded in the discrete data fields of the EHR (e.g., financial challenges, family dynamics, etc.). We will amend the Stage 1 IRB to include free-text physician notes. No protected health information will be released from Central Health System. Rather, for each participant, Central Health System study staff will develop a de-identified narrative, based on the EHR data, that summarizes the participant's experience with the health system, a methodology developed during Stage 1 with the smaller sample.

Data analysis will occur in three stages. After the interviews are fully transcribed, Drs. Silva and Durden will carefully read through the transcripts and provide a thorough summary of the respondent's story, removing identifying data and pulling out key quotes and themes. Dr. Hirsch will simultaneously create a de-identified narrative of each EHR, highlighting the key medical prescriptions, the history of the patient with the Central Health System, and the medical recommendations provided. The summaries of the qualitative interviews and the EHR will then be read in tandem by the entire team. We will code events and diagnoses where the medical record and the patient narrative overlap (such as accounts of prescriptions taken or of visits) but also where they diverge - such as in discrepancies between formal diagnoses and patients' understandings of their illnesses, and instances where the medical system did not register areas of respondents' concerns or experiences (such as domestic abuse or poverty). Rather than treat the medical record as the official, objective diagnosis compared with the subjective experience of this diagnosis in the interview, we aim to treat both the electronic health record and the narrative transcripts as two different stories being told, one by the health system and one by the patient. Moving back and forth between the electronic health records and the narrative transcripts, we begin with line-by-line coding that identifies patterns in how these two stories coexist.

Analysis Approach

Examples from Preliminary Data

For poor white women patients, we often found a dramatic difference between the EHRs and interview transcripts in understandings of causes for pain and disease, as well as strategies for healing. Specifically, formal diagnostic language seen in the EHR was rarely used in white women's interviews, which instead focus on social sources of suffering, especially poverty, trauma, and violent relationships. We also found that these women were frustrated and embarrassed by their lack of adherence to the physician's recommendations in the EHR. When they cannot afford to follow doctors' advice or have limited resources for healthy eating or returning to the doctor, they turn to self-treatment strategies such as eating, smoking, remaining in unhealthy relationships, and taking illegal drugs. The imperative to care for others makes caring for oneself too burdensome for these women in the face of financial constraints. The interviews uncover a sense of shame over these decisions, one that is magnified by their social interactions with employers, caregivers, and social service providers. Finally, we uncovered a pervasive sense of distrust in the medical profession, which women view as over-prescribing medication and prioritizing profit over care.

To provide an example from Stage 1, the EHRs from Central Health System show that Bree (a pseudonym), a white female, first entered the system in 2004 at the age of 26. She was a smoker. Bree returned for care multiple times in 2004, including separate visits for an "unspecified mood (affective) disorder"; back pain diagnosed as a sprain; and an eye infection. She was prescribed Effexor, an antidepressant. Bree returned to Central Health System in 2011, where she was treated for generalized anxiety disorder and panic disorder. During the next five years, she suffered from chronic pain and mental health conditions. She was prescribed generic Xanax. Ultimately, she was referred to rehabilitation medicine and the neuropsychology department for chronic pain and was diagnosed with fibromyalgia. In 2012, Bree was prescribed three different antidepressants: amitriptyline HCL, duloxetine HCL, and citalopram hydrobromide. She received multiple prescriptions for pain, including oxycodone-acetaminophen (Percocet), opioid agonists (Tramadol HCL), glucocorticosteroids, NSAIDs medications, and muscle relaxants.

In her interview, Bree details a decade of low wages as a waitress and domestic abuse from a former husband. We do not know if Central Health System is aware of the sources of Bree's pain and anxiety, as she admits to being "embarrassed" about the domestic abuse. She describes: "My first husband did this to my teeth [she points to two gaps in her mouth where there should be canine teeth]. He bent me over the baby's crib with her in it backwards. I literally was in half, so I deal with that. I don't go to the doctor for it. They want to send me to this specialist, that specialist, a psychiatrist to deal with the pain, living with pain. I don't even go. I just don't even go, because, honestly, pain medication doesn't really help me." Bree states simply: “my body is destroyed on the inside.” The pain medication “tended to make me sleepy a lot, so I stopped taking it.” She suspects she is “allergic” to the antidepressants she was prescribed: “They throw me off the reservation. They just make me real angry. It may even be in my chart that I’m allergic, because they’ve tried just about every single one for me.” Bree is reluctant to return to Central Health System because “it almost seems like they give you a lot of things that you don’t really need. Like, they send you to a lot of different doctors…” Another doctor prescribed both “Percocet and Dilaudid? They’re both painkillers. Why do you need both? He just would just shove so much shit in my face. I asked for physical therapy and he got pissed off.”

She says heatedly: “I was going to a psychologist, whatever the hell that is. I was going to, um, a neurologist. Um, they had me going to a pain specialist, and then physical therapy, and then a psychiatrist, or a psychologist, to talk about my pain. I said, *let’s talk about the gas money to get to [the specialist] every day*.” When Bree’s electricity was shut off last year, she and her children slept on her cousin’s pull-out couch for three weeks while she saved up enough money to turn the heat back on. A severe lack of financial resources forces Bree to choose between having her garbage collected at $3 a bag or providing food for her family. She says desperately, “I gotta choose whether to feed my kids or get fined for my trash.” Although she knows she needs to quit smoking — “if my mother died from this I will, so, like, if I don’t stop soon…I mean, I’m almost 40” — it keeps her from “ending up in the loony bin.”

As the case of Bree demonstrates, investigation of EHRs side by side with women’s personal stories revealed areas of convergence and areas of divergence between medical diagnoses, doctors’ advice, and patients’ lived experiences. It is often the case that patients simply cannot afford to follow doctors’ advice. We also see that Bree herself is overwhelmed by the sheer number of medications she is prescribed, suggesting that reliance on drugs to treat social problems is a normalized part of her care. The integration of patient narrative thus offers the possibility of fusing clinical diagnoses and practices with social determinants of health such as poverty, despair, and isolation.

Potentials of Adding a Diverse Sample

Based on in-depth interviews with women of color who moved to the coal region, Silva (2019) chronicles how these black and Latina women leave behind traumatic histories — stories of early childhood abuse and neglect, poverty, extreme neighborhood violence, and drug abuse. Upon arrival, these women face accusations that they are unfit mothers, have poor work ethics, and are undeserving of government aid. These women encounter multiple predatory institutions waiting to take advantage of their optimism. Living a life of emotional turmoil, relationship flux, racial hostility, and poverty, however, leaves these women emotionally raw, deeply distrustful, and physically depleted. For Stage 2 of this research, we propose to reconnect with 40 of these non-white women to interview them about their health and request access from Central Health System for their medical records with the goal of understanding how race compounds economic disadvantage and poor health in the coal region.

The case of respondent Stephanie provides insights into how electronic health records and an additional round of interviews focused on poverty and health can achieve this goal. Stephanie Rivera, a twenty-three-year-old woman who identifies as black and Puerto Rican, spent the early years of her life in a public housing project in Brooklyn, New York. When Stephanie was ten years old, her mother decided to move west to rural Pennsylvania, which promised more affordable housing, safety, and better jobs — "that's where everyone at the time was going, like everyone that wanted to get out of the city was going, and for her it was like, complete life-changing." Despite her mother's longing for peace and safety, their first apartment was "horrible"—"the landlord was this drug lord." She remembers: "A pipe busted and I don't remember if it was in the kitchen or the basement and we kept saying like our water bill was getting higher and higher and higher, and finally it burst, to a point where you stepped foot in the living room, your foot would go in the rug cause there was so much water. We couldn't live there." After high school, Stephanie got a job at a discount smoke shop that she could walk to, while her boyfriend got a job working in the shipping and receiving department at Walmart. The neighbors, however, "were like doing drugs there, and they caught a sofa on fire and it came into our house. It was horrible. And then we were homeless for three weeks cause we lost everything. I was three months pregnant. When I say we lost everything, the only thing we had was the clothes on our back, the phones cause we all sleep with our phones."

Stephanie's initial interview reveals how institutions, health, poverty, and race work together to shape life chances. When she was pregnant, she explains, she went to the local doctor and insisted something was wrong. At twenty-nine weeks "I kept saying I thought my water broke 'cause I had like fluid leakage. They said nope, it's not water, it's normal discharge. It was amniotic fluid coming out." It turned out she had preeclampsia, a serious and sometimes fatal complication. Stephanie finally went to a large hospital about twenty miles away with a more advanced maternity unit. She learned: "my preeclampsia was so severe. They explained to me what it was, high blood pressure during pregnancy. So I was high risk since I was twenty-nine weeks all the way to thirty-eight weeks and no one told me. And nobody said anything. I was working all the time. Always on my feet." To make matters worse, she adds, the doctors "thought I was on drugs because of how small she [her daughter] was, but it was because they neglected my pregnancy. She wasn't getting the nutrients due to preeclampsia. She was born five pounds. Itty bitty little thing." Stephanie, who does not smoke or drink alcohol, continues with outrage: "They tested her without my permission for alcoholism and marijuana and all of that. So they came out, 'Oh yeah by the way she doesn't have alcoholism' and I was like wait, what? They said, 'Oh yeah, we tested her.'" Stephanie suspects that the hospital workers automatically assumed that she was a drug addict because she was poor and not white.

Stephanie mostly stays in the house and takes care of her daughter. "I don't really go out besides work. Would I walk around at night? No. No," she says firmly. "There's a lot of drunk people around here, just stupid things. One time when I was trying to drive away, is when they was doing the fireworks [during the Fourth of July], I had a crowd of people around my car yelling the n-word and all this at me. My daughter's crying in the backseat, 'cause she didn't understand what's going on. It was horrible. It was the worst. I cried, I never cried so hard in my entire life." Stephanie's skin color clearly marks her as an unwelcome outsider in her rural community, increasing her isolation and fear in ways that could impact her health. Stephanie connects her fear of walking outside to her recent weight gain: "I just can't stop gaining weight." Stephanie's original interview suggests that both poverty and racism shape women of color's health experiences and behaviors on the one hand, and that negative interactions with the medical profession may increase distrust and isolation, stymieing potential opportunities for escaping poverty. Pulling the electronic health records and re-interviewing Stephanie more specifically about her health and mobility offers the possibility of deeper understanding of how the dual mechanisms of economic disadvantage and racial identity impact women's physical and emotional well-being. Furthermore, a nonwhite sample will allow us to explore possible racial patterns in medical treatments; for instance, while we see Bree prescribed multiple opioid medications, Stephanie is suspected of drug addiction in her medical encounters; both experiences affect their sense of trust, behaviors, and well-being in different ways.

Project Work Plan

This proposed research will be conducted over two years (January 2020 – December 2021).

Pre-Award Research Activities **(September 2015 – August 2019)**

- May 2015 – December 2016: Forged community connections in Central Pennsylvania and conducted 120 in-depth interviews with poor and working class residents, both male and female.
- June 2017 – May 2018: Conducted 13 semi-structured interviews with white women in Central Pennsylvania exploring experiences, worldviews, and formal barriers to health care (research funded by Bucknell Central Health System Research Initiative 2017).
- January – December 2018: The development of a new methodology for the integration of interview and EHR data. New data-sharing protocols were established, in collaboration with administrators from Central Health System and Bucknell, to merge data from both study teams while maintaining participant confidentiality (see Appendix A). The interdisciplinary team also established novel approaches to analyzing a dataset that includes both interview and EHR data. Initial analysis conducted, linking narratives with electronic health records.
- May 2019: Preparation of data collected — 13 transcribed interviews and 13 electronic records decoded.

- May – August 2019: Conducted, and to conduct an additional 27 interviews with white women, and collected additional electronic data, including free-text physician notes (research funded by Bucknell Central Health System Research Initiative 2019).
- August – December 2019: Additional interviews to be transcribed and electronic health records pulled and decoded.

***Year One* (January 2020 – December 2020)**

Silva, Durden, and Hirsch will oversee data collection for the sample of 40 black and Latina women and analyze data for the combined sample of 80 women. Ongoing research will be presented at academic conferences and submitted for publication.

- January – August 2020: Semi-structured interviews to be conducted with 40 non-white female respondents.
- March – December 2020: Interview subjects will be linked with their electronic health records; newly collected interviews will be transcribed; data from discrete electronic health record fields to be extracted — diagnosis codes, medication orders, medical procedure codes, etc.; extraction and summary of free text clinician notes will be documented during clinical encounters.
- August 2020: Conference paper to be submitted and presented at the American Sociological Association Annual Meeting in San Francisco.
- November 2010: Article to be submitted to *American Sociological Review* on research involving Stage 1 collected data.

***Year Two* (January 2021 – December 2021)**

- January – November 2021: Interview data and electronic health records will continue to be analyzed, with particular attention paid to the role of race in economic disadvantage, physical well-being, and health care responses.
- August 2021: Conference paper to be submitted and presented at the American Sociological Association Annual Meeting.
- November – December 2021: Book proposal and sample chapter prepared for advance contract with press.

Qualifications and Responsibilities of Researchers

This team is uniquely equipped to complete the proposed research. **Dr. Jennifer Silva** is an assistant professor at the O'Neill School of Public and Environmental Affairs at Indiana University. She has extensive experience conducting qualitative research. Her first book, *Coming Up Short: Working-Class Adulthood in an Age of Uncertainty* (Oxford, 2013), examines the transition to adulthood for working-class youth. Her new book, *We're Still Here: Pain and Politics in the Heart of America* (Oxford 2019), investigates how working-class residents in rural Pennsylvania respond to the decline of the American Dream. Additional scholarship has appeared in the *American Sociological Review, Social Forces*, and the *Journal of Consumer Research*. **Dr. T. Elizabeth Durden** is an associate professor of sociology at Bucknell University. Her research encompasses race and ethnic inequalities within the United States, the sociology of immigration, and medical sociology. Her research has been supported by a Fulbright Hays Faculty Research Award and the National Endowment of Humanities, and has been published in the *International Migration Review*, *Journal of American Ethnic History*, *Journal of Immigrant and Minority Health*, *Social Science and Medicine,* and other scholarly books and journals. **Dr. Annemarie Hirsch**, associate professor, focuses on novel applications of health system data to measure health outcomes, health care quality, medication adherence, and the epidemiology of chronic conditions such as diabetes and obesity. Dr. Hirsch secured a $3 million grant from the CDC to evaluate the role of social and community factors in type 2 diabetes incidence and control. Her research has been published in *Health and Place*, *JAMA*, *American Journal of Preventive Medicine,* and *Medical Care Research and Review,* among others.

The proposed research falls within the scope of scholarship and expertise for each investigator. Successful working relationships have already been established from previous funded research and demonstrate our ability to collaborate. Durden and Hirsch collaborated on research which illustrated the key roles of community resources and socioeconomic deprivation in influencing the effectiveness of formal health care, recently published in *Diabetes Care*. Silva, Durden, and Hirsh collaborated (2017–18 and 2019–20) for a pilot of the research proposed here that successfully established (1) new data-sharing protocols, in partnership with administrators from Central Health System and Bucknell, to merge data while maintaining participant confidentiality (see Appendix A); and (2) novel approaches to analyzing a concatenated dataset that included interview, EHR, and physician free text data.

Responsibilities of this project will be shared by all three co-principal investigators. Drs. Silva and Durden will take the lead on collecting the qualitative interviews while Dr. Hirsch will gather the EHR and physician notes. As previously discussed (see Research Methodology), all three collaborators will be involved in the analysis of the data and the writing of academic articles and manuscripts. In regards to a public release of the data, as detailed in “Transparency & Reproducibility,” the investigators request that Russell Sage consider an exception for this project due to the nature of the data (both qualitative and medical records). This research, which explores barriers to social mobility and health in a declining coal mining community, will be reported and shared at professional meetings, by peer-reviewed journal articles, and in book format.

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Appendix A: IRB Approval Process

Previous Grant Support: This research has previously been funded by two grants from the Bucknell Central Health System Research Initiative (2017–18: $20,000 and 2019–2020: $78,380).

The proposed research design, informed consent process, and data collection instrument was approved by IRBs at Bucknell University and Central Health System in December 2017 and renewed in May 2019. The IRBs at both the university and the hospital system have required us to adhere to Health Insurance Portability and Accountability Act (HIPAA) Health Information Technology for Economic and Clinical Health Act (HITECH Act) regulations. For Stage 1, we went through a six-month approval process that resulted in the creation of a data use agreement between Bucknell and Central Health System. For the Stage 2 research being proposed, we will modify the existing IRB to allow for 40 additional women to be interviewed. Our data use agreement between the hospital system and the university specifies the following procedures:

Step 1: Researchers at Bucknell University sends the names, dates of birth, and transcribed interviews of interviewees who consented to release their Central Health System data.

Step 2: Central Health System pulls de-identified medical record data on these patients.

Step 3: Central Health System merges the de-identified medical record data with the corresponding interview transcript.

Step 4: Central Health System replaces patient identifiers originally provided by the university with a randomly generated patient ID.

Step 5: Central Health System sends the university a completely de-identified dataset that merges medical record and interview data.

Step 6: Bucknell University researchers do not make any attempt to link the de-identified dataset back to any identifiable information that they may have collected during their interviews.

Appendix B: Interview Guide

Introduction/Background Questions

1. Would you tell me a little bit about yourself? How old are you, and where did you grow up? Where were you raised?
2. What did your parents do for work? Mother? Father? Other?
3. When you were growing up, were your parents married (or: never married, divorced, living with new partner, re-married)? If divorced, when? Whom did you live with? If partnered/remarried, when and to whom? How did your life change after the divorce/remarriage/new partner?
   – Probe: less attention from parent, financial hardship, adjusting to step-family.
4. Can you remember times when your parents seemed to struggle economically? Was there a time when they couldn't pay the bills, or worried about money? How did they talk about this? What did they do about it?
5. How would you compare yourself to your own parents? Do you think you will end up like they did?
   – Probe: financially but also as a person.

Current Life Questions

6. Can you walk me through a typical day in your life (from when you get up to when you go to bed)?
7. What jobs have you had, and where have you worked? How did you get those jobs?
8. Where would you say are the best opportunities around here for work? Why?
9. How competitive are these jobs? What stands in your way of getting them, if applicable?
10. Do you know people who have or have you ever left the area for better opportunities?
11. What keeps you here (in the area you currently live in)?

12. Would you move to a city for better jobs? To Lewisburg, to Philly?
13. Do you have a pension, disability pension?
14. Are you able to pay your bills? What kinds of bills do you have to pay?
    – Probe: income security, debt, do they get benefits like health insurance, and for how much?
15. How would you define your current standard of living? Do you have any assets like a house or a savings account?
16. Who do you live with? How long have you lived there? How did you make the choice to live there?
    – How does it compare to the neighborhood where you grew up?
    – Can you get everything you need nearby?
17. Do you feel like you can make ends meet? How do you do it? Do you ever worry about making it to the end of the month?
18. Would you say your income fluctuates substantially over the course of a year? Would losing your job, getting sick, or breaking up with your partner force you to dramatically reduce your assets, and/or significantly re-adjust your living standards?
19. How do you feel about your standing at work? Why? Do you think there are opportunities for promotion?
20. Have you ever received any kind of assistance like WIC (women, infant, children) or SSI (supplemental security income)? How did you find out about these? How do you feel about getting this kind of support?
    – Probe: SSI, food stamps, Section 8 housing.
    –Are you eligible for the EITC (earned income tax credit)? Do you claim it?.
21. Have you ever been arrested? Convicted?
22. Thinking about all we just discussed — when you were younger, did you imagine your life turning out this way?

Health Questions

23. Can you tell me about your physical health? What kinds of health issues are you currently experiencing? – Probes (diabetes, obesity, blood pressure, back pain).
    a. Who helps you with these health issues? Family, friends, church doctors?
24. Are you in pain right now? What hurts?
25. What have you been diagnosed with? Who diagnosed you? When were you diagnosed?
26. Tell me about your history of health issues. Have you had any major health issues?
27. When you have pain, does it prevent you from working?
28. How would you rate your mental and emotional health? Are you stressed out?
    a. How do you cope with stress?
    b. Do you take medication for stress?
    c. What do you think is causing your stress?
    d. Who do you turn to for help with your stress? Family, friends, church, doctors?

29. Can you tell me about the last time you went to the doctor?
    a. Where did you go?
    b. Why did you go?
    c. What doctor did you see? Have you seen this doctor before? How did you choose what doctor to see?
    d. How did you feel about the visit?
    e. How did you get to and from the appointment?
    f. How did the doctor explain your health to you?
    g. What did the doctor do for you? Prescribe a medication? Send you to another doctor? Talk about smoking, exercise, eating?
    h. Did you take their advice? Why or why not?
    i. Did they spend enough time listening to you?
    j. Do you trust your medical doctor?
30. Have you ever been unable to get an appointment with a doctor you thought you needed to see?
31. Have you ever been unable to pay for what you needed in terms of health care?
32. (If applicable.) What was your experience with Central Health System like when you were pregnant? How was your experience giving birth?
33. Do you smoke? Do you drink? Do you have a history of using illegal drugs?
    a. Why do you do it? What does it do for you?
    b. Do you tell your doctor this information?
34. Do you receive health care outside of Central Health System? Why or why not?
35. How do you think your experience with doctors and Central Health System compares to what you have heard from your family and friends? Have family and friends had good/bad experiences getting care?
36. How do you pay for medical care? (If on governmental assistance: how long? Where did you get it? How were you treated?)
37. Have you ever experienced violence (either in an intimate relationship or childhood)? Did you feel like you were able to get the help you needed?
    a. Did you stay in the relationship?
    b. Did a doctor ever ask you about this experience, if applicable?
38. What would you like to change about your personal health? Do you feel like you are in control of your health?
39. What would you like to change about your health care/the way you receive healthcare?
40. Do you worry about your children's health?
41. Do you trust the health care your child receives?
42. Whose responsibility is it to manage your health? (The government, you, your employer…)
43. Do you have people in your life that you trust? That you could rely on for rides, childcare, or to sleep on their couch? How about to borrow $30?

44. Do you trust social institutions, like the government? The police? Schools? Why/why not?
45. Do you feel hopeful about your future? Do you think there is opportunity for your children to achieve a good life?

Perceptions of Education Questions (specific to college experience that relocates)

46. Is/was going to college at a four-year school (that relocated you, like Bloomsburg, Wilkes, Bucknell) ever in your plans?
    – Follow-up: what would make going to college possible for you? If in your plans, what has stood in the way of you attending college or completing a degree?
47. Do you know anyone (family members, neighbors, friends?) from your community who went to a college where they had to leave their hometown area? How well did you know them before they started school? How far away did they go? Did they come back after they finished college?
48. What do you think college should do for people? If you received a degree, what changes would you expect to see in yourself and your life? Thinking back to the person(s) you described in the previous question, what changes, if any, did you see in them after they went to college?
    – Probe: How they interact with others, who they interact with, ways they speak.
49. What value do you see in obtaining a college degree? Is it worth the debt?
50. If you (or your child) got a college degree from somewhere like Bloom, Bucknell, or Wilkes, would you want to come back to get a job in this area? Or do you see college as something that would allow you to move you somewhere else? What would moving somewhere else mean to you? How connected do you feel to your 'home' area, wherever that is?
51. Have you ever had to move away from home for a time? Why did you have to move away? What was your experience like coming back?
    a. Follow up: if this (where you are now) is your temporary location, how do you feel about returning?

SAMPLE PROPOSAL #3

The racial wealth gap, 1860-2020

Ellora Derenoncourt (UC Berkeley), Chi Hyun Kim (DIW Berlin, Free University of Berlin)

Moritz Kuhn (University of Bonn), Moritz Schularick (University of Bonn)

March 8, 2021

1 Introduction

The racial wealth gap is the largest of the economic gaps between Black and white Americans, with a white-to-Black average wealth ratio of of 6 to 1 in 2019. Further, the gap has been remarkably stable over the late 20th and early 21st centuries. Although there is a large literature focusing on the wealth gap in recent decades, much less is known about the historical evolution of the racial wealth gap. In this project, we use historical Census data and state tax records, the historical and modern Survey of Consumer Finances ("SCF"), as well as additional data sources to document the evolution of the racial wealth gap over the last 160 years. A key contribution of this work will be a harmonized series of Black and white per capita wealth in the US from 1860 to 2020, which we will make publicly available.

Our project addresses the following questions: What has been the long-run evolution of the racial wealth gap? What factors have shaped the gap? We believe our findings will have implications for policies aimed at addressing racial wealth disparities.

Initial patterns in our data suggest that despite rapid accumulation of wealth by Black Americans in the decades after slavery and sharp episodes of income convergence during World War II and the Civil Rights era, racial wealth convergence stalled by the mid-20th century. We hypothesize that vastly different starting conditions and differential returns on wealth for Black and white Americans have contributed to a racial wealth gap approaching a "steady state," close to today's levels. We contribute some of the first evidence on the racial wealth gap during the mid-20th century as well as racial differences in wealth portfolios and returns on wealth during this time period as well. Finally, our project will shed light on the efficacy of policies such as reparations, baby bonds, and wealth taxes in accelerating convergence.

Substantial scholarship examines the contemporary racial wealth gap and its determinants, and a smaller literature documents Black wealth gaps in the immediate decades after Emancipation, yet there is no work to date on the evolution of the racial wealth gap over this full historical period. Through an ambitious data collection and harmonizing effort drawing on several data sources, we are working to fill in this missing time series of the racial wealth gap from 1860 to 2020. We collect information and harmonize across the following sources: state-level tax records, the Census of the Population, the Census of Agriculture, data on Black banks, and a harmonized version of the Survey of Consumer Finances spanning 1949 to 2019.

Our preliminary long-run series suggests two important facts about the long-run evolution of the racial wealth gap. First, the period of fastest convergence was the 50 years following Emancipation. Second, starting in the mid-20th century, convergence came to a halt, with racial wealth gaps slightly worsening over the last several decades. If present trends in the data continue, the racial wealth gap appears to be headed to a steady state with average white wealth at least five times greater than average Black wealth.

We rationalize this "hockey-stick" pattern in the long-run wealth gap with a simple model of wealth accumulation for each racial group. This framework reveals that even under equal conditions for wealth accumulation, in other words, equal capital gains, rates of return, and savings rates, and with the observed level of income convergence since 1870, the racial wealth gap would still be 2 to 1 in the year 2100. Further, the true evolution of the wealth gap shows even less progress than this stylized model. To understand why, we explore differences in wealth accumulation conditions faced by each group.

The harmonized SCF developed by Kuhn et al. (2020) allows for an in-depth study of the racial wealth gap over the second half of the 20th century, beginning roughly two decades before other commonly used sources, such as the PSID. The data allow us to document differences in portfolio composition, capital gains, returns on wealth, and income saved by racial group over this 70-year period. These differences shed light on the slow rate of convergence between Black and white households. For example, Black households tend to hold more wealth in housing and less in stocks relative to white households. While housing wealth has appreciated since 1950, stock equity appreciated by five times as much, leading white households to have enjoyed far greater capital gains over this period. Savings rates also differ by racial group although these differences can also be attributed to factors such as initial wealth, education, and age. These patterns point to potential mechanisms through which the gap persists or through which it might be ameliorated.

After documenting these patterns using the historical SCF, we examine counterfactual scenarios under which wealth convergence could occur within a reasonably short time frame, for example by 2050. We begin by choosing capital gains, rates of return, income growth rates, and savings rates for Black households that would lead to convergence by this date. The results of this exercise highlight how implausible convergence is via manipulation of any of these parameters. In short, Black households would have to be endowed with orders of magnitude greater income growth, savings rates, and rates of return to close the racial wealth gap by 2050.

In a final section, we discuss the implications of our findings for policies aimed at reducing wealth inequality and the racial wealth gap. We note that policies such as a wealth tax or baby bonds may induce virtuous cycles by not only improving the relative wealth position of Black households, but through feedback effects that close gaps in savings rates and rates of return, for example. Still, such policies are likely insufficient for addressing the vastly different starting conditions for Black and white Americans as a legacy of slavery. The wealth gap has largely followed a pattern of convergence in line with simple models of wealth accumulation under these starting conditions. Policies such as reparations may be the most effective at hastening convergence under these conditions.

Our project contributes to several strands of literature on racial wealth differences—both historical and contemporary. A number of papers study the racial wealth gap in the post-Emancipation years using state-level tax records and historical Census data. We review this literature and our contribution in detail in Section 2. A large literature focuses on the racial wealth gap and its determinants in the modern era.[1] This work has documented the role of marriage and family structure, income and demographics, differences in permanent income, inheritance, life cycle effects, the role of the Great Recession, and finally a suite of policies with potential for ameliorating the gap. Our paper contributes to this literature by providing historical perspective on the racial wealth gap. We

[1] An incomplete list of such works include Altonji et al. (2000); Altonji and Doraszelski (2005); Barsky et al. (2002); Charles and Hurst (2002); Chiteji and Stafford (1999); Gittleman and Wolff (2004); Wolff (2001).

show that only extreme distortions of savings rates, income growth, and capital gains can overcome the slow rate of convergence determined both by the starting conditions in the wealth gap and in decades-long disadvantages in wealth accumulating conditions for Black Americans. Policies that do not directly address the initial conditions of the racial wealth gap may be insufficient for bringing about convergence.

Our proposed project also contributes to the literature on wealth inequality and its long-run dynamics (Piketty, 2013; Piketty and Zucman, 2014; Saez and Zucman, 2016). These papers document rising wealth inequality in the 20th and 21st centuries, analyzing the role of returns on capital and rising top incomes, among other factors. We adopt a simple framework inspired by this literature to understand the evolution of the per capita white-to-Black wealth ratio over the last 160 years. The most simplified version of the model matches the basic shape of the long run gap we observe in our newly harmonized data. Allowing for differing wealth accumulation conditions per racial group enriches our simulation of the racial gap and generates an even better fit with the data, capturing in particular the complete stagnation and even reversal of racial wealth convergence in recent decades.

The rest of our proposal is structured as follows. In the next section, we review the literature on historical differences in wealth accumulation by Black and white Americans. Section 3 describes the construction of our long-run series on the per capita white-to-Black wealth ratio and our initial results. Section 5 provides a simple framework for wealth accumulation by racial group over the long run. In Section **??**, we utilize the newly harmonized historical and modern SCF to document differences in wealth portfolios, savings rates, capital gains, and return on assets by racial group dating back to 1950. Section 6 discusses counterfactual and policy scenarios that speed up wealth convergence, and Section 7 provides our project-work plan, qualifications and responsibilities of the researchers, and a description of how are results will be reported. We also include our plan for the public release of our data and documentation. Information on the data collection effort is detailed in Appendix B.

2 Related literature on the historical racial wealth gap

The limited availability of wealth data for Black and white individuals before 1968 has restricted much of the analysis of the literature to recent decades. Nevertheless, a number of papers investigate trends in Black and white wealth formation in the late 19th and early 20th centuries. These studies have largely relied on property tax records from select Southern states that tabulated assessed wealth or tax payments separately for Black and white populations.

Du Bois (1901) uses tax records for the state of Georgia to document patterns in landholding by Black individuals in that state. Higgs (1982) uses race-specific data from Du Bois (1901) and the Comptroller-General of Georgia to illustrate a substantial increase in the total assessed value of Black wealth in Geoargia over the period 1874-1915. Margo (1984) incorporates property tax data with race identifiers for available years from the additional states of Louisiana, North Carolina, Virginia, and Kentucky where he likewise finds sustained increases in aggregate Black wealth and declines in the per capita wealth gap in all of these states but Louisiana. Margo (1984) argues that the part of this growth may be due to discriminatory over-assessment of Black-owned property for tax purposes—a pattern that has been documented in tax assessment today (Avenancio-León and Howard, 2019)—but Higgs (1984) argues there is limited justification for this claim.

Several studies have modeled and empirically demonstrated the critical role of the post-Civil-War racial disparity in wealth endowments for continued inequality in this period and beyond. Using the same tax data from Georgia, the first study in this vein by DeCanio (1979) estimates that this initial wealth disparity accounts for 64-80

DeCanio (1979) uses a theoretical model to show that the redistribution of "40 acres and a mule" to Black families would have substantially improved their relative position, but in the best-case scenario would have only allowed Black families to eventually achieve half of per capita white wealth. Miller (2020) studies the impact of land grants to Black families in the Cherokee Nation after emancipation and finds reductions in the racial wealth gap in the Nation relative to the rest of the South.

Beyond this key early period, qualitative work has pointed to potential differences across states in the number of Black businesses and prosperous individuals that warrant investigation and/or confirmation by the quantitative methods crafted for this proposal. Specifically, two related studies, Schweninger (1989) and Schweninger (1990), show that a wealthy black entrepreneurial and planter class composed of freed Black people before the Civil War in the Lower South, especially in New Orleans, Charleston, and several other Louisiana parishes. Importantly, however, Schweninger (1989) claims this group?s wealth largely deteriorated by 1870 whereas an emergent urban Black population in the Upper South continued to gain wealth by becoming farmers, skilled artisans, and small business owners, beginning in the 1840s, but especially after emancipation. A study by Canaday (2008) uses individual property tax assessment records for Calhoun County, South Carolina matched to complete count Census data and finds that both Black men and women experience faster wealth accumulation than white individuals between 1910 and 1919.

A related literature focuses on racial inequality in homeownership. Collins and Margo (2011) traced the evolution of the racial homeownership gap from 1870 to 2007. The gap narrows in the 1870 to 1920 period but shows remarkable stability thereafter. These data do not incorporate information on the value of homes, however, which is only available starting in 1930 and for which complete count census data do not exist after 1940 (the full count 1950 census will not be declassified until 2022). A study by Akbar et al. (2019) documented how neighborhood racial transition in 10 northern cities during the first Great Migration led to changes in rental and house prices that eroded the value of Black homes and thus posed a barrier to Black wealth accumulation by 1940.

In prior work of two of this current project's coauthors, Kuhn et al. (2020) harmonized the historical and modern files of the Survey of Consumer Finances (SCF) creating a new dataset of household level wealth and income information for the US from 1949 to 2016. Although primarily focused on the role of asset prices and portfolio composition in wealth dynamics in the postwar period, the authors also provide a brief analysis of the racial wealth gap confirming stability and persistence in this large gap over the postwar period.

Our project will provide the first comprehensive picture of the racial wealth gap from the Civil War through the present. A key contribution will be a harmonized series of Black and white wealth per capita created by drawing on a large number of different data sources. The next section describes these sources and our methodology for constructing the historical series in detail.

3 Data sources on historical wealth measures by racial group

We investigate the evolution of the racial wealth gap using a variety of state- and national-level sources. Specifically, our wealth data were assembled from state fiscal reports (1866-1916); the US decennial Census (1860 and 1870); aggregate Black wealth estimates by Monroe Work (1863-1936); and the historical and modern Survey of Consumer Finances (1949-2019). Additionally, we use population data from the Census as well as the Census Bureau's report on the U.S. Black population from 1790 to 1915.

For the state-level data in the years following Emancipation, we follow the method of Higgs (1982) and Margo (1984). In doing so, we used the website HathiTrust Digital Library (https://www.hathitrust.org/) to access annual tax auditor reports for available Southern states in available years in the period 1866-1916. Data were obtained directly from such reports for the following states: Louisiana, North Carolina, Virginia, Kentucky, and Arkansas. These reports provide either county-level aggregates of assessed wealth by racial group or aggregate tax payments by racial group. In the latter case, we imputed Black and white aggregate wealth by assuming the Black-white ratio of property tax payments equalled the wealth ratio and multiplying the former by the state's reported aggregate wealth for that year or an adjacent year, drawing from the imputation strategy employed by Margo (1984). We also included similar data from Georgia, which had been previously assembled by Du Bois (1901). To complete the early state-level dataset, per capita wealth observations from Margo (1984) were combined with population figures to calculate aggregate wealth levels by race in years where the corresponding state fiscal report was not found online. Figure 1 depicts an excerpt from the Virginia state auditor report for the fiscal year ending in 1904.

For national wealth aggregates and per capita measures for the late 19th century, we rely on the US Decennial Census for the years 1860 and 1870.[2] Census enumerators were instructed to record personal property for those with at least $100 and real property for all. The 1850 Census only recorded real property, therefore we begin our analysis in 1860, prior to Emancipation and the Civil War. The 1860 Census of Population does not include a count of the enslaved, who were enumerated in separate slave schedules. We use the Census's 1918 publication "Black Population 1790-1915" to obtain estimates of the Black population in 1860 Cummings and Hill (1918). The 1870 Census of Population is the first full accounting of the Black population in the United States.

Currently, for additional estimates of Black wealth at the national level in the early 20th century, we digitize figures from *The Negro Year Book* (Work, 1922) in select years between 1863 and 1936. While information on Work's methodology is limited, the estimates seemingly incorporate extensive research conducted by Work on the growth of Black churches, farmlands, businesses, and other assets on top of additional indicators of Black social and economic progress. Notably, Work includes

[2]We use the IPUMS version of the complete count censuses for these years (Ruggles et al., 2020).

state-level wealth estimates in his yearbooks that are consistent with the data we digitized from state auditor reports, suggesting these state-level records figure prominently in his estimation of national Black wealth. Work's national Black wealth estimates are low compared to the 1870 Census; however, once the levels are adjusted, the trend matches well with the data from Census and the historical SCF, available from 1949 onwards.

For the years 1913-1936, we also incorporated estimates from Saez and Zucman (2016) on aggregate wealth for the United States. We subtract from these estimates Work's estimates for national Black wealth to generate a proxy for national white wealth during this period.[3] Given the demographic makeup of the country during this period and patterns of wealth-holding in the Census, we believe this generates a reasonable estimate of white national wealth.

Finally, from 1949 to the present, we utilize a newly harmonized series of the Survey of Consumer Finance (SCF+), which provides micro-level data on households' socioeconomic characteristics and wealth composition. The SCF+ is an extension of the Survey of Consumer Finances (SCF) provided by Kuhn et al. (2020). Before the modern Survey of Consumer Finances (SCF), which the U.S. Federal Reserve Board has conducted every three years since 1983, the Survey Research Center of the University of Michigan gathered data on household income and wealth along with their demographics at an annual frequency from 1947 to 1971, and again in 1977. Kuhn et al. (2020) extract this historical data based on the original codebooks and match the variables across the historical and modern waves. The final dataset allows us to study the joint distribution of income and wealth consistently over the period from 1949 to 2019.

Wealth in the SCF+ comprises marketable wealth, which is the current value of all marketable assets net the current value of debts. Assets include liquid assets (certificate deposits, checking and savings accounts, call and money market accounts, housing and other real estate, bonds, stocks, corporate and non-corporate equity, and defined contribution retirement accounts. Total liabilities are the sum of housing debt, car loans, education loans, loans for consumer durables, credit card debt, and other non-housing debt. We exclude social security and defined benefit pension claims, which are not available over the full period. Using these data, we compute decadal averages of per capita wealth by race.

[3] We have also identified an alternative source for national wealth: the US Census Bureau report on "Wealth, Debt, and Taxation" that was published in 1907, covering national wealth and state breakdowns from 1850 to 1904. We plan to compare the growth rate and levels of wealth in these data to the estimates from Saez and Zucman (2016).

4 Long-run trends in racial wealth inequality

We construct our long-run series on the racial wealth gap by combining data from the several sources described above. In this section, we first describe the insights that can be gleaned from state-level auditor reports on wealth accumulation by Black Americans after the Civil War and compare our results to those of Margo (1984). We then describe the methodology used to derive a long-run wealth series combining information from state reports, Monroe Work's national Black wealth estimates, and the US Decennial Censuses of 1860 and 1870. The construction of this series will require some assumptions and adjustments to harmonize the data sources over time that we discuss below.

Figure 3 plots our digitized data from state auditor reports on aggregate Black wealth by state between 1866 and 1916. Our findings are broadly consistent with Margo (1984), who finds that Black wealth accumulation was substantial over these years across the states in the sample.[4] We also find that the white-to-Black wealth ratio declines substantially in these states, consistent with the work of Margo (1984) and Higgs (1982).[5] Figure 4 depicts these results.

We now turn to our estimation of the national racial wealth gap using the data sources described above. The starting point for our analysis is the US Decennial Census data from 1860 and 1870. In the 1860 and 1870 Census, we have information on personal property and real estate for each person. We construct total wealth as the sum of the personal property and real estate of a person. Personal property is the contemporary dollar value of all stocks, bonds, mortgages, notes, livestock, plate, jewels, and furniture (in 1860, slaves are also included). Real estate is the contemporary dollar value of any real estate. The Census data cover the universe of enumerated individuals in the United States, an advantage over survey datasets. We assume that the enslaved, who are not enumerated in 1860, had no property, thus we impute zero wealth for the enslaved and obtain counts for the full Black population from the Black Population Census report (Cummings and Hill, 1918).

There are four challenges that arise with Census data. First, as in all survey-based data reported wealth in the Census exhibits substantial rounding. Second, values for personal property is not

[4] Here nominal aggregate wealth was adjusted to \$1910-1914 using the Warren-Pearson Index, following Margo (1984).

[5] In the reports identified by Margo (1984) for Louisiana, the only available data were 1) Black wealth for country parishes (outside of New Orleans or Orleans Parish), 2) white wealth for country parishes, and 3) total wealth for the state. Using the complete-count census data for 1870, we calculated the ratio of white-to-Black wealth in New Orleans in 1870 and used this to impute aggregate Black and white wealth for the entire state by assuming that the ratio for New Orleans is constant over the period. With this adjustment, the slowdown in wealth convergence in Louisiana is more muted than in Margo (1984). See Appendix Table 2.

collected if it is less than 100 dollars. This threshold applies to the vast majority of households, approximately 33 million out of 38 million observations. Third, real estate reports the gross value of real estate not taking into account any mortgage debt. Fourth, there is censoring at the top of the wealth distribution as personal property or real estate values are only reported up to 999,997 dollars. To deal with censoring, we provide below a sensitivity analysis with respect to the 100 dollar threshold that suggests that the effect is likely small and if anything tend to lower the racial wealth gap in 1870. For the censoring at the upper end of the distribution, we use a simple imputation approach. Using the estimate by Saez and Zucman (2016) on wealth concentration in 1913, we assume that the same wealth concentration applies to 1870. Saez and Zucman (2016) estimate that the richest 0.01 percent of households owned 8.8 percent of all wealth. We use the estimate of total wealth from Census (1907) to compute the total wealth owned by the top 0.01 percent of households.[6] We then compute per tax unit wealth in this group based on the population estimates and impute this value for all households who report real estate or personal property above the censoring point. Our estimate results in 3.4 million dollars of average wealth for these households.

Using the Census data, we group households in Black and non-Black households and compute average per person wealth. The ratio of these averages yields our estimate for the racial wealth gap of 20.2 in 1870. This racial wealth gap implies that for each dollar of wealth a non-Black person owned in 1870, a Black person owned 5 cents. There is no further wealth data from Census after 1870. To construct the time series for the wealth gap, we use the state tax records from Arkansas, Georgia, Kentucky, Louisiana, North Carolina, and Virginia. Based on the estimate for wealth owned by Black persons in these states, we construct an estimate for wealth growth over this time period by running a linear regression of log wealth on a time trend and state fixed effects. The estimated coefficient for the time trend is $\hat{\beta} = 0.057$.[7] We use this average time trend to extrapolate total wealth of the Black population after 1870 until 1904. We combine these estimates for the stock of wealth of the Black population with the estimates of total wealth from Census (1907) to construct wealth of the non-Black population as a residual. In a final step, we divide the stock of wealth for the Black and the non-Black population by the population in each group to get an estimate of per person wealth.

[6] We consider only reference persons when computing the number of households in 1870.

[7] The regression has an adjusted R^2 of 0.8236.

For the time period from 1910 to 1936, we rely on estimates for wealth of the Black population from Work (1922). Work (1922) provides estimates for wealth of the Black population going back to 1863. Using his available estimates to derive a growth rate of wealth for the same time period (1870-1904) results in a very similar growth rate of $\tilde{\beta} = 0.061$. His estimates for wealth of the Black population differ however substantially in level. Using his estimates around the time of the 1870 Census results in a wealth level of the Black population that is less than 20 percent of the Census numbers. We will therefore rely on the time trend from his estimates for the time period from 1913 to 1936 but we adjust the level of the resulting wealth gap to align with our estimates. For total wealth, we rely on estimates as reported in Saez and Zucman (2016) and construct wealth of the non-Black population and per person numbers as before. For the period starting in 1950 until today, we rely on the SCF+ data compiled in Kuhn et al. (2020). Kuhn et al. (2020) report racial wealth differences for the time period from 1950 to 2016 but consider wealth differences at the household level. We use the SCF+ data to construct per person estimates of the racial wealth gap.

Using the data from Work (1922) (see 2 below, we estimate an average wealth gap over the time period from 1913 to 1936 of 19.6, which is almost at the level of 1870. This level is substantially above our estimate for 1904 based on the extrapolated Census data (9.1) and the resulting 1936 estimate of 14.7 is also substantially above the estimate for the 1950s from the SCF+ data (6.2). We therefore adjust the level of the wealth gap based on the data from Work (1922) to match the linear trend of connecting our estimates until 1904 to the SCF+ data starting in 1950. The resulting adjustment factor is 0.515 so that the wealth gap is roughly cut in half compared to the unadjusted estimates.

Figure 5 shows the resulting time series. Our current long-run series shows the rapid convergence in the racial wealth gap after Emancipation, continued progress over the late 19th and early 20th century followed by stagnation. Remarkably, the racial wealth gap in 1920 was only moderately higher than it is today. In addition, it appears that convergence has completely stopped. The slope in the wealth gap after 1970 is slightly positive. Under these conditions, if trends continue as they have over the last four decades, there is no indication that further progress will be made in closing the racial wealth gap.

Our current long-run series is our best approximation of the national racial wealth gap from 1860 to the present given the data we currently have. Below we outline a number of ways in which we plan to improve these data.

Additional state-level tax records We have identified several sources of individual-level pre-World-War-II tax records from additional southern states and localities. Our plan is to link selected years for states that will maximize our coverage of Black wealth to complete count censuses where we observe an individual's race. This extends the method of Canaday (2008)–who linked individuals from a single county in South Carolina–to all counties in all states where records are available. Thus far, we have identified the following states where promising additional records are available: Virginia, Texas, Tennessee, and Mississippi. We have already begun digitizing tax records for New Orleans, for which race-specific property estimates are missing in the Louisiana state auditor reports. Our proposed digitization methods are detailed in Appendix B.

Census of Agriculture We also intend to use 1900-1940 Censuses of Agriculture which recorded information on farm values and farm ownership separately by racial group. Although these data provide information only on the farm sector, agriculture was a key sector of both employment and land ownership for Black Americans, particularly in the decades following Emancipation.

1930 and 1940 Census of Population The 1930 Census is the first to ask households about the value of their homes. Given the importance of real estate as a source of Black wealth as we document in Section **??**, the aggregate value of farms and homes owned by Black Americans will provide an important second estimate of national Black wealth prior to the SCF+ series, which begins in 1949.

Black banks Information on the deposits and liabilities of Black banks covering the period are available from Harris (1936), Work (1922), Stein and Yannelis (2020), and Ammons (1996). These data cover a time period that overlaps with race-specific farm ownership and farm values data from the Census of Agriculture as well as data on housing values from the Census of Population. We intend to use these data to refine our measures of Black wealth for the pre-WWII period and to provide additional information on the composition of Black wealth during this time period. The data on bank holdings are particularly important for non-southern Black wealth where agricultural land is a less likely source of wealth.

5 Determinants of the racial wealth gap

In this section, we introduce a simple yet intuitive theoretical framework to understand the long-run dynamics of the racial wealth gap documented in Section 4 and Figure 5. We start with the assumption of equal rates of return, capital gains, and savings rates across the two groups. Given starting conditions in wealth and income gaps in 1870 and observed growth in per capita income by racial group, we show that under these ideal conditions, wealth convergence is a distant, even unattainable, prospect. Still, under these conditions, the wealth gap would be about half the size it is today. We then address differences in (i) returns on wealth and (ii) saving rates across groups as potential determinants of the slower convergence of the racial wealth gap as observed in the data. Afterwards, we utilize micro-level household survey data of the SCF+ to shed light on the differences in these two components across racial groups.

5.1 Understanding long-run wealth gap dynamics

We start by introducing a simple conceptual framework of wealth accumulation to understand the long-term dynamics of the racial wealth gap. In the spirit of Garbinti et al. (2020), we utilize the following transition equation:

$$
\begin{aligned}
W_{t+1}^{j} &= (1+q^{j})\left[W_{t}^{j} + s^{j}(Y_{t}^{j} + r^{j}W_{t}^{j})\right], \text{where} \\
Y_{t}^{j} &= (1+g^{j})Y_{t-1}^{j}.
\end{aligned}
\tag{1}
$$

Subscription $j = \{b, w\}$ represents the two racial groups (b for Black and w for White), W_t^j and W_{t+1}^j the real per capita wealth of group j at time t and $t+1$, and Y_t^j the per capita labor income of group j at time t, which evolves with a growth rate g^j. In the equation, wealth is accumulated with regard to three distinct components: rate of return r^j, capital gains q^j, and saving rates of households s^j.

As a starting point, we assume that r, q, and s are identical across the two racial groups. The purpose of this exercise is to analyze how the racial wealth gap would have converged starting from Emancipation to the current period, if Black and White households faced equal conditions for accumulating wealth. The only difference we allow is their income growth; our estimates of annualized income growth indicate that Black income per capita grew at a higher rate than white (2.4% vs. 1.8%).[8] For r, q, and w we plug in the annualized average of the national estimates of Saez and Zucman (2016), which are $q = 1\%$, $r = 6\%$, and $s = 8\%$. We start with initial values that are in line with white-to-Black per capita wealth- and income ratios in 1870, which are 20:1 for wealth and 3.6:1 for income.[9] Figure 6 presents the evolution of the simulated wealth gap in comparison to our historical estimates.

Our simulated wealth gap (grey solid line) converges in a similar manner as the observed wealth gap (blue dots), where we observe rapid convergence from the post-Emancipation years until the early-to-mid 20th century, after which convergence slowed down considerably. After 1950, our simulation shows continued convergence while the observed wealth gap has stagnated or even worsened (in the 1970s, the slope is positive). In addition, the simulated wealth gap is always below the actual data, which suggests that if Black and white individuals had had equal wealth accumulation conditions in terms of returns, capital gains, and saving rates, the wealth gap would have been lower than it is today.

An additional question arises at this point: under equal conditions, would we be able to reach full wealth convergence in the near future? Table 1 presents the simulated wealth- and income gaps for the future periods. The real wealth- and income ratio of the year 2020 are in the first column, while column 2 to 4 present the simulated values in the year 2020, 2050, and 2100. Our results show that even under equal conditions, the wealth gap will not fully disappear within the next 200 years. 30 years from now, we would still have a ratio of 2.3:1, while the income gap is by 1.2:1. In the year 2100, by which time income will have fully converged, the wealth ratio would be still by 1.8:1. This is a striking result, as our simple exercise shows that (i) full income convergence will not be able to close the wealth gap, and (ii) even with equal wealth accumulating conditions, the initial conditions in 1870 are so severe that we may never experience racial wealth convergence.

In Appendix C, we analyze capital gains, yields on wealth, and saving rates by racial group using the historical SCF and show that there are indeed differences across Black and white households, with Black households having more or less worse conditions for wealth accumulation than white.

[8] For 1870, we utilize the historical income data of Margo (2016).

[9] Wealth ratios are from our historical wealth measure and the income ratio comes from Margo (2016).

Differences are especially pronounced in their capital gains, where white households have 60% higher rates, followed by gaps in savings rates. Yield differences, by contrast, are rather minor.

6 Policy implications: When (and how) will we reach convergence?

Based on the insights described above, we now look ahead and ask under what scenarios would we reach convergence in the racial wealth gap in the not-too-distant future. Figure 7 presents the evolution of the white-to-Black wealth ratio after 2020, plugging into our simulation equation (1) the values estimated for q, r, and s for each racial group from Appendix C. Once again, we draw annualized income growth rates from the data.

The answer, strikingly, is never. Rather, it seems that we are not far from a steady state white-to-Black per capita wealth ratio of 5:1 (the racial wealth gap today is 5.7:1). This is in line with the development of the wealth gap of the last 50 years, where convergence literally stopped.

If we instead assume that conditions for wealth accumulation were equal across racial groups (light grey solid line), the ratio would converge further; however, full convergence is not yet in sight. So what conditions would be necessary to bring about convergence in the near future, for example in thirty years from now? Further simulation exercises show that Black households would either need 12.5% income growth, a 33% savings rate, a 6.4% capital gains rate, or a 75% rate of return, see Figure 8. These can be compared to the rates for the white population, which we take from the data for income growth (1.8%) and from Saez and Zucman (2016) for the savings rate (8%), the capital gains rate (6%), and the rate of return (4%). However, as we observe in the data, it is not only unrealistic for Black individuals to experience these extremely high growth rates, but it is rather the case that they experience persistently *lower* capital gains, rates of return, and savings rates due to historical and ongoing discrimination in labor and financial markets.

Our results highlight the importance both of policies designed to address contemporary wealth gaps, which can also have feedback effects on rates of return and savings rates, but also policies that directly address initial conditions in the white-Black wealth gap stemming from the institution of slavery.

Among the former set of policies, a wealth tax for households in the top 0.1% wealth distribution would help slow the growth in the white-Black wealth gap stemming from existing wealth and labor income gaps. Another policy with potential feedback effects is baby bonds. Zewde (2020) analyzes the effect proposals like "baby bonods" would have on wealth inequality and the racial wealth gap by allowing young adults to start with higher wealth, crucial not only for building a base for wealth accumulation, but also for enabling investment in education. Black households would disproportionatey benefit from a progressive baby bonds policy.

Our analysis has shown, however, that even under equal wealth accumulation conditions in financial markets from Emancipation onwards, the white-to-Black wealth ratio today would still be 3:1, about twice as large as the labor income gap. Researchers and policymakers have introduced proposals such as reparations, which specifically target this legacy of slavery on the racial wealth gap. For instance, Darity and Mullen (2020) analyze in their recent book how payments of approximately $267,000 per person among the 40 million eligible black descendants of the American enslaved would eliminate the racial wealth gap caused by systematic discrimination of the Black population prior to and after Emancipation. Our own calculations (see Figure 9) suggest that this policy would greatly eliminate wealth gaps and move us into a scenario where convergence would occur as opposed to a steady state positive wealth gap.

Convergence would likely be further accelerated through a combination of the policies discussed above as all three would not only disproportionately boost the relative wealth of Black Americans, but also move them into wealth groups with higher capital gains and savings as wealth levels have a significant affect on investment and savings behavior (Dynan et al., 2004; Juster et al., 1999; Kuhn et al., 2020).

7 Project work-plan, personnel, and results reporting

Our proposed project will involve an intensive data collection effort to establish the best national estimates of Black and white wealth per capita and the racial wealth gap from 1860 to 2020. Our approach is three-pronged. First, under time and resource feasibility constraints, we collect the maximum amount of data on Black wealth from a variety of sources. Next, we impute Black wealth in areas and years where we are unable to directly observe it by using data on growth rates of Black wealth and the predicted relationship between county-level characteristics, such as demographics, homeownership rates and home values, farm values, and other observables, and wealth in the counties where the wealth data are available. We then use this predicted relationship to impute Black wealth in areas of the country where they are not available.

Timeline We expect to devote the first year of the project to our data collection efforts, from June 1, 2021 to June 1, 2022. The first six months will be devoted to ramping up our digitization procedures for states where scanned microfilms of county tax rolls are available online. Over the summer, a team of undergraduates will be trained in the digitizing procedure. We anticipate that this initial wave of digitization will be completed after six months. Following this, under our supervision, the project's full-time research assistant will work on the linkage of the data to the restricted full count census, which we have already obtained access to at the Population Center at UC Berkeley.

In the second year of the project, we will harmonize the data we have collected and refine our imputation procedure to produce a continuous series covering the full time period. In the last six months of the second year of the project, we will also draft our results and submit the paper to a journal for publication.

7.1 Qualifications of the researchers

Ellora Derenoncourt (Assistant Professor of Economics & Public Policy, UC Berkeley) is a co-PI on this project who will oversee the digitization process and linkage of tax records to Census at UC Berkeley. She will supervise the team of undergraduates and the full-time research assistant working on this project. She will also assist in the imputation procedure, data analysis, and drafting of the paper. She brings expertise in studying the long-run evolution of racial inequality in the United States and a deep familiarity with historical US data sources.

Chi Hyun Kim (PhD student at the Freie University Berlin and DIW Berlin) is a co-PI on this project who will mainly work on the data analysis to study the determinants of the racial wealth gap and examining the efficacy of diverse policy measures. She will also assist in data collection on black banks and drafting of the paper. Her expertise lies in empirical macroeconomics and household finance.

Moritz Kuhn (Professor of Economics, University of Bonn) is a co-PI on this project who will work on data collection and data processing to reconcile the different data sources in this project. He will also work on developing a theoretical framework to explore the sources of the long-run racial wealth gap. He brings expertise in data analysis of microdata on the financial situation of U.S. households and connecting empirical analysis to the theoretical literature on the sources of income and wealth inequality.

Moritz Schularick (Professor of Economics at the University of Bonn) is a co-PI on this project. He has worked and published widely on the economic and financial history of the 19th and 20th century. He brings expertise in the analysis of long-run developments in asset prices, housing markets, and historical returns that are essential for the evolution of long-run wealth growth. He has also worked on U.S. banking history, private debt, and household micro data.

7.2 Reporting of the study's results

The results of this study will be drafted into an article and submitted for publication in a journal. We also plan to make our data and programs publicly available upon publication. Prior to submission to a journal, we plan on submitting the paper to academic conferences and presenting the work at seminars. After our draft working paper is out, we may also circulate non-technical briefs summarizing the work.

7.3 Plan for the public release of the data

A key priority for our project is to produce a public-use series on Black and white per capita wealth levels from 1860 to the present. It is our hope that this series can be used by future researchers to better understand the dynamics of racial wealth inequality. Whenever possible, we will try to provide disaggregated data, for example, at the state or county level. Our plan is to release the data and documentation after the paper detailing our findings is accepted for publication. It is our hope that this will occur within two years of the project end date, or by 2024.

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All money on deposit with any bank or other corporation, firm, or person. Value.	Shares of stocks of incorporated companies.	TOTAL VALUE	Total value of personal property owned by whites.	Total value of personal property owned by negroes.	COUNTIES.
[illegible]	....	[illegible]	[illegible]	[illegible]	Shenandoah.
29,389	....	570,785	566,695	4,090	Smyth.
45,226	10	1,782,249	1,574,839	207,410	Southampton.
7,282	....	348,807	304,423	44,384	Spotsylvania.
250	....	306,787	290,532	16,255	Stafford.
45,428	4,250	446,656	371,288	75,368	Surry.
34,798	....	609,788	510,358	99,430	Sussex.
97,602	....	1,242,088	1,221,560	20,528	Tazewell.
700	....	353,297	349,011	4,286	Warren.
1,550	....	149,739	115,799	33,940	Warwick.
18,605	....	748,168	739,670	8,498	Washington.
....	....	316,659	266,346	50,313	Westmoreland.
82,159	50	857,007	850,017	6,990	Wise.
103,220	10,000	1,124,340	1,117,860	6,480	Wythe.
3,500	....	252,476	204,429	48,047	York.
114,165	618,523	$80,254,537	$75,901,055	$4,353,482	Total, Counties.

Figure 1: Virginia auditor report, 1903-1905

Fifty-three Years of Progress 1866-1919

To a very large degree January first, 1866 was the beginning of the opportunity for the Negro in every part of the Nation to make progress. Thirteen days before this, that is, on December the eighteenth, 1865, the Thirteenth Amendment, declaring slavery abolished in the United States was adopted.

The Emancipation Proclamation of 1863 applied only to those states and sections of states then in rebellion against the Federal Government. There were almost a million slaves who were "for the present left precisely as if this proclamation were not issued." The decree of December 18, however, freed all. On and about the first day of the following January the late masters and the late slaves entered into agreements whereby the former were to furnish the land and the latter the labor to the end that both perchance might live and prosper. Thus white and black set to work to rebuild the wasted and devastated South. In this rebuilding the Negro not only tilled the soil of the South, cleared her forests and helped to build her cities, but in fifty-three years he has himself made a most remarkable progress The extent of this progress is shown in what follows:

Statistical Statement of Negro Progress in Fifty-three Years.

	1866	1919	Gain in Fifty-Three Yrs.
Economic Progress—			
Homes Owned	12,000	600,000	588,000
Farms Operated	20,000	1,000,000	980,000
Businesses Conducted	2,100	50,000	47,900
Wealth Accumulated	20,000,000	$1,100,000,000	$1,080,000,000
Educational Progress—			
Per Cent Literate	10	80	70
Colleges and Normal Schools	15	500	485
Students in Public Schools	100,000	1,800,000	1,700,000
Teachers in all Schools	600	38,000	37,400
Property for Higher Education $	60,000	$ 22,000,000	$ 21,940,000
Annual Expenditures for Education $	700,000	$ 15,000,000	$ 14,300,000
Raised by Negroes $	80,000	$ 1,700,000	$ 1,620,000
Religious Progress—			
Number of Churches	700	43,000	42,300
Number of Communicants	600,000	4,800,000	4,200,000
Number of Sunday Schools	1,000	46,000	39,000
Sunday School Pupils	50,000	2,250,000	2,200,000
Value of Church Property $	1,500,000	$ 85,900,000	$ 84,400,000

Figure 2: Excerpt from *The Negro Year Book* (Work, 1922)

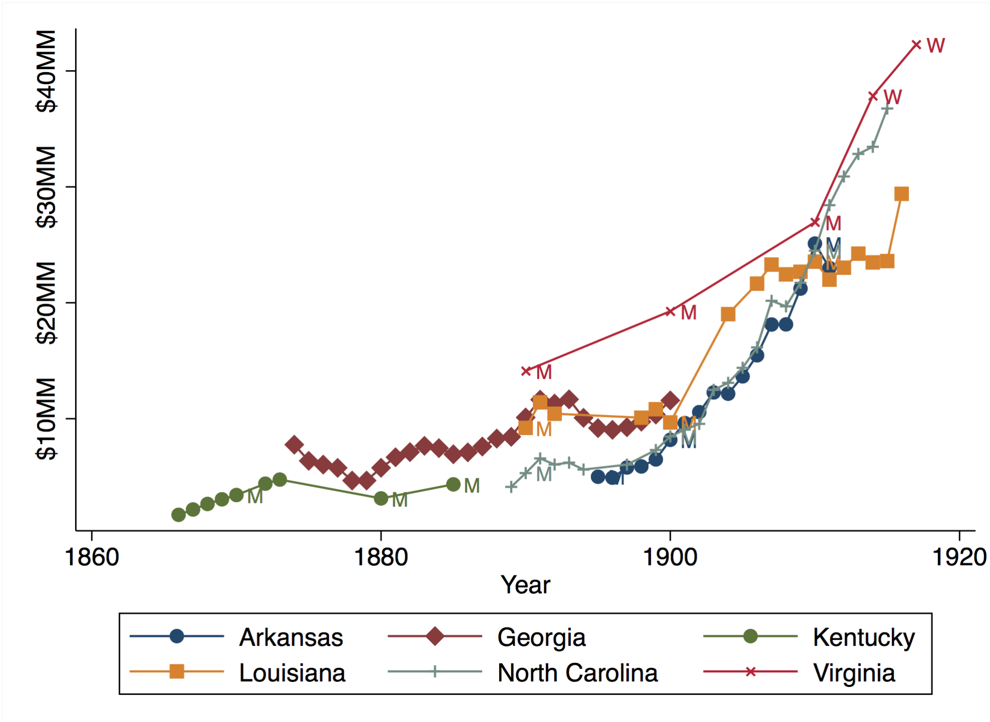

Figure 3: Aggregate Black wealth by state, 1860-1920 ($1910-1914)

Notes: Estimates adjusted to be in real $1910-1914 using the Warren-Pearson Index. *Source*: State auditor reports; Margo (1984): "M"; Work (1922): "W".

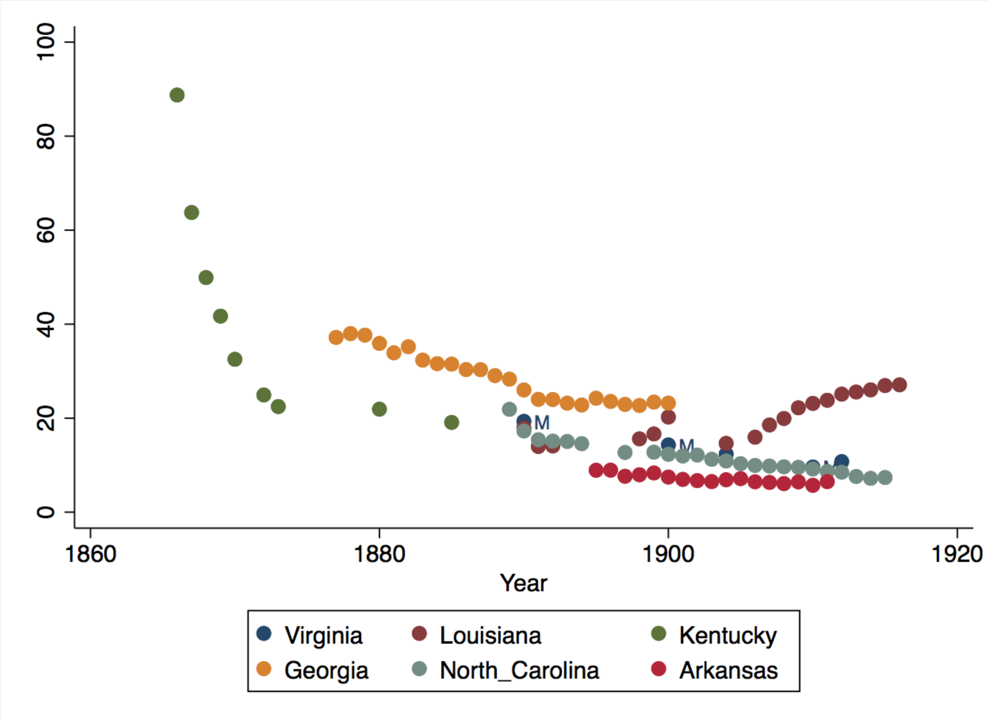

Figure 4: White-Black per-capita wealth ratio by state, 1860-1920

Source: State auditor reports; Margo (1984): "M".

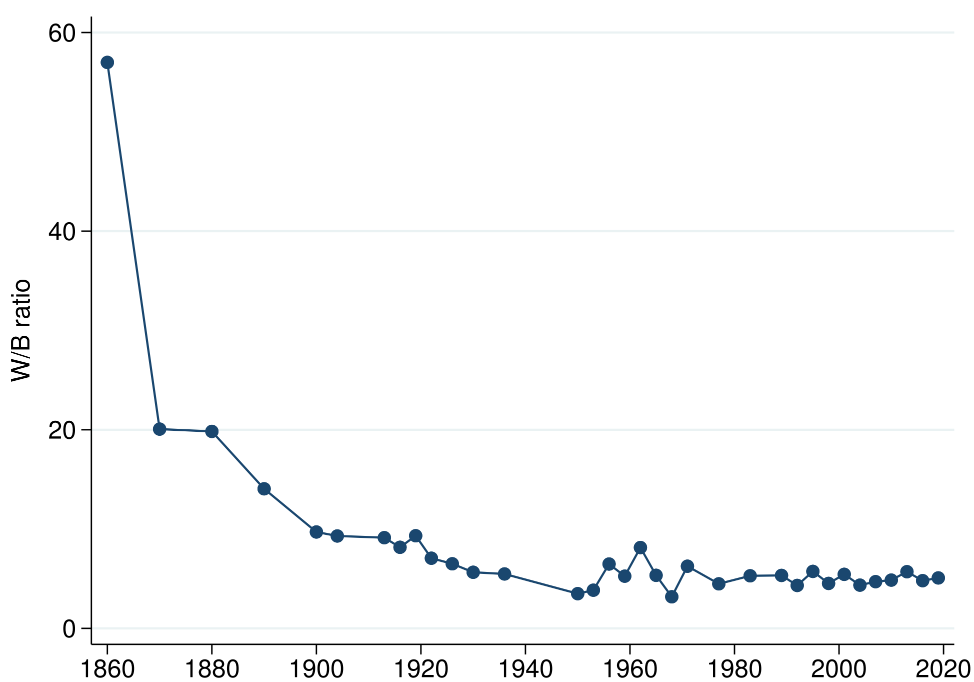

Figure 5: White-Black wealth ratio: 1860-2020

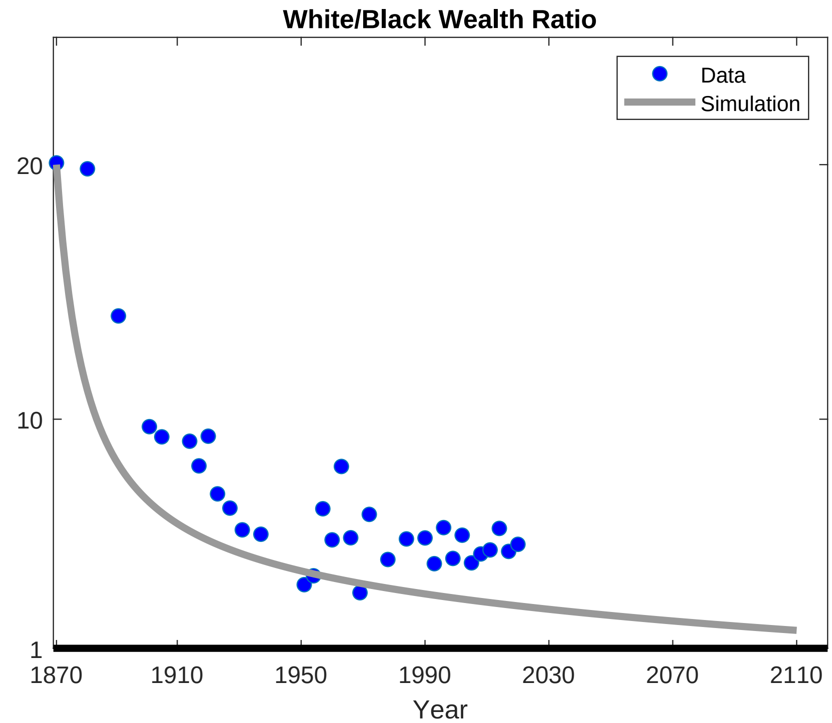

Figure 6: Simulation exercise with equal conditions

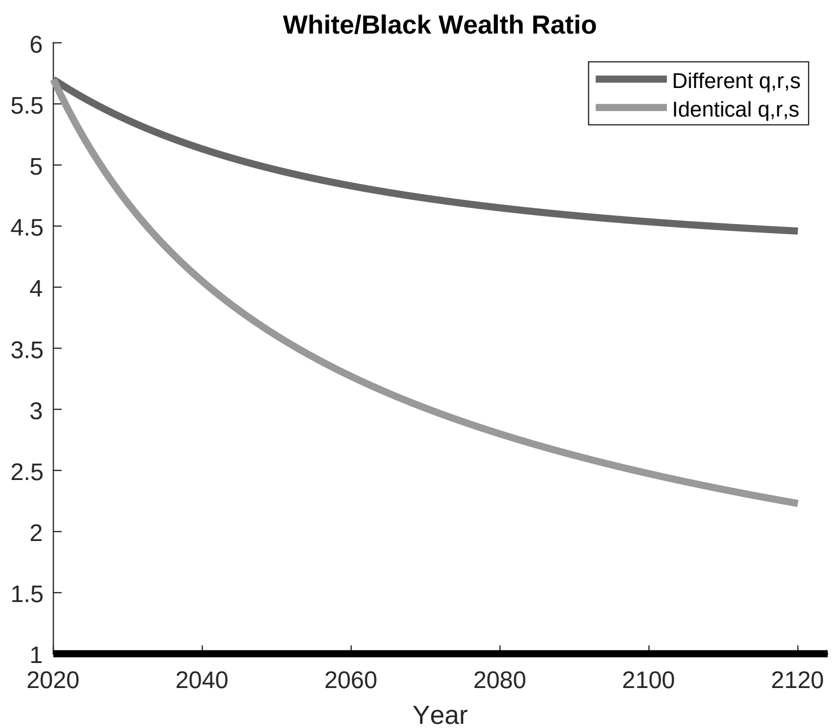

Figure 7: Wealth convergence in the near future?

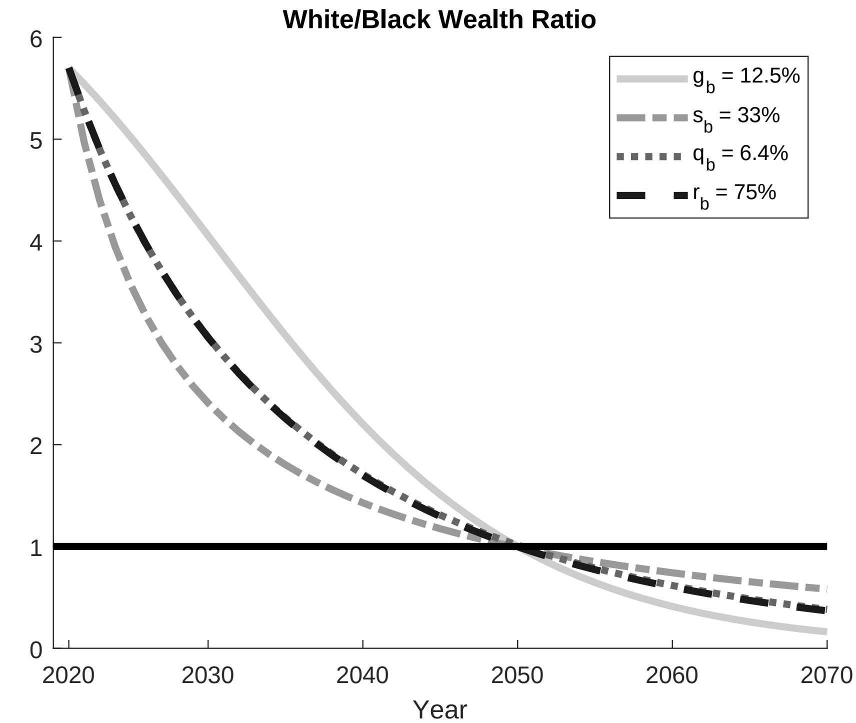

Figure 8: Wealth convergence in 2050?

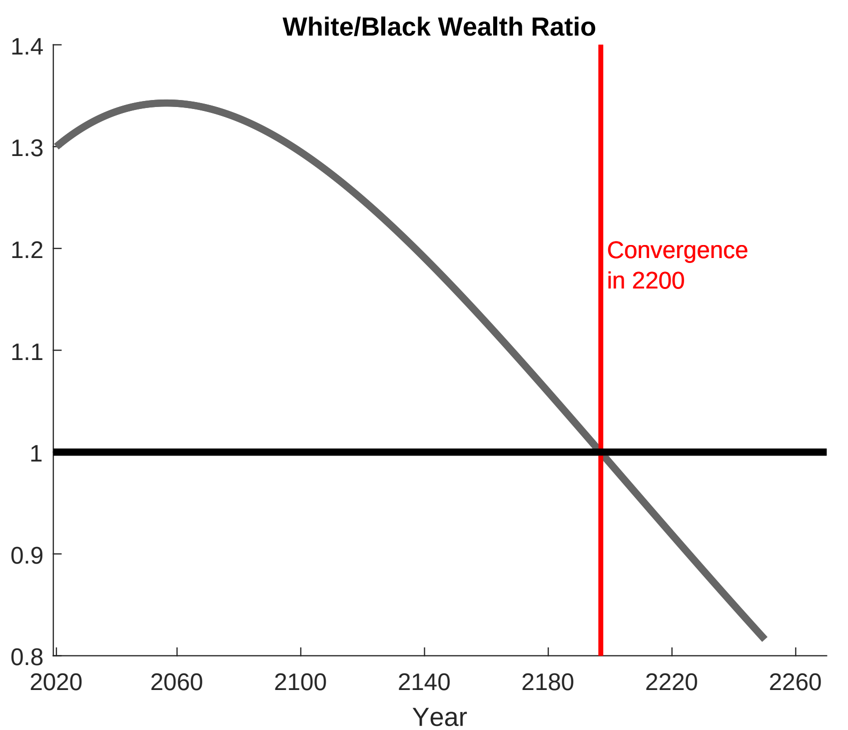

Figure 9: Wealth convergence under Darity and Mullen (2020) reparations

	2020 (data)	2020	2050	2100
Wealth ratio (W/B)	5.7	2.7	2.3	1.8
Income ratio (W/B)	1.5	1.5	1.2	1

Table 1: Simulated wealth gap: 2020-2100

Appendices

A Comparison of historical state wealth ratios to Margo (1984)

Below we compare our estimates for the white-Black per capita wealth ratio derived from our digitization of state auditor reports to those of Margo (1984). Table 2 shows that results are broadly similar for most states with Louisiana being the exception. This is due to the fact that the Louisiana state auditor reports exclude data for Orleans Parish, which includes New Orleans. Margo (1984) assumes that country parish ratios apply to the state overall, for which aggregate wealth is available, and computes the state-wide wealth ratio this way. We use a different approach to account for the possibility of greater wealth holding by Black Americans in New Orleans relative to the country parishes. We take the 1870 Census and compute white-to-Black wealth ratios in New Orleans. We then subtract total country parish wealth from total wealth in Louisiana to derive wealth in New Orleans every year for which tax data are available. Assuming that the white-to-Black wealth ratio in New Orleans holds constant over time, we compute Black and white wealth in New Orleans using this method and then recompute the per capita wealth ratio for the state of Louisiana using these adjusted measures for aggregate Black and white wealth in the state.

Table 2: Average white-Black wealth ratios: Margo (1983) & DKKS (2020)

	1870	1880	1885	1890	1895	1900	1910	1910
Arkansas								
Margo(1983)						9	7	6
DKKS(2020)						9	7	6
Georgia								
Margo(1983)								
DKKS(2020)		36	36	32	26	24	23	
Kentucky								
Margo(1983)	36	22	22	19				
DKKS(2020)	33							
Louisiana								
Margo(1983)					18		20	25
DKKS(2020)					14		16	19
North Carolina								
Margo(1983)					17		13	9
DKKS(2020)					17		12	9
Virginia								
Margo(1983)					19		14	10
DKKS(2020)							13	11

Source: Margo (1983): Margo's (1983) data originally collected from southern state auditor reports and reported for selected years in Table 1. DKKS (2020) calculated from their new digitization of these same reports and supplemented by W.E.B. Du Bois's data on property holdings by race in Georgia from 1877 to 1900.

B Digitization of individual tax records and linkage to census

We have already scanned the microfilms of individual-level tax records for New Orleans in 1870. Below we illustrate our Census linking method to determine race of the wealth holder. In our full data set, we will use probabilistic matching, following Aneja and Xu (2020). The authors predict the probability an individual belongs to a particular racial group using the share of all Census respondents who share the full name and state of birth as the individual in the record in question. For our purposes, we will use information on the individual's county, or when possible, their enumeration district, to predict their racial group. We will match records in Census years to avoid issues of potential migration. For every first name, last name, and county-of-residence combination, we calculate:

$$\text{Black}_i = [\Pr(\text{Black}|\text{First name, Last name, County}) > c] \tag{2}$$

where person i is assigned Black as their racial identity if the conditional probability of their being Black given their name and county-of-residence exceeds a certain threshold $c \in [0, 1]$. Below is an illustration of a match for an 1870 wealth holder in New Orleans, Dominick Madden.

namefrst	namelast	realprop	persprop	us1870c_1033
DOMINICK	MADDEN	14000	2000	WHITE

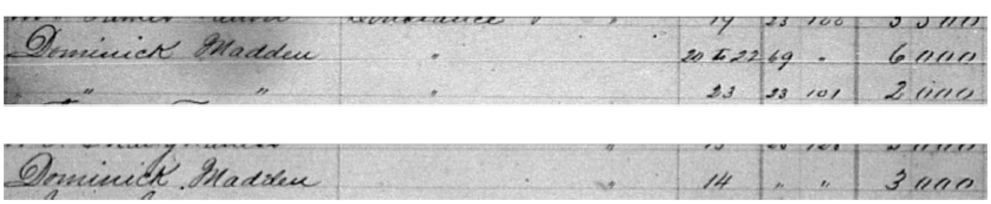
Dominick Madden 20 22 69 6000
23 33 101 2000
Dominick Madden 14 3000

Figure 10: Example of match between New Orleans tax records and 1870 Census

We have identified similar tax records for several southern states. Expanding our estimates to include wealth from Texas, Mississippi, Tennessee, and South Carolina would expand our coverage of the Black population to 81%, up from 41% in the current set of states whose auditor reports we use. The table on the following pages indicates the full set of additional tax records we have identified. For feasibility, we will pick a limited set of years for each of the states where satisfactory and readily accessible individual tax records exist. We will also focus on the years between 1870 and 1930 when other national level data on Black wealth become available (e.g., via the Census of Agriculture, data on Black banks, and the Census of Population with data on home values).

We will also explore a second approach: randomly sampling among Black and white adults in the complete count censuses and locating these individuals in county tax rolls. We will also oversample homeowners from both racial groups as these individuals are known wealth holders. Linking these individuals to the county tax rolls will provide information on the total value of their assets. Throughout our use of census linking methods, We plan to follow the census-record linking literature and explore robustness to alternative linking procedures (Abramitzky et al., 2019).

Finally, we plan to digitize additional county-level wealth information from the six states whose auditor reports we rely on in the current set of results. For example, as can be seen in Figure 1, assessed property by racial group is available for each county in the state. By digitizing this more detailed breakdown of wealth, we will be able to predict wealth based on county observables for these states. By carefully matching these counties to counties in other states based on observables, we will generate predicted wealth by racial group in states where data from state auditor reports or individual tax records are not available. We will check the resulting figure against national estimates in Census and from Monroe Work.

Record	State	Data	Link	Note1	Note2	
New Orleans (La.) Board of Assessors Records	Louisiana	Tax Assessment Rolls, 1856-1975 (New Orleans)	http://nutrias.org/~nopl/inv/new%20cj%20films.htm			
Mississippi County Tax Rolls	Mississippi	County Tax Rolls, 1818-1902 Series 1202	http://da.mdah.ms.gov/series/osa/s1202			
Personal Property Tax Records, 1782-1925, On Microfilm	Virginia	Tax lists by county, years vary	https://www.lva.virginia.gov/public/guides/pptax.htm	https://www.lva.virginia.gov/public/guides/m3_persprop.pdf		
Texas County Tax Rolls	Texas	Tax lists by county, years vary	https://www.tsl.texas.gov/arc/taxrolls.html	Partially digitized by Family Search : https://www.familysearch.org/search/collection/1827575		
Early Tennessee Tax Lists at the Tennessee State Library and Archives	Tennessee	Tax lists by county, years vary	https://sos.tn.gov/products/tsla/early-tennessee-tax-lists-tennessee-state-library-and-archives#index			
Records of the South Carolina Direct Tax Commission	South Carolina	Certificates of land sold for taxes, 1863-86, including certificates for land sold in South Carolina to heads of black families, 1863-72.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.4.8			
Records of the Texas Direct Tax Commission	Texas	Receipts for direct taxes, 1866-68	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.4.10			
Records of the Alabama Direct Tax Commission	Alabama	Applications to redeem land sold for taxes, 1880-89.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.4.1			
Records of the Arkansas Direct Tax Commission	Arkansas	Applications to redeem land sold for taxes, 1870-87.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.4.2			
Records of the Florida Direct Tax Commission	Florida	Claims, 1875-87. Applications to redeem land sold for taxes, 1864-87. Lists of land sold, 1864- 82. Tax sale certificates, 1864-66.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.4.3			
Records of the Tennessee Direct Tax Commission	Tennessee	Tax sale certificates, 1864-66. Applications to redeem lands, 1864-74. Applications for refunds of surplus proceeds of property sold for taxes, 1864-84.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.4.9			
Records of the Virginia Direct Tax Commission	Virginia	Tax certificates, 1864-66. Applications to redeem lands, 1864-84.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.4.11			
Records of Internal Revenue Collection Districts	Alabama	Assessment lists, 1st District (Mobile), 2d District (Selma), and 3d District (Huntsville), 1867-73. Assessment lists, 1910-17.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.5.1	Partial previous digitization by Archives partners here: https://www.archives.gov/digitization/digitized-by-partners	States and years digitized by ancestry.com : https://www.ancestry.com/search/collections/1264/	

Records of Internal Revenue Collection Districts	Arkansas	Assessment lists, 1st District (Helena), 1867-74, 1910-17; 2d District (Little Rock), 1867-74, 1910-17; and 3d District (Harrison), 1867-71, 1910-17.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.5.3	Partial previous digitization by Archives partners here: https://www.archives.gov/digitization/digitized-by-partners	States and years digitized by ancestry.com : https://www.ancestry.com/search/collections/1264/	
Records of Internal Revenue Collection Districts	Florida	Assessment lists, 1867-73, 1917-18.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.5.9	Partial previous digitization by Archives partners here: https://www.archives.gov/digitization/digitized-by-partners	States and years digitized by ancestry.com : https://www.ancestry.com/search/collections/1264/	
Records of Internal Revenue Collection Districts	Georgia	Assessment lists, 1st District (Savannah), 2d District (Macon), 3d District (Augusta), and 4th District (Atlanta), 1867-73. Assessment lists, 1913-17.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.5.10	Partial previous digitization by Archives partners here: https://www.archives.gov/digitization/digitized-by-partners	States and years digitized by ancestry.com : https://www.ancestry.com/search/collections/1264/	
Records of Internal Revenue Collection Districts	Kentucky	Assessment lists, 1st District (Paducah), 2d District (Greenville), 3d District (Bowling Green), 4th District (Lebanon), 5th District (Louisville), 6th District (Covington), 7th District (Lexington), 8th District (Lancaster), and 9th District (Louisville), 1867-73.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.5.17	Partial previous digitization by Archives partners here: https://www.archives.gov/digitization/digitized-by-partners	States and years digitized by ancestry.com : https://www.ancestry.com/search/collections/1264/	
Records of Internal Revenue Collection Districts	Louisiana	Assessment lists, 1st District (New Orleans), 2d District (Baton Rouge), and 3d District (Delta), 1867-73, 1910-17.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.5.18	Partial previous digitization by Archives partners here: https://www.archives.gov/digitization/digitized-by-partners	States and years digitized by ancestry.com : https://www.ancestry.com/search/collections/1264/	
Records of Internal Revenue Collection Districts	Mississippi	Assessment lists, 1st District (Brookhaven), 2d District (Jackson), and 3d District (Holly Springs), 1867-73. Assessment lists, 1915-17. Records of special taxes, 1887-90.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.5.24	Partial previous digitization by Archives partners here: https://www.archives.gov/digitization/digitized-by-partners	States and years digitized by ancestry.com : https://www.ancestry.com/search/collections/1264/	
Records of Internal Revenue Collection Districts	North Carolina	Assessment lists, 1st District (Weldon), 2d District (New Bern), 3d District (Fayetteville), 4th District (Raleigh), 5th District (Greensboro), 6th District (Salisbury), and 7th District (Asheville), 1867-73. Assessment lists, 1915-17.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.5.33	Partial previous digitization by Archives partners here: https://www.archives.gov/digitization/digitized-by-partners	States and years digitized by ancestry.com : https://www.ancestry.com/search/collections/1264/	

Records of Internal Revenue Collection Districts	South Carolina	Assessment lists, 1st District (Kingstree), 2d District (Charleston), and 3d District (Columbia), 1866-73. Assessment lists, 1910-17.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.5.40	Partial previous digitization by Archives partners here: https://www.archives.gov/digitization/digitized-by-partners	States and years digitized by ancestry.com : https://www.ancestry.com/search/collections/1264/	
Records of Internal Revenue Collection Districts	Tennessee	Assessment lists, 1st District (Johnson City), 2d District (Knoxville), 3d District (Chattanooga), 4th District (Murfreesboro), 5th District (Nashville), 6th District (Clarksville), 7th District (Huntington), and 8th District (Memphis), 1867-73. Assessment lists, 1910-17.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.5.42	Partial previous digitization by Archives partners here: https://www.archives.gov/digitization/digitized-by-partners	States and years digitized by ancestry.com : https://www.ancestry.com/search/collections/1264/	
Records of Internal Revenue Collection Districts	Texas	Assessment lists, 1st District (Galveston), 1867-74; 2d District (Corpus Christi), 1916-17; 3d District (Austin), 1870-74, 1908-17; and 4th District (Tyler/Marshall), 1866-73, 1904, 1910-12. Records of personal taxes, 3d District (Austin), 1866. Records of the 4th District (Tyler/Marshall), consisting of collector's correspondence, 1885-89 (in Washington Area); assessment lists, 5th Division, 1866-67 (in Washington Area); tax returns, 1866-70 (in Washington Area); a register of applications for occupational licenses, 1866-67; record book of abated taxes, 1867-79; record book of cotton shipped, 1866-67; and miscellaneous records, 1866- 74.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.5.43	Partial previous digitization by Archives partners here: https://www.archives.gov/digitization/digitized-by-partners	States and years digitized by ancestry.com : https://www.ancestry.com/search/collections/1264/	
Records of Internal Revenue Collection Districts	Virginia	Assessment lists, 1st District (Onancock), 2d District (Petersburg), and 3d District (Richmond), 1867-73. Assessment lists, 6th District (Richmond), 1914-17.	https://www.archives.gov/research/guide-fed-records/groups/058.html#58.5.46	Partial previous digitization by Archives partners here: https://www.archives.gov/digitization/digitized-by-partners	States and years digitized by ancestry.com : https://www.ancestry.com/search/collections/1264/	

C Differences in returns on wealth

In this section we depart from our simulation exercise and explore the role that observed differences in returns on wealth and savings rates may have played in the slowdown in racial wealth convergence in the post-1950 period. We use the SCF+ to measure these differences and to provide empirical evidence on how wealth is distributed across Black and white households and how their asset holdings differ. Finally, we estimate average capital gains and yields separately for Black and white households and discuss the impact of each on wealth accumulation for each group.

Returns on wealth: 1950-2019 We start by presenting the asset portfolio composition of Black and white households during 1950 and 2019. Figure 11 shows the average portfolios of white and Black households.[10] They do not only greatly differ in size, but also in composition. In particular, the share of non-financial assets is substantially larger for Black households. with housing accounting for almost 60% of their wealth (see Table 3). Compared to this, Black households have much lower business and equity wealth compared to white households.

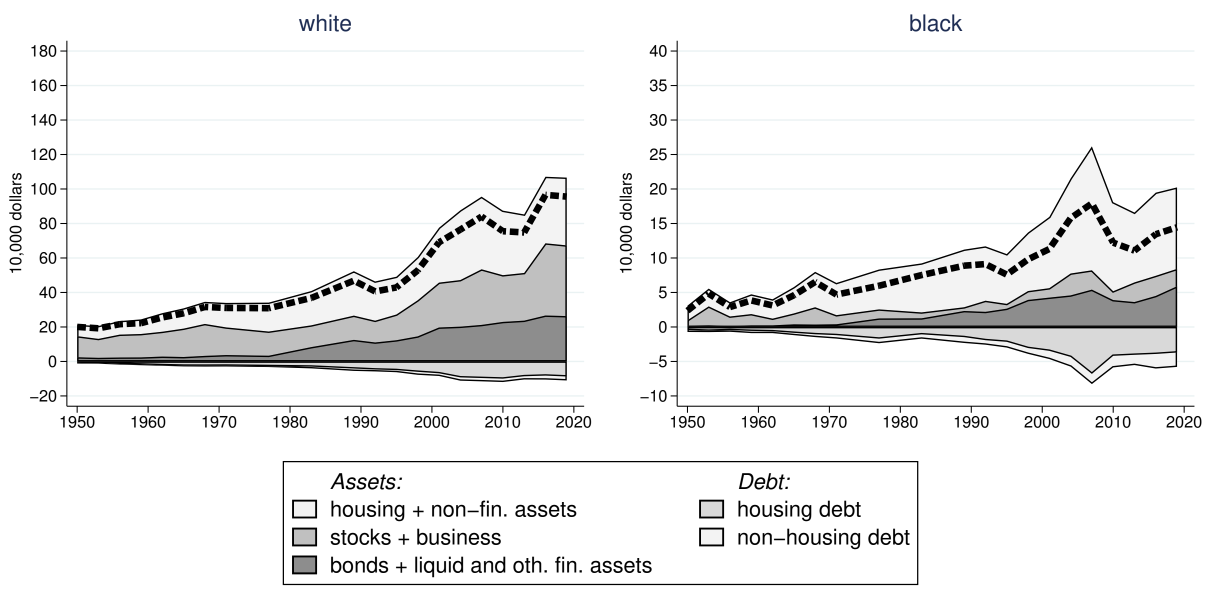

Figure 11: Portfolio composition: 1950-2019

Differences in portfolio composition are linked to different exposures to asset price developments and yields, which are crucial for wealth accumulation (Kuhn et al., 2020; Xavier, 2020). In particular,

[10]For our purpose, we exclude household heads that are categorized as Hispanic or other.

Table 3: Portfolio shares

Decade	Other nonfin	Housing	Business	Equity	Liquid assets	Other fin
White						
1950	0.03	0.31	0.37	0.19	0.11	-
1960	0.02	0.33	0.30	0.24	0.10	-
1970	0.02	0.37	0.24	0.27	0.10	-
1980	0.04	0.45	0.24	0.11	0.12	0.04
1990	0.05	0.44	0.19	0.08	0.13	0.11
2000	0.05	0.39	0.18	0.14	0.09	0.15
2010	0.04	0.39	0.19	0.13	0.08	0.17
2020	0.03	0.33	0.22	0.17	0.07	0.18
Average	0.03	0.38	0.24	0.17	0.10	0.08
Black						
1950	0.05	0.49	0.36	0.05	0.05	-
1960	0.07	0.56	0.20	0.12	0.05	-
1970	0.07	0.61	0.15	0.11	0.06	-
1980	0.09	0.65	0.11	0.01	0.10	0.04
1990	0.09	0.62	0.08	0.01	0.07	0.13
2000	0.08	0.57	0.07	0.04	0.06	0.19
2010	0.07	0.60	0.09	0.03	0.05	0.16
2020	0.07	0.53	0.10	0.04	0.07	0.20
Average	0.07	0.58	0.15	0.05	0.06	0.09

low holdings of stock- and business equity by Black households may have substantial effects on their wealth accumulation, as these asset classes have not only experienced a strong increase in their prices during the last several decades, but also yield high returns. In addition, the Black population has been exposed to discrimination and constraints with regard to their investment, starting from limited access to banks after Emancipation (Stein and Yannelis, 2020; Baradaran, 2017) and red-lining in the real estate market (Jackson, 1980; Aaronson et al., 2020). All these can exacerbate differences in wealth returns, as Black households may possess lower-quality assets than white households.

We define the total return on an household's asset portfolio as a weighted sum of the return on different asset classes with regard to its share of total wealth:

$$R_w = \sum_c \omega_c R_c, \tag{3}$$

where R_c denotes the return on asset class c and ω_c its weight as a share of total wealth. In turn, the total return R_w can be decomposed into (1) capital gains, which reflect asset price fluctuations, and (2) a yield component, which captures the net income generated by the asset. We estimate these two components separately for Black and white households and examine how the differences affect their wealth accumulation.

Capital gains Capital gains may also explain the slowdown in Black-white wealth convergence, as portfolio compositions differ substantially by racial group. We first calculate the average yearly rate on capital gains of different asset classes (equity, housing, and business) and calculate the average Black- and white capital gain rates according to their portfolio composition. For real estate and equity, we use the values provided by the Macrohistory Database of Jordà et al. (2019).[11] To calculate capital gains of businesses, we use data from the US Financial Accounts.[12] We assume that liquid assets do not yield any capital gains. Afterwards, we calculate the average capital gains rate of Black and white household's total asset portfolio using equation (3). Table 4 presents the yearly average capital gains rate from 1950 to 2019.

Between 1950 and 2019, stock equity has experienced the highest price increase with an average

[11] We deflate the nominal capital gain rates provided in their dataset.

[12] For noncorporate equity, we use the series "Nonfinancial noncorporate business; proprietors' equity in noncorporate business (wealth)," and for corporate equity the series "Households and nonprofit organizations; corporate equities." Both series are deflated by the CPI deflator.

Table 4: Real capital return on portfolio, yearly average over 1950-2019

	Average capital gain	White	Black
Equity	5.50%	0.94%	0.28%
Liquid assets	0%	0%	0%
Housing	0.8%	0.30%	0.50%
Business	3.37%	0.81%	0.51%
Total on portfolio	1.99%	2.01%	1.29%

Note: Race-specific capital gains are calculated using the average capital gain of a specific asset class multiplied by the average share of this asset of the total portfolio during 1950-2019 (see Table 3).

rate of 5.5%, followed by business equity (with 3.37%). Housing, on the other hand, had much lower capital gains with an average of 0.8%. In total, white households have earned on average 2.01% on their total portfolio due to capital appreciation, which is about 1.6 times higher than the capital gains of the average portfolio of Black households (1.29%).[13]

Yields on wealth Another channel that can affect the wealth gap is differential returns by racial group within a given asset class. We address this channel by calculating yields on different asset classes by racial group using the method of Moskowitz and Vissing-Jørgensen (2002) and Kartashova (2014) using data of the SCF+. Specifically, we calculate average annualized yields over two waves t and $t+1$ using information on the value of an asset and the value of the associated income flow during the year preceding it. For example, the average annualized yield R over two consecutive waves t and $t+1$ is computed as the geometric average of returns R_1 and R_2:

[13]These estimates, however, assume that Black and white households are exposed to the same asset price development. In reality, they may hold assets of different quality, due to race-specific discrimination in the asset market. For instance, in the real estate market, institutionalized racial discrimination in lending practices among financial institutions may have restricted Black households' access to real estate in high-rated neighborhoods (Jackson, 1980; Akbar et al., 2019). We address this issue in Appendix D and calculate different capital gains rates of Black- and white households using the PSID. Results show that the difference in capital gains is larger when allowing for different capital gains rates within the same asset class.

$$R_1 = \left(1 + \frac{3CI_{t-1}}{P_t}\right)^{\frac{1}{3}} \tag{4}$$

$$R_2 = \left(1 + \frac{3CI_t}{P_t}\right)^{\frac{1}{3}} \tag{5}$$

$$R = (\sqrt{R1 \times R2} - 1) \times 100, \tag{6}$$

where CI represents the capital income and P the price of an asset.[14]

For the whole sample period 1950 to 2019, the SCF+ provides information on two aggregate sources of capital income. First, there is an aggregated variable that includes income from interest, dividends, and rent. Second, business income data is available. Only after 1983 does the SCF+ include information on capital income of different asset classes, including non-taxable investments such as municipal bonds, dividend income, other interest income, and income from rents, royalties, and trusts. We utilize both information and first estimate yields of the two broad capital income definitions for the whole sample period 1950-2019, and afterwards estimate yields on four different asset categories for the post-1989 period: (1) interest-bearing assets (includes all liquid assets, certificates of deposit, directly and indirectly held bonds, and the cash value of life insurance), (2) public equity (households' direct holdings of stock and other public equity that are indirectly owned through mutual funds), (3) business (unincorporated- and incorporated businesses), and (4) real estate.[15] Table 5 presents the averages.

For the whole sample period 1950-2019, Black households have slightly higher yields on their wealth (3.04% vs. 2.72%). However, estimates for Black households are volatile due to small numbers of Black households in the SCF+, giving rise to potentially greater measurement error.[16] . If we turn to the estimated yields for the post-1989 period, Black households have lower yields than white households, except for in business wealth (which is also highly volatile for Black households, probably due to limited data). Interestingly, there is a large difference in yield on financial assets, for public equity in particular. On average, white households earn 2.1%, while Black households earn only 0.59%. Nevertheless, the yield on the total portfolio does not differ substantially across Black

[14]We also calculate yields on wealth utilizing the method of Bartscher et al. (2020). Results remain robust.

[15]For a detailed description of how to calculate the variables for the post-1989 period, see Appendix E.

[16]The time series of the yields are provided in Figure 13 in Appendix E.

Table 5: Yearly average yield on wealth

Asset	White	Black
1950-2019		
Interest, dividend, rent	3.0%	3.13%
Business	3.21%	5.84%
Total yield	2.72%	3.04%
1989-2019		
Interest-earning assets	1.62%	0.53%
Public equity	2.1%	0.59%
Private businesses	12.12%	17.37%
Real estate	3.18%	3.07%
Total yield	4.64%	4.45%

Note: The total average yield is calculated as a weighted sum of the yield of the four asset categories (interest-earning assets, public equity, private businesses, and real estate) with respect to the average portfolio share in Table 3.

and white households, as real estate generates similar yields for these two groups, which comprises almost 60% of Black asset portfolios.

In summary, we explored the extent to which Black and white households have accumulated wealth at different rates from 1950 to 2019 due to differences in capital gains and yields. Our results suggest that this may be the case to some extent: on the one hand, white households enjoyed 1.5 times higher appreciation than Black households via capital gains on total portfolios. On the other hand, yield on capital does not differ substantially across Black and white households.

C.1 Differences in saving rates

Finally, we also address the hypothesis that different saving rates across Black and White households may explain the wealth gap. The literature shows that savings rates of households depend heavily on their socioeconomic characteristics such as age, income, and wealth (Juster et al., 1999; Dynan et al., 2004). It is also possible that experiences of historical betrayal by banking institutions may have reduced some Black households' trust in the financial system.[17] Baradaran (2017) describes the failure of the Freedman's Bank in 1874 after bank leaders mismanaged the funds and engaged in speculative lending. The incident purportedly led to the loss of about half of accumulated freed persons' savings after the Civil War.

We adopt the method of Dynan et al. (2004) and estimate the so-called *active* saving rates of households for the period 1984-2017, which reflect the amount of money that households actively supply for new investment.[18] For this we utilize data of the Panel Study of Income Dynamics (PSID); a detailed description of the calculation, see Appendix F. In addition, we calculate the saving rates of Black- and White households for three different income groups: the bottom 50%, 50%-90%, and the top 10% of the whole income distribution. Table 6 presents the results.

	White	Black
Bottom 50%	6.08%	4.11%
50%-90%	7.97%	6.15 %
Top 10%	10.02%	8.75%
Total	7.23%	5.39%

Table 6: Active saving rates across different income groups

Overall, Black households on average have lower active saving rates than White households. The difference is the highest among the bottom 50% of the income distribution, where White households have 47% percent higher saving rates, with a decreasing trend as we move to the upper groups (30% for 50%-90% and 15% for the top 10%). During the whole time period, White households have 34% higher saving rates than Blacks.

It is worth noting that here we are looking at the unconditional saving rates as we are interested in examining differences in wealth accumulation conditions that are driving the slow wealth convergence. Nevertheless, it is interesting to analyze whether saving rates of Black- and White households would significantly differ once we condition the saving rates for other socioeconomic characteristics such as wealth, education, or age. A simple regression analysis shows that once we

[17]For example, Alsan and Wanamaker (2018) find that the Tuskegee experiment reduced Black men's trust in the medical system leading to higher mortality and reduced longevity among that population relative to other demographic groups.

[18]Total saving rates, which is the change in net wealth in proportion to income, include capital gains and therefore not suitable in visualizing the pure amount of money households additionally invest in wealth.

control for these characteristics, the race of the household head does not have a significant effect on saving rates. This first-order result provides more evidence for the hypothesis that differences in saving rates can be explained by socioeconomic differences, rather than for instance, different preferences or trust levels towards the banking system compared to White households.

D Heterogeneous capital gains: the PSID

We calculate capital gains across the two racial groups by utilizing the data of the Panel Study of Income Dynamics (PSID). The PSID is a nationally representative longitudinal study of US families over time since 1968. Starting from 1984, the PSID introduces a detailed wealth module, where households are asked to report their holdings in different asset classes. One advantage of the PSID over the SCF+ is its panel dimension, which is useful for estimating the change in households' investment decisions over time that allows us to estimate capital gains for each asset class separately. In every wave, respondents are asked to report the present value of their asset, i.e. how much money they would receive if they sold it today. In addition to the current value of an asset, households are also asked to report whether they have further invested (or withdrawn) money in the asset since the last survey wave. In order to obtain a clean measure of the pure capital gain of an asset, we need to subtract this actively invested amount. The average yearly return on capital of an asset i during two waves t and $t-p$ is calculated as follows:

$$cg_{i,t,t-p} = \left(\frac{W_{i,t} - AS_{i,t}}{W_{i,t-1}} \right)^{\frac{1}{p}} - 1 \tag{7}$$

where $W_{i,t}$ is the current value of an asset i at time t, AS_t the actively invested (or de-invested) amount, and $cg_{i,t,t-p}$ is the rate of capital gain or loss. Again, we calculate capital gains of three asset categories: equity, housing, and business. As data is available starting from 1985, we are able to calculate capital gain rates during 1989-2017.[19] Table 7 presents the results.

[19] Before 2001, the PSID does not separate between private stock investment and investment in IRAs. Therefore, capital gains on stock equity is calculated for the 2001-2017 period. Note that our capital gain measures are exposed to measurement error, as the answers to the amount actively invested in assets are very noisy. Especially for Black households, there are much less data points compared to White households, which also affects the quality and accuracy of our capital gain rate measure. Therefore, we adjust for outliers for each asset type in a different way because, for instance, business wealth is very scarce among Black households and thus must be adjusted in another way than the value of main dwelling. Nevertheless, our measures provide insights to which degree capital gains on different types of assets may differ across Black and White households.

Table 7: Yearly capital gains on wealth

Asset	Average		White	Black
	PSID	Other		
Equity*	4.03%	6.73%	5.78%	0.98%
Liquid assets	0%	0%	0%	0%
Housing	2.70%	1.03%	2.37%	2.16%
Business	5.56%	4.89%	6.17%	2.78%
Total on portfolio	3.01%	2.64%	3.36%	1.72%

Note: The total capital gain on portfolio is calculated as a weighted sum of the capital gain rates of the asset categories with respect to their average portfolio share. The second column provides estimates of capital gains using external sources such as the Macro History Database of Jordà et al. (2019) and the Financial Accounts.

* Prior 2001, the PSID does not provide information on pure stock holdings, as they combine the information on stock holdings in form of IRAs.

Indeed, the rate on capital gains/losses differ substantially across Black and White households. In particular, capital gains differ greatly for business- and stock equity wealth, where on average White households experienced capital gains of 5.78% on stocks and 6.17% on businesses, while only 0.98% and 2.78% for Black households, respectively. For housing, capital gains do not substantially differ, with White households having on average 0.1 times higher capital gains on their main dwelling and other real estate. For private businesses, White households experienced approx. 2% higher gains. As a result, capital gain on the whole asset portfolio for White households is 1.95 times higher than for Black households. This is slightly larger than the ratio we obtain by assuming equal capital gain rates (1.6).

E Calculating yields

For the period 1989-2019, we closely follow the method of Xavier (2020) to calculate the yields on wealth. In this appendix, we provide information on which data is used to estimate income flows of different asset classes. Again, the average annualized yield R over two consecutive waves t and $t+1$ is computed as the geometric average of returns R_1 and R_2:

$$R_1 = \left(1 + \frac{3CI_{t-1}}{P_t}\right)^{\frac{1}{3}} \tag{8}$$

$$R_2 = \left(1 + \frac{3CI_t}{P_t}\right)^{\frac{1}{3}} \tag{9}$$

$$R = (\sqrt{R1 \times R2} - 1) \times 100, \tag{10}$$

where CI presents the capital income and P the price of an asset.

Interest-bearing assets This asset category includes all liquid assets, certificates of deposit, directly and indirectly held bonds, and the cash value of life insurance. Capital income on this asset is the total annual interest income that the households report.

Public equity Public equity is defined as the sum of households' direct holdings of stocks and other indirectly held stocks through mutual funds. The income flow are the dividends generated by these assets.

Private business equity Wealth from private businesses are defined as the share of net equity in non-publicly traded businesses, which includes both unincorporated and incorporated businesses. We estimate the profits generated by private businesses by closely following the method of Moskowitz and Vissing-Jørgensen (2002) and Kartashova (2014). They adjust the reported income from businesses for corporate taxes, retained earnings, and the unreported labor income of entrepreneurs.

Real estate Exact data on the total income generated by real estate is not provided by the SCF+. Rather, the households are asked to report their overall earnings on rent, royalties, and trust. We follow the method of Xavier (2020) and extract the capital income that is exclusively generated by rent. We assume that if (1) households do not own primary residence or any real estate or (2) they do not own any other real estate and has declared royalties, their reported income is associated with royalties or trust, but not rents. We deduct these values from the total income of this category.

Figure 12 presents the yields calculated with the above-mentioned method for 1989-2019 and Figure 13 are the yields with the more rough estimates of capital income for the whole period 1950-

2019. Remember that for pre-1989 period, the SCF+ only provides two broad categories of income flows of assets, namely (1) income from dividends, interest, and rent, and (2) business income. Therefore, for the first category we aggregate financial wealth and real estate wealth to calculate the yields.

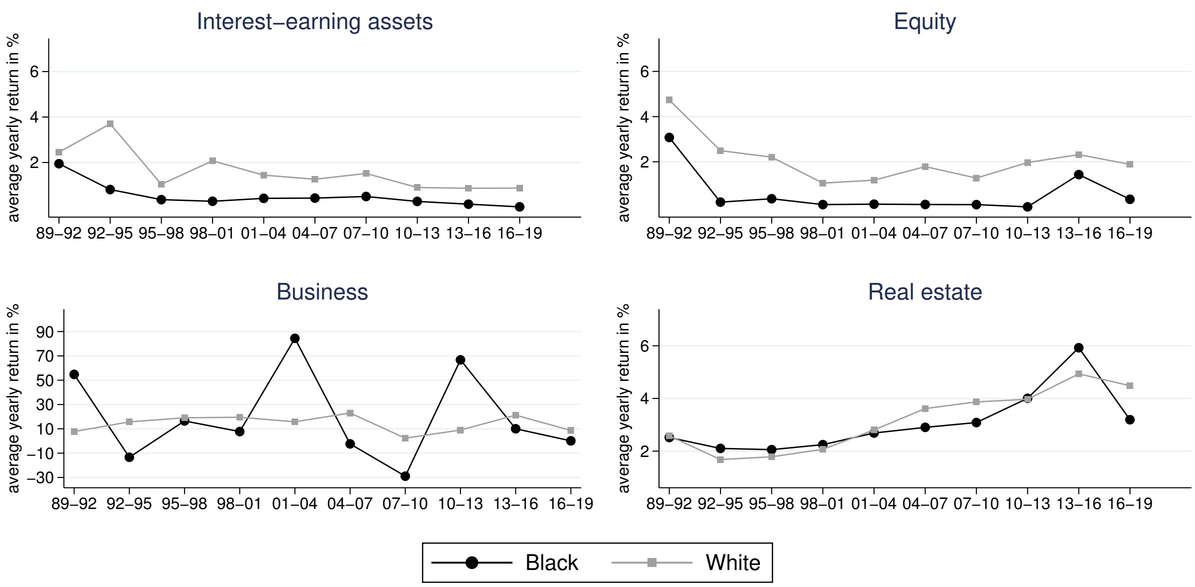

Figure 12: Yearly yield on different asset classes

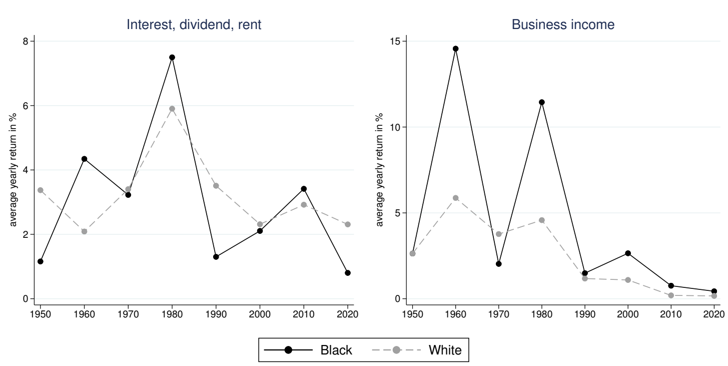

Figure 13: Yearly yield on different asset classes, 1950-2019

F Active saving of households

Active savings are defined as the following:

· Active savings =

+ Active savings in main dwelling

+ net amount invested in real estate (excluding main dwelling)

+ change in the net value of vehicles

+ net amount invested in business

+ net amount put into IRA

+ net investment into stocks

+ change in the value of cash assets

+ change in the net value of other assets

- change in the value of other debt

Active savings in main dwelling is not straightforward and thus be estimated separately for households that live in the house and those who moved out. If the family did not move, the active savings are the reduction in mortgage principal. If the household moved out, then the change in the net value of the house is considered as active savings. Also, we consider the value of additions and improvements to the house as active savings as well. For real estate, vehicles, business, IRA, and stocks, the PSID provides information on how much money the households actively put in (or cash out) since the previous wave. We use this information to calculate the active savings for these asset categories. Finally, the PSID assumes that the change in cash assets and other (financial) assets is purely driven by active savings. Nevertheless, the category "other assets" may include interest-generating assets, such as this assumption may overestimate the pure amount households have actively saved. Therefore, we assume a 1% annual real rate of return for this asset category and deduct this amount from its change in value.

The active saving rate is then calculated by taking the ratio of active savings and the sum of total family income during the two consecutive waves. Figure 14 presents the results for 1989-2017. Note that the starting from 1990s, the PSID does not provide information on the amount of income taxes. Therefore, we cannot calculate the saving rates of households with respect to their *disposable income*. Nevertheless, our estimates in Figure 14 is quite in line with the NIPA measures of saving rates, with a slight level shift (our estimates being lower than the NIPA). Nevertheless, this is an important channel that we must address in the near future.

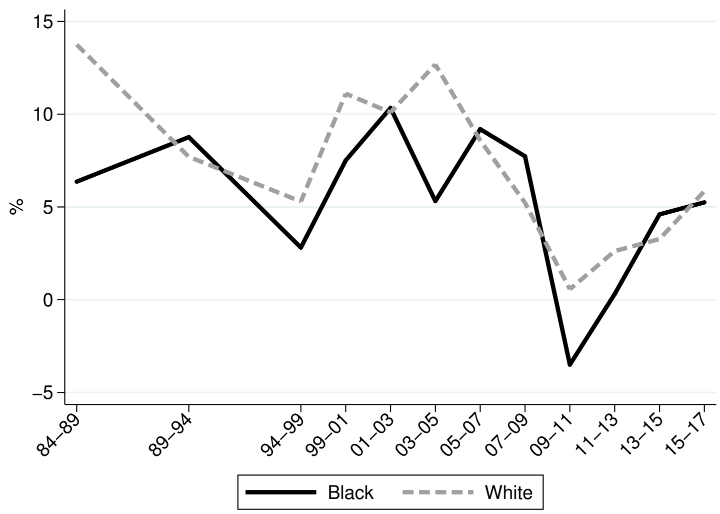

Figure 14: Average annualized saving rates: 1984-2017

SAMPLE PROPOSAL #4

Emergency Relief Fund for the Most Vulnerable and Disenfranchised: Evidence from CUNY, the Public University System in New York City

By Núria Rodríguez-Planas (PI) and Rafael de Balanzó Joue (Co-PI)

1. Motivation and Problem Under Study

Closing college campuses and moving learning online has disrupted the educational careers of students and raised significant concerns about those students who depend on college housing, meal plans, jobs, and other support to stay safe and secure. Moreover, the pandemic has suddenly changed the economic environment many students depend on to maintain the financial support for their studies. Jobs and internships, which ensure students' financial well-being during their studies, have vanished overnight. In addition, grim labor-market prospects have halted graduates' career aspirations and professional dreams. As working-class neighborhoods in New York City's outer boroughs became the epicenter of the COVID-19 outbreak in March and April 2020, many in those dense, lower-income areas struggled due to lack of resources or because of the emotional impacts of isolation. The unsettling and difficult health and economic implications of this crisis were disproportionately felt by the most vulnerable people in these communities. For instance, at the City University of New York (CUNY), the public university system in New York City (NYC), 38% of students reported having lost their job by the end of April 2020 due to the COVID-19 pandemic[1], and 90% of them indicated increased need in food, childcare, housing, and utilities.[2]

To provide rapid-response financial support so the most vulnerable and disenfranchised students could cover their basic living expenses and to help ensure that they could remain in school and complete their degrees as the pandemic and its economic consequences continued to unfold, CUNY offered the

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[1] Two-thirds of these students had worked at least 21 hours per week pre-COVID-19, and one-fifth at least 35 hours per week.

[2] Estimates are from an online student survey conducted by CUNY Office of Institutional Research and Assessment during May 2020.

Chancellor's Emergency Relief (CER) grant program, a one-time $500 lottery-based grant targeted to undocumented and low-income students. During the second quarter of 2020, a total of $3 million fund was distributed in three separate waves to 6,000 qualifying students.[3] Importantly, receiving the CER grant did not affect student financial aid, and there were no restrictions on how students could use the grant.

The recipients were chosen randomly from a pool of 19,168 students who were eligible and had applied to the program. To be eligible students had to: (1) seek a degree at CUNY during school year 2019-20, and (2) belong to one of the following groups: undocumented or low-income students. In the case of low-income students, eligibility was determined by being within 12 credits of earning an undergraduate degree, and either having an Expected Family Contribution (EFC) of zero on their federal financial aid application (FAFSA) or being a parent with any EFC. In contrasts, undocumented students did not have to be within certain credits of graduation to be eligible, and they could be seeking an undergraduate or graduate degree.[4] Eligible students amounted to about 25,000 students or 9% of CUNY's undergraduate and graduate student population of 275,000 students. Eligible students were notified by email of their lottery eligibility and instructed on how to enter the lottery within a specified deadline as specified in Table 1. They were also informed that entering the lottery was no guarantee of being selected to receive a grant. Close to 77% of the eligible students (19,168 students) applied for the CER grant program. All participating students were notified of their status within a week of the lottery-application deadline. Those selected received their grants within two weeks of selection (precise dates are shown in Table 1).[5]

[3] In each of the three waves, 2,000 qualifying students received the grant.

[4] Starting in wave 2, 10% of the grants were targeted to international students seeking an undergraduate or graduate degree.

[5] Students received cash payments either through direct deposit or by physical check mailed via the US Postal Service. Students were advised to review the mailing information and direct deposit information on their CUNYfirst account to avoid delays in receiving payment.

This project aims to: (1) analyze how the COVID-19 pandemic and the shutdown of NYC[6] has impacted the educational careers and economic wellbeing of CUNY students; (2) evaluate the effectiveness of CUNY's CER grant program to enhance its most vulnerable students' financial support and reduce racial and socioeconomic inequalities in academic outcomes during the COVID-19 pandemic; and (3) identify how CUNY students' perceptions of the challenges experienced by their communities have changed because of the pandemic, and document students' resilient visions to overcome such collective challenges. To do so, we propose a threefold project consisting of:

1. ***COVID-19 Consequences on Students' Economic Well-Being and Academic Performance.*** Combining originally collected survey data with academic administrative records, we propose to document the financial and personal burdens faced by CUNY students during the pandemic, and trace the medium-run consequences of the pandemic on these students' economic well-being and academic performance. We will exploit variation on the percentage of people who tested positive for COVID-19 across boroughs (and zip codes if sample size allows) and over time to identify whether higher rates of positive PCR testing are associated with worse students' outcomes. This analysis will give us a better perspective on how COVID-19 may be widening inequality and increasing poverty in NYC.
2. ***Causal Impact of the CER Grant Program on Students' Academic Outcomes.*** Using academic administrative records, we will exploit the randomization in the distribution of the CER grant program to evaluate the short- and medium-term impacts this one-time cash grant has on students' academic persistence, academic performance, and degree completion up to two years after grant receipt. Using survey data, we will explore the potential mechanisms behind these

[6] NYC went "on pause" effective March 22, closing all non-essential retailers and services. Re-opening happened by phases, beginning on June 8 with the reopening of construction, manufacturing, agriculture, forestry, fishing. On July 22, the last phase allowed low-risk outdoor activities at 33% capacity and low-risk indoor activities at 25%.

findings, including online-learning challenges, child- or family-care, employment stability, anxiety and stress, and food, housing and financial insecurity, among other potential explanations. Our findings will be helpful in shaping policies to anticipate and respond to future challenges, especially among the most underserved populations of students in NYC.

3. ***COVID-19 and the Transformation of Neighborhoods and Communities.*** Using in-depth group workshops and the resilient-thinking approach, a methodology borrowed from ecology science, we will explore how COVID-19 has affected CUNY students' perceptions of the challenges experienced by their communities. Post-pandemic qualitative data will be compared to pre-pandemic qualitative data collected during action research conducted during 2019 by the Co-PI, Professor Rafael de Balanzó Joue. This analysis will move beyond students' academic outcomes and self-reported wellbeing to explore their perceptions of how COVID-19 has changed their own communities' priorities and challenges related to mobility, housing, social justice, food security, and social safety networks. The resilient-thinking approach will provide students with the tools they need to brainstorm on how to overcome such community-level challenges and come up with bottom-up visions that will be useful to city-policy analysis.

All three research approaches will focus on both the short- and medium-term effects, covering students' outcomes spanning from spring 2020 to summer 2022. The CUNY student population is arguably a population of substantial interest given its social and economic vulnerability and ethnic diversity. The severe economic vulnerability and wide diversity of CUNY, while making it a specifically interesting setting to analyze, does not impair the external validity of lessons learned about student behavior, as low-income students at CUNY are representative of US low-income college students (Marx and Turner 2018).

2. Literature Review

2.1. COVID-19 Consequences on Students' Economic Well-Being and Academic Performance

By describing the short- and medium-term effects of the pandemic on students' well-being and educational outcomes, we connect to a well-developed literature that documents the effect of crises on student well-being, such as violent conflicts (Brück et al. 2019), natural disasters (Sacerdote 2012) or financial crises (Oreopoulos et al. 2012; Fernández-Kranz & Rodríguez-Planas 2018). We add to this literature a timely perspective on the arguably most severe disruption of educational careers that has been observed in recent history. At the same time, we contribute to a recent but growing literature analyzing the consequences of the COVID-19 pandemic on poverty (Bitler et al. 2020; Cortes & Forsythe 2020; Han et al. 2020) and college education (Education Trust 2020; Chirikov 2020; DREAM.US 2020; Soria 2020 a&b). A recent study by the PI, Núria Rodríguez-Planas, reveals that the early stages of the pandemic were grimmer for urban college students who ever received the federal Pell grant than students in the same college who had never received the Pell grant. During the spring semester, Pell recipients were more likely to experience challenges while attending online classes—mostly due to childcare responsibilities, lack of internet, being sick, or stressed—, and more likely to consider dropping a course because of concerns that their grade would jeopardize their financial assistance. Our proposed analysis would expand the analysis to two years after the pandemic. Most importantly, the use of administrative academic data in our proposed study would inform on academic persistence, performance, and degree completion for a representative sample of CUNY students, eliminating concerns with survey non-response bias. Furthermore, our proposal to exploit variation on the percentage of people who tested positive for COVID-19 across NYC and over time, would inform on whether higher rates of positive PCR testing are associated with worse students' outcomes.

2.2. Causal Impact of the CER Grant Program on Students' Academic Outcomes

While there is a well-established literature on the effectiveness of tuition financial assistance on students' academic and labor-market outcomes[7], the evidence on the effectiveness of non-tuition financial assistance is considerably scarcer. Tables 2 and 3 summarize key elements and findings of five randomly controlled

[7] See Dynarski (2003); Broton et al. (2016); Fack & Grenet (2015); Castleman & Long (2016); Denning (2019); Bettinger et al. (2019); Page et al. (2019).

trials (RCT) interventions including some form of non-tuition financial assistance in US colleges.[8] Similar to the CER grant program, these five programs targeted low-income college students and offered non-tuition awards comparable to that of the CER grant program.[9] They were mostly successful in retaining students one to three years after enrollment into the program and/or granting them a degree three to six semesters after enrollment. However, with the exception of *Wisconsin Scholars Grant* evaluated by Goldrick-Rab et al. (2016), the other four programs were more comprehensive as they offered additional support services such as advising and tutoring, making it difficult to extrapolate their findings to the CER grant program. Indeed, there is evidence that the impact of financial incentives for good grades are short lived unless they are accompanied with academic support services (Angrist et al. 2009). Our proposed study would be the first to conduct a randomized evaluation of emergency funds targeted to college students during a time of unexpected income loss and extreme uncertainty like the current pandemic, yielding tremendous value both for understanding the consequences of COVID-19 on college students, and for emergency aid more generally.

2.3. COVID-19 and Resilience Thinking

Thomas Homer-Dixon (2010) explains that "the resilience thinking approach offers conceptual tools to help us cope with the bewildering surprises and challenges of our new century". In such context, the adaptive cycle model (Holling 1986) is a useful metaphor and conceptual model for understanding long-term dynamics of change for social systems as complex systems (Sundstrom & Allen, 2019). According to Berinyuy et al. (2014), the adaptive cycle model is also useful to understand the dynamics of community

[8] Geckeler et al. (2008) also offer insightful descriptive results and lessons learned from the Dreamkeeper and Angel fund emergency financial aid programs, but no causal analysis.

[9] Because the awards are given over time in some cases, through Metrocards for public transportation and books in other cases, or are performance-based in others, comparison is not straightforward. Nonetheless, the dollar amount in these five interventions ranges between $300 and $1,000 dollars per student over the course of one to three years. Even in the case of the Wisconsin Scholars Grant, the $3,500 per year could be smaller depending on the students' pre-treatment out-of-pocket costs.

engagement and partnership building. We propose to use the resilient thinking approach to understand the dynamics of change in CUNY students' communities caused by the coronavirus pandemic and to do so using action research.

The applicability of the adaptive cycle into action research has been frequently applied to describe processes of change in a community of stakeholders within the context of agricultural land uses (Allison & Hobbs 2014), urban environments (Chaffin et al. 2016) and waste management (Bohensky 2008). It has also been used in urban economics to understand and compare urban policies from two different cities in the United Kingdom (Simmie & Martin 2010), and in the field of urban planning to analyze cities and their vulnerabilities—see Sellberg et al. (2018) in Australia; Schlappa & Neill (2013) in Europe; and Pelling & Manuel-Navarette (2011) in Mexico. However, few studies have used the adaptive cycle model to analyze college communities (Ratliff 2019; Berinyuy et al., 2014). Walker and Salt (2012) explain that communities, including college communities, are systems putting resilience thinking into practice to guide their trajectories so as to avoid crossing undesirable thresholds. Miller et al. (2011) explains that "the adaptive cycle allows those who are shaping academic research and higher education programs to think where and when the constructs of epistemological pluralism and reflexivity are most critical in the context of knowledge processing and learning in academic institutions". Our contribution to this literature is to apply the adaptive cycle model as a diagnostic tool enabling us to explore through a participatory and inclusive approach the dynamics and trajectories of change caused by COVID-19 on CUNY students' communities and neighborhoods.

3. Main Hypotheses

3.1. Unexpected Negative Shocks

Since the first cases of COVID-19 were diagnosed in December 2019 in the city of Wuhan, the outbreak developed exponentially into a worldwide pandemic that has infected millions of people (55.2 million cases of which 11.3 in the US as of mid-November), with a global death toll of 1.33 million (247,000 in the US).[10] As the pandemic progressed people's fear and anxiety soared, uncertainty reigned, schools and colleges closed, and the economic activity halted, generating unexpected negative income shocks.

Such disruptions to the economy can create child-care overload, employment loss, housing instability, food insecurity, and inability to pay regular expenses, bills or debts. Any of these events (or the combination of several of them) generates further disarray, which is likely to impact students' academic performance and persistence. In addition, these events also cause stress and worsens anxiety, and may affect cognition, encouraging focus on immediate (Mullainathan and Shafir, 2013) rather than long-run consequences, ultimately affecting academic performance in both the short and longer run.

For college students, learning has been affected directly through the closing of college campuses and subsequent move to learning online by clearly changing students' ability to interact with courses, faculty, and classmates; and indirectly through the effects COVID-19 disruptions to society have had on them, personally. To better understand the impacts of the coronavirus on CUNY students, we will document how COVID-19 has affected CUNY students' academic performance and persistence, and degree completion, as well as their wellbeing. More specifically, we will focus on documenting how COVID-19 has affected students' (1) COVID-19 incidence rate; (2) challenges related to online teaching; (3) financial support received to cover student expenses related to the disruption of campus operations or the economy due to COVID-19, and its subsequent use; (4) need of services and resources to remain in college and succeed academically; (5) personal wellbeing (including mental health, and food and shelter security); (6) child- and family-care responsibilities; and (6) employment and household income.

To the extent that minorities: (1) have had a higher risk of getting sick and dying from COVID-19 (Price-Haygood et al. 2020), (2) work more in essential jobs, and (3) live in denser and more deprived areas, it is also likely that their lives have been more disrupted by COVID-19. At the

[10] *The New York Times*, November 17 2020. https://www.nytimes.com/interactive/2020/us/coronavirus-us-cases.html

same time, evidence seems to indicate that women have carried a heavier load than men in the provision of childcare during the COVID-19 crisis, even while still working, increasing the psychological distress of mothers of young children (Zamarro and Prados 2020). To explore whether COVID has had differential effects on students based on their socio-demographic characteristics, we will conduct subgroup analysis by gender, race and ethnicity, age groups, and presence of children in the household. Similarly, we will explore whether there is a differential impact across subgroups based on different measures of poverty and levels of disenfranchisement, including being a Pell recipient, transfer student, first-generation college student[11], English-Second-Language learner, or undocumented student. As we expect disruptions to be greater among those students living in boroughs with higher rates of positive PCR testing, we will exploit borough and time variation to identify whether a higher incidence or COVID-19 infection in students' neighborhood is associated with worse students' outcomes.

3.2. One-Time Emergency Grant

Despite being a one-time payment of $500, the CER grant program may well have had a positive impact on students' academic outcomes because it was offered during a major and unexpected public health crisis and economic shutdown, becoming a life saver for those awarded with the emergency relief grant. To put it into perspective, the in-state full-time tuition at CUNY for 2020-21 is $6,930 for those enrolled in a four-year college and $4,800 for those enrolled in a two-year college; the Pell Grant award for 2019-20 ranged between $320 and $3,097.50 per semester, and the CARES Act HEERF Students Emergency Grant[12] for full-time students at CUNY ranged between $356 and $1,024.[13]

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[11] First-generation college students are students who are the first in their family to attend college.

[12] Coronavirus Aid, Relief, and Economic Security (CARES) Act Higher Education Emergency Relief Fund (HEERF) Student Emergency Grant. Undocumented students were excluded from the CARES Act stimulus package as they are not eligible for federal student aid.

[13] The grant amount varied with the student's EFC and the CUNY college attended, as well as whether the student had dependents. Part-time students received half of the amount.

In theory, emergency financial assistance targeted towards vulnerable and disenfranchised students facing an unexpected decline in income should have a positive impact on their academic persistence, performance and graduation. The reason is that such cash payment can be used to cover any unexpected expense caused by the pandemic or its disruption to the economic environment. To the extent that the $500 award increased vulnerable and disenfranchised students' food, shelter, course materials, technology, health care, child-care, and/or financial security, and allowed them to cover crucial expenses during the toughest months of the pandemic, the program sought to encourage students' focus on their studies, improving their academic performance in the short run and reducing their odds of dropping a course. Doing well during the spring 2020 semester and summer 2020 term should help students progress through their degree requirements faster, and increase their odds of graduating or transferring to a four-year college. Receipt of non-tuition financial support in the midst of a pandemic could also impact their intrinsic motivation, which would also have medium- to long-term effects on their academic performance.

3.3. Students' Communities as Complex Systems Prompt to Change and Resilience

The hypothesis, here, is that the resilient-thinking approach, which will be taught to a subset of CUNY students through four workshops, will provide students with the tools they need to analyze key challenges experienced by their communities during the COVID-19 pandemic, and brainstorm on how to overcome them providing bottom-up solutions. More specifically, the resilient-thinking approach will: (1) teach students a conceptual framework that ought to assist them in identifying the different stakeholders in their community and how COVID-19 has impacted those stakeholders' relevance and weight within the community; (2) assist students in understanding the dynamics of change within their communities caused by the COVID-19 pandemic; (3) help students understand the dynamics of community engagement and partnership building generated as a consequence of the disruptions caused by COVID-19; (4) support students cope with the community-related uncertainty generated by COVID-19; and (5) assist students in identifying resilient solutions that will be useful to prepare for future crisis. Students will work in groups focusing on different topics including mobility, housing, social justice, food security, and social safety networks provided by both public and private organizations and colleges. At CUNY, the CER grant program is one of many social services the university provides to its most vulnerable students.

4. Data

Table 4 summarizes key research elements for the proposed project, including a thorough description of the pre- and post-pandemic student-level data available, targeted populations, and sample sizes for each of the three proposed approaches. The timeline for instrument design, data collection, analysis, writing and deliverables for each of the three components of this proposal is attached in a separate document at the end of the proposal.

4.1. The Survey

The first part of the project entails a series of three large-scale online student surveys that will cover the following two populations: (1) a representative sample of the student population of CUNY; and (2) the 25,000 CUNY students eligible for the CER grant program. The objective of these surveys is to understand the impact of: (1) the pandemic on student financial and personal well-being as well as student coping behavior; and (2) the receipt of any stimulus payments received to cope with COVID19 challenges[14] on students' consumer behavior, and wellbeing. The surveys will be administered via email, sent from an official email address of the CUNY administration. In addition to being less costly than telephone or in-person interviewing, online interviews can still be an effective way to interview a representative population (Yeager et al. 2011), it is also the mode used by other surveys, including the Survey on Economic Well-Being of US Households (SHED) conducted by the Board of Governors of the Federal Reserve System. For the full project, we aim at combining data of three survey waves, fielded in spring 2021 and 2022 and fall 2022 as described in the timeline.

[14] This includes but is not limited to CER grant, CARES Act student grant, IRS economic impact payment of $1,200, federal pandemic unemployment compensation and pandemic unemployment assistance for workers not traditionally eligible for unemployment insurance benefits.

All three surveys will collect students' baseline characteristics that we cannot observe in the administrative data, namely the number of family members the student lives with by age brackets; the household annual income in 2019; country of birth; first-generation college student status; pre-pandemic employment status including part- or full-time status, and essential worker status. In addition, the first survey, fielded in spring 2021, will cover the first year experience of students during the COVID-19 pandemic. We will ask students about their own financial and personal well-being, including financial support received to cover student expenses related to the disruption of campus operations or the economy due to COVID-19[15], and its subsequent use (consumption, saving, or paying debt). Further, we will elicit expectation measures on how students believe the lockdown has impacted their own educational progress and economic well-being. The survey will also contain some questions assessing students' trust, anxiety, and financial, housing and food insecurity (see instrument for pilot survey #3 attached at the end of this proposal for more details on the types of outcomes we will collect). The second survey, fielded during fall 2021, will focus on medium-run personal and financial well-being as well as the labor-market situation of students who depend on paid work. We expect this period to be vital as we will have more clarity on whether the public health crisis has ignited a financial and economic crisis or has, instead, vanished, allowing the labor market to recover. Therefore, a focus of this questionnaire will also be put on student's expectations on graduation probabilities, labor market prospects, and job choice after graduation. Beyond repeating modules on financial and personal well-being and economic expectations, we will use the third survey (fielded during spring 2022) to gain additional insight into how the COVID-19 crisis has changed the academic environment in the medium run (such as the higher usage of distance learning and digital environments) and in how far students believe to benefit from these changes. The responses to all three surveys will be merged to CUNY administrative student records. The combination of survey responses with the administrative data will allow us to track students above and beyond the topics covered by the

[15] Information on whether the student has received a federal Pell grant or has been awarded the CER grant is also available from CUNY administrative records.

survey by observing their full academic career (including grades, credits taken and earned, and major choice) from their entry into the CUNY system up until graduation. It will further enable us to analyze in how far survey response is associated with students' demographics and pre-pandemic academic performance.

4.2. The Experiment

The second part of the project will exploit the randomization of the CER grant program to estimate the causal effect of this program on CUNY students' academic performance, persistence and degree completion. The analysis will cover the universe of eligible students, namely 25,000 students and will focus on academic administrative data. The lottery-based assignment of the grants alleviates concerns about selection into grant receipt based on observable and unobservable characteristics and allows to estimate the causal impact of the program on the aforementioned outcomes. The focus on academic outcomes from CUNY administrative data, namely college continuation, credits taken and earned, GPA, college graduation and on time graduation, will avoid the concerns related to bias non-response that may emerge with outcomes from the surveys. Estimates will be intention-to-treat (ITT) estimates as presented in Research Methods Section below (Section 5.2).

We will also estimate the impact of the CER grant on students' financial and personal wellbeing as well as their expectations after graduation. To address potential concerns that may threaten internal validity of the causal impact of the CER grant program on outcomes obtained from the survey we will take a three-prong approach summarized in Table 5.

The main hypotheses and the detailed research design will be worked out and pre-registered at the America Economic Association RCT Registry before data sources are merged.

4.3. The Resilient Thinking Approach

We will conduct seven qualitative in-depth semi-structured group workshops: three of these group workshops were conducted before the coronavirus pandemic at Queens College during the fall semester 2019. The other four will be conducted, also at Queens College, at four different points in time in spring and fall 2021 and 2022 (as shown in the timeline). Each time, between 20 and 30 students from different majors, races and ethnicities, and graduating years will be invited to participate.

These workshop will be facilitated by one or two moderators (the co-PI Rafael de Balanzó Joue and the trained-in-resilient-thinking Research Assistant). They will generally last 90 minutes. At the beginning of the workshop, students will be introduced to resilient-thinking analysis. They will then be asked to use such approach to: (1) ask themselves questions about the current systemic crisis related to COVID-19; (2) analyze the current risks; (3) develop a brainstorming session; and (4) define how to initiate a sustainable "transition" process. Through this process, students will analyze COVID-19-related challenges in their neighborhoods and identify visions on how to address them. Students will work in groups focusing on different topics including mobility, housing, social justice, food security, and social safety networks provided by both public and private organizations and colleges.

Post-pandemic qualitative data will be compared to pre-pandemic qualitative data (see Section 4.4 below for examples of such data) to identify how COVID-19 has modified students' perceptions of the challenges in their communities, and their visions on best practices on how to address them.

4.4. Data Transfer Agreement, IRB Approval, Pilot Survey, and Pre-Pandemic Qualitative Data

We have already signed the De-Identified Data Transfer Agreement with The Office of Institutional Research & Assessment (OIRA) at CUNY to have access to students' de-identified academic administrative records. We also received IRB approval (IRB File #2020-0475) to conduct the surveys, collect the de-identified academic records, merge both data sources using students' CUNY ID, and conduct the analysis. Both documents are attached at the end of this proposal. We would like to request a waiver because our data would make it possible to identify a particularly at-risk population of undocumented students. Both the De-Identified Data Transfer Agreement with OIRA and the IRB protects the proprietary data to preserve the confidentiality of students' survey responses as well as their academic administrative records.

We have already developed and fielded one survey instrument (pilot survey #1) at Queens College (QC), and are currently fielding two additional surveys (pilot surveys #2 and #3), one of which is targeted to QC students and the other to CUNY students eligible to receive the CER grant program. Analysis of these three pilot surveys will help us with the design of the survey instruments for the proposed research, and to increase survey non-response among at hard-to-reach socio-demographic groups in the proposed surveys to be conducted between spring 2021 and 2022 as explained in Appendix Table A.1. Pilot survey #3, which is the most comprehensive of the pilot surveys, is attached at the end of the proposal.

With pilot survey #1, which was fielded between July 24 and September 18 2020 to QC students enrolled in the spring semester, the Co-PI Rodríguez-Planas has already produced the IZA Discussion Paper entitled, "Hitting Where It Hurts Most: COVID-19 and Low-Income Urban College Students", and submitted to the COVID-19 special issue at the *Journal of Public Economics*. The main findings of this manuscript were discussed in the Literature Review Section above (Section 2.1.). For your convenience, a copy of the IZA Discussion Paper can be found at: http://ftp.iza.org/dp13644.pdf .

The Co-PI Rafael de Balanzó Joue has already conducted three qualitative in-depth semi-structured group workshops using the resilient-thinking approach at Queens College during the fall semester 2019. Such data will serve as baseline for pre-pandemic students' perceptions of their community challenges and pre-pandemic students' visions, and will be compared to post-pandemic findings. Attached at the end of this proposal are examples of output produced from these pre-COVID-19 workshops. In particular, these two examples cover discussions on the availability of social services, and local education in the neighborhood of Jamaica, Queens. Importantly, Dr. de Balanzó Joue has continued to facilitate several workshops using the resilient-thinking analysis during the current pandemic via zoom workshops (for example, at the Pratt Institute, the Barcelona

Design Week 2020, the Civic Lab Art 2020, and the II International Network Conflicts, Policies and Social Movements Conference, among others).[16]

5. Research Methods and Preliminary Findings

5.1. Geographic and Time Variation in the Rates of Positive PCR Testing

The analysis documenting CUNY students' experiences during the pandemic and thereafter up until summer 2022 will study how different socio-demographic characteristics are associated with differential experiences post-COVID-19. These associations will not be causal. To the extent students living in boroughs with higher rates of positive PCR testing may experience greater COVID-19 related disruptions, we may expect them to experience worse outcomes. We will merge New York City data on the level of COVID-19 infections across boroughs (and zip codes if the sample size allows) and time (from spring 2020 to summer 2023)[17] to the students' zip code of residence (available from CUNY administrative data), and exploit variation in infection rates across geographic areas and time to identify whether higher rates of infection in the students' area of residence is associated with worse students' outcomes. Such analysis will preclude us from picking up confounding effects between infection rates and other structural time-invariant characteristics of the boroughs (or zip-code areas) CUNY students live in because we will be able to identify how students' outcomes vary with the infection rate in their area of residence holding constant the area of residence. As we will observe the universe of students who are registered every semester from administrative academic records, we will be able to build a student panel dataset for each of the terms between spring semester 2020 and summer 2023, and hence, estimate an individual fixed effects model with semester and year fixed effects and borough (or zip-code) fixed effects for outcomes such as academic performance, enrollment, credits taken and earned, and college graduation. Most importantly, such model

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[16] https://barcelonadesignweek.com/en/activities/workshop-resilient-thinking-design/
https://greenspacenyc.org/ ; http://conflictosurbanos.org/

[17] A dataset on the rates of positive PCR testing overtime across boroughs and zip codes in NYC is available at: https://github.com/nychealth/coronavirus-data

will control for individual time-invariant unobserved heterogeneity. While we will explore whether we have enough individuals who respond to more than one survey to allow for the same regression model when using students' self-reported outcomes, the analysis on survey outcomes will most likely use a time-of-survey fixed effects and borough (or zip-code) fixed effects model as the dataset will be a repeated cross-sectional panel. In such case, our estimates will control for geographic-area time-invariant unobserved heterogeneity.

5.2. Impact Evaluation of the CER Grant Program

A common concern among randomly-designed impact evaluations is whether they will have enough statistical power. To inform us on what kinds of effect sizes we may expect, and whether the design allows us to detect such effects, we identified five randomized interventions offering some form of non-tuition financial assistance to low-income college students (discussed in Section 2.2). Because most of these interventions find beneficial statistically significant impacts on college persistence and/or completion in the medium-run, and given that the sample size of these earlier RCT interventions ranged between 410 students and 4,274 students, well below the sample size of our proposed evaluation of the CER grant program—19,168 students, of which 6,000 received the grant—, we would expect measurable outcomes in our intervention.

Importantly, preliminary findings for the spring 2020 semester using administrative academic data for the population of Queens College students who were eligible to receive the CER grant program— 1,687 students, of which 427 received the $500 award—indicates that the CER grant was successful in improving students' grades and increasing credits taken and earned. To obtain ITT estimates, we estimated the following regression:

$$Y_{ij}=\alpha_0 + \alpha_1\, CER_{ij}+ X'_{ij}\, \alpha_2 + w_1 + w_2 + \alpha_3 UNDOC_i + \alpha_4(w_1 * UNDOC_i) + \alpha_5(w_2 * UNDOC_i) + \varepsilon_{ij} \quad (1)$$

where Y_{ij} is the outcome of interest (for example, spring semester GPA) for student *i* in wave *j*; $CER_{ji,}$ is a dummy variable that takes value 1 if student *i* was awarded the CER grant in wave *j* and value 0 otherwise; X'_{ij} is a vector of individual socio-demographic characteristics at baseline (that is, measured before the lottery took place); w_1 and w_2 are wave dummies that take value of 1 if student i was eligible in that particular wave and 0 otherwise; $UNDOC_j$ is a dummy variable that takes value 1 if student i is an undocumented student and 0 otherwise; and $(w_1 * UNDOC_i)$ and $(w_2 * UNDOC_i)$ are the interactions between the wave dummies and the undocumented dummy variable. The wave dummies and the interaction between the wave dummies and the undocumented dummy variable are included because there were three separate lotteries (one for each wave) and within waves grants were awarded by lottery based on students' undocumented and low-income student status. Students can only be awarded the grant once. However, eligible students who were not awarded the grant in wave 1 are eligible to receive the grant in subsequent waves. ε_{ij} is the error term. Standard errors are clustered at individual level. Estimates are calculated using OLS regression for continuous outcomes and will be calculated using Logit or Probit for binary outcomes.

Our coefficient of interest, $\hat{\alpha}_1$, captures the intention-to-treat (ITT) estimates. It measures the treatment effect of the program's impact on outcome Y. Table 6 presents ITT estimates for spring 2020 semester GPA, credits taken, earned, and dropped. The first column displays control-group means for each of the outcomes, while the other columns present ITT estimates from estimating equation (1) with different controls in the vector X_{ij}' as indicated in the bottom of each column. We find that the CER grant increased the spring semester GPA by 19.9 percentage points, a 6% increase relative to the control-group spring semester GPA of 3.362[18] (based on the raw data shown in column 1, which is the regression with no baseline controls). Sequentially adding different baseline characteristics only reduces the estimate a tad, which is expected since the award was randomized. In fact, we tested for equivalence in the socio-demographic characteristics of students in the treatment and control groups *before* the program began, and found that both groups looked alike with no statistically significant differences across the two groups. In the specification with all the controls, the CER grant increased the spring semester GPA by 5% (17.8 percentage points). We also observe that the CER grant increased both the number of credits taken and earned over the

[18] While this GPA may seem high, grading was more lenient during spring 2020 semester. As a comparison, respondents of pilot survey #1 at Queens College had a spring semester GPA of 3.41.

spring semester by 5% (50.7 percentage points) and 7% (69.4 percentage points), respectively. All three estimates are statistically significant—albeit the estimate on credits taken only marginally so with p<0.10. While the CER grant also reduced the credits dropped during the spring semester by 29% (18.7 percentage points), this estimate is only marginally statistically significant and loses precision once we add baseline controls. These preliminary estimates for the spring 2020 semester for Queens College suggest that the CER grant program was successful in improving students' grades and increasing credits taken and earned.

Our proposed research will expand the analysis to all CUNY colleges and analyze whether the beneficial effects of the CER grant persist overtime. For the CUNY-wide analysis, we will add to the equation (1) college fixed effects. We will also conduct a battery of sensitivity analysis such as clustering the standard errors at different levels or adjusting for multiple hypothesis testing. Subgroup analysis will be conducted by the timing of the award (wave 1 vs wave 2 vs wave 3), and undocumented and low-income status as the latter were most likely to also receive CARES Act emergency relief funds on top of the CER grant. Finally, we will use survey outcomes to identify potential mechanisms driving these results.

6. Dissemination and Team's Qualifications and Responsibilities

To maximize the outreach and impact of our results, we will adopt a range of different approaches. We emphasize that while academic excellence and publication at a high level is a key aim, the nature of the research is inherently policy-orientated. As a result, our aim is to reach both the academic audience but also stakeholders and policy makers in the realm of tertiary education. We describe some of our strategies to these joint aims in Appendix Table A.2.

The research team consists of two principal investigators, Núria Rodríguez-Planas (CUNY, and IZA) and Rafael de Balanzó Joue (CUNY and Urban Resilience Thinking Institute), a pre-doctoral research assistant, a researcher from *The Office of Research, Evaluation, and Program Support* (REPS) at CUNY and a data analyst from *The Office of Institutional Effectiveness* (OIE) at Queens College. Professor Rodríguez-Planas will be responsible for ensuring the project's success in the design and fielding of the surveys, methodology development and design, data analysis and writing of one policy brief, and two academic paper of objectives 1 and 2. The research team will be strengthened by the participation of REPS as well as OIE. Both offices have agreed to provide support with extraction and management of student-level educational administrative data, survey administration, data analysis, and contributing to the writing of policy briefs or reports (see timeline and data agreements). Requested funds to cover a pre-doctoral research who will provide support to both PI and Co-PI in different tasks as indicated in the timeline and budget justification. Professor Rafael De Balanzó Joue (Civil Engineer Ph.D. in Sustainability) will lead the qualitative analysis contained in objective 3 and be responsible for writing of one policy brief, and one academic paper. His ample experience applying the *Resilient Thinking Approach* to urban design and planning participatory processes and facilitating community engagement in different communities will guarantee the success of the qualitative analysis. To bridge the quantitative and qualitative analyses, he will collaborate closely with Professor Núria Rodríguez-Planas. He will train a junior researcher in resilient-thinking analysis and who will thereafter assist him in conducting the workshops and analysis. Both professors have co-authored and published an article together applying the resilient-thinking approach to analyze urban planning cycles in Barcelona (De Balanzó & Rodríguez-Planas 2018). Because the Co-PIs Rafael de Balanzó Joue is the spouse of the PI Núria Rodríguez Planas, a CUNY COI management plan will be instituted as discussed in Appendix A.1.

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Tables (do not count against the 20-page limit for the proposal)

Table 1. Timing of the CER Grant Program

	Eligible students were invited to apply to the program	Applications were accepted within this timeframe[1]	Award status was notified to students	Funds were distributed
Wave 1	April 6	April 6 to April 10	April 15	April 20
Wave 2	May 5	May 5 to May 10	May 13	May 18
Wave 3	June 29	June 29 to July 5	July 8	July 20

[1] No application was accepted after 5 pm on the closing date.

Table 2. Randomized Control Trials (RCT) of College Interventions Offering Non-Tuition Financial Support in the US, Key Elements of the Evaluations

	ASAP	Stay the Course	Opening Doors	One Million Degrees	Wisconsin Scholars Grant
RCT sites and study duration	CUNY from 2010 to 2013	Tarrant County Community College from 2013-2016	Multiple locations in Ohio from 2003-2006	Ten different sites in and around Chicago from 2016-2017	13 public universities in Wisconsin, cohort entering 2008
Intervention description	Comprehensive support for up to three years for full-time	Comprehensive case management and limited access to emergency financial assistance	Access to counselors and $150 stipend per semester for each semester they work with a counselor (for a maximum of 2 semesters)	Regular meetings with a program coordinator who offers financial, academic, personal and professional support to students	Maximum of $3,500 grant renewable for up to five years. Total amount per year depends on pre-treatment out-of-pocket costs
Targeted population	Low-income students (Pell eligible or below 200% FPL) with fewer than 12 credits earned.	Full-time (initially enrolled in at least 9 credit hours), low-income (Pell eligible or below 200% FPL) students with fewer than 30 credits earned	Part-and full-time, low-income (below 250% FPL) students with fewer than 12 credits earned at entry	First-time, low-income (Pell-eligible or Chicago STAR eligible) students with at least one full year of college remaining and a GPA over 2.0.	Wisconsin residents who graduated from a state public high school within three years of matriculating full-time to university. They had to have completed FAFSA and qualified for a Pell Grant
Non-tuition financial assistance	Free use of textbooks and MetroCard	Access to emergency financial assistance for qualified	$150 stipend each semester (for 2 semesters) without	a $750-$1000 annual stipend as a performance-based grant as	Maximum of $3,500 grant renewable for up to five years. Total amount

		expenses up to $1500 over three years	restrictions on use	well as access to $250 in enrichment grants	per year depends on pre-treatment out-of-pocket costs
RCT evaluations	Scrivener et al. (2015) for CUNY	Evans et al. (2017)	Scrivener and Weiss (2009)	Bertrand, Hallberg, Hofmeister, Morgan and Shirey (2019)	Goldrick-Rab et al. (2016)
RCT sample sizes	896 students in CUNY	869 students	2,139 students	4,274 students	1,500 students

Notes: See Fulcher et al. (2020) for a thorough description of these interventions and findings. ASAP stands for Accelerated Study in Associate Programs.

Table 3. Key Findings of College Interventions Offering Non-Tuition Financial Support in the US, Evaluated through Randomized Control Trials (RCT)

	ASAP	**Stay the Course**	**Opening Doors**	**One Million Degrees**	**Wisconsin Scholars Grant**
Intention-to-treat (ITT) estimate on academic persistence					
Outcome	Enrolled in college after six semesters	Enrolled in college after six semesters	Continuous enrollment from the 1st through the 3rd semester	Enrolled through the 1st year	Enrolled after 2 years
Control means	0.173	0.44	0.93	.556	0.76
ITT estimate	+0.08**	+0.06*	+0.01	+0.06**	+0.018**
Percent increase (relative to the control mean)	+46%	+14%	+1%	+11%	+2.4%
Intention-to-treat (ITT) estimate on degree (or certificate) completion					
Outcome	Earned a degree from any college after six semesters	Earned a degree from any college after six semesters	Earned a degree or certificate through the 3rd semester	Not available	Earned a four-year degree
Control means	0.218	0.182	0.025	n.a.	0.16
ITT estimate	+0.18 **	+0.04	-0.01	n.a.	+0.047**
Percent increase (relative to the control mean)	+83%	+22%	-40%		+29%

Notes: ITT estimates are basically the difference in mean outcomes between the treatment and control groups. Frequently, the ITT estimates are obtained from linear regressions with a dummy indicating program participant (treatment) and site controls and other socio-demographic controls measured before random assignment into the program. See Fulcher et al. (2020) for a thorough description of these interventions and findings. ASAP stands for Accelerated Study in Associate Programs. This table was built using information from Figures 3 and 4 in Fulcher et al. (2020) and Goldrick-Rab et al.(2016).

** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 4. Summary Table of Main Research Elements for the Proposed Project

	Objective 1	***Objective 2***	***Objective 3***
	Quantitative Analysis	***Quantitative Analysis***	***Qualitative Analysis***
Research Design	***Descriptive Analysis***: We will document academic and economic outcomes of CUNY students. We will also document differential outcomes by undocumented and low-income status.	***Causal Analysis***: Exploiting the lottery assignment of the Chancellor's Emergency Relief (CER) Fund, we will compare the academic and economic outcomes of ***6,000 recipients of the CER grant*** to ***control students who qualified for the CER grant but did not receive the grant by lottery***. Estimates will be ***Average Treatment Effect on the Treated.*** Regression analysis will control for baseline characteristics to increase precision.	***In-depth Group Workshops***: Post-COVID-19 responses on community challenges will be compared to pre-COVID-19 responses on community challenges using the ***resilient thinking approach*** to investigate how interactive systems of people and nature cope and continue to develop in the face of the coronavirus pandemic.
Original Data & Administrative Data	Three surveys collected during school year 2020/21 and 2021/22. They will be merged with administrative academic data since student enrolled in CUNY	CUNY administrative academic data since the student enrolled in CUNY merged with survey data from objective 1.	Four post-COVID-19 in-depth group workshops and three pre-COVID-19 in depth group workshops.[a]
Pre-Pandemic Information, observed before the money was distributed	***From CUNY student-level educational administrative data:*** Socio-demographic characteristics: gender, age, race/ethnicity, citizenship, zip code, residency type, Pell grant receipt, full-time/part-time status, transfer student indicator, major, seniority in college, college major, CUNY college(s) attended, first admission data, degree, degree completed term. In addition, we also have the following academic information: each term and cumulative GPA, credits earned and credits taken since enrollment at CUNY up to fall semester 2019. In addition, high-school GPA or 2-year college GPA (for transfers students) is available. ***From survey data:*** Retrospective self-reported baseline socio-demographic characteristics (including number of family members they live with by age brackets; 2019 household income; country of birth; and first-generation college student status) and pre-pandemic employment status including part- or full-time status, and essential worker status.	***From CUNY student-level educational administrative data:*** Socio-demographic characteristics: gender, age, race/ethnicity, citizenship, zip code, residency type, Pell grant receipt, full-time/part-time status, transfer student indicator, major, seniority in college, college major, CUNY college(s) attended, first admission data, degree, degree completed term. In addition, we also have the following academic information: each term and cumulative GPA, credits earned and credits taken since enrollment at CUNY up to fall semester 2019. In addition, high-school GPA or 2-year college GPA (for transfers students) is available. We also have CER program participation data including eligibility and participant indicators, wave indicators, as well as several indicators allowing us to identify treatment and control students in each of the three waves (including an undocumented student indicator). ***From survey data:*** Retrospective self-reported baseline socio-demographic characteristics and pre-pandemic health and employment status.	Students' perceptions of their community's challenges regarding mobility, housing, racial/ethnic disparities/discrimination, food security, and social safety networks.

Post-Pandemic Information	***From CUNY student-level educational administrative data:*** Covering from spring semester 2020 to summer term 2022 (or earlier if they graduate, transfer out of CUNY or drop out of CUNY: cumulative and each semester GPA, credits taken and earned, as well as date of graduation, degree and major. In addition, we also know Pell grant receipt, full-time/part-time status, and major (we can identify those who changed majors). ***From survey data:*** Self-reported wellbeing, financial situation and employment status (including job loss information); Employment expectations after graduation; Self-reported services and financial assistance received due to COVID-19, and use of aid—includes Federal CARES act assistance as well as CER grant; Questions on trust, anxiety, and financial, housing and food insecurity. ***See pilot survey instrument #3.***	***From CUNY student-level educational administrative data:*** Covering from spring semester 2020 to summer term 2022 (or earlier if they graduate, transfer out of CUNY or drop out of CUNY: cumulative and each semester GPA, credits taken and earned, as well as date of graduation, degree and major. In addition, we also know Pell grant receipt, full-time/part-time status, and major (we can identify those who changed majors). ***From survey data:*** Self-reported wellbeing, financial situation and employment status (including job loss information); Employment expectations after graduation; Self-reported services and financial assistance received due to COVID-19, and use of aid—includes Federal CARES act assistance as well as CER grant; Questions on trust, anxiety, financial, housing and food insecurity. ***See pilot survey instrument #3.***	Same as pre-pandemic information
Targeted Population	A representative sample of 30,000 CUNY students	***CER eligible student population:*** (1) Undocumented undergraduate and graduate students; and (2) undergraduate students within 12 credits of earning a degree, and having an EFC of zero on their federal financial aid application (FAFSA) or being a parent with any EFC.	A representative group of CUNY students from different socio-economic backgrounds, races/ethnicities, majors and years of graduation
Expected Sample Sizes	6,000 students per survey (based on a 20 percent response rate).	***Eligible population:*** 19,168 students. Treatment group: 6,000 students. Control group: 13,168 qualified students who applied and did not get the CER grant.	***Pre-pandemic:*** 80 students ***Post-pandemic:*** 120 students

Note: [a] Pre-COVID-19 in-depth group workshops have already been conducted.

Table 5. Three-Prong Approach to Address Internal-Validity Threats Using Survey Data

Targeted Communication Plan to Maximize Representativeness of Survey Respondents   Using our pilot surveys (described in Section 4.4), we will first identify those demographic groups who have lower response rates, and to increase survey participation and completion among those hard-to-reach demographic groups, we will utilize a targeted communication plan as explained in Appendix Table A.1, which addresses the proposal's risk assessment. The objective is to obtain a sample of survey respondents that is representative of the CER grant program eligible population.
Control for Baseline Proxies of Ability, Grit and Academic Commitment   We will use pre-pandemic administrative academic information (including cumulative GPA and credits earned) as proxies of students' ability, grit and academic commitment to include as covariates in the regression analysis. While this will not eliminate the bias, to the extent that cumulative GPA and credits earned are correlated with both students' outcomes and their decision to respond the survey, controlling for them will reduce the bias and provide an indication of the direction of the survey non-response bias.
Propensity Score Matching so Treated and Control Groups Have Balanced Baseline Characteristics   We will explore the use of baseline cumulative GPA and credits earned as well as socio-demographic characteristics and propensity score matching to obtain a group of treated and control students who responded to the survey and was balanced in terms of these baseline characteristics.

TABLE 6. Queens College Chancellor's Emergency Relief Fund, Spring 2020 Academic Outcomes

OUTCOMES	*Control population means*	No controls *(1)*	Sex & age controls *(2)*	Race & ethnicity *(3)*	ESL & NY residence *(4)*	Pre-QC GPA *(5)*
Spring 2020 semester						
Spring 2020 GPA	3.362 [0.860]	+0.199*** (0.05)	+0.175*** (0.05)	+0.181*** (0.05)	+0.185*** (0.05)	+0.178*** (0.05)
Spring 2020 credits taken	10.957 [4.556]	+0.649** (0.25)	+0.557* (0.23)	+0.525* (0.23)	+0.509* (0.23)	+0.507* (0.23)
Spring 2020 credits earned	10.306 [4.671]	+0.897*** (0.26)	+0.766** (0.24)	+0.739** (0.24)	+0.704** (0.24)	0.694** (0.24)
Spring 2020 credits dropped (credits taken – credits earned)	+0.650 [1.873]	-0.247* (0.11)	-0.209 (0.11)	-0.214 (0.11)	-0.196 (0.11)	-0.187 (0.11)
COVARIATES						
Sex and age controls			X	X	X	X
Race and ethnicity controls				X	X	X
ESL student, International student, NY state residence status, and transfer student controls					X	X
Pre-QC GPA						X

Notes: Robust standard deviation in brackets. The table reports estimates of treatment effects on the dependent variables indicated in row headings. Robust standard errors are reported in parentheses. Standard errors are clustered at the individual level. All specifications include wave dummies, an indicator for being undocumented or low-income student indicator, and such indicators interacted with the waves indicator as randomization was done within waves and by undocumented or low-income student status. Sample sizes are C=2,433 students and T= 427 students.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.