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TOPICS AND INSTITUTIONS IN THE REPRODUCTION OF INTERSECTIONAL INEQUALITIES IN SCIENCE

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CHAPTER 1. INTRODUCTION

In a context of strong economic (Chancel & Piketty, 2021) international (Starosta, 2016b) inequalities, systemic discrimination based on race (Foucault, 1998), gender (Federici, 2012), or sexual orientation (Butler, 2006) are mechanisms that structure those inequalities towards targeted populations. Science, as a core element of society (Bernal, 2010), cannot be independent of its context.

Inequalities in science are a complex, multi-causal, persistent, structural problem. Inequalities in science can be sorted into three different categories: entry and retainment barriers, epistemic injustice, and biased outcomes. The research endeavor is reserved to a small group of highly qualified workers, with less than 1% of the global population holding a PhD (OECD, 2022b). To organize who gets in and who is left out, the institutional organization of science is set in place with large entry barriers. These barriers change by country and field (Bourdieu, 2004), and going through them is not just a problem of merit. This sets up an uneven field in which disadvantages cumulatively pile up, resulting in an underrepresentation of marginalized groups and overrepresentation of people from privileged backgrounds. The disproportional representation of the population builds the grounds for the uneven distribution of epistemic authority (Bourdieu, 1975). After crossing the entry barriers, there is a set of mechanisms that diminish the voice of marginalized authors within the scientific community, in what Fricker (2009) defines as epistemic injustice. Entry barriers and epistemic injustice result in a knowledge production that is biased against the interests of those marginalized populations (D'Ignazio & Klein, 2018).

This thesis is devoted to the study of some specific components and relations that are part of this larger structure of inequalities in science. Using a large-scale database with more than 5 million articles and 1.5 million authors, this thesis aims to be an empirical contribution to the study of inequalities in science. As a cumulative type of dissertation, the three main chapters of this work are self-contained articles —chapters 3, 4, and 5— with their own introductions and conclusions.

Nevertheless, given the extension limits for research articles, the theoretical framing that guides their analysis is limited, to prioritize the analysis of empirical results. There are two fundamental sources that contribute to the conceptual framework of this thesis: Bourdieu's theory of academic capital (Bourdieu, 2004) and intersectionality (Crenshaw, 1991). This introduction will draw from these theories to contextualize the work by showing a more ample frame of analytical categories and dimensions of inequality. The next chapter will briefly explain some analytical categories that are essential for the understanding of inequalities in science, how they have been operationalized in the past, and highlight those elements that are later used in the thesis' main chapters, and proposes a discussion on which are the best quantitative methods that can be used for the study of inequalities in science.

Figure 1 highlights those dimensions and relations in which this thesis is focused, within a more general conceptual framework of the multiple dimensions of inequality. Some of those dimensions not highlighted are still part of the empirical design for this study, such as journals, discipline, or migration status, but do not constitute the focus of the research. Other dimensions are out of the scope of the empirical analysis, due to data limitations (funding, economic background), or because they are unmeasurable dimensions that frame the interpretation of results (individual ideology).

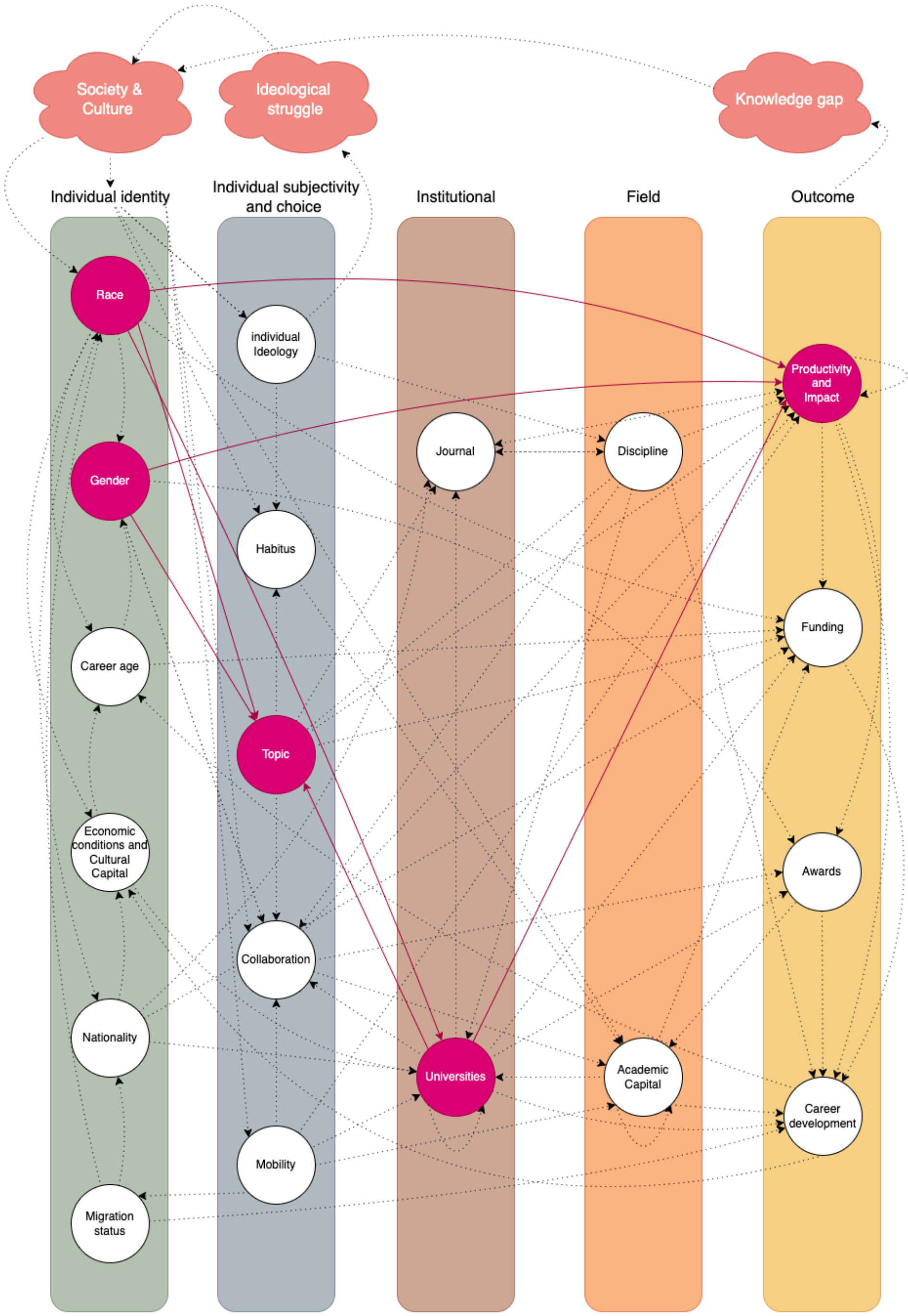

Figure 1. Illustrative framework of systemic inequalities in science and contributions of this thesis. Each column represents a dimension of analysis, and each node is an analytical category. Links between nodes refer to a relation between nodes: a directed link from a to b means that a is a determining factor of b. These analytical categories are grouped into five general dimensions. The three red elements above refer to social phenomena that go beyond the scope of inequalities in science but refer to the relation between inequalities in society overall and inequalities in science. Highlighted nodes and links constitute the focus of study of this thesis. Other analytical categories such as career age, nationality, migration status, or journal were partially considered as control variables in some parts of the thesis, while concepts such as habitus, ideology and academic capital are part of the theoretical framework that informs the understanding of results.

There is an extended research literature on large-scale analysis of gender inequalities in science, but research that takes an intersectional perspective is mostly based on qualitative approaches. While the role of institutions in the reproduction of inequalities has recently gathered more attention, there is a need to explain how this relates with research topics, and race and gender identities. The improvement of the data quality of bibliometric databases —the inclusion of given names since 2008— and the development of new methods from NLP opens the possibility to partially close these research gaps using a combination of techniques. Also, this thesis comes timely with a live discussion in the field on inequalities in science. Journals are self-reflecting on their role in the reproduction of systemic inequalities (Nature, 2022), and scholars are discussing their citational practices (Kwon, 2022). Yet, there is still a long way to go, and this thesis pretends to be a step in that direction.

Since I started my PhD in January 2020 I published six articles, two of which compose this thesis together with another article currently submitted for review. All these articles are in some way related to inequalities, and half of them are related to science studies. The decision to select the articles that compose this thesis is that they are all parts of an overreaching question: how lived experiences of marginalized identities reflect on research topics, and which consequences this implies? This can be further specified in the following research questions:

> RQ1. Is it possible to operationalize the racial identities of authors from the information available in bibliometric databases?
>
> RQ2. Is it correct to use thresholding for individual-level classification of authors' race?
>
> RQ3. How is the composition of the US scientific labor force by race and gender?
>
> RQ4. How does this composition vary by discipline?
>
> RQ5. Which is the relation, if any, between race and gender identities and research topics?
>
> RQ6. What is the relation between research topics and citations?
>
> RQ7. What would the research space look like if the authors' composition by race and gender matched the census distribution?
>
> RQ8. What is the representation of marginalized scholars in institutions, given their mission and prestige?
>
> RQ9. How do women and minority serving institutions reflect their mission on their topical profile?
>
> RQ10. How does prestige relate to the topical profile of institutions?
>
> RQ11. Are marginalized authors from top institutions more topically aligned with other marginalized authors or with other authors from top institutions?
>
> RQ12. How does institutional prestige and topical profile relate to impact?
>
> RQ13. What is the impact gap of marginalized scholars and how this relates with topics and institutional prestige?

As shown in Figure 1, there are several key concepts that frame this thesis, including those that are out of scope for the empirical analysis, as they help to understand up to which point the answers that this work can give to the above research questions are complete, and how they could be improved. **Chapter 2** delves into a literature review of the conceptual framework, and a discussion of the proposed research methods.

The first two research questions aim to the operationalization of the concept of race on bibliometric databases. This presents several challenges and can lead to the underrepresentation of marginalized groups, in particular Black authors in the US. **Chapter 3** shows the potential biases that different inference algorithms can carry, and highlights how crucial the understanding of the context of data is to avoid biases. This work concludes with a proposal that reduces bias when inferring author's racial identity, which is used on Web of Science (WOS) US authors between 2008 and 2019. This curated dataset will be used on chapters 3 and 4.

Research questions RQ2 to RQ7 aim to understand how race and gender identities affect the topical interests, and how topics that are aligned with marginalized identities receive different attention from those that are aligned with White men's interests. For this, in **chapter 4** I use topic modeling to infer the distribution over topics of articles. I study how authors from different identities contribute differently to the topical space. I also study the distribution of citations by topic, and the within-topic biases.

Research questions RQ8 to RQ13 further enquire about the role of institutions on the relation between race, gender, topic, and impact. I work on this in **chapter 5**, using the racial inference of chapter 2, and the topical inference of chapter 3; and further curating the dataset with an institutional name disambiguation. With this new information I assign authors to universities, and to the universities their Carnegie classification and US News & World report ranking. I work with different proxies of prestige and dedicate special attention to mission- and threshold-driven classifications, like Historically Black Colleges and Universities, Women's Colleges, and Hispanic Serving Institutions. This allows us to understand the topical profile of institutions by several classifications, and the relation between these topical profiles and those of race and gender identities. Finally, I study how the race and gender citation gap changes by institutions.

This thesis ends with the **summary and outlook**, where the main findings are reviewed together with the future directions of research.

Scope of the thesis

This thesis focuses on the case study of articles from US first authors between 2008 and 2019. Therefore, it does not represent the intersectional inequalities across the globe. The decision to restrict the analysis to this subset of the population has two main reasons. First, the conceptualization of race needs to have a clear contextualization. Given that race is a social construct, the used categories can only be significant within a context of shared meaning of those categories.

My operationalization of the categories of race and gender suffers from data and technical limitations that do not allow to account all races and genders. People beyond the gender binary and trans identities are not captured by my approach, which constitutes a problematic omission. Also, the racial inference cannot identify Native Americans or Two or More races authors (see more details on chapter 3), which also constitutes a major limitation of this analysis.

Multiple sections of chapters 4 and 5 focus on the disciplines of Social Sciences, Humanities and Professional Fields, and Health. This is because, although I built the topic modelling representation for all fields, certain parts of the analysis demanded an in-depth view of topics, which requires to focus on a specific discipline. I have chosen to highlight these fields as their research topics are deeply intertwined with the social issues that marginalized populations face beyond academia. As a result, they offer opportunities for authors to reflect on their identity-related struggles in their research topics.

Positionality statement

As my PhD thesis examines race and gender inequalities in science in the United States, it is crucial that I clarify my positionality. As a White cis man that migrated from Argentina to Luxembourg, my experiences and background have significantly influenced my perspective. I attended the University of Buenos Aires, a regionally prestigious but materially deprived institution, where I studied economics and data science. Throughout my education, I have been actively involved in activism, particularly in defense of public education. I recognize the limitations of my perspective on the experiences of marginalized researchers in the US. Nevertheless, I strive to account for my positionality by interpreting my findings with caution and collaborating with a diverse group of scholars. These collaborations helped me in broadening my understanding of the subject matter. I am committed to remaining open to feedback and critique from others, as I recognize that my work is part of a broader dialogue on race and gender inequalities in science that demands ongoing reflection and engagement.

CHAPTER 2. LITERATURE REVIEW: THE INTERTWINED INEQUALITIES IN SCIENCE

2.1 Background

Figure 2 shows an illustrative framework of the systemic inequalities that scientists face during their career paths. The diagram presents a conceptual graph with nodes that represent analytical categories that are relevant to the understanding of inequalities in science. Any of these concepts is a standalone idea, but they are all part of the intertwined system of inequalities in science. Links represent those relations between conceptual nodes. These analytical categories are concrete forms that can be generalized into more comprehensive concepts. To organize the discussion, the analytical categories are grouped into more comprehensive dimensions of analysis, except for those concepts that are not specific to science —in red—. Figure 2 is divided into 5 main dimensions: The first two (individual identity and individual subjectivity and choice) refer to the individual level of inequality: without losing track on how individuals' identities and subjectivities are shaped by society, these two dimensions explain the analytical categories that refer to the entry conditions of individuals into science—their identity— and how these can shape their subjectivity as scientist, and their interactions with other scientists. The following two dimensions represent the macro level in which inequalities take place: the institutional structures that reproduce inequality and the field dynamics in which power-struggle and accumulation of academic capital takes place. The final dimension refers to the outcomes of inequality: the differences in publishing, impact and ultimately career development. This diagram does not intend to be holistic. Analytical categories can be generalized into different dimensions, and therefore the grouping could be different. The decision to create these five dimensions was to organize the discussion from the individual to the macro level, and from the inputs to the outputs of the system. Nevertheless, this figure is only illustrative, and its aim is to help the reader follow the background literature review that follows.

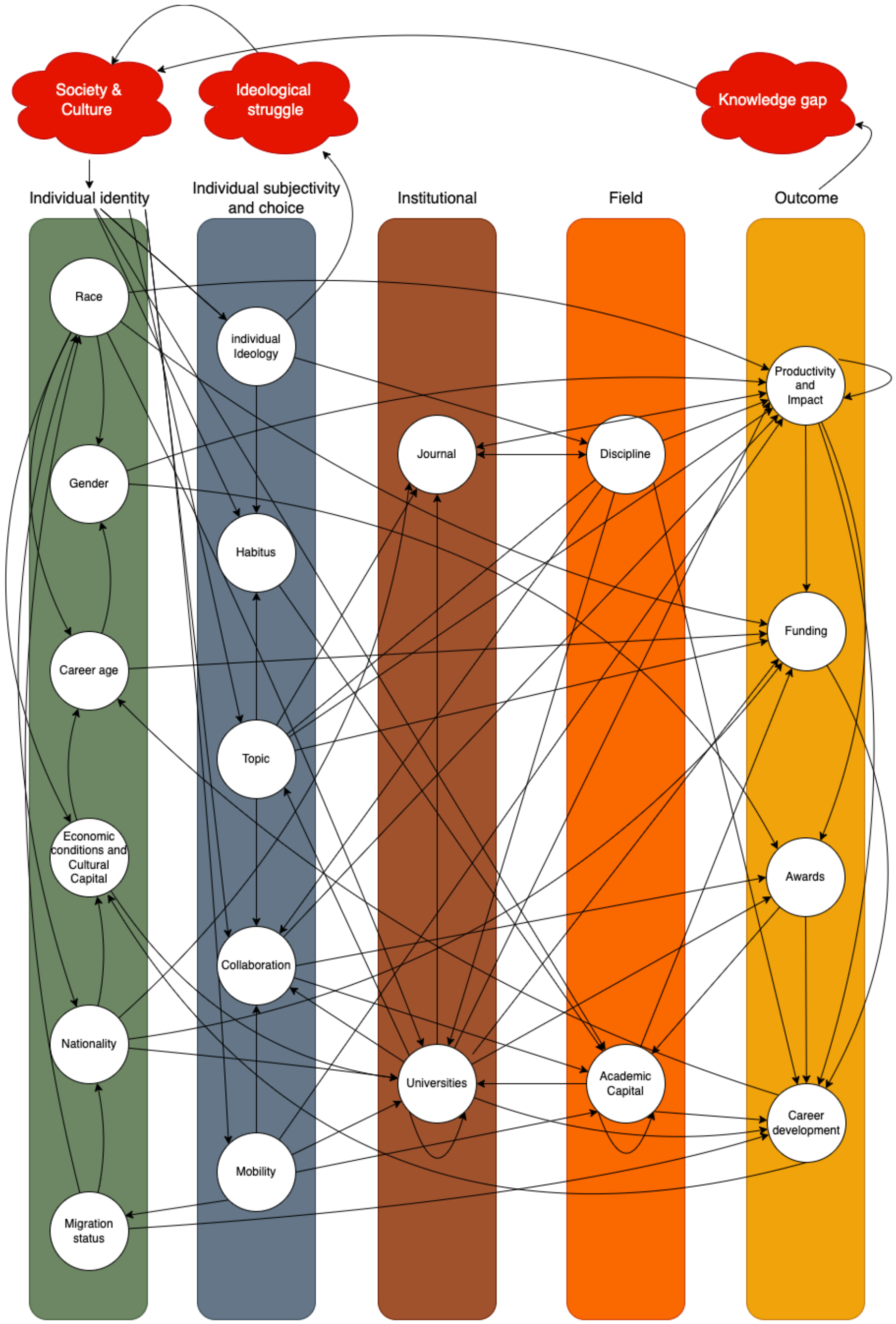

Figure 2. Illustrative framework of systemic inequalities in science. Each column represents a dimension of analysis, and each node is an analytical category. Links between nodes refer to a relation between nodes: a directed link from a to b means that a is a determining factor of b. These analytical categories are grouped into five general dimensions. The three red elements above refer to social phenomena that go beyond the scope of inequalities in science but refer to the relation between inequalities in society overall and inequalities in science.

2.1.1 Individual identity

The Individual identity dimension of inequality does not refer to objective physical traits of individuals, but social constructions loaded upon individuals. As social constructs, they are objective and carry material consequences on individuals.

2.1.1.1 Race

The concept of race is perhaps the clearest example of the individual dimension as a social construct that is rigidly imposed to individuals. In words of Delgado & Stefancic:

> "*(…) race and races are products of social thought and relations. Not objective, inherent, or fixed, they correspond to no biological or genetic reality; rather, races are categories that society invents, manipulates, or retires when convenient. People with common origins share certain physical traits, of course, such as skin color, physique, and hair texture. But these constitute only an extremely small portion of their genetic endowment, are dwarfed by that which we have in co*mmon, and have little or nothing to do with distinctly human, higher-order traits, such as personality, intelligence, and moral behavior." (Delgado & Stefancic, 1984, pp. 7–8)

Following Foucault's genealogy of racism (Foucault, 1998), systemic racism is not just an irrational prejudice, but a form of government designed to manage population (Su Rasmussen, 2011). It is the ideology inherited from colonialism that justifies social stratification. Prejudice about intellectual and physical abilities of people based on their race serve as justification of the distribution of the population across different types of jobs and incomes. Science, since eugenics, has played an important role in building that ideological apparatus (Nature, 2022).

On the individual level, we have no control over the social construction of race that frames our existence. Nevertheless, this is not static, and it changes by time and place. It is important therefore to make a clear delimitation of the context of study when we operationalize the racial categories for studying systemic inequalities. At the same time, science production operates on a global scale, making national delimitations only an analytical abstraction. Each scientist carries subjectively the concepts of race that prevail in their specific context, but directly or indirectly interact with scientists from different backgrounds and constructs of race. This could prove impossible to operationalize in practice, especially on quantitative studies of science and race. Nevertheless, this does not mean that quantitative studies of race and science should be avoided. On the contrary, they are needed to understand the large-scale implications of systemic racism in academia. As Zuberi says, "*The racialization of data is an artifact of both the struggles to preserve and to destroy racial* stratification." (Zuberi, 2003, p. 102).

In this thesis, there is a geographical delimitation of the analysis to the US, which makes possible to operationalize a single racial categorization. The following chapter will focus on how bibliometric databases can be curated to include an inference of the racial identity of authors, which will be later used as one of the main categories of analysis in chapters 4 and 5.

2.1.1.2 Gender

Gender studies has a large literature on the social determination of gender. Simone de Beauvoir's seminal contribution explains that gender is a social construct imposed on our bodies, not just as physiological traits. In her words "*One is not born but rather becomes a woman*"(Beauvoir, 2011, p. 301). Teresa De Lauretis conceives gender as a representation of a social relation, with material implications on individuals' life. This social relation builds the representation of gender, although that construction can change in different contexts and can even be mediated by the discourse of gender deconstruction (Lauretis, 1987). The social construct of gender has historically been built in a binary way, on the dichotomic pair masculine/feminine. Maffía studies the projection of this dichotomy into multiple exhaustive and exclusive cultural stereotyped pairs, commonly associated with men and women: Rational vs emotional, public vs private, facts vs values are antagonistic cultural concepts that are imprinted on the idea that society builds of men and women (Maffía, 2019). For Butler this dichotomy is *performative*, and gender is the set of discursive acts, behaviors and rituals that by their preformation constitutes and reproduces our notion of gender, closely related with the concept of *habitus* in Bourdieu (Bourdieu, 2001). Gender is, therefore socially constructed and only exists through this performativity, made to fit a *matrix of intelligibility* that links sex to gender to sexuality in the binary relations female/male, woman/men, attracted to men/attracted to women. This matrix creates a mental association that produces intelligible identities for the society, and that punishes everyone that falls out of the norm. For example, discriminating against trans and nonbinary people because they deviate from the sex-gender norm by performing gender in different ways as what society expects (Butler, 2006). For Bourdieu, gender is the symbolic organization of the sexual division of labor, "*it legitimates a relationship of domination by embedding it in a biological nature that is itself a naturalized social construction."* (Bourdieu, 2001, p. 23). This means that the social vision of the world is partially based on the social division of gender, and only through this gendered vision is that society interprets and understands the anatomical sexual differences, which then become the "(…) apparently natural justification of the social vision which founds it, there is thus a relationship of circular causality."(Bourdieu, 2001, p. 11)

Gender has a much more stable representation across countries than race. Nevertheless, it is still historically determined. Gender categories that go beyond the binary men-women are still only recognized in some countries, whereas some gender identities are specific to some regions, like *travesti* identity in Latin America (Berkins, 2006) and two-spirits identity for Native Americans (Jacobs et al., 1997). Also, the degree to which gender stereotypes are enforced, and the level of punishment that receive those who go beyond the norm, can vary by region. Nevertheless, gender studies of science can be implemented on the global level, and are indeed informative of the inequalities that non cis-men researchers suffer (Larivière et al., 2013).

The study of gender inequalities in science is important not only as a normative discussion, but also it is central to the debate about which science is produced, and for whom. The feminist standpoint epistemology explains that every author has a situated point of view, which can drastically change the way in which they understand scientific evidence. The underrepresentation of some gender identities in science implies that science is missing the chance to hear different points of view that could enrich its outcomes. Indeed, underrepresented students were found to produce more innovative research (Hofstra et al., 2020). The epistemic advantage of marginalized authors is a central element of this thesis. Chapter 4 focuses on how race and gender marginalized identities show a research interest that is aligned with the conflicts that their communities experience. The higher rate of publications on topics like racial discrimination for Black authors, gender violence for women authors, or migration for Latinx authors is an empirical demonstration that these groups bring a different set of questions to science. Chapter 5 will go delve into the relation between marginalized authors' points of view and the points of view that universities collectively produce.

2.1.1.3 Career age

Career age refers to the number of years an author has been in academia. It also relates with the biological age of researchers, but this relation is not equal for all authors. This concept is closely related with seniority, which defines the position within the power dynamics of research teams, and the types of contributions made. For example, older researchers mostly contribute on the conception and design of experiments, writing of the manuscript, and contribution of materials, while younger researchers mostly contribute to the conducting experiments. This shows older researchers in a position of leadership in the conceptualization, and in power of resources needed to conduct research, while younger researchers need to do the "dirty work" to legitimate their space (Larivière et al., 2016). Those resources come from grants and funding for which researchers normally apply on later stages of their career. Career age comes with a shift in responsibilities, from research itself to a larger administrative burden, but also shows a shift in the bar with which an author is evaluated. While on younger stages—PhD, post-doc— researchers need to prove their value mainly through publications and impact, senior researchers also need to prove that they can acquire funding for their research. The cumulative nature of academic capital gives older researchers a position of power, as they have —on average— more publications and citations. But attrition rates are higher for women and racialized authors (Hopkins et al., 2013; Xu, 2008), which makes it more difficult for these groups to reach more senior positions.

2.1.1.4 Economic conditions and cultural capital

Socioeconomic inequality is a central aspect of almost every social theory (Piketty, 2015; Sen, 1995). Income inequality refers to the extremely biased distribution of economic resources in society. Income inequality is closely related to income poverty, that refers to the lack of access to basic goods needed to fulfill a normal life. There are several techniques widely used by national statistical offices to measure income inequality and poverty, which are basic tools to assess life quality in a given context (Kakwani, 1980). Multidimensional approaches to income inequality and poverty are also important. For example, Amartya Sen proposed to shift the focus from economic poverty to individuals' capabilities to do and be what they choose to. To achieve this, not only income but a larger set of environmental conditions is needed, such as political freedom.

Although the study of socioeconomic inequality is largely beyond the scope of this thesis, it is important to understand how it is reproduced within the context of science. As a background carried by authors, it defines the possibilities of achieving the needed academic success to become part of the scientific endeavor. The material conditions in which an individual is born and raised will define—in Amartya Sen terms— their capabilities to access higher education and an academic career. Therefore, our object of study—academia—is already delimited by the entry barriers imposed by the material restrictions to access higher education. For most countries, PhD graduates represent 1% or less of their population (OECD, 2022a), which shows that our object of study is already mounted on top of a highly unequal access to higher education.

Beyond economic inequality, Bourdieu finds the roots of social inequality in cultural capital, which comprises all the social assets of an individual. Cultural capital can be objectified in property, but also embodied through the process of socialization of the individual. Cultural capital can be also institutionalized by the recognition of, for example, their academic credentials. All these forms of symbolic capital will define the individuals' possibilities to succeed in their academic careers (Bourdieu, 1986). As an example, first-generation students might face more difficulties during their studies (Janke et al., 2017). Cultural capital is directly linked with socioeconomic backgrounds. For example, kids coming from neighborhoods with higher material deprivation show lower academic success (Ingram, 2018).

The socioeconomic conditions and cultural capital are not only entry conditions that authors carry along their careers but are also reproduced within the context of science. Researchers' salary varies drastically based on factors such as region (Ciocca & Delgado, 2017), race (Thomson et al., 2021) and gender (Barbezat & Hughes, 2005). Economic inequality is both an input and output of systemic inequality in science. This analytical category could be split into two —economic conditions on the one hand, and cultural capital on the other—, and much more analysis could be done on each of this. Nevertheless, the research on the following chapters will not focus on these analytical categories. Given the data limitations, it is not possible from bibliometric databases to know the past and present economic conditions of authors, nor their academic capital —for example from which they graduated—. For this reason, these conditions remain as unobservable factors that relate with the studied dimensions of inequalities, and for simplicity are summarized in a single category. Along this chapter I will also use the term *socioeconomic conditions* to refer to this dimension of analysis.

2.1.1.5 Nationality

As mentioned above, the nationality of authors plays an important role in the economic conditions as outcome. But it is even more important determining the material conditions and cultural capital of researchers in their formative years. Global income inequality has been persistently high in the last century (Chancel & Piketty, 2021). The world is not just unequal at random but stratified into very specific country roles within the global economy. The New International Division of Labor (NIDL) brings a shift from the classical industrialized vs non-industrialized dichotomy. During the 70', the robotization of the assembly line and the development of telecommunications set the technical basis for the decentralization of work, moving simple steps to east and southeast Asia, leaving the most complex work in Europe and US (Fröbel et al., 1978). Since then the NIDL has become ever more complex, with an increase of hardware production in south east Asia, while keeping some countries as producers of raw materials (Kozlowski, Semeshenko, et al., 2021). This fragmented world also comes with a fragmentation of the qualifications needed in each country's labor force (Iñigo Carrera, 2008a; Starosta, 2016b), and the strategic research fields of each country (Miao et al., 2022). All these differences create a highly unequal world in which a few countries produce the vast majority of measurable research production and impact (King, 2004), and even define what gets to be measured and what not (Beigel, 2014).

The unequal conditions of researchers based on their nationality goes beyond the material restrictions some countries face when doing science (Ciocca & Delgado, 2017), but it is also a clear example of differences in embodied cultural capital. English has become the dominant language in global science production (Hamel, 2007), which creates a differentiation between native and non-native English speakers (Céspedes, 2021; Clavero, 2010). Being a native English speaker becomes a form of embodied cultural capital, as well as the language training received during researchers' formative period; both of which are heavily mediated by nationality.

2.1.1.6 Migration status

Researchers' nationality defines in many aspects their endowed cultural capital and socioeconomic background, but not necessarily the place where they perform their work. Migration and nationality are complementary concepts. While authors from poor countries suffer disadvantages on their working conditions when they stay in their country, they can migrate to other nations, which carries a new set of prejudices. Indeed, highly skilled workers, such as scientists, tend to migrate more (OECD, 2008). Although mobility for research scientist is not bad per se (Sugimoto et al., 2017), the migrant status for authors can create further burdens that can range from the extra paperwork that any visa requires, to conditioning the career path given the visa requirements of having a job to stay in the country, or even the impossibility to take a position given the visa status. All of which can end up with lower salaries and satisfaction levels for foreign-born researchers (Corley & Sabharwal, 2007).

2.1.1.7 Operationalization of identity categories in bibliometrics

Race and gender are hard to operationalize in quantifiable variables. The socioeconomic background on the other hand has been largely instrumentalized into quantitative variables regularly measured by official statistical offices (Kakwani, 1980). Nevertheless, given the data availability in bibliometric databases, it is not possible to merge information on socioeconomic background with publications and impact of authors. On the other hand, using authors' names it is possible to make partial identification of authors' race and gender identities (see chapter 3 for race, and Larivière et al. (2013) for gender). For the country, it is not possible to know the place where authors where born and raised, but using the country of the institution in which they first published allows to know their academic origin, and the country of their current affiliation gives a hint of the region in which they work (Robinson-Garcia et al., 2019). This only attains a limited dimension of regional differences, especially as some authors gather multiple affiliations on different countries, which indicates that not always the country of affiliation is where they are located. Their visa status is almost impossible to access without specialized surveys. Career age of authors can be accounted for using the first year of publication. The accuracy of this method is bounded by the disambiguation algorithm used (Caron & van Eck, 2014), and the completeness of the corpus.

Large scale bibliometric analysis always depends on partial information, and proxies —as names or country of institutions— to infer personal attributes of authors. This not only leads to potential misclassifications, an acceptable limitation of any large-scale study, but to the inability of including all relevant groups of analysis. For gender, given that almost no country collects census level data on non-binary population, inference based on names falls on the binary men-women. Not being able to recognize non-binary and trans authors is a major problem as these groups face more marginalization on their daily life than cis authors. For racial categories, groups that represent a small proportion of the population are hard to infer as algorithms may fail to make robust predictions, which leads to the need to exclude them from the analysis (see chapter 3). These limitations have in common that the most vulnerable populations are further invisibilized from the analysis. To properly account for authors' intersectional identities, self-identification through surveys is needed. But survey analysis cannot be easily matched to bibliometric databases. Institutions such as journals, universities, and national funding agencies need to collect relevant information on race and gender of authors to allow for large-scale analyses. Nevertheless, this can potentially entail new dangers on the privacy of authors and their self-identified identities, which are critically important to protect. There is a need for multiple approaches —quantitative and qualitative— that can complement the study of inequalities.

In this thesis, race is inferred based on family names, and chapter 3 is devoted to the methods used for this. Gender is inferred based on given names, following (Larivière et al., 2013). Career age is based on the year of first publication, and as the thesis focus on US authors, it samples papers from US-based first authors. I used National Science Foundation (NSF) doctorate recipients survey (NSF, 2021a) to assess the migration status of authors. The economic conditions and cultural capital are not operationalized in this thesis.

2.1.2 Intersectionality

All the above-mentioned analytical categories of identity are carried by individuals, and in many cases an individual can be the subject of marginalization in more than one dimension. Intersectional theory explains that the lived experiences of those people that are at the same time in more than one discriminated group, such as Black or Latinx women, or queer Black men, are qualitatively different to the experiences lived by people with whom they might share a single disadvantage (Crenshaw, 1991), in what Collins (2008) called the *matrix of oppression*. Understanding how the different social classifications interplay is essential both from a theoretical and practical stand. Although it is important to define each dimension individually, this is only an analytical exercise; and all these need to be considered together to properly understand the full scale of each dimension. For example, the cultural constructs of race and gender change by country, and even by socioeconomic background. The racial history of a country defines the racial categories that operate within that context. For example, for the case of gender, in Latin America *travesti* is a gender identity reclaimed by the queer community that goes beyond the binary and intentionally differentiate from the transgender category in order to reflect the special conditions under which Latin-American travesties experience their gender (Berkins, 2006; Pierce, 2020). But also in practical terms, when inclusion policy is made considering only a single aspect of the problem, the needs of people that live in the intersection of multiple injustice might go unnoticed (Delgado & Stefancic, 1984).

Intersectional theory started as a framework to shed light on how social categorizations such as race and class compound with gender oppression to create new forms of discrimination and privilege (Collins & Bilge, 2016; Crenshaw, 1989; Gutierrez y Muhs et al., 2012; E. O. McGee & Bentley, 2017). The omission of the intersectional reality of racialized women can reproduce their invisibilization if representation only accounts for each analytical category separately (N. E. Brown & Gershon, 2017). This framework has been expanded to many other social categories, including sexual orientation, nationality and disability (May, 2012).

Intersectional lenses are therefore an important framework to study inequalities in science. While several large-scale analysis have been made on gender inequalities in science (Holman et al., 2018; Larivière et al., 2013; Macaluso et al., 2016; Murray et al., 2019a; West et al., 2013; Witteman et al., 2019), not as many studies have focused on racial discrimination (Cook, 2014; Leggon, 2006; Witteman et al., 2019), and even fewer have taken an intersectional stand (Lord et al., 2009), and have been mostly qualitative analysis focused on very specific disciplines (A. Johnson et al., 2011; Kachchaf et al., 2015; K. Owens, 2016). Although qualitative analysis provides important evidence on intersectional inequalities, there is a research gap in large-scale studies that consider both race and gender.

2.1.3 Individual subjectivity and choice

All the dimensions above correspond to the conditions that authors are confronted with during their lives that constitute their intersectional identities. This context will have a projection on their subjectivity. I will use two concepts to define the relation between the identity and subjective dimensions: ideology and habitus. Ideology will be used in a broad sense to specify the relation between the individual and collective values and worldviews. Habitus, on the other hand, refers to the return from subjectivity into the material world, in the form of practices and dispositions. Individual's subjectivity will define their choices and actions in their topic selection, and dispositions to collaborate and move to other institutions and countries. Of course, those decisions are also mediated by the material possibilities of being able to collaborate and move, which exceeds the individual will.

2.1.3.1 Ideology

The concept of Ideology has been historically used in multiple different ways. Within the proposed framework, it is purposefully considered in a broad way, as the reflection on the subjectivity of individuals of their material conditions. It is the subjective interpretation of the objective conditions that surround the individual and takes the form of values and worldviews. The intention to include ideology—with this broad definition— is to leave a clear mark on the schematic representation of inequality of the mediation of subjectivity between the material conditions and the institutional or field outcome dimensions. It is important to state that this subjectivity is not considered to be the result of free will, but to spring from the material conditions of existence (Marx & Engels, 1998a). This will be crucial for the interpretation of the results. Ideology can also be thought of as something that transcends individuals and constitutes an ideological struggle among different interests in society. The material conditions not only determine the ideology on the individual level, but also the conditions of the ideological struggle, its power dynamics and what will constitute the hegemonic ideology (Gramsci, 2011; Marx & Engels, 1998a). Nevertheless, critical race theory shows how there are moments in history where those material conditions can create an *interest convergence* between the privileged and marginalized groups that leads to shifts in the ideological struggle and to acquired rights for marginalized communities (D. A. Bell, 1980). The Society and Culture dimension that defines the Individuals' identity conditions appears now as the result of the historical development of the ideological struggle, which itself responds to the need to the material conditions of society along that history. The analysis of those material conditions is beyond the scope of this thesis.

Following feminist epistemology, ideology will reflect on research itself, as any form of knowledge reflects the position of the researcher in a given time and place (Longino & Lennon, 1997). Given the privileged position of White men in society—and science—feminist epistemologists conclude that there is an androcentric bias in scientific production (Maffia, 2007).

2.1.3.2 Habitus

The *habitus* corresponds to the embodied habits, dispositions, and skills that the individual uses for their practice. In Bourdieu's terms habitus can be thought

> "*(…) as principles which generate and organize practices and representations that can be objectively adapted to their outcomes without presupposing a conscious aiming at ends or an express mastery of the operations necessary to attain them. Objectively 'regulated' and 'regular' without being in any way the product of obedience to rules, they can be collectively orchestrated without being the product of the organizing action of a conductor."* (Bourdieu, 1992, p. 53)

In the case of science, it is every element of the scientific practice that falls off the codified protocols and methods of the scientific endeavor, i.e., the *craft* of science. Although portrayed in the individual scientist as part of their embodied cultural capital, the habitus is learned through training, which has a contextual dimension. Bourdieu explains that there exists a disciplinary habitus, built upon the shared experiences during training for researchers of a common field, and a habitus linked to the *trajectory* and *position* within the field. This latter is determined by the individuals' identity dimension. This implies that the "*habitus are principles of production of practices differentiated according to variables of sex and social origin and no doubt by country(…)*" (Bourdieu, 2004, p. 42).

In the same way as with ideology, the habitus has an individual and a collective dimension, or in Bourdieu's terms, there is a *class habitus*. People that share characteristics on the Individuals' identity dimension are prone to also share life experiences that shape their individual habitus, also through ideology. This relation defines the individual perception of factual evidence (S. T. Stevens et al., 2018).

Ingram (2018) explains that the family-ingrained habitus of working class boys crashed against the field habitus of educative institutions, and there can be different possible outcomes: From abandoning their originary habitus or reconfirming it against the new proposed habitus by the field, to either reconciliation or ambivalent relations between both. This can be extrapolated to the scientific practice and observing that authors from marginalized backgrounds carry with them the conflict between their class habitus and a field habitus that is constructed to the image of White men.

Ideology and habitus are broad concepts that cannot be easily operationalized. Although there are attempts to instrumentalize ideology in a limited sense (S. T. Stevens et al., 2018), this hardly begins to grasp its complexity. Only qualitative observation can come close to such elements.

2.1.3.3 Research Topic

Research topics refer to the object of inquiry, which can be approached from different disciplinary lenses. In contrast to research fields with a shared habitus and an academic community, I propose the idea of a research topic as an object of study that can potentially traverse multiple communities. For example, phenomena like food insecurity can be studied by Sociology, Health studies or economics. Racial discrimination is a subject studied by Sociology, Economics, Psychology, and Law. Juana Robledo Martín explains that one of the elements of the androcentric bias is the researchers bias when they decide what they will study (Martín, 2010). Which questions are deemed relevant for science has of course an individual and a social level. First, individual researchers need to find the object of study that they consider is sufficiently important to devote their time and effort to it. Then, their community must validate that decision, together with the quality of their work. The relevance of the research question is a usual criterion for the evaluation of funding and in peer review. But what is relevant is not independent from the reviewers' context, values, and worldviews. Chapter 4 shows the relation between race and gender identities and research topics (Kozlowski, Larivière, et al., 2022a), showing that there is an alignment between identities and research topics that reflect on life experiences suffered by marginalized populations. The adequacy of research questions also evolves over time. For example, a century ago those questions posed by the eugenics school were deemed relevant for the elite of the scientific community (Nature, 2022). Also, the impact of topics is not homogeneous, and reflects the shared values by the scientific community, which can draw attention biases (see chapters 4 and 5).

2.1.3.4 Collaborations

Ever more, authors engage in collaboration with other colleagues for their research (Barlow et al., 2018; Wuchty et al., 2007). Naturally, this goes beyond the sphere of the individual choice, as all researchers involved in a collaboration must agree upon it. The habitus is embodied at the individual level, validated at the field level as good scientific practices, but takes place as the collective daily practice of the team. This is why it is at this level where observational studies of the habitus can take place (Latour et al., 1986).

As it was mentioned above, career age—through seniority— has an important impact on the structure of teams and the forms of collaboration (Larivière et al., 2016). Gender also plays a role in the organization of the collective endeavor, as women tend to be more associated with performing the experiments, even after controlling for academic age (Macaluso et al., 2016).

Gender even plays a role in authorship practices. This is, the decision of the team on how they communicate to the rest of the field which author played which role in a research project (Ni et al., 2021). In Kozlowski et al. (2022b) we found that the intersectional race and gender identity of authors plays a role in the construction of research teams. Authors from marginalized identities need to make an active search to find co-authors with which they share a common identity. In terms of habitus, sharing an identity with co-authors also implies a common class habitus, which is essential for a fruitful research practice. Authors from majority groups, as White men in US do not need to make any especial effort as they have large chances to collaborate with other White men by default, given the demographic composition of US authors. Field and research topic will obviously define the composition of teams as co-authors work on the same topic and field. The different habitus of fields also defines the division of labor in teams (Larivière et al., 2016).

2.1.3.5 Mobility

Mobility refers to the movement of researchers across institutions, and especially across countries. It has been shown that mobile scholars have 40% more citations on average than non-mobile scholars (Sugimoto et al., 2017). Nevertheless authors that migrate internationally represent only 4% of authors (Robinson-Garcia et al., 2019). Mobility is not an equal process for all. There are many non-meritocratic factors that define the mobility path of researchers. Women authors tend to be less mobile than men (Jöns, 2011), and gender roles also have an influence on the mobility decisions of couples (Schaer et al., 2017). Socioeconomic background will also play an important role in the possibilities and intents of international mobility (Lörz et al., 2016).

Migration of researchers exists within a context of larger migration flows. The NIDL needs migration to accentuate the differentiation of the labor force within national borders, mediated by citizenship (Starosta, 2016a). Africa for Europe and Latin America for the US have become a source of cheap low-skilled labor, where the stricter conditions to achieve citizenship for certain countries are the way to limit the civil rights of those migrant workers (Iñigo Carrera, 2008b). Migration bureaucracy is designed based on this intelligibility chain —taking Butler's concept— of poor countries or origin–unskilled labor–intentionally difficult migration towards rich countries of destination; and rich countries or origin–skilled labor–easier migration procedures. Nonetheless, researchers that migrate from poor countries break these intelligibility chains, as they are highly qualified workers. This creates a burden for researchers that come from non-European or North American countries (Waruru, 2018). The relation between country of origin and country of destination reshapes the experience of researchers in many other dimensions. It changes their migration status, their institutional belonging, their collaboration network, and —as mentioned above— their impact. But it can also even change their race, as this is a social construct that changes by country. A White researcher from upper-middle income in a Latin American country can suddenly become a Latinx from a relatively low-income background if they decide to migrate to Europe or US.

2.1.3.6 Operationalization of individual subjectivity and choice in bibliometrics.

Habitus and ideology are considered in the schema of Figure 2 because they express the ideal and practical analytical categories through which the lived experiences carried with identity can influence researchers' choice. Therefore, although these two elements cannot be quantified in any model, they are central for the right interpretation of results. In this thesis, this implies that the topic choice cannot be uncontextualized, but rather understood as a reflection of lived experiences. This conceptual framework leads to the interpretation of results in chapter 4, and especially the policy recommendations, where our conclusion is not that researchers from marginalized populations should change topics, but rather that those topics need to be empowered.

As topics are reflected on articles, the operationalization of research topics can be based on text mining of abstracts and titles, with methods such as Topic Modeling or pre-trained language models (Blei et al., 2003; Grootendorst, 2022; Kozlowski, Dusdal, et al., 2021). In this thesis, LDA is used to infer topics from articles using their titles, keywords, and abstracts. Collaborations are out of the scope of this thesis, but on a related project (Kozlowski, Larivière, et al., 2022b) we explored collaboration homophily by looking at article-level co-authorships. As this thesis is focused on US, mobility is out of scope and not operationalized.

2.1.4 Institutional

If we move up from the individuals and the research teams, there are higher levels of organization that structure the scientific practice. The Stanford encyclopedia of philosophy defines institutions as "(…) complex social forms that reproduce themselves such as governments, the family, human languages, universities, hospitals, business corporations, and legal systems."(Miller, 2019). In science, research universities are a key institutional form around which research is structured (Powell et al., 2017). Journals are another institutional form that structures the gatekeeping of what products of research are deemed valuable by the research community. There are other types of institutions, such as non-university research institutions. Also, international associations and funding agencies play a relevant role in the inputs —as funding— and outcomes —as awards and medals— of science. Given the scope of this thesis, in this section I will focus on journals and universities.

2.1.4.1 Journals

During the last century, scholarly journals have become the dominant outlet for scientific communication (Shuttleworth & Charnley, 2016). It is through peer reviewed research articles that authors create an objectified public result of their work, which can be later used in future research by other researchers. Journals, as the place through which this form of meta collaboration within the field takes place, are a key institution that can also be the channel through which inequalities take place, both by publishing work that gives appearance of scientificity to racist ideologies (Nature, 2022), or—less evidently— by limiting possibility of publishing to specific groups. This latter form is based on the objectified form of scholarly communication. The scientific endeavor is a highly complex process where researchers need to self-organize within their teams. Their publications are one of the few instances where their work takes a quantifiable form. New Public Management in research strives for evaluation metrics in their quest for efficient assignment of science's resources. Therefore, since the 70', scholarly communication does not just mean a way to communicate research results, but primarily the way in which scientists' work is evaluated (Münch, 2020). First by the administration of their institution and then, by extension, by their own research community. Productivity and derived metrics have become the currency of academic capital, and "publish or perish" the motto of science. Journals are also subject to evaluation, with the Journal Impact Factor (JIF) influencing the perception of prestige and quality of journals and their articles (Larivière & Sugimoto, 2019).

Any bias on publishing practices will therefore be a path to inequalities in the outcome of scientific careers, and many types of biases have been studied by the literature (Lee et al., 2013). The prestige of the author's institution affects the probability of their article to be accepted (Garfunkel et al., 1994). So does their nationality, benefiting authors from North America and Europe, from where most of the gatekeepers—editors and reviewers— come from (Ernst & Kienbacher, 1991; Murray et al., 2019b); Language biases in favor of native English speakers have also been documented (Herrera, 1999; J. S. Ross et al., 2006). Partially in recognition of this potential problem, some publishers are currently trying new forms of peer review (Eisen et al., 2022).

Within this context of extreme pressure to publish, other problems beyond bias emerge. Predatory publishers are illegitimate outlets that charge publication fees without performing any quality control or care for the scientific content. Authors might submit their work naively, or victims of the publish or perish pressure, ultimately damaging their own academic careers (Siler et al., 2021). Other authors might try to publish algorithmically generated articles in order to raise their metrics (Cabanac et al., 2021; Cabanac & Labbé, 2021).

Journals are not moved by the same motivation as researchers. Many journals are private business and as such are profit-seeking institutions. In the case of authors, I have mentioned how the economic conditions can affect their further development in academia. Economic capital creates differentiating conditions for the accumulation of academic capital. In the case of journals, the academic capital can be a means for the accumulation of economic capital (Khelfaoui & Gingras, 2020). Historically, the paid access to scientific literature implied a limitation for those researchers outside of universities with paid subscription to journals. The criticism that was raised from the open access movement in academia was transmuted by editorial companies into the gold open access business model, where authors must pay to have their article directly accessible to any reader. This business model shifts the financial burden from the reader to the writer (Siler et al., 2018), making it difficult for authors from low resourced institutions to publish their work, especially for those low GDP countries (Klebel & Ross-Hellauer, 2022). Editorials permute academic for economic capital, as they increase prices for high JIF journals (Siler & Frenken, 2020). From the researchers' point of view, authors from low-income institutions and countries are now unable to publish in those highly prestigious journals and might shift to venues with a smaller JIF.

In chapter 5, the JIF is used as a proxy of journal-impact to measure the impact-gap by race, gender and institutional prestige.

2.1.4.2 Universities

Universities are the most important institutional form of science. Their management structure defines the career development and —in many cases— research funding for authors. It is within their buildings where most of the daily work of scientists takes place. Accumulation of academic capital is also central for the life of universities. As they compete for attracting prospective students, professors, researchers, and funds, they use institutional prestige as a magnet. Academic capital finds its ultimate form in the competition between institutions, objectified in university rankings. This apparently objective metric to compare institutions has become an essential tool of institutional governance (Münch, 2020). For many institutions, these poor proxies of institutional quality became the sole benchmark for the evaluation of the administration. As Cathy O'Neil (2016) explains, once improving a metric—such as university rankings for quality— becomes the only goal, then hacking the algorithm becomes more important than succeeding in what the metric really wanted to capture. If rankings focus on productivity rather than impact, the university will promote practices such as salami-slicing of articles. If the ranking focuses only on the number of articles in Science or Nature, then it will focus its resources only on the selection of high impact authors from that institution that can possibly publish in those venues, defunding other research(ers). University rankings have been widely criticized for not being a good measure of institutional quality (Altbach, 2012). Such an incentive system is doomed to reproduce intra- and inter-university inequalities (Pusser & Marginson, 2013). Indeed, 80% of faculty in the US studied in the top 20% universities (Wapman et al., 2022), which means that it is highly unlikely for PhD graduates from non-top institutions to be able to pursue a career in academia. Hierarchy also plays a fundamental role in faculty hiring, where upward mobility is most unlikely (Clauset et al., 2015). In terms of Figure 2, this implies a temporal cycle in the graph: the previous institution explains the actual institution of authors. In previous work, we have shown the imbalance between race and gender and institutional types (Kozlowski, Doshi, et al., 2022), that can be partially explained by the worse placement that women get after controlling by the prestige of the institution that grants the PhD (Clauset et al., 2015). Socioeconomic background plays an important role in the access to highly prestigious institutions for the undergraduate education —especially in countries with expensive higher education— that later impact on the career path across institutions (Posselt & Grodsky, 2017). The US is a country where high fees function towards the stratification of the student population, where student loans only reinforce race and gender inequality (Price, 2004). But institutional rankings also create international barriers, with English-speaking countries dominating the top positions (Safón, 2013), and a general correlation between GDP and ranking positions (M. Li et al., 2011).

As Bhopal and Myers (2023) explain, the relation between privilege in elite institutions and systemic racial discrimination is complex, and some of the current trends can be better understood through the lenses of *interest convergence* from critical race theory: The apparent fostering of racialized researchers within the elite institutions happens because it is of the interest of White people to do so. This would be the case if racist discrimination within those institutions becomes so evident that affects their public image. This implies that the policies put in place (for example recruiting more non-white students or researchers) aim first and foremost to improve the image of the university than to truly diversify the institution, which can create a hierarchy of eliteness within the institutions (Bhopal & Myers, 2023). In this thesis, chapter 5 will delve not only into the changes in representation on elite universities, but also on their citation gaps and topical profiles, as possible spaces where inequalities can persist beyond the interest convergence.

Within the context of US, not all universities are drive by the same prestige-seeking logic. Mission-driven institutions like Womens' Colleges (WC) and Historically Black Colleges and Universities (HBCU) were founded with the special goal to server those communities. WC were founded in 1836 by advocates of gender equality (Harwarth et al., 1997), and present the highest assignment of reading about gender, race and ethnicity (Sax et al., 2014). Chapter 5 will show that this is also true for the articles published by these institutions. Black Americans where historically excluded from higher education. Until Brown vs. Board of Education (*Brown v. Board of Education*, 1954) schools were segregated, and Black Americans were excluded from most higher education institutions. In 1965, HBCUs were officially stablished as institutions of higher education dedicated to educated Black Americans. These institutions have as a mission to empower those Black students that only 10 years before the constitutions of HBCUs where formally excluded from the great part of the US education system. Although HBCUs represent only 2.3% of the post-secondary educative institutions, they graduate a disproportionate number of Black students. For example, 23% of Black students who earned a doctorate degree in science and engineering between 2015 and 2019 received their bachelor's degree from an HBCU (E. W. Owens et al., 2012).

It worth mentioning that universities are not the only institutional form where research is conducted. Authors from private industries also publish articles, although their importance on basic research is decreasing (Larivière et al., 2018). In some countries, research institutes, separated from universities, also play an important role (Powell & Dusdal, 2017). Nevertheless, as this thesis is focused on US, universities are the most distinctive locus for basic research.

Chapter 5 is centered around the role of universities in the reproduction of race and gender inequalities in science. The topical profile of institutions is compared to the topical profile of different race and gender identities, and the impact gap is assessed on different tiers of institutional prestige.

2.1.4.3 Operationalization of institutions in bibliometrics

Institutional information is directly codified in bibliometrics databases. Collecting journals' information of articles has been a historical driver of bibliometrics. Therefore, this information can be easily collected from the database. Information on universities can raise more problems. Although this information appears as metadata of articles, it appears in the same way as authors submitted their affiliations. This implies a lack of systematization of institutional affiliations that can be problematic. In this thesis, chapter 5 focuses on universities, and a cleaning process and homogenization of affiliation strings was made to use the variables provided by the WOS databases —see implementation details on appendix II—. With the normalized affiliations, universities were classified into several groups for analysis. First, I matched universities to their Carnegie ID, and with this information, I sampled HBCU, WC and Hispanic Serving Institutions (HSI), as mission- and threshold-based institutions. I also classified institutions by their perceived, research, and selectivity prestige, using US News & World report, historical citations, and the Carnegie Selectivity Index respectively. Please refer to appendix II for implementation details.

2.1.5 Field

2.1.5.1 Discipline

A scientific discipline is a community of scholars working on a specific knowledge domain and sharing their results through different ways of scholarly communication (Sugimoto & Larivière, 2018). In a sense, a discipline can be identified with the research field, in what Bourdieu defines as the locus of the competitive struggle for scientific authority (Bourdieu, 1975), where members of the field depend on their competitors for the recognition of the academic capital that scientific authority entails.

Between the institutional and the field levels, scientific societies are global level institutions that structure the fields. The idea of disciplines as communities of scholars rather than a strict epistemic demarcation is important given that the thematic boundaries between disciplines can be fuzzy. As mentioned above, the same research topic can be studied from multiple disciplinary perspectives. Even more important, there is a hierarchy in the academic capital accumulated by disciplines, which results in different entry barriers, and uneven amounts of resources to distribute within each discipline (Bourdieu, 2004). Therefore, if the individual level features affect the distribution of authors by disciplines, this will have an impact on their possibilities to accumulate academic capital. Indeed, chapter 4 shows that there are large differences by race and gender on authorship by discipline. Evidence has been found on the role of race and gender stereotypes in career choice, particularly on STEM (Ceci et al., 2009; Schuster & Martiny, 2017; Eaton et al., 2020). For example, introductory courses in STEM have a discouraging effect that especially affects marginalized populations (Hatfield et al., 2022)

2.1.5.2 Academic capital

Although it appeared several times along the discussion of other dimensions, a more specific definition of academic capital is needed. Academic Capital refers to the accumulation of scientific authority within a field. It is a kind of social capital that can be transmitted and permuted with other types of capital (Bourdieu, 1975). The structure of the scientific field is defined by the distribution of the scientific capital among the scientific community. Bourdieu takes Marx's (2010) notion of capital, as the subject that puts its own movement. This means that the logic of capital accumulation is the driving force that sets the motion of the process as a whole. Capital accumulation depends on the size of its initial endowment. The larger the accumulated capital at the beginning, the larger will be the newly accumulated capital, in a process that the literature has also called the Matthew Effect (Merton, 1968). Academic capital is also transmitted by co-authorship, as collaborations with prestigious scientists for young scholars can predict future success (W. Li et al., 2019). Moreover, the accumulation of academic capital has effects on the accumulation of other types of capital, such as funding for their future research, fueling the further accumulation of academic capital (Bol et al., 2018); and the above mentioned permutation of academic capital for economic revenue made by some journals.

To enter a field, there is an entry cost that increases with the accumulated scientific resources of the field. These entry barriers imply a minimum amount of cultural capital (Bourdieu, 1975). This means that the Individuals' identity conditions determine the starting point of the continuous process of academic capital accumulation. Also, mobility has an important effect on the accumulation of academic capital. In many countries, the national circuit of prestige recognition is dislocated from the international field (Beigel, 2017), therefore mobility can have an effect of increasing the international social capital but isolate the author from its local circuit (Bauder, 2020).

2.1.5.3 Operationalization of fields in bibliometrics

The operationalization of disciplines is normally defined in hierarchical subject classifications, mostly following academic units (Sugimoto & Larivière, 2018). The definition of disciplines used in this thesis is based on a journal classification developed for the US NSF (Hamilton, 2003). This classification is first used in chapter 4 to show the under/overrepresentations of authors by race and gender across fields, and then to limit the scope of the analysis to Social Sciences, Humanities and Professional Fields, and Health, as the two case studies.

In terms of operationalization, academic capital—in the same way as ideology or habitus— is hardly a quantifiable concept. In Homo Academicus (1988), Bourdieu builds a series of indicators of academic capital, based on where professors did their studies, if they studied abroad, and received awards and medals, among other indicators. In this thesis, given that bibliometrics is at the heart of the analysis, and that those bibliometrics indicators are only proxies of academic capital, I decided to use the concept of academic capital as a theoretical framework to understand results, and use bibliometric indicators (especially those related with impact) as a separate element that is related with the concept of academic capital, but not a direct operationalization of it. As such, the concept of academic capital is used to understand that each individual metric —such as citations or JIF— is part of an overreaching race for the accumulation of academic capital and cannot be understood independently.

2.1.6 Outcomes

All the above-mentioned dimensions of inequality will have tangible consequences in the careers of authors.

Embodying a specific intersectional identity has direct and indirect effects on productivity, funding, awards and ultimately their dropout probability. But the unfair possibilities of entering and staying in academia for authors with marginalized identities is just one side of the problem. The other side is that the scientific production itself is worse because of inequalities. It is worse because when it is not merit what determines the possibilities of researchers, then science loses valuable potential researchers that could increase the absolute endowment of scientific knowledge. Even more important, the relative distribution of the knowledge production is biased. As mentioned above, who makes science determines which science is made. The research questions and methods choose for research will be more aligned with the interests of those identities overrepresented in science. Artificial Intelligence has become a clear example of those gaps, where algorithmic bias emerges from decisions like testing new models on the all-white-men lab members. For example, Buolamwini and Gebru (2018) showed how facial recognition works worse on women and racialized subjects. All this constitutes a knowledge gap, where marginalized identities receive less benefits from the knowledge produced in science. This knowledge gaps will, in turn, affect society and culture, closing the systemic circle of inequalities (see figure 2). This point will be retaken on chapter 4 where I present the cumulative knowledge loss on the contrafactual scenarios where identities representation follows the census.

This section will focus on how career outcomes are affected by the individual, institutional and field dimensions, through productivity and impact, funding, awards and career development inequalities.

2.1.6.1 Productivity and impact

Productivity and impact will be the two key measures of academic success. These are used on a regular basis on research evaluation and promotions, although they are widely criticized as a valid evaluative tool (DORA, 2012; Hicks et al., 2015). Most of the research on biases in science focuses on the effects on productivity and impact. Men tend to publish more articles on average than women (West et al., 2013), specially on those fields where research demands high funding (Duch et al., 2012), and tend to occupy more the first and last places in the authors list (West et al., 2013). There are a number of potential explanations for the productivity bias, from the work climate and collaboration opportunities within peers (Fox, 1991), to the work-family conflict based gender roles, especially on parenthood (Zheng et al., 2022). Chapter 4 shows that different research topics receive different numbers of citations, and that there is both an intra-topic and within-topic citation bias, as authors from marginalized populations tend to publish more on topics that receive less citations, and to receive less citations on average across the topical space. In chapter 5 I show how institutional prestige plays a role in race and gender citation gaps. Race and gender imbalances have been observed in reference lists (Bertolero et al., 2020). Authors from elite institutions have the privilege of a work environment that boosts their productivity and citations (Way et al., 2019). The above mentioned Matthew effect (Merton, 1968) shows the cumulative nature of citations, which implies that highly cited authors will have an advantage on their future work, in what Barabási and Albert formalized as preferential attachment in citation networks (1999).

The journal in which an article gets published gathers its own academic capital, which can boost the impact of an article, thus generating new biases (Callaham et al., 2002; Larivière & Gingras, 2010; Abramo et al., 2019; Traag, 2021). Also mobility has been found to influence impact (Sugimoto et al., 2017).

Chapter 4 shows that different research topics receive different numbers of citations, and that there is both an intra-topic and within-topic citation bias, as authors from marginalized populations tend to publish more on topics that receive less citations, and to receive less citations on average across the topical space. In chapter 5 I show how institutional prestige plays a role in race and gender citation gaps.

2.1.6.2 Funding

Financial support is essential for conducting research. The amount of funds determines which type of research can be made, which questions can be answered and ultimately what impact the work can get. Funding is directly associated with productivity (Jacob & Lefgren, 2011). But the relation is not linear. On the national level, more funding does imply a larger research output (King, 2004), but at university level it can show diminishing returns (Adams & Griliches, 2000). Diminishing returns on research funding has also been found when resources are concentrated in a small scientific elite (Mongeon et al., 2016). Funding acquisition has become a sign of accomplishment (Laudel, 2005), and therefore a goal for scientists rather than the means for performing their research. It is not surprising, therefore, that funding has become a metric of academic success (Sugimoto & Larivière, 2018). In the same way the Matthew effect explains how past citations drive future citations, past success in funding explains future funding (Bol et al., 2018). In Bourdieu's terms, the size of grants as a metric of academic prestige is the instrumentalization of heteronomy in science (Bourdieu, 2004).

International differences in research funding, both in terms of percentage of GDP or per capita Purchasing Power Parity (PPP) are sizable (OECD, 2022b), and are arguably the biggest source of inequality in terms of international differences of scientific output. Yet, as research—including research on inequalities in science— is focused on Europe and North America, little attention was paid to this source of inequality (O. H. Petersen, 2021). As most agencies for scientific funding operate on a national or regional level, there are no simple policy solutions for this problem. Even more, in poor and developing countries, where the access for public funds is limited, the private investment in science is particularly constrained (Salager-Meyer, 2008). For young scholars in developing countries, APC costs can be even higher than the total amount of their average research grants (AJA & TYAN, 2021).

Bias in funding against Black scientists have also been found for NIH grants (Chen et al., 2022). This bias is mediated by Black scientists' topic choice towards community and population studies, instead of basic research (Hoppe et al., 2019). In line with the above, Steinþórsdóttir et al. (2020) explain the relevance of the gendered distribution of fields to understand gender inequalities in funding. The gendered dichotomies (Maffia, 2007) takes form on the hierarchies of fields and funding. An intersectional approach is also relevant, as evidence shows that racialized women face more difficulties than White women on R01 research awards (Ginther et al., 2011, 2016).

2.1.6.3 Awards

Academia has an extensive system of awards, such as honorary degrees, medals —like Fields medal and the Nobel prize— and fellowships. These are given to scientists by universities, scientific societies, and academies. Publications also get awarded, with best papers awards from conferences and journals (Frey, 2007). Awards are a sign of credibility (English, 2008), and therefore a sign of academic capital. Prizes can also represent an important boost to those topics that get awarded (Jin et al., 2021).

The distribution of awards is concentrated among a small elite, where authors from prestigious institutions and those who collaborate with other prestigious authors have a higher chance to win awards (Ma & Uzzi, 2018). A large literature shows the underrepresentation of women in scientific awards. For example, there is a gender bias in the Nobel prize that cannot be acknowledged only by the different gender ratio among researchers on the laureates' disciplines (Lunnemann et al., 2019). Women are almost absent from awards given by medical societies (Silver et al., 2017). Awards and prizes themselves are not equal, as some carry more prestige than others. While women are underrepresented among awards overall, they are particularly underrepresented on the most prestigious and onerous awards (Ma et al., 2019). While there is a large increase in the proportion of women prize winners over the last two decades, they are concentrated among prizes for service and teaching instead of scholarly research, as well as on prizes that are awarded only for women (Lincoln et al., 2012). This reinforces the stratification of the symbolic capital signalized by awards. This shows that there is no easy solution for inequality: if policy only focuses on the system of awards, it only affects the symptoms of a much larger problem. Awards are a form of academic capital that generate prestige, but the members of the field need to recognize the authority of those prizes for them to retain this symbolic power. If the conditions of the field—its gender biases— do not change, then positive actions such as women-only prizes will be regarded as lacking merit and will not receive the symbolic capital of other prizes.

2.1.6.4 Career development

All the above-mentioned dimensions of inequality will have a direct or indirect impact on the career development of researchers by changing their possibilities to stay in the field and climb the rungs of the academic ladder. All other outcomes in science such as productivity and impact, funding, and awards are the objective measures of success used in quantitative or qualitative evaluations for hiring and promotion. The most stable pattern of inequality across the globe is the progressive underrepresentation of women as we observe higher stages of the academic career. From lecturers to full professors, in every step of the path, a smaller proportion of women can be found (Diezmann & Grieshaber, 2019). Women are tenured at a much smaller rate than men when compared to PhD graduates (Mandleco, 2010). There is an apparent paradox, as while there is consistently less women in higher ranks, once controlled by productivity and impact, evaluation committees do not show gender bias against women (Ceci et al., 2014; Webber & González Canché, 2018). But this paradox disappears if we question the validity of the evaluation criteria. First, research output has become a dominant element of tenure evaluation (Schimanski & Alperin, 2018), while teaching and service roles have become less influential over time (Green, 2008). This comes as the result of the race for prestige in which universities are immersed, where the total research output is a key measure of institutional success. But women faculty perform a larger amount of service work (Guarino & Borden, 2017). Misra et al. (2011) have found that, while both women and men see service work as a burden, and people from both genders work a similar amount of hours, over an year women spend 220 hours more on teaching, mentoring, and service; while men spend 200 hours more on research. A second element to question the promotion evaluation based on productivity and impact measures is that even beyond the time taken on non-research activities, our schema shows that there is a deep and complex system of inequalities that drives results in terms of prestige and impact. Therefore, these are poor proxies of quality in terms of what the prospective faculty could contribute to the department. Mobility also has an important role in expanding researchers' network and career options (Sugimoto & Larivière, 2023). Yet it is less probable for women to move, and in heterosexual academic couples' women tend to move due to their partner's career more than the other way around (Jöns, 2011; Schaer et al., 2017).

Of course, gender is not the unique path to unequal career developments. Other factors such as race and socioeconomic background affect career choices (Arday, 2021, 2022; Wood et al., 2016). Cultural capital both determines the career development and defines the starting conditions for the kids of those scholars, in a generational reproduction of inequalities. For example, in Harvard, more than 20% of White students enter as legacy admissions —their parents are alumni—, while legacy admissions are only less than 7% for any other racial group. The Deans' list —based on donors to Harvard— is almost 14% of White admissions, but less than 6% for all other groups (Arcidiacono, 2018). This shows how academic capital can be inherited by the next generation, and how economic capital can be exchanged for academic capital.

Postdoctoral research has become an important intermediate step between the PhD graduation and faculty placement. These are temporary jobs that extend labor insecurity further in the academic career. In the US and UK a large proportion of postdocs are temporary visa holders (Wood et al., 2016) which cannot wait for the best placement choices as their visa status demands them to be hired, and their supportive network is abroad.

2.1.6.5 Operationalization of outcomes in bibliometrics

The measurement of productivity and impact of research articles has been one of the most important goals of bibliometrics analysis. From the traditional Journal Impact Factor (Larivière & Sugimoto, 2019) and h-index (Costas & Bordons, 2007), to the more recent altmetrics indicators (Costas et al., 2015), there are many ways to quantify productivity and impact. In this thesis, I use field-normalized number of citations (Waltman & van Eck, 2019), and topic-normalized citations in chapter 5, and journal impact factor as impact metrics. Funding, awards, and career development need special databases in order to be operationalized and are out of the scope of this thesis. Nevertheless, this work is informed by the abovementioned research on funding, awards and career development, and the analysis of results is made considering that these categories of analysis, although implicit from our data, are relevant for the holistic understanding of the phenomena. Especially, the work from Hoppe et al. (2019) shows how topic choice is a driver of systemic discrimination in NIH funding, which complements with the findings of this thesis.

2.2 <u>Quantitative methods for the study of inequalities in science</u>

2.2.1 The limitations of statistical and causal modelling for the study of inequalities in science

Figure 2 shows only a simplistic version of the structure that builds the systemic inequalities in science. Some units of analysis could be further divided. For example, gender could be divided into gender and sexual identity. Professional associations could be added as specific institutional types, as well as the working environment and working conditions. Also, all these elements exist and relate in a historical process. At any given point, they are the result of the historical conditions, and their interaction develops the conditions of the upcoming periods. Some historical relations are embedded in the diagram, such as past institutions determining future institutions, but these only represent a small fraction of the role of history within the process.

Nevertheless, this simplistic picture suffices to start a discussion on which are the most appropriate methods that quantitative social scientists can use to study inequalities. Statistical models whose goal is to prove the existence of bias against a specific population suffer from several limitations. As Narayanan (2022) recently pointed out, these models invert the burden of proof. They work with the null hypothesis stating that there is no discrimination, and the statistical evidence needs to show with enough confidence that discrimination exists. But data limitations, both in size and in comprehensiveness, and the cumulative nature of disadvantages along careers, lives and generations can make it impossible for a statistical model to detect the underlying phenomena. Statistical modeling works under the premise "correlation does not imply causation", which in this case means that statistical disparity is not enough to prove inequalities. Nevertheless, we could also work with a framework in which, if disparities are observed, then inequalities are assumed until the opposite is proven. Given that systemic racism and sexism are largely proven and documented, we could conclude that the presence of discrimination should be considered the null hypothesis to work with instead of its absence. Until empirical evidence proves the opposite, systemic discrimination is the most plausible explanation of an observed difference.

This thesis is not about proving there is discrimination in science. The macro level disparities (Fig S1 chapter 4) are deemed sufficient to show that there is systemic inequality in science. The goal of this thesis is to move forward in the discussion and start enquiring about the specific mechanisms that drive this inequality. Otherwise, if the study of inequalities is only expected to prove repeatedly the existence of its object of study, then few advances will arise from this field. There is a need to move forward in the discussion.

Even more, the idea that any single article on inequalities in science needs to build an absolute proof of bias is based on an archaic concept of science. Scientific knowledge is built by accumulation of partial results, with organized skepticism over any particular contribution (Merton, 1979). It is far more useful to develop a comprehensive body of knowledge to describe specific aspects of what is known to be a more complex phenomenon, than to make a simplistic abstraction of the reality to be able to show what looks like uncontestable empirical evidence but hides foundations in assumptions that are not met. This conclusion is based on the fact that it is impossible to build a comprehensive model of systemic inequalities, in the way in which, for example, causal theory demands.(Pearl, 2009).

More specifically, there are two elements that make it impossible to build a well-defined causal model of inequality in science: First, all causal models work with the assumption of unconfoundedness, which means that there are no relevant confounders omitted from the model (Traag & Waltman, 2022). This implies that the model is complete. As mentioned above, Figure 2 is just a simple representation of the system of inequalities that could be further complexified. Nevertheless, even for this simple representation a full modeling is impossible for two reasons. First, because of data limitations. Models need to be built from data sources that can be combined somehow. But it is impossible to build a dataset with information on all the dimensions of our system. While multiple elements of the system can be operationalized into quantifiable variables, it is currently impossible to have all those variables into a single comprehensive dataset.

Additionally, many elements are just not operationalizable, but still remain a relevant part of structural inequalities that needs to be qualitatively accounted for.

Second, a large part of causal theory is built around causality structures that can be defined as Directed Acyclic Graphs (Pearl & Mackenzie, 2018). Figure 2 shows several cyclical paths that cannot be disentangled. This implies that only a simplistic representation of the object of study could be represented in the terms that causal models demand.

Even more, the social constructs of race and gender cannot be thought independently of other confounders. Gender *is* the sexual division of labor; it is the subjective preferences for topics and fields related with care and domestic labor or engineering and technology, following the dichotomical pairs that define gender. Therefore, the relation between gender and topic selection cannot be thought of as a problem of individual choice. Race is not just related to economic background, but the racialized structure of society is intrinsically based on economic differentiation of people based on the social construct of race. Therefore, using socioeconomic background as a control to conclude that after such control there is no discrimination is fundamentally misunderstanding how systemic racism works. What is left after such controls is a grotesque version of discrimination. But assuming that is the single problem to fix can cause more damage than good.

The scientometrics community has gone through a phase of building a plethora of indicators as proxies of quality, to arrive at the conclusion that no metric can unequivocally measure quality of research, and that a mix of qualitative and quantitative approaches is needed in evaluation (Hicks et al., 2015). There is no need to traverse the same path for definitions of inequality. No single method can unequivocally address the complexity of inequality, and a deep understanding of the historical context and structural roots of this phenomena is a condition sine qua non for the right assessment of this problem.

2.2.2 A case for quantitative narratives of inequalities in science

Critical race theory draws from law the use of storytelling to counter racist preconceptions and myths. Our worldviews create a background mindset to which we contrast factual evidence. In court, preconceptions about black criminality or muslim terrorism invert the burden of proof and can determine the outcome of a trial. "*Critical writers use counterstories to challenge, displace, or mock these pernicious narratives and beliefs*." (Delgado & Stefancic, 1984, p. 50)

In science, standpoint theory shows how our lived experiences affects the point of view from which we interpret scientific evidence (Harding, 2003). Qualitative analysis that makes a deep focus on case studies can build the counternarratives that break the status quo, and open relevant questions and discussion that the default —i.e., White men— point of view can hardly come-up to (A. Johnson et al., 2011; Kachchaf et al., 2015; K. Owens, 2016). But case studies are necessarily limited in scope, and their conclusions are difficult to extrapolate to other cases. Qualitative methodologies are powerful tools to open relevant questions but can only give partial answers. The skepticism with which parts of the scientific community and science policy makers consider the results that emerge from qualitative studies also creates the need for quantitative analysis that complement qualitative analysis and give different types of answers to the open questions. Large-scale quantitative research can shed light into systemic mechanisms of inequality that affect most of the population, but that generality also limits the capability of large-scale studies of considering marginalized groups of the population for which they cannot give a statistically significant explanation. In these latter cases qualitative analysis is especially important and can give complementary answers to quantitative studies. There is an epistemological divide that emerges when statistical modeling is framed as the only valid tool of analysis, and empirical causal evidence the only way to scientifically approach a phenomenon. With this positivist mindset, any object of study that cannot be statistically modeled cannot be scientifically inquired, or a hard set of unmet assumptions needs to be put in place. As the section above shows, this is the case of inequalities. On the other hand, qualitative and quantitative storytelling can create complementary explanations.

This thesis focuses on the quantitative description of inequalities. And for this it uses several different methods. Chapter 3 uses statistical simulations, explores weighting schemes and imputation to build an algorithm that can infer the racial identity of authors. It does so while giving especial relevance to the historical contextualization of the data and the categories used, with the aim of minimizing potential biases. Chapter 4 uses Natural Language Processing (NLP) techniques —in particular LDA (Blei et al., 2003)— to infer the research topics of articles. This is combined with tools and methods from bibliometrics, such as citations counts and normalizations, statistical definitions of relative over/under representation, and even tools from causal analysis such as counterfactual scenarios —see appendix I— to build a quantitative narrative of the underrepresentation of racialized and women authors and their research topics from science. Chapter 5 also uses non-parametric correlations and linear models to delve into the story of universities' research agendas and impact gaps.

Linear models are also used in chapter 5. This is a traditional technique from the statistical and causal modelling frameworks criticized in the above section. In those frameworks, these models are used under the assumption of completeness, which means that all relevant confounding factor are included in the model. Also, in those frameworks there is an implicit search for explicit direct discrimination, where all other covariables are just controls that are either unrated with the phenomena or —for causal models— are indirect paths that are only deemed problematic if at some point of the path there is direct discrimination. Also, as the determinants of individual subjectivity are difficult to model, the individual choice is considered to be free, which means that when factors like discipline or topic choice are found as indirect paths of inequalities, then this is a problem of the individual, and not a systemic issue (Pearl & Mackenzie, 2018). In this thesis, linear models are used to build a quantitative description of a phenomena with complex interactions between multiple factors —such as research topics, race, gender, institutional prestige, career age or number of authors—. Linear models can be used to see impact gaps on a specific dimension —race and gender identities— while controlling for other factors —topics and universities prestige—. Research topics and institutional prestige are key elements in the systemic reproduction of inequalities. When we control for these factors, it is not to rule them out, but to carry out an analytical separation of the system that allows us to understand its intricate relationships. Also, completeness is not assumed. The models are used knowing that funding, awards, and other identity dimensions are present and intertwined with the dimensions that are being measured.

This methodological stand also reflects on the relevance that this thesis gives to compelling data visualizations. The graphical representation of results is a fundamental step for a truthful quantitative storytelling (Cairo, 2016) that can focus on accurate representations of reality. Data storytelling has widely extended as a branch of journalism that builds evidence-based stories with clear and rich data visualizations. In this thesis, the visualizations can be considered a part of the methodology, as they are an essential part of the reasoning of the evidence found. This is especially true for the interactive visualizations presented at https://sciencebias.uni.lu/app, as they were used in the daily work of results exploration, discussion, and analysis.

2.3 Ontological and epistemological position

As mentioned above, this thesis reflects on my position regarding which are the best methodological approaches to study inequalities in science. This positionality is framed within my point of view on larger epistemological and ontological debates. Although these discussions are out of scope for this thesis, it is important to state my epistemological and ontological stand. I found the currently dominant ontological positions in science very problematic. I consider that although formally opposed, both empirical realism and postmodernism contribute to the ideological justification of the status quo.

Empirical realism considers that reality is only what can be directly observed or measured. This leaves the unobservable underlying structures outside the realm of scientific knowledge. To work, positivism needs to assume that social patterns are stable across time and space and define that social sciences' main goals are to identify causal laws and predict future events. For this to work, the observer needs to be considered neutral from their object of study and avoid contaminating the results with personal values and beliefs. The assumption that social patterns are stable over time is conservative by nature, as it denies any possibility of change. From my point of view, science main goal is to change society, and the directionality of this change is defined by the interests being represented in science, which is an ever-ongoing power struggle. Therefore, our act of research must change the object of study up to some degree. Causal patterns and predictions can be used towards this general goal but are not the main reason of science. Personal interests, projected onto researcher's values and beliefs are unavoidably part of science, and can influence the directionality of change that science promotes.

On the other hand, the linguistic turn proposed by postmodernism is not less apologetic of the current state of affairs. As Jessop (1990) explains, postmodernism advocates for an empty realism, as the discursive articulation is considered the main level of construction of the real. In the case of inequalities in science, many of underlying mechanisms of systemic discrimination go beyond the discursive level, and understanding those is a central piece for social change. Postmodernism also states that truth is always relative to discourse, and therefore negate the possibility of judgmental rationality (Buch-Hansen & Nielsen, 2020). By denying the social structures that organize inequality, postmodernism is disabling of social change.

Marx concludes his thesis on Feuerbach stating that *"The philosophers have only interpreted the world, in various ways; the point is to change it."*(Marx & Engels, 1998b). My interpretation of Marx's thesis is that our study of the world is itself a way of changing it (Iñigo Carrera, 2008b). By analyzing the real material truth that surround us we transform reality because both ourselves and the work objectified in our research outputs are part of that reality. Our research is an objectified form of a reality that knows and transforms itself through our actions as subjects. In this sense, I consider that critical realism has a better toolset the relation between the pre-existing social structures that condition our existence, and its relation with human agency (Bhaskar, 2010).

2.4 Thesis contribution

As shown on this literature review, a large amount of research has been devoted to race and gender inequalities in the recent years, and in particularly on inequalities in science. Most literature is focused on either race or gender inequalities exclusively, and those articles devoted to the intersectionality between both dimensions of inequality are mostly of qualitative nature, which limits their ability to generalize, and the granularity in which results can be explored. On the other hand, there is an increasing literature on inequalities using quantitative methods. Recently, causal models have stand out as the de facto methodology to study inequalities, which risks to heavily restrict the scope of the analysis to the few very specific relations that can be properly defined within that methodology. There is a research gap for general yet granular analyses that can present both the big picture and a detailed representation of inequalities. Although this thesis is also limited in scope with respect of the more general system presented above, it combines multiple dimensions using a quantitative approach. Within the scope of contemporary US publications, this research focuses on the race and gender identity of authors and their institutional belonging to study how these relate to participation, discipline and topical choice, and impact. The large-scale quantitative analysis allows for fine-grained descriptions with a high degree of generality, within the scope of work. The interpretation of results is bounded by the geographical and temporal constrains of the data, and therefore are not applicable to other countries or time-periods. Nevertheless, as one of the largest science producers in the globe, the inequalities in science on US have a large influence on the global scientific enterprise. The presented results, therefore, will show a broad description of the systemic inequalities in US science. This thesis shows how marginalized identities at the intersection of race and gender are underrepresented, and how this representation varies by discipline. It will also show an the yet underexplored role of research topics, which are many times discarded as an individual choice issue, into the reproduction of inequalities both in terms of representation and impact. With this, this thesis aims to work on the research gap of the mechanisms that derive citational injustice. Although this thesis does not aim to provide causal proof of topic selection as a mediating factor, it will highlight how some research topics are dearer to the needs of marginalized identities, and how those topics are undervalued in terms of impact. This thesis will also work on the research gap regarding the role of universities into the prestige distribution of topics and authors, to find how even going beyond the underrepresentation of marginalized identities in elite universities, there are other mechanisms from these institutions that reproduce inequalities, based on topical alignments and differential impact gaps. Taken together, this thesis contributes to the understanding of the systemic inequalities in science and opens the doors for multiple future research lines of work.

CHAPTER 3. AVOIDING BIAS WHEN INFERRING RACE USING NAME-BASED APPROACHES

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Contributions:

Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.

3.1 Abstract

Racial disparity in academia is a widely acknowledged problem. The quantitative understanding of racial-based systemic inequalities is an important step towards a more equitable research system. However, because of the lack of robust information on authors' race, few large-scale analyses have been performed on this topic. Algorithmic approaches offer one solution, using known information about authors, such as their names, to infer their perceived race. As with any other algorithm, the process of racial inference can generate biases if it is not carefully considered. The goal of this article is to assess the extent to which algorithmic bias is introduced using different approaches for name-based racial inference. We use information from the U.S. Census and mortgage applications to infer the race of U.S. affiliated authors in the Web of Science. We estimate the effects of using given and family names, thresholds or continuous distributions, and imputation. Our results demonstrate that the validity of name-based inference varies by race/ethnicity and that threshold approaches underestimate Black authors and overestimate White authors. We conclude with recommendations to avoid potential biases. This article lays the foundation for more systematic and less-biased investigations into racial disparities in science.

3.2 Introduction

The use of racial categories in the quantitative study of science dates from so long ago that it intertwines with the controversial origins of statistical analysis itself (Galton, 1891; Godin, 2007). However, while Galton and the eugenics movement reinforced the racial stratification of society, racial categories have also been used to acknowledge and mitigate racial discrimination. As Zuberi (Zuberi, 2003) explains: "The racialization of data is an artifact of both the struggles to preserve and to destroy racial stratification." This places the use of race as a statistical category in a precarious position, one that both reinforces the social processes that segregate and disempower parts of the population, while simultaneously providing an empirical basis for understanding and mitigating inequities.

Science is not immune from these inequities (Ginther et al., 2011; Hoppe et al., 2019; Prescod-Weinstein, 2020; K. R. Stevens et al., 2021). Early research on racial disparities in scientific publishing relied primarily on self-reported data in surveys (Hopkins et al., 2013), geocoding (Fiscella & Fremont, 2006), and directories (Cook, 2014). However, there is an increasing use of large-scale inference of race based on names (Freeman & Huang, 2015), similar to the approaches used for gender-disambiguation (Larivière et al., 2013). Algorithms, however, are known to encode human biases (Buolamwini & Gebru, 2018; Caliskan et al., 2017): there is no such thing as *algorithmic neutrality*. The automatic inference of authors' race based on their features in bibliographic databases is itself an algorithmic process that needs to be scrutinized, as it could implicitly encode bias, with major impact in the over and under representation of racial groups.

In this study, we use the self-declared race/ethnicity from the 2010 U.S. Census and mortgage applications as the basis for inferring race from author names on scientific publications indexed in the Web of Science database. Bibliometric databases do not include self-declared race by authors, as they are based on the information provided in publications, such as given and family names. Given that the U.S. Census provides the proportion of self-declared race by family name, this information can be used to infer U.S. authors' race given their family names. Name-based racial inference has been used in several articles. Many studies assigned a single category given the family or given name (Brandt et al., 2020; Hofstra et al., 2020; Kim et al., 2021; Marschke et al., 2018; Sood & Laohaprapanon, 2018). Other studies used the aggregated probabilities related with a name, instead of using a single label (Bertolero et al., 2020). In this research, we assess the incurred biases when using a single label, i.e. thresholding. The main goal of this research is to define the most unbiased algorithm to predict a racial category given a name. We present several different approaches for inferring race and examine the bias generated in each case. The goal of the research is to provide an empirical critique of name-based race inference and recommendations for approaches that minimize bias. Even if prefect inference is not achievable, the conclusions that arise from this study will allow researchers to conduct more careful analyses on racial and ethnic disparities in science. Although the categories analysed are only valid in the U.S. context, the general recommendation can be extended to any other country in which the Census (or similar data collection mechanism) includes self-reported race.

3.3 <u>Racial categories in the U.S. Census</u>

The U.S. Census is a rich and long-running dataset, but also deeply flawed and criticized. Currently it is a decennial counting of all U.S. residents, both citizens or non-citizens, in which several characteristics of the population are gathered, including self-declared race/ethnicity. The classification of race in the U.S. Census is value-laden with the agendas and priorities of its creators, namely 18th century White men who Wilkerson (Wilkerson, 2020) refers to as "the dominant caste." The first U.S. Census was conducted in 1790 and founded on the principles of racial stratification and White superiority. Categories included: "Free White males of 16 years and upward," "Free White males under 16 years;" "Free White females," "All other free persons," and "Slaves" (U.S. Census Bureau, 1975).At that time, each member of a household was classified into one of these five categories based on the observation of the census-taker, such that an individual of "mixed white and other parentage" was classified into "All other free persons" in order to preserve the "Free White…" privileged status. To date, anyone classifying themselves as other than "non-Hispanic White" is considered a "minority." The shared ground across the centuries of census survey design and classification strata reflects the sustained prioritization of the White male caste (D'Ignazio & Klein, 2020; Zuberi, 2003).

Today, self-identification is used to assign individuals to their respective race/ethnicity classifications (U.S. Census Bureau, 2011), per the U.S. Office of Management and Budget (OMB) guidelines. However, the concept of race and/or ethnicity remains poorly understood. For example, in 2000 the category "Some other race" was the third largest racial group, consisting primarily of individuals who in 2010 identified as Hispanic or Latino (which according to the 2010 census definition refers to a person of Cuban, Mexican, Puerto Rican, South or Central American, or other Spanish culture or origin regardless of race). Instructions and questions which facilitated the distinction between race and ethnicity began with the 2010 census which stated that "[f]or this census, Hispanic origins are not races" and to-date, in the U.S. federal statistical system, Hispanic origin is considered to be a separate concept from race. However, this did not preclude individuals from self-identifying their race as "Latino," "Mexican," "Puerto Rican," "Salvadoran," or other national origins or ethnicities (Humes et al., 2011). Furthermore, 6.1% of the U.S. population changed their self-identification of both race and ethnicity between the 2000 and 2010 censuses (Liebler et al., 2017), demonstrating the dynamicity of the classification. The inclusion of certain categories has also been the focus of considerable political debate. For example, the inclusion of citizenship generated significant debates in the preparation of the 2020 Census, as it may have generated a larger nonresponse rate from the Hispanic community (Baum et al., 2019). For this article, we attempt to represent the fullest extent of potential U.S.-affiliated authors; thereby, we consider both citizens and non-citizen.

The social function of the concept of race (i.e., the building of racialized groups) underpins its definition more than any physical traits of the population. For example, "Hispanic" as a category arises from this conceptualization, even though in the 2010 U.S. Census the question about Hispanic origin is different from the one on self-perceived race. While Hispanic origin does not relate to any physical attribute, it is still considered a socially racialised group, and this is also how the aggregated data is presented by the Census Bureau. Therefore, in this paper, we will utilize the term race to refer to these social constructions, acknowledging the complex relation between conceptions of race and ethnicity. But even more important, this conceptualization of race also determines what can be done with the results of the proposed models. Given that race is a social construct, inferred racial categories should only be used in the study of group-level social dynamics underlying these categories, and not as individual-level traits. Census classifications are founded upon the social construction of race and reality of racism in the U.S., which serves as “a multi-level and multi-dimensional system of dominant group oppression that scapegoats the race and/or ethnicity of one or more subordinate groups” (Horton & Sykes, 2001). Self-identification of racial categories continue to reflect broader definitional challenges, along with issues of interpretation, and above all the amorphous power dynamics surrounding race, politics, and science in the U.S. In this study, we are keenly aware of these challenges, and our operationalization of race categories are shaped in part by these tensions.

3.4 Data

This project uses several data sources to test the different approaches for race inference based on the author's name. First, to test the interaction between given and family names distributions, we simulate a dataset that covers most of the possible combinations. Using a Dirichlet process (Teh, 2017), we randomly generate 500 multinomial distributions that simulate those from given names, and another 500 random multinomial distributions that simulate those from family names. After this, we build a grid of all the possible combinations of given and family names random distributions (250,000 combinations). This randomly generated data will only be used to determine the best combination of the probability distributions of given and family names for inferring race.

In addition to the simulation, we use two datasets with real given and family names and an assigned probability for each racial group. The data from the given names is from Tzioumis (Tzioumis, 2018), who builds a list of 4,250 given names based on mortgage applications, with self-reported race. Family name data is based on the 2010 U.S. Census (U.S. Census Bureau, 2016), which includes all family names with more than 100 appearances in the census, with a total of 162,253 surnames that covers more than 90% of the population. For confidentiality, this list removes counts for those racial categories with fewer than five cases, as it would be possible to exactly identify individuals and their self-reported race. In those cases, we replace with zero and renormalize. As explained previously, changes were introduced in the 2010 U.S. Census racial categories. Questions now include both racial and ethnic origin, placing "Hispanic" outside the racial categories. Even if now “Hispanic” is not considered a racial category, but an ethnic origin that can occur in combination with other racial categories (e.g., Black, White or Asian Hispanic), the information about names and racial groups merge both questions into a single categorization. Therefore, the racial categories used in this research includes “Hispanic” as a category, and all other racial categories excluding people with Hispanic origin. The category "White" becomes "Non-Hispanic White Alone", and "Black or African American" becomes "Non-Hispanic Black or African American Alone", and so on. The final categories used in both datasets are:

- Non-Hispanic White Alone (*White*)
- Non-Hispanic Black or African American Alone (*Black*)
- Non-Hispanic Asian and Native Hawaiian and Other Pacific Islander Alone (*Asian*)

- Non-Hispanic American Indian and Alaska Native Alone (*AIAN*)
- Non-Hispanic Two or More Races (*Two or more*)
- Hispanic or Latino origin (*Hispanic*)

We test these data on the Web of Science (WoS) to study how name-based racial inference performs on the population of U.S. first authors. WoS did not regularly provide first names in articles before 2008, nor did it provide links between authors and their institutional addresses; therefore, the data includes all articles published between 2008 and 2019. Given that links between authors and institutions are sometimes missing or incorrect, we restricted the analysis to first authors to ensure that our analysis solely focused on U.S. authors. This results in 5,431,451 articles, 1,609,107 distinct U.S. first authors in WoS, 152,835 distinct given names and 288,663 distinct family names for first authors. Given that in this database, 'AIAN' and 'Two or more' account for only 0.69% and 1.76% of authors respectively, we remove these and renormalize the distribution with the remaining categories. Therefore, in what follows we will refer exclusively to categories *Asian, Black, Hispanic,* and *White.*

3.5 Methods

3.5.1 Manual validation

The data is presented as a series of distributions of names across race (Table 1). In name-based inference methods, it is not uncommon to use a threshold to create a categorical distinction: e.g., using a 90% threshold, one would assume that all instances of Juan as first name should be categorized as Hispanic and all instances of Washington as a given name should be categorized as Black. In such a situation, any name not reaching this threshold would be excluded (e.g., those with the last name of "Lee" would be removed from the analysis). This approach, however, assumes that the distinctiveness of names across races does not significantly differ.

Table 1. Sample of family names (U.S. Census) and given names (mortgage data).

Type	*Name*	*Asian*	*Black*	*Hispanic*	*White*	*Count*
Given	Juan	1.5%	0.5%	93.4%	4.5%	4,019
	Doris	3.4%	13.5%	6.3%	76.7%	1,332
	Andy	38.8%	1.6%	6.4%	53.2%	555
Family	Rodriguez	0.6%	0.5%	94.1%	4.8%	1,094,924
	Lee	43.8%	16.9%	2.0%	37.3%	693,023
	Washington	0.3%	91.6%	2.7%	5.4%	177,386

To test this, we began our analysis by manually validating name-based inference at three threshold ranges: 70-79%, 80-89%, and 90-100%. We sampled 300 authors from the WoS database, 25 randomly sampled for every combination of racial category and inference threshold. Two coders manually queried a search engine for the name and affiliation of each author and attempted to infer a perceived racial category through visual inspection of their professional photos and information listed on their websites and CVs (e.g., affiliation with racialized organizations such as *Omega Psi Phi Fraternity, Inc.*, *SACNAS*, etc.).

Figure 3 shows the number of valid and invalid inferences, as well as those for whom a category could not be manually identified, and those for whom no information was found. Name-based inference of Asian authors was found to be highly valid at every considered threshold. The inference of Black authors, in contrast, produced many invalid or uncertain classifications at the 70-80% threshold, but had higher validity at the 90% threshold. Similarly, inferring Hispanic authors was only accurate after the 80% threshold. Inference of White authors was highly valid at all thresholds but improved above 90%. This suggests that a simple threshold-based approach does not perform equally well across all racial categories. We thereby consider an alternative weighting-based scheme that does not provide an exclusive categorization but uses the full information of the distribution.

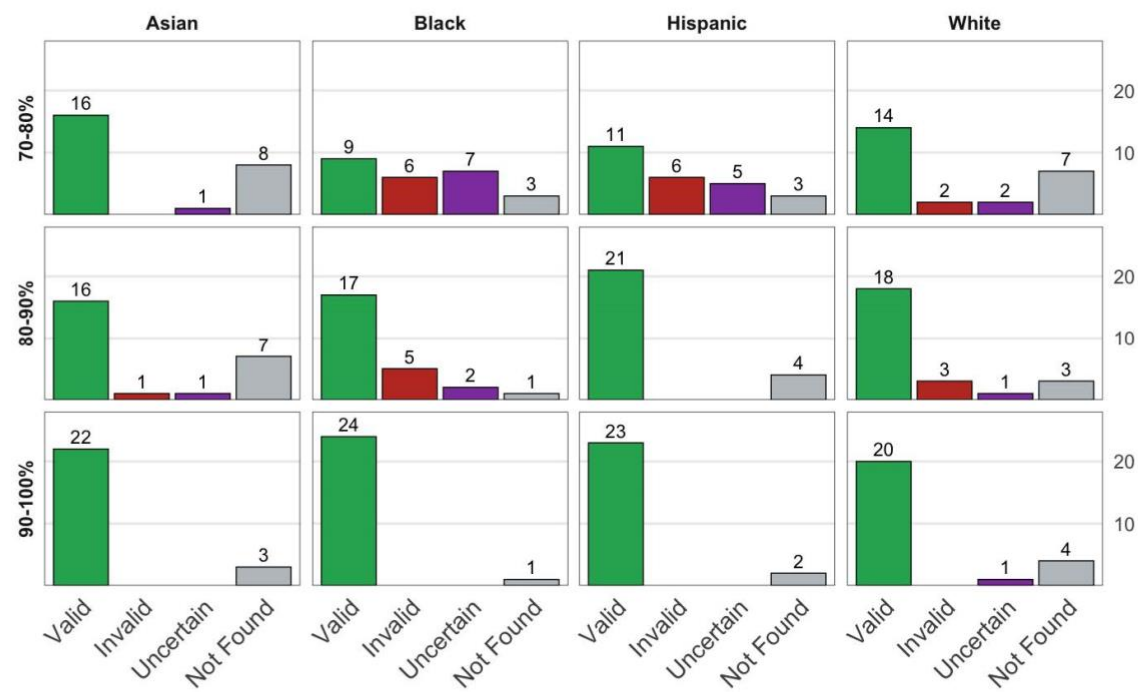

Figure 3. Manual validation of racial categories

3.5.2 Weighting scheme

We assess three strategies for inferring race from an author's name using a combination of their given and family name distributions across racial categories (Table 1). The first two aim at building a new distribution as a weighted average from both the given and family name racial distributions, and the third uses both distributions sequentially. In this section we explain these three approaches and compare them to alternatives that use only given or only family name racial distributions.

The weighting scheme should account for the intuition that if the given (family) name is highly informative while the family (given) name is not, the resulting average distribution should prioritize the information on the given (family) name distribution. For example, 94% of people with Rodriguez as a family name identify themselves as Hispanic, whereas 39% of the people with the given name Andy identify as Asian, and 53% as White (see Table 1). For an author called Andy Rodriguez, we would like to build a distribution that encodes the informativeness of their family name, Rodriguez, rather than the relatively uninformative given name, Andy. The first weighting scheme proposed is based on the standard deviation of the distribution:

$$(1)\ SD = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

Where x_i is in this case the probability associated with category *i*, and *n* is the total number of categories. With four racial categories, the standard deviation moves between 0, for perfect uniformity, and 0.5 when one category has a probability of 1. The second weighting scheme is based on entropy, a measure that is designed to capture the informativeness of a distribution:

$$(2)\ entropy = -\sum_{i=1}^{n} P(x_i)\log\ P(x_i)$$

Using these, we propose the following weight for both given and family names:

$$(3)\ x_{weight} = \frac{f(x)^{exp}}{f(x)^{exp} + f(y)^{exp}}$$

with *x* and *y* as the given (family) and family (given) names respectively, *f* is the weighting function (standard deviation or entropy), and exp is the exponent applied to the function and a tuneable parameter. For the standard deviation, using the square function means we use the variance of the distribution. In general, the higher the exp is set, the more skewed the weighting is towards the most informative name distribution. In the extreme, it would be possible to use an indicator function to simply choose the most skewed of the two distributions, but this approach would not use the information from both distributions. For this reason, we decided to experiment with $exp \in \{1,2\}$, which imply a trade-off between selecting the most informative of the two distributions, and using all available information.

Figure 4 shows the weighting of the simulated given and family names based on their informativeness, and for different values of the exponent. The horizontal and vertical axes show the highest value on the given and family name distribution, respectively. This means that a higher value on any axis corresponds with a more informative given/family name. The color shows how much weight is given to given names. When the exponent is set to two, both the entropy and standard deviation-based models skew towards the most informative feature, a desirable property. Compared to other models, the variance gives the most extreme values to cases where only one name is informative, whereas the entropy-based model is the most uniform.

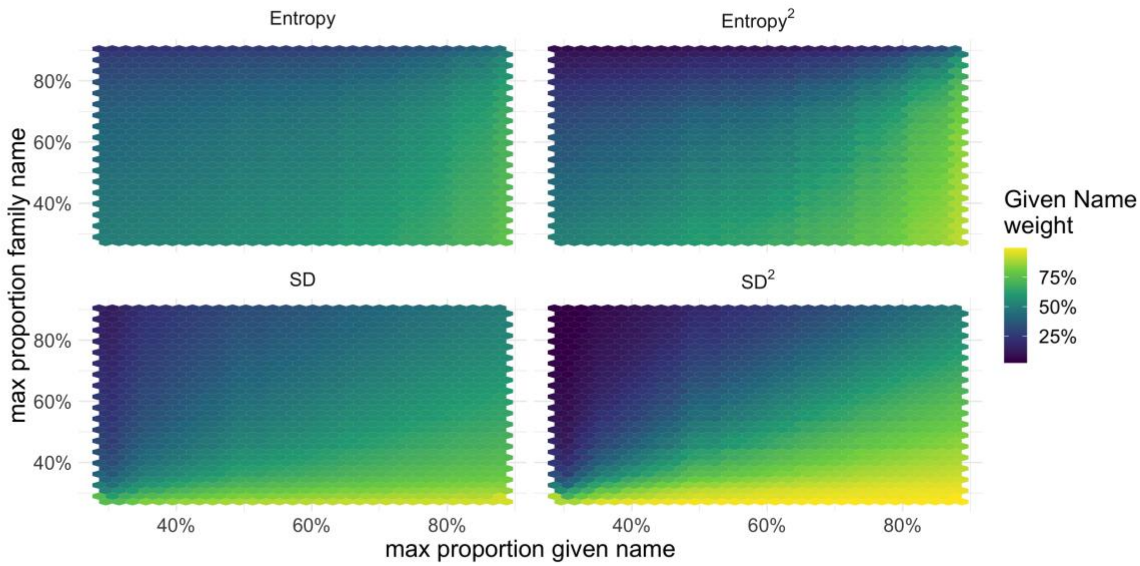

Figure 4. Given names weight distribution by given and family name skewness. Simulated data

3.5.3 Information retrieval

The above weighting schemes result in a single probability distribution of an author belonging to each of the racial categories, from which a race can be inferred. One strategy for inferring race from this distribution is to select the racial category above a certain threshold, if any. A second strategy is to use the full distribution to weight the author across different racial categories, rather than assigning any specific category. We also consider a third strategy, which sequentially uses family and then given names to infer race.

We first retrieve all authors who have a family name with a probability of belonging to a specific racial group greater than a given threshold. This retrieves N authors. Second, we retrieve the same number of authors as in the first step, N, using their given names. Finally, we merge the authors from both steps, removing duplicates who had both given and family names above the set threshold. This process results in between N and $2N$ authors. There are several natural variations on this two-step method. For example, a percentage threshold could be used for both steps, or the first step could use given names, rather than family. We select family names first, because they are sourced from the larger and more comprehensive census data.

In summary, the following methods will be used on the empirical analysis.

1. Only family names with thresholding,
2. Only given names with thresholding,
3. Weighted average of given and family names using the variance as weighting scheme,
4. Two-step retrieval,
5. Fractional counting, for comparison.

3.6 Results

3.6.1 The effect of underlying skewness

Before comparing the results of the proposed strategies for using both given and family names, we present characteristics of these two distributions on the real data, and in relation to the WoS dataset. Table 2 shows the population distribution on the family names, based on the U.S. Census, and on the given names, based on the mortgage applications. Considering the U.S. Census data as ground truth, we see that the mortgage data highly over-represents the White population, particularly over-represents Asians, and under-represents Black and Hispanic populations; this likely stems from the structural factors (i.e., economic inequality, redlining, etc.) that prevent marginalized groups from applying for mortgages in the U.S. People may also choose to self-report a different racial category when responding anonymously to the census bureau than when applying for a mortgage loan. Due to this bias in the distribution of given names, we decided to implement a normalized version of the given names racial distribution. This was obtained by computing the total number of cases for each racial group in each dataset, and the expansion factor for each group, obtained by the ratio between the total number of cases in the census data (family names) with respect of the Mortgage data (given names). We use this expansion factor to multiply the cases of each group for each name, and finally divide by the total number of cases in each name to have the proportion of each racial group on each name. By doing this, the average distribution of the given names data matches the one in the U.S. Census. In what follows, we use both the normalized and not normalized version of given names, for comparison.

Table 2. Racial representation of family names (U.S. Census) and given names (mortgage data)

Racial group	*Family names*	*Given names*
Asian	5.0%	6.3%
Black	12.4%	4.2%
Hispanic	16.5%	6.9%
White	66.1%	82.6%

Both given and family names share a characteristic not considered in our simulated data: the informativeness of names varies across racial groups. Inferring racial categories based on a set threshold will, then, produce biased results as typical names of one racial category are more informative, and thus more easily meet the threshold, than another. Figure 5 shows the ratio of the proportion of each racial group for different thresholds with respect to a 0% threshold, which implies fractional counting and the closest we can get to ground truths with the available information. This figure shows how the representation of inferred races changes based on the assignment threshold used. Increasing the threshold results in fewer total individuals returned (top), as some names are not sufficiently informative. For family names, only a small proportion of the population remains at the 90% threshold. The Asian population is highly over-represented between the 90% and 96% threshold, after which they suddenly become under-represented. The White population is systematically over-represented for any threshold, whereas the Black population is systematically under-represented. The Hispanic population is over-represented between the 65% and 92% threshold and under-represented after. Similar results are observed based on given names. Again, the Asian population is highly over-represented after the 96% threshold, whereas the White population is over-represented across nearly all thresholds and the Black and Hispanic population were under-represented across all thresholds. With given names, the White population is systematically overestimated for every threshold until 96%, where the Asian population is suddenly overestimated to a high degree. The fact that Asian, and to some degree Hispanic, populations have more informative given and family names reflects their high degree of differentiation from other racial groups in the U.S.; White and Black populations in the United States, in contrast, tend to have more similar names (as verified in (Elliott et al., 2009)). Given that the White population is larger than the Black population in the U.S., the use of a threshold (and assigning all people with that name to a single category), generates a Type I error on Black authors, and Type II error on White authors, thereby overestimating the proportion of White authors. Likewise, the descendants of African chattel slavery in the U.S. were assigned names by their rapists/slavers as a form of physical bondage and psychological control. Furthermore, family members who had been sold away, often retained their names, including those of U.S. Presidents George Washington and James Monroe, in hopes of making it easier to reunite with loved ones. (Feagin, 2006; Furstenberg, 2007; Yager, 2018). After the 1960's however —and coinciding with the Black Power movement (Girma, 2020)— distinctively Black first names became increasingly popular, particularly among Black people living in racially segregated neighborhoods (Fryer & Levitt, 2004).

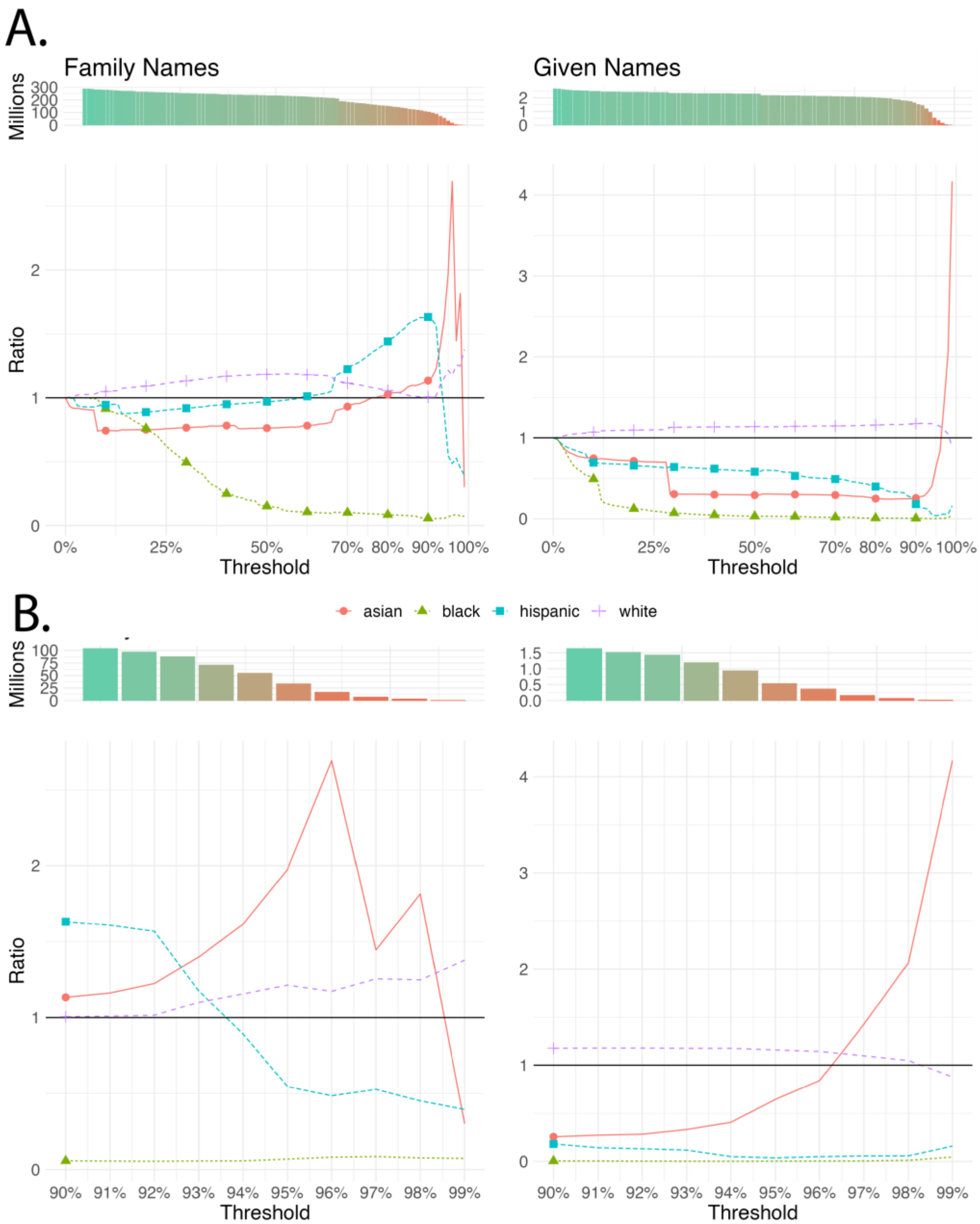

Figure 5. Changes in groups share, and people retrieved, by threshold. Census (Family names) and mortgage (Given names) datasets. A. The evolution of thresholds between 0 and 1, B. and detail on thresholds between 0.9 and 1.

3.6.2 The effect of thresholding

Figure 6 shows the effect of using a 90% threshold on the WoS dataset of unique authors. The first column (A) corresponds to each author counting fractionally towards each racial category in proportion to the probabilities of their name distribution, using family names from the census, i.e., this is the closest we can get to ground truths with the available information. The remaining columns represent inference based on family (B) and given names (C-D) alone; the two-steps strategy, using both normalized (E) and unnormalized (F) given names, and the merged distributions of given and family names, with normalized (G) and not normalized (H) given names; always with a 90% threshold. All models severely under-represented the Black population of authors. Compared to the fractional baseline (A), all models except normalized given names (C) under-represent the Hispanic population. The unnormalized given name, either alone (D) or in the variance model (H), under-represents the Asian population. Finally, the White population is over-represented by all models except family names and the variance with normalized given names.

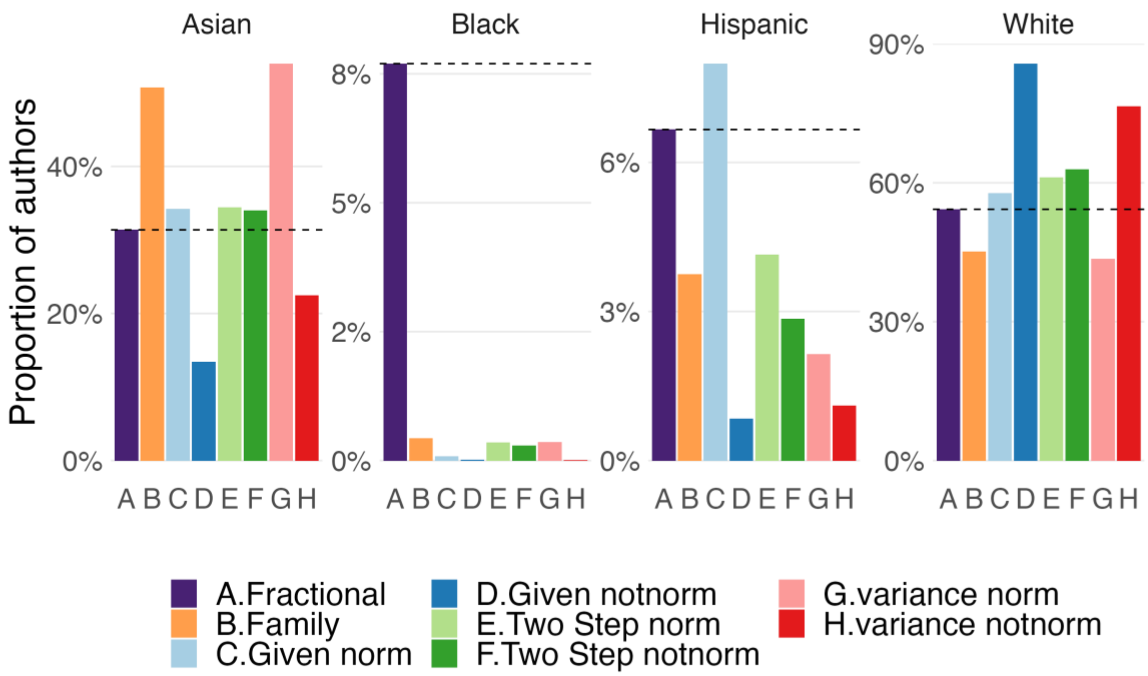

Figure 6. Resulting distribution on different models with 90% threshold. Fractional counting on family names for comparison.

Figure 7 shows the seven different models' evolution over the threshold. First, the number of retrieved authors as the threshold increases; second, the ratio between the proportion a group represents given a model and a threshold, and the proportion using the fractional counting with family names. The dashed line represents the expected total cases per group using fractional counting, and the unbiased ratio of 1, respectively. A high threshold is expected to retrieve less cases than the expected total. For thresholds until 80%, this is not always the case for White authors. This means that for the two-step strategy, for a threshold below 80%, we would overestimate the total number of White authors. For Asian authors, given names have the worst retrieval, whereas Hispanic and especially Black authors are always underestimated. The retrieved authors fall sharply for all models after the 95% threshold.

As in Figure 6, we can compare for a given threshold the aggregate proportion of authors in each group, with respect to the expected ground truth. In this case, we can see that almost every model overestimates the proportion of White authors until the 90% or 95% thresholds, where Asian authors begin to be overestimated. Again, Hispanic and especially Black authors are heavily underestimated, with the single exception of the normalized given names, that overestimate Hispanic authors in the thresholds between 90% and 95%.

We conclude from this that a threshold-based approach, while intuitive and straightforward, should not be used for racial inference. Rather, analysis should be adapted to consider each author as a distribution over every racial category; in this way, even though an individual cannot be assigned into a category, aggregate results will be less biased.

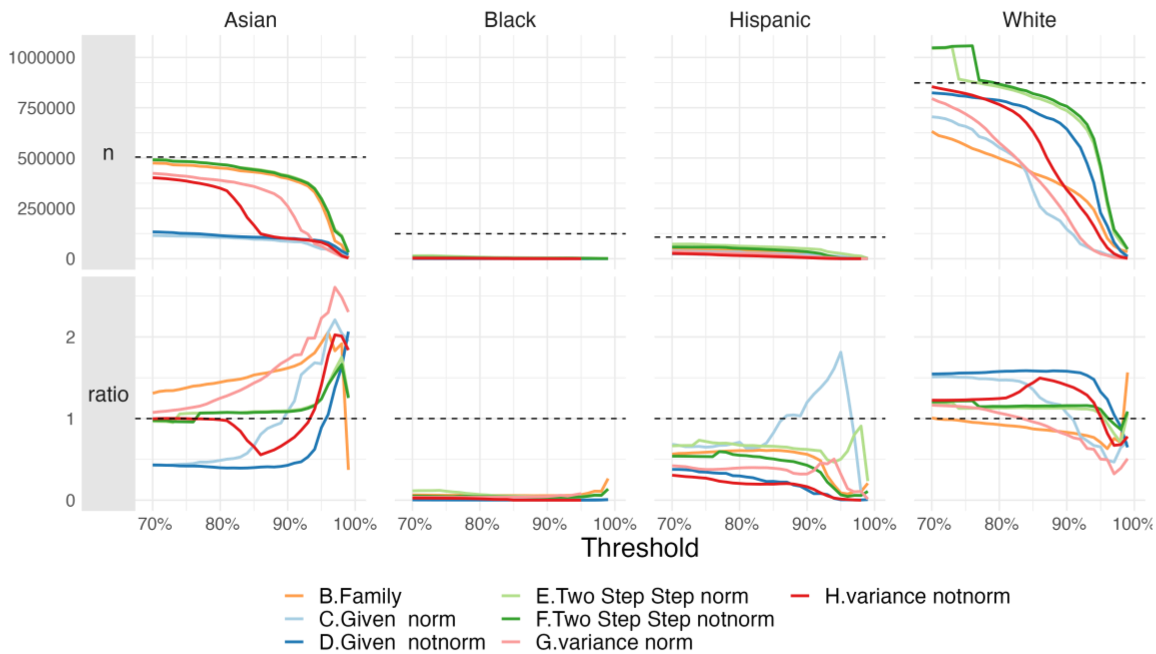

Figure 7. Retrieval of authors by race using different inference models for varying thresholds.

3.6.3 The effect of imputation

Another consideration is how to deal with unknown names. As mentioned in the Data section, the family names dataset provided by the Census Bureau covers 90% of the U.S. population. The remaining 10%, as well as author names not represented in the census, represents 774,381 articles, or 18.75% of the dataset, for which the family name of the first authors has an unknown distribution over racial categories.

An intuitive solution would be to impute missing names with a default distribution based on the racial composition of the entire census. Alternatively, the "All other names" category provided by the U.S. Census could be used. Table 3 shows the distribution among racial groups in the U.S. Census, the "All other names" category, and in WoS for first authors with family names included in the U.S. Census data. The Asian population is highly over-represented among WoS authors, whereas Hispanic and Black authors are highly under-represented, with respect to their proportion of the U.S. population. Imputing with the census-wide racial distribution or the special wildcard category is, therefore, equivalent to skewing the distribution towards Hispanic and Black authors and under-representing Asian authors. Since the ground truth is contingent to the specific dataset in use, a better imputation would instead be the mean of the population most representative of an individual. For example, in the case of a missing author name in the WoS, the racial distribution of that individual's discipline could be imputed. Our recommendation is -in cases where imputation is needed- to first compute the aggregate distribution of racial categories with the dataset in which the inference is intended, and then use this aggregate distribution to impute in those family names missing from the census dataset. Statistically, this preserves the aggregate distribution on this dataset.

Table 3. Racial distribution in U.S. Census and WoS U.S. Authors with known family names.

Racial group	*U.S. Census aggregate*	*U.S. Census "All other names"*	*U.S. WoS*
Asian	5.0%	8.2%	24.5%
Black	12.4%	8.8%	7.2%
Hispanic	16.5%	14.1%	5.4%
White	66.1%	68.8%	59.4%

Nevertheless, this type of imputation can also introduce new biases. If the missing family names correlate with a specific racial group, then the known cases cannot be considered a random sample of the data, and their mean will be biased toward those groups that have fewer unknown names. Knowing which group has more unknown cases is in principle an impossible task. Nevertheless, it is possible to infer this, considering the citizenship status of authors. Authors that are temporary visa holders in US are more likely to have a family name that doesn't appear on the census. The Survey of Earned Doctorates provides information on doctorate recipients, by ethnicity, race, and citizenship status between 2010 and 2019 (NSF, 2021a). Figure 8 shows the average proportion of Temporary Visa Holders among Earned Doctorates from each racial group. This can be seen as a proxy of the distribution of authors by race and citizenship status. There is a large majority of Asian authors that are migrants, followed by a 30% of Hispanic authors, 19% of Black authors and 11% of White authors. Imputing by the mean of the known authors would also underestimate Asian authors, and partially too Hispanic authors, while overestimating White authors. Nevertheless, omitting the missing cases would have the same effect on the overall distribution, given that the imputation by the mean does not change the aggregate proportion of each group. There is no perfect solution for this, as the distribution shown on Figure 8 is only a proxy of the problem. Therefore, it is important to acknowledge this potential bias on the result, both if the imputation is used or if the missing cases are omitted.

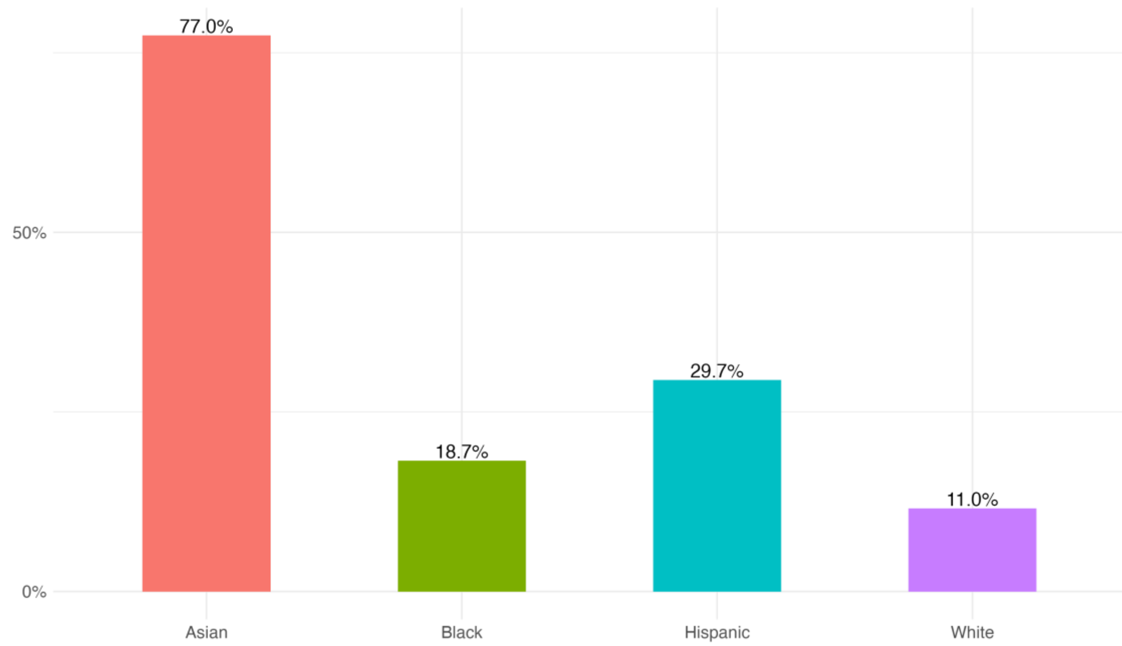

Figure 8. Proportion of Temporary Visa Holders by racial group.

3.7 Conclusion

Race scholars (Emirbayer & Desmond, 2012) have advocated for a renewal of Bourdieu's (Bourdieu, 2004) call for reflexivity in science of science (Kvasny & Richardson, 2006). We pursue this through empirical reflexivity: challenging the instrumentation used to collect and code data for large-scale race analysis. In this paper we manually validate and propose several approaches for name-based racial inference of U.S. authors. We demonstrated the behaviour of the different methods on simulated data, across the population, and on authors in the WoS database. We also illustrated the risks of underestimating highly minoritized groups (e.g., Black authors) in the data when using a threshold, and the overestimation of White authors introduced by given names when they are based on mortgage data. A similar result was identified by Cook (Cook, 2014), in her attempt to infer race of patent data based on the U.S. Census: she found that the approach "significantly underpredicted matches to black inventors and overpredicted matches to white inventors" and concludes that the name-based inference approach was not suitable for historical analyses.

From our analysis, we come away with three major lessons that are generally applicable to the use of name-based inference of race in the U.S., shown in table 4.

Table 4. General recommendations for implementing a name-based inference of race for U.S. authors.

	Do's	*Don'ts*
Given Names	Use only family names from U.S. Census to avoid bias.	Do not use given names, except when the underlying distribution of your dataset matches that of mortgage data.
Thresholding	Consider each person in your data as a distribution and adapt your summary statistics.	Do not use a threshold for categorical classification of each person, as this under-represents Black population, due to the correlation between racial groups and name informativeness.
Imputation	If needed, calculate first the aggregated distribution on your dataset, and use this for imputation of missing cases. Acknowledge the potential bias of imputation.	Do not use the census aggregate distribution for imputation, except when your target population matches the U.S. population.

Inferring race based on name is an imperfect, but often necessary approach to studying inequities and prejudice in bibliometric data (Freeman & Huang, 2015), and in other areas where self-reported race is not provided. However, the lessons shown here demonstrate that care must be taken when making such inferences in order to avoid bias in our datasets and studies.

It has been argued that science and technology serve as regressive factors in the economy, by reinforcing and exacerbating inequality (Bozeman, 2020). As Bozeman (2020) argued, "it is time to rethink the economic equation justifying government support for science not just in terms of why and how much, but also in terms of who." Studies of the scientific workforce that examine race are essential for identifying who is contributing to science and how those contributions change the portfolio of what is known. To do this at scale requires algorithmic approaches; however, using biased instruments to study bias only replicates the very inequities they hope to address.

In this study, we attempt to problematize the use of race from a methodological and variable operationalization perspective in the U.S. context. In particular, we acknowledge variability in naming conventions over time, and the difficulty of algorithmically distinguishing Black from White last names in the U.S. context. However, any extension of this work across country lines will necessarily require tailoring to meet the unique contextual needs of the country or region in question. Ultimately, scientometrics researchers utilizing race data are responsible for preserving the integrity of their inferences by situating their interpretations within the broader socio-historical context of the people, place, and publications under investigation. In this way, they can avoid preserving unequal systems of race stratification and instead contribute to the rigorous examination of race and science intersections toward a better understanding of the science of science as a discipline. Once again, we quote Zuberi (Zuberi, 2003): "The racialization of data is an artifact of both the struggles to preserve and to destroy racial stratification."

3.8 Limitations

The name-based racial inference proposed in this article avoids individual identification of authors and instead uses the distribution of probabilities associated with each name. This has limitations: for the two U.S. Census groups that account for a small proportion of the population —American Indian and Alaska Native (AIAN) and Two or more races— the inference power of the method is weak and can lead to spurious results on the aggregate level. To avoid misleading results, we exclude these groups from the analysis and re-normalize the distribution. This is an acknowledged limitation of this work and—to the best of our knowledge—an unavoidable effect of algorithms that seek to infer race based on names. An alternative methodology would be to survey authors to obtain their self-declared race data to investigate racial inequalities in scholarly publications. However, given that individuals' identities are also critically important to protect, the distributional approach proposed in this article presents the advantage that it cannot be used to identify authors' race on an individual basis.

There is a pressing need for large-scale analyses of racial bias in science. That said, algorithmic approaches which fail to account for all minoritized and marginalized groups are limited. Therefore, this study demonstrates the need for complementary sets of quantitative and qualitative studies focused on the racialized identities of groups that would otherwise be excluded from large-scale studies such as the one presented here.

CHAPTER 4. INTERSECTIONAL INEQUALITIES IN SCIENCE

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Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing

4.1 Abstract

The US scientific workforce is primarily composed of White men. Studies have demonstrated the systemic barriers preventing women and other minoritized populations from gaining entry to science; few, however, have taken an intersectional perspective and examined the consequences of these inequalities on scientific knowledge. We provide a large-scale bibliometric analysis of the relationship between intersectional identities, topics, and scientific impact. We find homophily between identities and topic, suggesting a relationship between diversity in the scientific workforce and expansion of the knowledge base. However, topic selection comes at a cost to minoritized individuals for whom we observe both between- and within-topic citation disadvantages. To enhance the robustness of science, research organizations should provide adequate resources to historically underfunded research areas, while simultaneously providing access for minoritized individuals into high prestige networks and topics.

4.2 Introduction

Strong disparities are observed in the composition of the scientific workforce. At the global level, women account for less than a third of scientists and engineers (UNESCO, 2019); a percentage that is similar to their proportion of scientific authorships (Larivière et al., 2013). In the U.S., women represent 28.4% of the scientific workforce, and this percentage varies by domain, with a high of 72.8% in psychology and a low of 14.5% in engineering (NSF, 2021b). Disparities are also observed at the intersection of race and gender, with White men comprising a disproportionate amount of the U.S. workforce (L. Davis & Fry, 2019). Although the trend is changing—faculty of color increased from 20% of the scientific workforce in 2005 (Taylor et al., 2010) to 25% in 2018 (Hussar et al., 2020)—increases have not been observed equally across all racially minoritized groups. For instance, the proportion of Black (5-6%) and American Indian/Alaska Native (1%) scholars remained relatively stable, while Latinx representation nearly doubled (3.5% to 6%) and Asian representation increased from 9.1% to 11%. Gender differences are also observed within racial categories: men account for a higher share than women, especially for White and Asian/Pacific Islanders (Hussar et al., 2020). Likewise, the presence of minoritized groups varies substantially by discipline. Science, Technology, Engineering/Computer Science, and Mathematics (STEM) disciplines exhibit less demographic diversity than non-STEM fields (D. Li & Koedel, 2017). For example, in Biology, only 0.7% of faculty identify as Black, despite representing 12.2% of the U.S. population (D. Li & Koedel, 2017).

These differences characterize the unequal representation of populations within the scientific community. Such disparities are often a manifestation of *inequality*—unequal outcomes—and *inequity*—the degree to which these outcomes are a result of impartiality or bias in judgement. Women and other minoritized populations are underrepresented in scientific publishing (Bertolero et al., 2020; Huang et al., 2020), for example, and this can be associated with unequal outcomes in peer review (Erosheva et al., 2020; Murray et al., 2019a). Inequalities have been observed at several other pivotal evaluation points in science, including applications for lab manager positions (Moss-Racusin et al., 2012), grant submissions (Ginther et al., 2011, 2016), and scholarly impact (Larivière et al., 2013). Several forms of implicit bias may contribute to these inequities, from perceptions of brilliance (Leslie et al., 2015) to gendered scripts on women's commitment to science (Rivera, 2017). Overt forms of discrimination found in other spheres of society are also observed within the scientific community, such as stereotypes about gender and race (Eaton et al., 2020), anti-Black institutional policies (Mustaffa, 2017), and structural racism (Kaiser, 2021; Odekunle, 2020).

Studies that examine inequities and inequalities at the individual-level are often anchored in a justice perspective (Cozzens, 2007), whereby scientific principles such as universalism (Merton, 1988) are tested against the current system, thus challenging the conception that science is a meritocracy. In contrast with studies of individual-level success, utilitarian studies focus on collective gains and test whether higher equity improves the robustness of science. Extant studies have demonstrated that racial diversity leads to increased productivity (i.e., sales and profits) in industry (Herring, 2009) and that diverse groups outperform homogeneous ones in cognitive tasks (Freeman & Huang, 2015). In science, diversity in the composition of scientific teams has been linked to higher citations (AlShebli et al., 2018) and tied to gains in innovation (Hofstra et al., 2020). This emergent body of literature suggests that there are scientific and societal benefits to increasing diversity in science. Studies should, therefore, consider the rich interplay between social identities and scientific work.

A growing body of work examines the affinity between social identities and topic selection. For example, in medical research, decades of male dominance led to little attention to sex differences in medicine (Clayton & Collins, 2014; Klein et al., 2015). The changing demographics of the research community improved the situation, as women are more likely to include female subjects (Sugimoto et al., 2019) and to report sex as an analytical variable (Nielsen et al., 2017). Women are also more likely to produce scientific discoveries that lead to women's health patents and to contribute to patenting in this area (Koning et al., 2021). Funding—one of the main drivers of research activity--is similarly affected by researcher's social identifies and align with topic selection. For example, funding outcomes at the National Institutes of Health were found to be lower for Black and African American applicants. This was largely explained in topic selection: these investigators were more likely to propose research on topics with lower success rates (e.g., human subjects research and research on health disparities) relative to White and Asian investigators (Hoppe et al., 2019). These outcomes have implications for innovation and scientific competitiveness: racialized and gendered groups are more likely to contribute novel scientific contributions, yet their work is often neglected by other scientists (Hofstra et al., 2020). Taken together, these studies suggest that unequal representation in science leads to under-investigation of particular topics and may serve to stymie innovation. This motivates a more nuanced understanding of barriers to success for minoritized populations, and how these observed disparities intersect with complex social identities, fine-grained topic selection, and the reward structure of science.

Intersectionality was initially introduced as an analytic framework for understanding how interrelated and mutually shaping categories of race and gender served to compound inequalities for minoritized women (Collins & Bilge, 2016; Crenshaw, 1989; Gutierrez y Muhs et al., 2012; E. O. McGee & Bentley, 2017). These studies emphasize women's racialized and gendered experiences by explicitly situating minoritized women as central actors in power struggles and social inequalities (N. E. Brown & Gershon, 2017; Collins, 2015; Crenshaw, 1989, 1991; Herring, 2009; Hong & Page, 2004; Lord et al., 2009). The intersectional framework has since been expanded and used to frame the marginalization experienced by minoritized groups at the intersection of race, gender, sexual orientation, class, and other identities (May, 2012). While gender inequities and inequalities have been the focus of several recent large-scale analyses (Holman et al., 2018; Larivière et al., 2013; Macaluso et al., 2016; Murray et al., 2019a; West et al., 2013; Witteman et al., 2019), very few studies have focused on the racial and ethnic composition of authors (Cook, 2014; Leggon, 2006; Witteman et al., 2019). Studies from an intersectional perspective (e.g., women of color) have been predominantly qualitative, based on self-reports or focused on a particular field or set of sub-fields (A. Johnson et al., 2011; Kachchaf et al., 2015; K. Owens, 2016). These studies provide rich evidence of the impact of structural biases on career trajectories through valuable storytelling and suggest a need for an intersectional lens to large-scale studies. Furthermore, these studies reveal that a failure to disaggregate at the intersection of race and gender may obfuscate novel findings and lead to the generation of overly simplistic insights and policy recommendations (Leggon, 2006).

Therefore, we seek to interrogate the space between the composition of the scientific workforce and the topical profile of science, from an intersectional perspective. This study extends investigations of gender disparities in science, by providing a macro-level of view of the phenomena that accounts for the intersection of race, gender, and topic. Our focus on the U.S. enables us to contend with the unique contextual factors that have led to disparate representation between genders and racial groups in science. Despite the acknowledged importance of race and gender as factors of inequality and decades-long policy interventions, there remains a paucity of evidence on how the selection of fields and topics is scattered across groups at a detailed level, and the relation between topics and scientific impact. This paper attempts to demonstrate that the election of the object of study is related to race and gender, with implications for scientific progress and the evaluation of scientists.

4.3 Materials and methods

We examine the publication patterns of U.S. affiliated first authors between 2008 and 2019. Our data consist of 5,431,451 articles indexed in the Web of Science (WOS) database and 1,609,107 distinct U.S. first authors. We focus on first authors as they are generally the person who has contributed the most to a piece of research (Larivière et al., 2016, 2021), and represent the most visible name in bibliographic references. The metadata includes authors' given and family names, which are used to infer race and gender. Authors were disambiguated using the algorithm developed by Caron and van Eck (2014). The gender disambiguation algorithm builds on the method presented in Larivière et al. (2013), which uses census data and country-specific lists of men and women names to assign probable gender to given names and, in the case of certain countries (e.g., Russia, Ukraine), family names. Gender is considered in a binary way, as other genders can only be assigned through self-identification. This is an acknowledged limitation of the study.

Racial categories are a country-dependent social construct, and not all countries have such categorizations. Therefore, our analysis focuses on the specific cultural construct of race found in the U.S. For the inference of race/ethnic origin, we use the 2010 U.S. Census information on family names and racial groups (U.S. Census Bureau, 2016). Racial groups considered in the US Census are: I) Non-Hispanic White Alone (*White*), II) Non-Hispanic Black or African American Alone (*Black*), III) Non-Hispanic Asian and Native Hawaiian and Other Pacific Islander Alone (*Asian*)[1], IV) Non-Hispanic American Indian and Alaska Native Alone (*AIAN*), V) Non-Hispanic Two or More Races (*Two or more*), and VI) Hispanic or Latino origin (*Latinx*)[2]. Given that *AIAN* and *Two or more* account for only 0.69% and 1.76% of WOS-authors, respectively, they were removed from the analysis. Census data provides the number of people that identify with each racial group for the 162,253 most common family names. Using family names, we compute each author's associated probability to each racial group, instead of assigning the most probable group, and using these probabilities to compute weighted aggregates, where each author contributes to each group's aggregate as a function of the racial group distribution associated with its family name. This means, for example, that when computing the average citations by race, we assign the citations of an article

[1] Per 2010 U.S. Census classifications 'Asian' refers to a person with origins East Asia, Southeast Asia, or the subcontinent of India; meanwhile 'Native Hawaiian and Other Pacific Islander refers to a person having origins in Hawaii, Guam, Samoa, or other Pacific Islands.

[2] The authors use the term Latinx as a gender-neutral term, consistent with its perceived meaning, according to the 2019 National Survey of Latinos (Noe-Bustamante et al., 2020).

fractionally to each group according to the corresponding distribution. In other words, we do not assign authors to a unique racial category. In previous work (Kozlowski et al., 2022) we have shown that, given the overlap of Black and White family names (Fryer & Levitt, 2004; Girma, 2020), the use of a threshold—filtering those names with a probability for a single group above a threshold and assigning all authors with that name to that single category—underestimates the proportion of Black authors. This distinction is critical: we do not aim to identify each author's self-perceived racial category, but to build aggregates of racial group disparities. For those names that do not appear in the Census, we impute the mean distribution in the subset of authors used at each point in the analysis. For a detailed description of the racial inference methods, see chapter 2, the Appendix I as well as the accompanying website[3].

Fields and subfields are defined according to the journal classification developed for the U.S. National Science Foundation (Hamilton, 2003). Following (Blei et al., 2003), we used articles' abstract, title, and keywords to train a Latent Dirichlet Allocation (LDA) model to infer the topics within a corpus of papers, and the distribution of topics within each article. LDA is an unsupervised model that assumes that there is a fixed number of topics within the corpus that correctly describes its content. Each topic is defined as a distribution over words, and we use the top five words from each topic to infer its semantic content. Given an article's topic, there are some words that are more likely to repeat than others, LDA provides the list of most repeated words for each topic, and we use those to infer topicality. The objective of this model is to create research topics as detailed as the sampling allows, implying a trade-off between granularity and repetition of topics. LDA models are performed on groups of disciplines to identify topics with an independent meaning (Kozlowski, Semeshenko, et al., 2021). Given the sample size in Social Science and Health and interpretability of results across different experiments, we found the optimal number of topics for our analysis to be 200 for Health and 300 for Social Sciences. Using manual inspection, a higher number of topics in each case led to the repetition of words between topics, while fewer topics led to less detailed results. For a selected group of topics, we defined a single label, based on these top words. See the Appendix I for an explanation of the robustness analysis of the LDA model.

Scholarly impact is assessed through field- and year-normalized citations (Waltman, 2016), using an open citation window covering publication years through the end of 2019. For each article, we infer the first authors' gender and distribution over racial categories as well as over topics. Each article then has a probability distribution over racial categories, a binary classification over gender, and a probability distribution over topics. Aggregate results are obtained using fractional counting over these three dimensions. For example, an article can have a first author whose name has a 0.7 racial classification probability of being a Black author and 0.3 of being a White author, and whose gender is inferred to be woman. It also has an 0.8 probability on topic A, 0.1 on topic B, and so on. Therefore, this article contributes an additional 0.56 (0.7*0.8) authors to the group of Black women in topic A, 0.07 (0.7*0.1) authors to the group of Black women in topic B, and so on, across all topics and racial groups for women. The weighted sum over these dimensions, plus the citations, gives us the aggregate results of the distribution over topics by race and gender, and the average number of normalized citations per topic, race, and gender. Over and under representation

[3] https://sciencebias.uni.lu/app/

in topics of racial groups and genders are based on the overall proportion that each group represent across all papers combined[4].

4.4 Results

Comparison of the race and gender demographics of U.S first authors with that of the U.S. population shows that White and Asian populations are overrepresented among U.S. authors, while Black and Latinx populations are underrepresented (Figure SI 1). Relative representation varies by field (Figure 9). Black, Latinx, and White women exhibit similar representation: they are highly underrepresented in Physics, Mathematics, and Engineering and overrepresented Health (Figures SI2 - SI3), Psychology, and Arts. Asian women follow a different pattern, with under representation in Arts, Humanities, and Social Sciences, and overrepresentation in Biomedical Research, Chemistry, and Clinical Medicine. Black, Latinx, and White men are underrepresented in Psychology and Health, together with Asian men, but this latter group is also underrepresented in Humanities and Social Sciences, and overrepresented in Physics, Engineering, Math, and Chemistry. Men first authors are generally more cited than women, and Asian authors are more cited than Black, Latinx, and White authors, both in raw citations and field-normalized citations. For White, Black and Latinx women the citation gap reduces when considering normalized citations, showing that they are more present in lower-cited fields. Nevertheless, even when considering field-normalized citations, the gap remains.

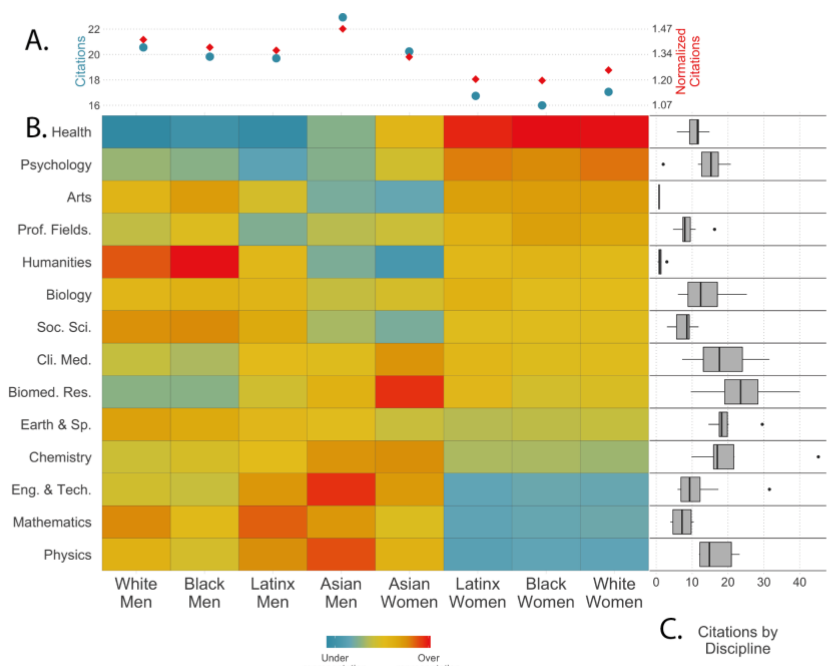

Figure 9. Scholarly impact and distribution of race and gender of authors by field. A. Average number of raw and of field-normalized citations by group**. B.** Over and underrepresentation of groups by discipline, with respect of their average proportion in all fields. **C.** Distribution of the average number of raw citations

[4] See the Appendix I for how we operationalize over and underrepresentation.

by specialty within each discipline, the hinges of the box correspond to the first and third quartiles, the whiskers extend to the lowest values no further than 1.5 time the inter quartile range (IQR) from the hinge; dots represent values further than 1.5 times IQR. U.S. first authors of Web of Science 2008-2019. Racial categories from the census corresponding to AIAN and Two or more were excluded from the racial inference due to lack of data. On the vertical axis, fields are sorted by the relative over/under representation of Black women authors. On top, we show the average number of citations by group, while on the right, each boxplot summarizes the distribution of citations of all papers published in those fields.

To better understand and explain intersectional differences in citations, we explore the role of research topics for disciplines in the Humanities, Social Sciences, Professional Fields, and Health.[5] Figure 10 presents feminization--i.e. the proportion of women authors—of each topic (y-axis) by racialization—i.e. the proportion of authors from a racial group in each topic (x-axis) for Social Sciences (Figure 10A)[6] and Health (10B).[7] The color of each node (topic) provides mean number of citations while size represents relative importance in the dataset.

In the Social Sciences, topics with the highest proportion of Asian authors are related to topics in economics and logistics, like *stocks*, *consumers*, *firms,* and *market*. These topics are also those where White and Black authors are least represented. Black authors are highly represented on topics of *racial discrimination, African American culture,* and *African studies and communities. Religion* is one of the few topics where both Black and White men are overrepresented. Latinx authors are highly represented in topics related to *immigrants, political identity,* and *racial discrimination*, the latter of which is also shared with Black authors. Black and Latinx authors perform research on topics specific to *language literacy*, as well as on African and Latin-American countries, respectively. Latinx authors publish on topics associated with Latin-American issues and those that redefine the Latinx identity within the U.S. Of particular interest is the topic of *language literacy*, which is both highly feminized and highly Latinx, and constitutes a mixture of a traditional gender role (teaching, related with reproductive labor) and the learning of a second language, a topic that is highly relevant to migrant communities.

Figure 10 also shows the coefficient of variation (CV) for each racial group's proportion on topics. A high CV means that the group has a high participation on some topics and a small participation on others, relative to its average proportion. Asian authors present the highest CV, while White authors exhibit lowest. This suggests that Asian authors are highly specialized, focusing on certain topics, while White authors are present in a wider range of topics. Black and Latinx authors show greater specialization, focusing on a smaller number of topics. White authors are more evenly distributed among topics, however, this is expected as they account for the majority of the author population. The most highly feminized topics include *gender-based violence, families, learning*, and *LGBT* studies. These results implicate a relationship between traditional gender roles, and topics that relate specifically with gender-based identity and inequality, and to non-hegemonic

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[5] The analysis was also carried out for all fields: https://sciencebias.uni.lu/app/.

[6] Table SI 1 provides the top words of each of these topics. An interactive version of this plot with labels for all topics is available at https://sciencebias.uni.lu/app/.

[7] Table SI 2 provides the top words of each of these topics. An interactive version of this plot, with labels for all topics is available at https://sciencebias.uni.lu/app/.

gender representations (i.e., gender expressions that do not correspond to binary male/female categorizations).

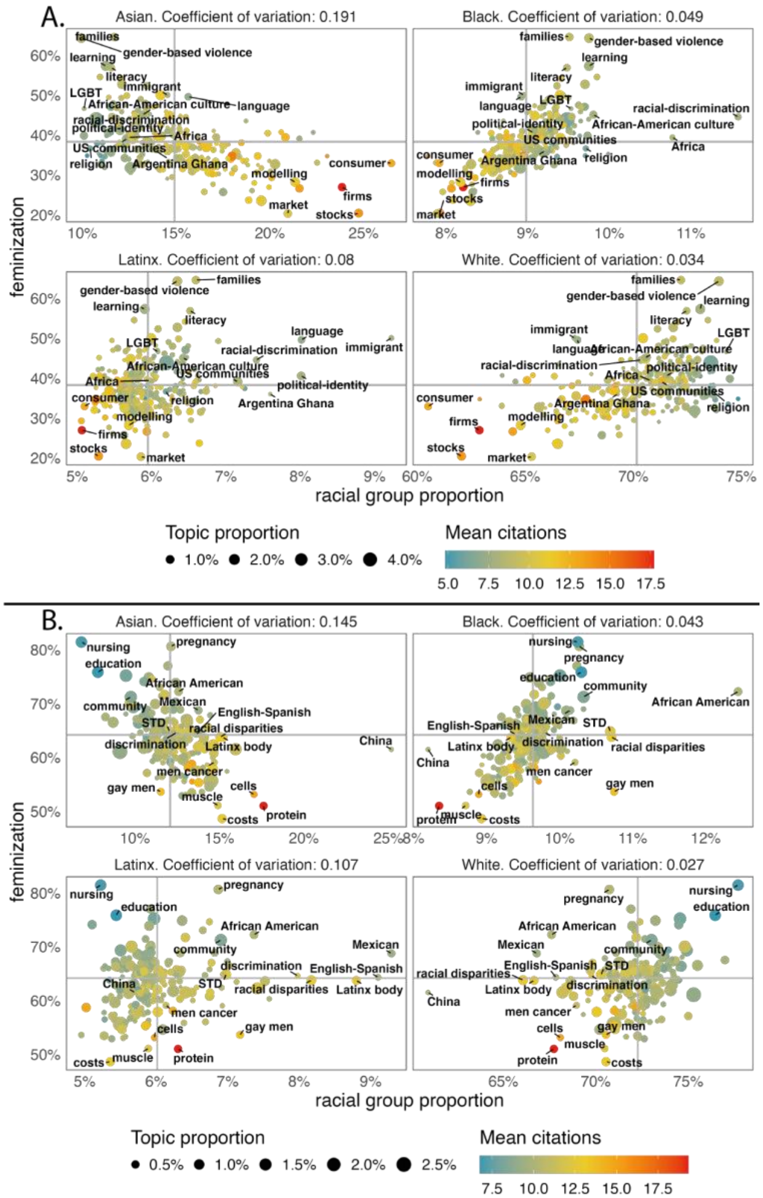

Figure 10. Distribution of topics by racial group and gender participation. A. Social Sciences, Humanities and Professional Fields, **B.** Health. For Social Sciences, Humanities and Professional Fields (N=283,589 articles), we train an LDA model for 300 topics. For Health (N=142,032), we train the LDA model for 200 topics. The vertical axis shows the proportion of women, while the horizontal axis shows the proportion by each racial group. In color, the mean number of citations by topic. The coefficient of variation as a standardized measure of variability is provided for each racial group. Topics with the highest proportion in each race and in each gender are highlighted (labelled). Racial categories from the census corresponding to AIAN and Two or more were excluded from the racial inference due to lack of data. Minimum number of average citations: 4.37, max. 15.74, mean 9.25.

Several important topics appear at the intersection of race and gender. Due to space constraints, it is not possible to assign a label for all topics in Figure 10; however, the accompanying website presents an interactive visualization displaying topics along the diagonal of Quadrant I that are both highly feminized and racialized. Among Black women authors for example, we find topics such as *black women violation* (topic 122), *equality promotion* (topic 149), and *social identity* (topic 210). Among Latinx women authors, in addition to topics on *language*, we find *residential segregation* (topic 103), *gender gap and international migration* (topic 300), *social class* (topic 64) and *global south* (topic 225), among others.

In Health, the topics with the highest representation of Asian authors are *China, proteins, cells,* and the economics of health, i.e., *costs*. Black authors publish on topics about *racial disparities* and *STDs* (sexually transmitted diseases)—with a special emphasis on *African-Americans* among Black women, and *gay men* for Black men. This latter topic is also relevant for Latinx men. Latinx authors publish more on topics that mention the Latinx population, *racial disparities,* (a topic that is shared with Black authors), and *English-Spanish*, a topic similar to that which was previously found in the Social Sciences. The CV between topics by racial group also shows that while Asian authors are the most specialized, followed by Black and Latinx authors, White authors are the most ubiquitous. The most feminized topics are about *nursing, pregnancy,* and *education* reinforcing the association of women with care- and service-related research (Cockburn, 1990; Witz, 1992).

4.4.1 Scholarly impact by topic

Our results demonstrate that macro-level differences in citation rates are observed at the intersection of race and gender—even when controlling for disciplines (Figure 9)—and that topic selection is related to author race and gender (Figure 10). It stands to reason, therefore, that there might be a relationship between the populations engaged in certain topics and the citation density of these topics. Figure 11 presents the over and underrepresentation of race and gender of authors by topic, sorted by the participation of Asian men in Social Sciences (Figure 11A) and by White men in Health (Figure 11B), the two most highly cited groups in each discipline. The average number of citations of a topic is positively correlated with the presence of Asian and White men. Figure 11C and 11D provides the average number of citations by race and gender within each topic[8] for each discipline, respectively. In the Social Sciences, Asian men have a higher number of citations; they tend to be more present within highly cited topics and are more cited than other groups within lower-cited topics. All other groups start with a relatively similar number of citations, which later split into three branches. White and Black men increase their relative number of citations to equalize those of Asian men in the highest cited topics. Latinx men and Asian women follow a similar course, but yield fewer citations for the highest cited topics. Black, White and Latinx women form a block with systematically fewer citations than all other groups. Health presents a stronger gender split: men, regardless of racial categorizations, are significantly more cited along the distribution of topics, with White and Black men having slightly more citations than Asian and Latinx men. Women from all racial groups present a lower number of citations, with White women presenting a slightly higher number of citations for highly cited topics than

[8] An interactive version of this visualization with information on each topic and group is available at https://sciencebias.uni.lu/app/

Asian, Latinx and Black women. This provides evidence of the intersectional between- and within-topic disadvantage for minoritized groups: 1) minoritized groups are over-represented in lowly-cited topics and underrepresented in highly cited topics, and 2) their work is less cited within and across topics, especially where they are underrepresented.

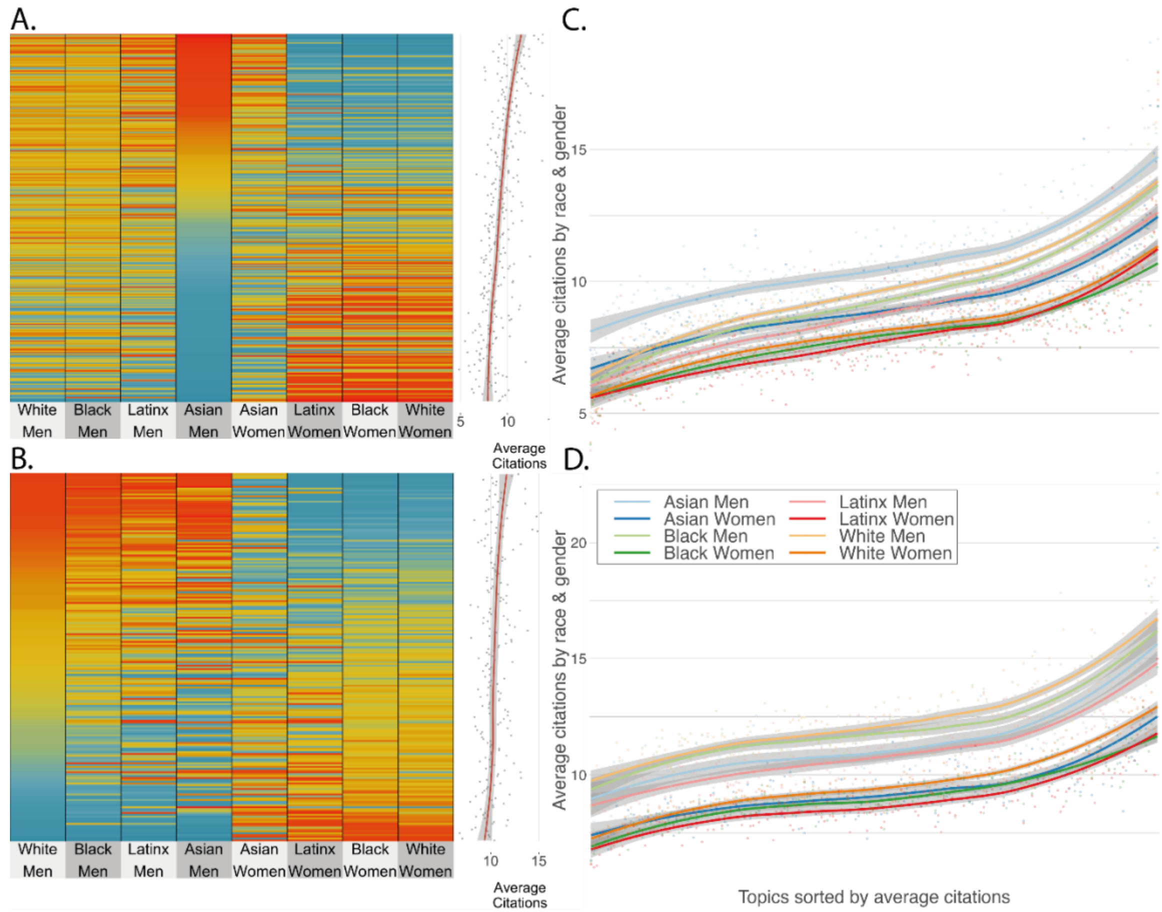

Figure 11. Scholarly Impact by topic. Over and underrepresentation of groups by topic, in **A.** Social Sciences, **B.** Health. Topics sorted by the participation of the most cited group in each case. On the right margin, number of citations by topic, and loess smoothing. C. Distribution of average topic citations by race & gender in Social Sciences and in Health (D.). Topics are sorted by average number of citations, and a smoothing function is drawn for each group using loess to model the evolution of the expected number of citations as the topics become more cited on average. The grey shadow in each model represents the 95% confidence level, and therefore when these shadows do not overlap, the differences between groups are significant. Racial categories from the census corresponding to AIAN and Two or more were excluded from the racial inference due to lack of data.

4.5 Discussion

Inequalities in science have been studied for a century (Cole & Cole, 1981; Lotka, 1926), and several analyses have shown that these inequalities are the consequence of a non-meritocratic scientific system (A. C. Johnson, 2007; Rodriguez, 1998; Zivony, 2019). Our results show that minoritized authors tend to publish in scientific disciplines and on research topics that reflect their gendered and racialized social identities. Specifically, we have shown a contrast between the topic specialization of U.S. Asian, Black and Latinx first authors, reflected via a higher coefficient of variation, and the ubiquity of White authors. The even participation of White authors across topics shows that the relation between race and research topic operates primarily on minoritized authors. In other terms, there is a privilege of choice in scientific knowledge production, wherein research on a particular topic is influenced by scientist's race and gender. As Bourdieu explains, the amount of scientific capital possessed by a researcher defines the strategies they can follow (Bourdieu, 1975). The ubiquity of White men in science and across topics implies that this demographic group has a wider range of possible strategies to follow, and an advantage in the way their scientific capital can be invested, reinforcing inequalities in scholarly outcomes.

We found that differences in research impact can be at least partially explained by topics' citation density, but that within topic differences remain. The compound effect of different citation rates of topics and unequal distribution on topics by race and gender leads to negative effects for marginalized groups and for science itself, as some topics become systematically less studied. History of science is ripe with examples of understudied topics, such as female genitalia, which had direct implications on the life expectancy of women (Ah-King et al., 2014). Assuming constant productivity (Fanelli & Larivière, 2016) and considering career age of authors, we can estimate the cumulative loss in particular topics over the last 40 years, assuming that researchers with 20 years of publication activity produced 20 times that of incoming researchers. If the author distribution over the last forty years would have matched the 2010 U.S. Census, there would have been 29% more articles in public health, 26% more on gender-based violence, 25% more in gynecology and in gerontology, 20% more on immigrants and minorities, and 18% more in mental health (Figures SI 4-SI 6). While this counterfactual scenario is coarse, it highlights the fact that a different body of knowledge would be produced in the absence of inequalities and that this body would more closely reflect the spectrum of topics relevant across society. The diversification of the scientific workforce is necessary to create a scientific system whose results benefit all of society.

This paper has provided evidence of the relation between race, gender, research topic, and research impact, and contributes to the wider dialogue on intersectional inequalities in science. However, race and gender are not the only spaces of inequality in science; several other variables should be included to create a fully intersectional understanding of inequalities in science. Socioeconomic status, when intersected with race, gender, and topic, is likely to have large effects: a recent study suggested that the estimated median childhood income among faculty is 23.7% higher than that of the general population (Morgan et al., 2022). Inequities have also been observed on the basis of disability (Yerbury & Yerbury, 2021) and sexual orientation (Gibney, 2019)—variables that are often excluded or underreported in studies of the scientific workforce. Attrition and career age (NSF, 2018; A. M. Petersen et al., 2012) may also play an important role here, as well as the prestige of institutional affiliations (Clauset et al., 2015; Crane, 1967). Causal modeling that considers topic choice, along with markers of prestige, would be germane in understanding the different mechanisms through which systemic inequalities are mediated. Finally, racial categories used in this research are only meaningful in the context of the US academic workforce; further research should be performed to understand general patterns across the globe and provide insights on the role of science policy in mitigating disparities.

Discrimination defies notions of objective, apolitical, and meritocratic ideals in scientific discourse (Cozzens, 2007); a perception that serves to reinforce and mask race and gender biases in science (Clauset et al., 2015). Structural racism (Bailey et al., 2017) remains a persistent source of mental and physical strain on minoritized groups (Curtis et al., 2021; M. Davis, 2021; Jackson et al., 1996; Lewis et al., 2017; Williams et al., 2019), whose calls for justice across socio-economic (e.g., healthcare, housing, education, finance, criminal justice) and professional domains are intermittently elevated (and subsequently ignored) in accordance with the ebbs and flows of American racial discourse (Kennedy, 2020). Academia is no different in this regard (E. O. McGee, 2020; Wingfield, 2020). The underrepresentation in science is similar to other sectors and may be attributed to the pervasive legacy of U.S. federal and state sanctioned campaigns of systemic racialized exclusion aimed to reduce the representation and participation of minoritized race groups in all aspects of human life (Bailey et al., 2021; K. S. Brown et al., 2019; Eaton et al., 2020; Morris, 2015; Moss-Racusin et al., 2012; Norton & Sommers, 2011; Odekunle, 2020). Recent calls for increased transparency and accountability in graduate student recruitment, retention, and faculty hiring and promotion (M. P. Bell et al., 2021; Jindal et al., 2020) are particularly notable after the marked increase in media attention on anti-Black police violence, the Black Lives Matter movement, and the disproportionate impact of the COVID-19 pandemic on Black and Latinx populations (Dorn et al., 2020; Garcia et al., 2021; Laurencin & McClinton, 2020; E. McGee et al., 2021) and on women academics (Myers et al., 2020; Ribarovska et al., 2021; Vincent-Lamarre et al., 2020). The effect of related policy interventions in response to these events remains to be tested.

Our analysis suggests structural effects that reproduce systemic inequities in terms of value assigned to particular topics, in both scientific evaluation and distribution of resources. Several policy recommendations emerge from this analysis. First, scientific institutions need to recognize the existence of knowledge gaps related with author race and gender segregation and promote topics where gendered and racially minoritized authors are more present. Funding agencies can take immediate action to allocate increased funding in areas that have been historically underrepresented (Koning et al., 2021). Such funding will affect the entire academic reward system: funding is strongly correlated with productivity and impact; both of which are associated with institutional advancement and rewards (Jacob & Lefgren, 2011; Mongeon et al., 2016). This has implications for individual scientists, but also serves to increase the visibility of and participation in understudied areas. Second, institutions need to promote diverse participation within high impact topics, taking into account the need for resources and initiatives that provide access for marginalized populations into high prestige networks. Taken together, these activities will serve to both reduce the variance in impact across topics and reduce the within topic disparities at the intersection of race and gender, thereby increasing equity in science and expanding the knowledge horizon.

4.6 Appendix I: Supplementary information for chapter 3

Accompanying website with additional methodological details: https://sciencebias.uni.lu/app/.

4.6.1 Definitions

Joint probability is the proportion of articles for each racial group, gender, and topic, where:

(1) $jp = P(r, g, t)$,

with *r*: racial group, *g*: gender and *t*: topic. In this way, the sum of the joint probability of all articles, races, and genders equals 1.

Marginal probability by group is the proportion of each topic by racial group and gender, where:

(2) $mpg = \frac{P(r,g,t)}{P(r,g)} = \frac{jp}{P(r,g)}$

Each racial group and gender sums to 1 in *mpg*.

Marginal probability by topic is the proportion of each racial group and gender by topic, where:

(3) $mpt = \frac{P(r,g,t)}{P(t)} = \frac{jp}{P(t)}$

The marginal probability by topic sums to one for each topic.

The *over or underrepresentation* by racial group and gender is, proportionally, how much more or less present a group is with what is expected at random, given the overall share of that racial group and gender in the full dataset,

(4) $x = \frac{\frac{P(r,g,t)}{P(t)}}{P(r,g)} - 1 = \frac{mpt}{P(r,g)} - 1$

4.6.2 Data Sources

The bibliometric database used for our analysis is Clarivate Analytics' Web of Science (WOS). In addition to country information and citation indicators, we used given names of authors to infer their probably gender, and their family names to infer their probable race. Field and subfield classification is that of the National Science Foundation (Hamilton, 2003). To build topics, we use titles, keywords, and abstracts. Given that before 2008 first names are not provided by WOS, we restrict our analysis to the period 2008-2019 in order to infer author gender. Racial categories are a social construct that varies by country. Therefore, our analysis is limited to the United States. The information provided by the 2010 US Census on family names and their distribution by race and Latinx origin was used for racial inference (see below).

4.6.3 Topic Modeling

To compare the robustness of the LDA, we developed an experimental approach. The randomness of LDA can be controlled by a random seed. Each random seed provides different results for the same model and dataset. A non-robust model would provide very different results with each iteration. A robust model should only display minor changes. The latter guarantees that the results observed are not the product of chance. To test for this, we ran the LDA model for Social Sciences, Humanities, and Professional Fields ten times with different random seeds. By comparison, we used the pre-trained model on Health to predict the data from Social Sciences and generated a completely random case using a Dirichlet distribution with the same dimensions. Importantly, the order of topics in the LDA is not fixed. What may be referred to as topic #2 in one model may be topic #17 in another. Therefore, we used a column-permutation invariant metric of distance to compare models.

The result of the LDA model was a matrix of dimensions NxT, with N articles and T topics. The proposed measure of distance first gets the L2 norm of each article. This assigns a single value for every article and, for each run of the model, a vector. We then use these vectors to compare the similarity between models using cosine similarity. The results (see figure S7) illustrate that all runs using random seeds are very similar between each other, while the results using a model trained on a different dataset and the random case are both very different to all other cases. This result validates our model and demonstrates that the results are not a simply a product of chance.

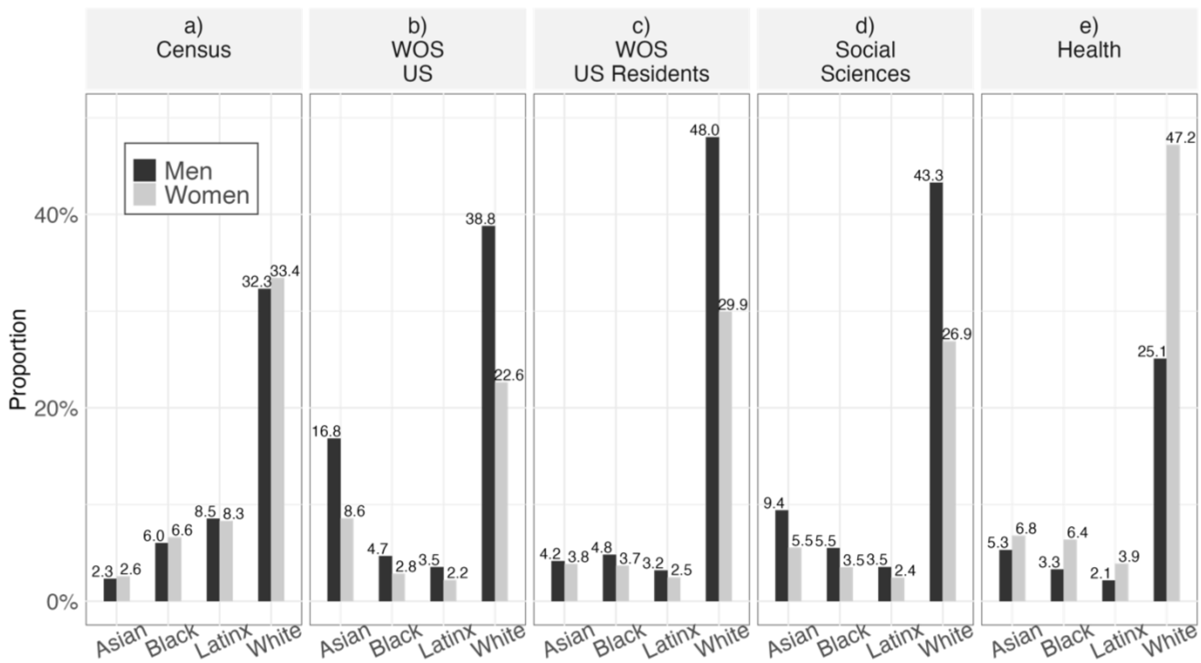

Figure S I 1. Distribution of the population by race & gender. A. in U.S. Census 2010, B. U.S. first authors of papers indexed in Web of Science 2008-2019, c. U.S. first authors normalized by the proportion of U.S. permanent residents who hold a doctorate, d. U.S. first authors of articles from Social Sciences, Humanities and Professional Fields and e. U.S. first authors of articles from the Health discipline. Racial categories from the census corresponding to 'AIAN' and 'Two or more' were excluded from the racial inference due to lack of data.

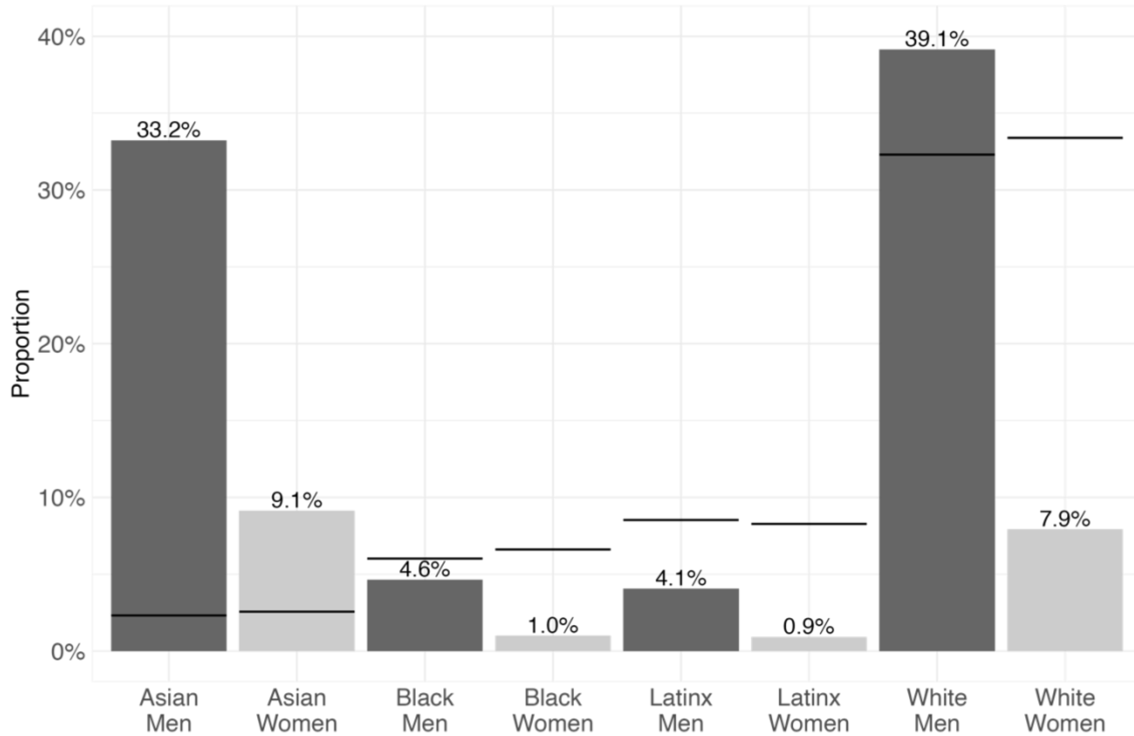

Figure S I 2. Distribution by race and gender of US authors in Engineering and Technology, 2008-2019.

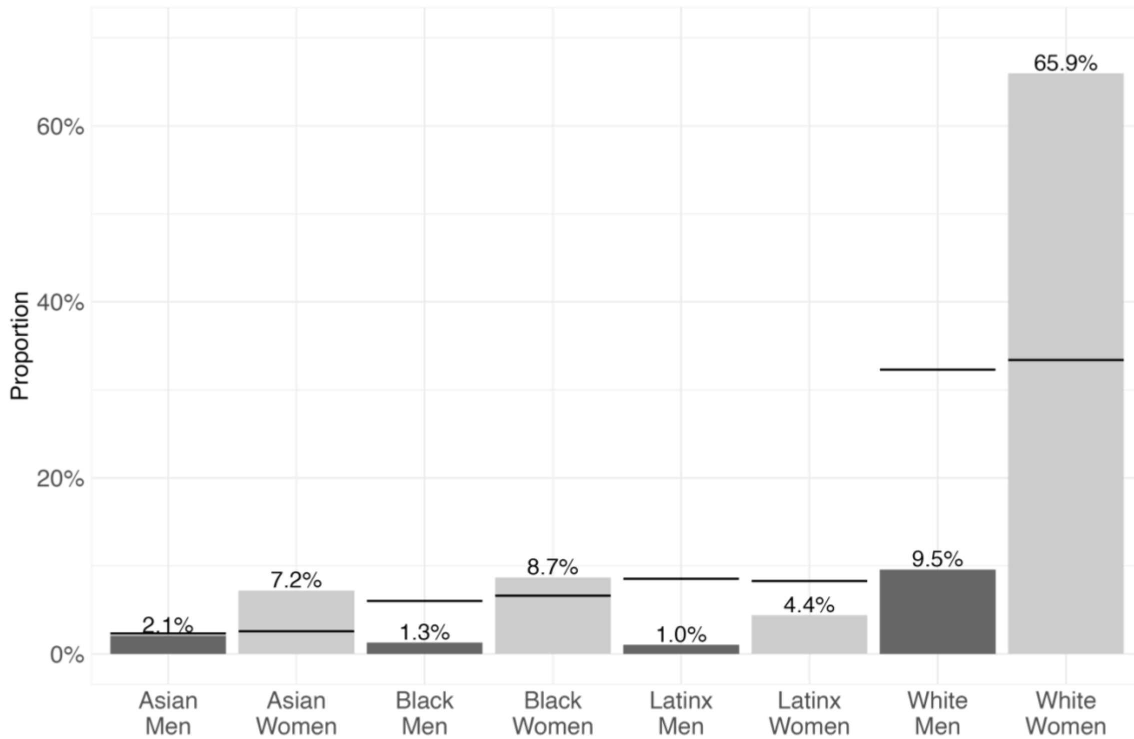

Figure S I 3. Distribution by race and gender of US authors in Nursing, 2008-2019.

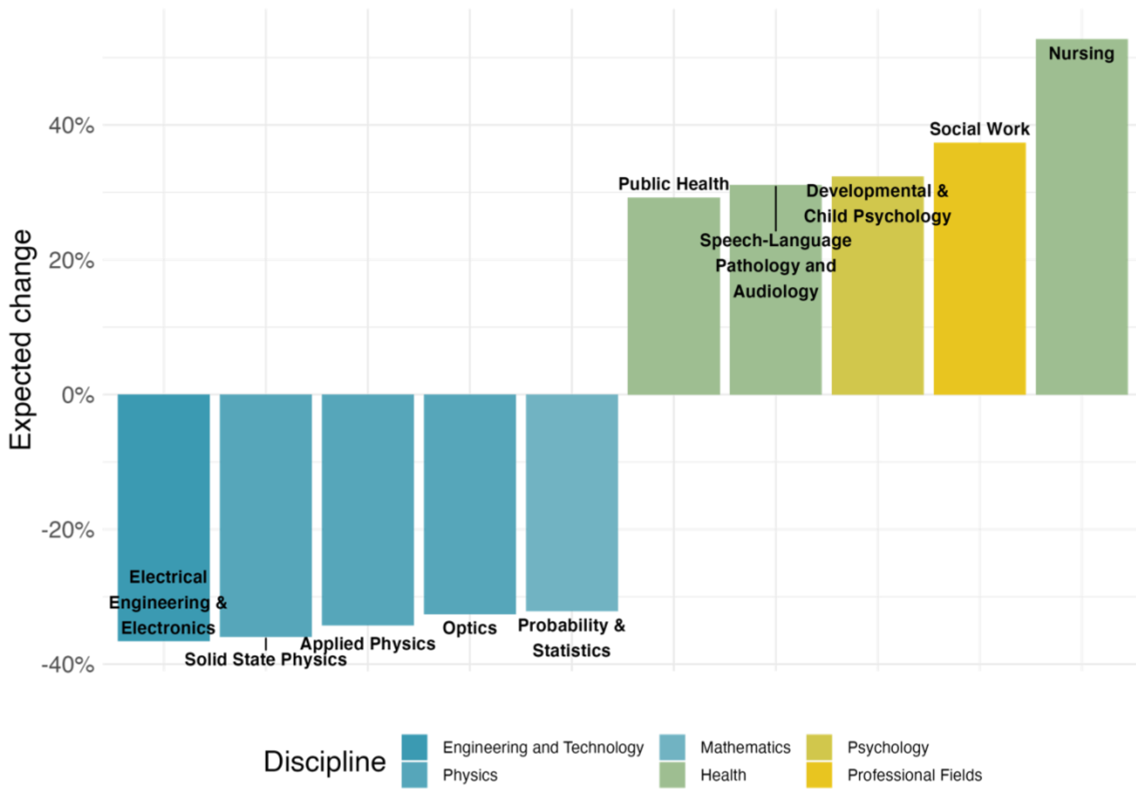

Figure S I 4. Distribution by race and gender of US authors in Nursing, 2008-2019. Assuming that authors are equally productive along their career, the y-axis represents the expected cumulative change in the number of papers per speciality, if the proportion of authors by race & gender would be that of the 2010 US Census. The x-axis shows the 5 specialities with highest decreases and increases

Figure S I 5. Counterfactual analysis, Social Sciences, Humanities and Professional Fields, US 2008-2019. Assuming that authors are equally productive along their career, y-axis represents the expected cumulative change in the number of papers per topic if the proportion of authors by race & gender would be that of the 2010 US Census, for the 5 topics with the highest decrease and increase. This does not assume a change in the proportion of the Social Sciences, Humanities and Professional Fields disciplines in the overall distribution.

Figure S I 6. Counterfactual analysis, Health discipline, US 2008-2019. Assuming that authors are equally productive along their career, the y-axis represents the expected cumulative change in the number of papers per topic if the proportion of authors by race & gender would be that of the 2010 US Census, for the 5 topics with the highest decrease and increase. This does not assume a change in the proportion of the Health discipline in the overall distribution.

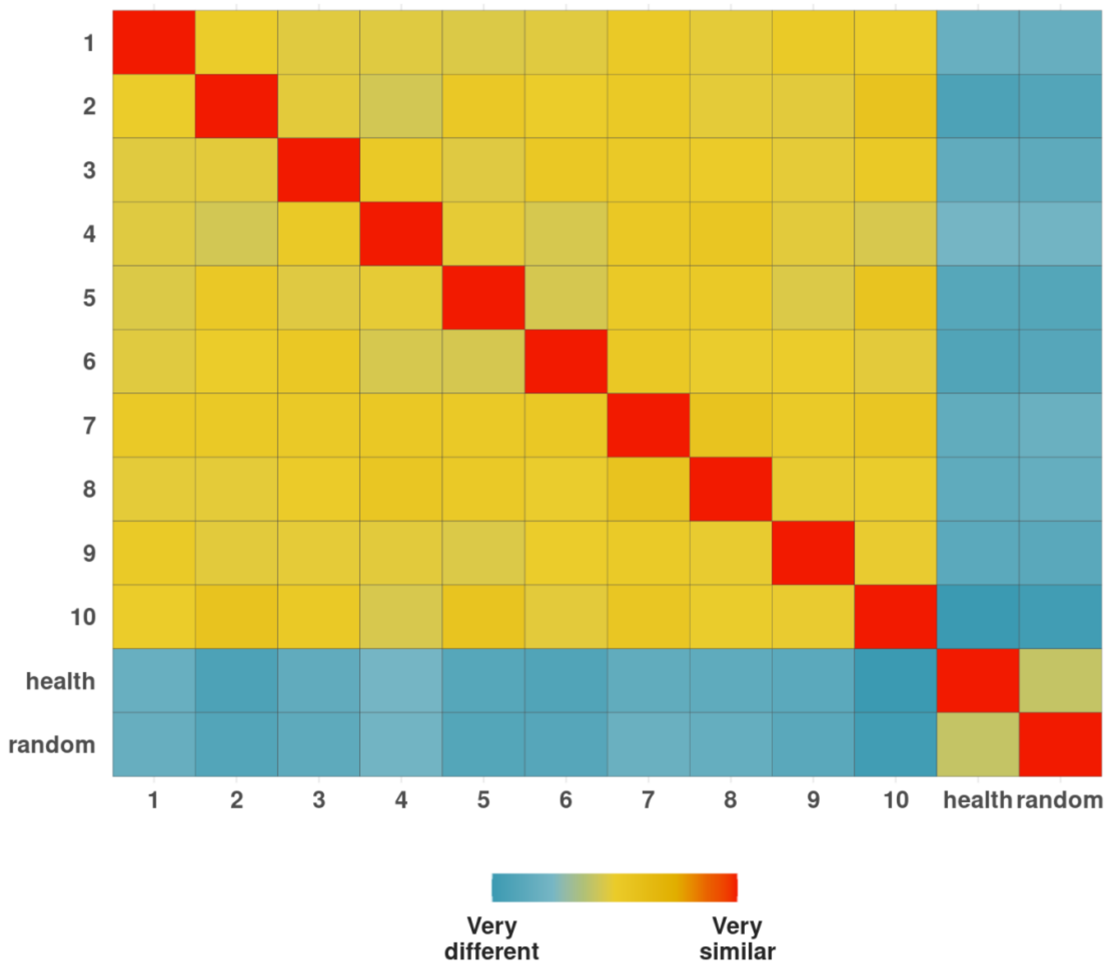

Figure S I 7. Cosine similarity between multiple runs of the LDA model. Models 1 to 10 represent a model trained on the same social science dataset, with different random seeds. Model 'health' is a model with the same number of topics trained on the health dataset. All models were used to predict the same cases (social science data), resulting in a distribution of topics by document. The 'random case' uses a Dirichlet distribution that replicates the dimensions of the results. All results are compared using L2 norm and cosine similarity. All models trained on the same data showed a similar behavior, while the to control groups show a very different pattern. This confirms that the LDA results are not a product of chance, but reflect the properties of the database.

Table S I 1. Most frequent words and labels for a selection of topics in Social Sciences Humanities and Professional Fields.

Topic	Top Words	Label
1	women, violence, gender, sexual, men	gender-based violence
14	risk, stock, price, market, volatility	stocks
17	reading, skills, literacy, comprehension, awareness	literacy
18	price, demand, competition, games, market	market
28	states, united, united states, community, communities	US communities
36	african, democracy, sub, income inequality, saharan	Africa
51	political, politics, identity, participation, latin	political-identity
77	gay, transgender, lesbian, bisexual, lgbt	LGBT
83	religious, religion, human rights, socialization, church	religion
110	firm, strategy, strategic, firms, performance	firms
160	race, racial, black, white, discrimination	racial-discrimination
201	argentina, ghana, pension, nonresponse, oaxaca	Argentina Ghana
204	model, models, selection, search, modeling	modelling
218	american, cultural, culture, seeking, african american	African-American culture
251	language, life, english, chinese, reliability	language
254	learning, teachers, education, teacher, student	learning
267	children, child, family, home, families	families
273	minority, learners, immigrants, immigrant, second	immigrant
297	product, consumer, consumers, brand, products	consumer

Table S I 2. Most frequent words and labels for a selection of topics in Health.

Topic	Top Words	Label
11	women, health, pregnancy, pregnant, reproductive	pregnancy
14	human, cell, cells, expression, stem	cells
16	african, american, african american, south, americans	African American
57	screening, cancer, mexican, cervical, cancer screening	Mexican
61	english, power, comparative, spanish, born	English-Spanish
66	men, hiv, gay, msm, sex	gay men
72	response, muscle, activation, resistance, dynamic	muscle
73	costs, financial, expenditures, estimated, incentives	costs
83	discrimination, identity, european, meaningful, cycle	discrimination
87	index, status, body, latino, mass	Latinx body
92	education, students, learning, educational, suicide	education
104	sexual, risk, sex, prevention, hiv	STD
116	men, lung, cancer, lung cancer, prostate	men cancer
119	beta, aging, protein, regulation, mice	protein
132	disparities, disease, racial, race, ethnic	racial disparities
160	china, chinese, affecting, elder, republic	China
187	community, engagement, prevention, communities, focus	community
196	nurses, nursing, work, practice, care	nursing

CHAPTER 5. THE HOWARD-HARVARD EFFECT: INSTITUTIONAL REPRODUCTION OF INTERSECTIONAL INEQUALITIES IN SCIENCE

This chapter was submitted as an article in co-authorship with Thema Monroe-White, Vincent Larivière, and Cassidy R. Sugimoto.

Contributions:

Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing

5.1 Abstract

The US higher education system concentrates the production of science and scientists among a few institutions. This has implications for minoritized scholars and the topics with which they are disproportionately associated. This paper examines topical alignment between institutions and authors of varying intersectional identities, and the relationship with prestige and scientific impact. We observe a Howard-Harvard effect, in which mission-driven institutions support, and other prestigious institutions suppress, the topical profile and scientific impact of minoritized scholars. Results demonstrate a consistent and disturbing pattern of inequality in topics and research impact. Specifically, we observe statistically significant differences between minoritized scholars and White men in citations and journal impact. The aggregate research profile of elite US universities is highly correlated with the research profile of White men, and highly negatively correlated with the research profile of minoritized women. Furthermore, authors affiliated with more prestigious institutions are associated with increasing inequalities in both citations and journal impact. Academic institutions and the funders that support them are called to create policies to mitigate the systemic barriers that prevent the United States from achieving a fully robust scientific ecosystem.

5.2 Introduction

Racial and gender disparities in the research workforce affect what type of research is produced and its relevance for society (Kozlowski, Larivière, et al., 2022a). These intersectional disparities are persistent and pervasive: women and Black or African American, Hispanic or Latino, and American Indian or Alaska Native students account for fewer earned doctorates (NSF, 2021b) and produce fewer scientific articles (Kozlowski, Larivière, et al., 2022a; Larivière et al., 2013) than would be expected given their representation in the population. Disparities are amplified across the research pipeline: the share of academic positions held by minoritized scholars is less than 9%—a percentage that is considerably less than their share of doctoral graduates (NSF, 2021b). Barriers to entry and participation in science can be seen as consequences of inequalities in peer review in journals (Erosheva et al., 2020; E. Ross, 2017) and funding applications (Chen et al., 2022; Ginther et al., 2011). Once published, the work of minoritized scholars tends to receive less visibility in the media (Peng et al., 2022) and fewer citations (Bertolero et al., 2020; M. B. Ross et al., 2022; Teich et al., 2022). These disparities are compounded by the intersection of race and gender (Crenshaw, 1991), and mediated by research topics (Bertolero et al., 2020; Kozlowski, Larivière, et al., 2022a).

Universities play a key role in creating policies and practices that shape the social structure in which research is conducted. In the United States (US), there is considerable heterogeneity across institutions in terms of history, mission, and resources, with implications for the composition of the faculty, staff, and students. This is particularly the case in mission-driven institutions, such as Historically Black Colleges and Universities (HBCUs) and Women's College (WCs) (E. O. McGee et al., 2021; Sax et al., 2014), which focus recruitment on specific populations. These specific orientations have significant implications for the diversity of the scientific workforce. For example, 23% of Black and African American students who earned a doctorate degree in science and engineering between 2015 and 2019 received a bachelor's degree from an HBCU (NSF, 2021b; E. W. Owens et al., 2012).

The US higher education system is an extremely stratified environment, with sharp inequalities in access. For example, graduates from the most "prestigious" 20% of US universities occupy 80% of all faculty positions in the country (Wapman et al., 2022), with universities rarely hiring graduates from lower-ranked institutions (Clauset et al., 2015)). Faculty at prestigious institutions tend to accumulate other benefits, such as increased funding and access to larger doctoral student labor markets (Zhang et al., 2022). These benefits lead to higher productivity and recognition (Way et al., 2019), which reinforces hiring inequalities, particularly for women (Clauset et al., 2015; LaBerge et al., 2022). The scientific consequences are important: scientific ideas spread more quickly and with greater impact when they come from prestigious institutions (Morgan et al., 2018). Knowledge generation, dissemination, and human capacity development are strongly concentrated among a few institutions, with implications for the research portfolio of the nation.

In this paper, we analyze how institutional prestige relates to the socio-demographic representation of authors, research topics, and scientific impact. To understand how this is mediated by the mission and service orientation of institutions, we analyze Historically Black Colleges and Universities (HBCU), Women's Colleges (WC), and Hispanic Serving Institutions (HSI). Furthermore, we examine three different levels of institutional prestige: *perceived* prestige, drawn from the US News & World Report institutions rankings; *research* prestige, measured as the institution's average of field-normalized citations; and *selectivity* prestige, using Carnegie's

Selectivity Index which measures acceptance rates of undergraduate students. Two main questions are addressed: (1) how do institutions of varying prestige differ in topical orientation and how does this relate to intersectional identities of authors? and, (2) how does institutional prestige mediate scientific impact for authors of varying intersectional identities?

To answer these questions, we leverage a dataset of more than 4.5 million articles published between 2008 and 2020, indexed in the Web of Science (WOS), and affiliated with 685 US universities. Following the method developed by Kozlowski, Murray et al. (2022), authors of the selected papers were assigned a probability over each racial group based on the association between their family names and racial categories found in the 2010 US Census (USBC, 2016). Gender was inferred using authors' given names, based on Larivière et al. (2013). We consider an author's identity as the combination of four racial categories—Black, Latinx[9], Asian, and White—and a binary gender indicator. Given the limitations of the data and inference algorithms, we were unable to assign distributional properties for Native American and "Two or more races", nor were we able to code beyond a binary operationalization of gender. We acknowledge the complex history of the U.S. Census classifications of race (Zuberi, 2000) and the assumption of within group homogeneity that is implied (e.g., Black and African American) and encourage the use of disaggregated data when available (e.g., taking into account immigration and citizenship status, and language). Furthermore, we acknowledge that we do not analyze all dimensions of intersectionality, such as class, sexual orientation, disability, or other minoritized and marginalized identities. These limitations highlight the importance of triangulation and comparison with studies based on surveys and author self-identification (Langin, 2020).

We use historical WoS data to compute the average of field-normalized citations of US universities between 1980 and 2019. We divide each prestige indicator (i.e., *perceived*, *research*, and *selectivity*) into three groups: 'high', 'middle' and 'low' prestige. For the US News & World Report, we divide universities into Top 10, Top 100 (excluding the Top 10), and institutions ranked below 100. The average citation rank divides institutions into three equally sized groups as a function of the mean impact of their research articles, while the Carnegie Selectivity Index classifies institutions into three groups: 'More selective', 'selective' and 'inclusive'. We also include mission- and enrollment-driven institutional classifications: Historically Black Colleges and Universities (HBCU) and Women's Colleges (WC) (*mission-driven*) and Hispanic Serving Institutions (HSI) (*enrollment-driven*) (Kozlowski, Doshi, et al., 2022). Table SII 1 provides numbers of papers, number of authors, and number of institutions for each of those groups of universities.

Following our previous work (Kozlowski, Larivière, et al., 2022a) we used topic modeling (Blei et al., 2003) to infer the research topics of articles based on their titles, abstracts, and keywords. We define the topical profile of an intersectional race and gender identity group as the proportion of papers this group contributes on each topic with respect to the total number of publications in the topic. Topical profiles can be calculated for both author identity groups and institutional categories. To compare topical profile groups, we use the Spearman rank correlation, as the relation between topical profiles is non-linear. If the correlation between groups (i.e., institutions

[9] Black and African American are considered as a single category and termed "Black" in this paper; Latinos are referred to as Latinx. We acknowledge and consider the complexities of this aggregation in the Discussion.

and intersectional identity) is high, it suggests that the institution and population tend to publish on similar topics. We also build a linear model to predict the effect of author's identities on impact (citations and Journal Impact Factor—JIF). Despite their limitations, citations remain, at the aggregate level, an appropriate indicator for the measurement of the visibility and research impact of papers (Sugimoto and Larivière, 2018), and JIF provides an indication of the selectivity of journals in which they are published (Sugimoto et al., 2013). Splitting articles by their institutional prestige groups and running the linear model for each, we examine differential effects on race and gender by institutional prestige and topic.

5.3 Results

5.3.1 Topical profiles of institutions and authors

White men constitute the largest author population across all institution types, with the exception of WCs, where they are surpassed by White women (Figure SII 1). Relative representation, however, allows for the examination of how certain identities are represented at rates relative to their proportion across all US authors. For Black, Latinx, and women authors, this relative representation demonstrates a strong alignment to mission- and enrollment-driven categorizations of institutions. Specifically, we observe an over-representation of Black men and Black women authors in HBCUs, of Latinx men and Latinx women authors across HSIs, and of women authors in WCs (Figure SII 1). Given that HBCUs, HSIs, and WCs are not principally defined by their faculty composition, this finding demonstrates the relationship between institutional mission and author composition. The composition of authors by race and gender also varies as a function of institutional prestige: we observe an overrepresentation of Asian authors among institutions with high *research* and *perceived* prestige, with underrepresentation of Black and Latinx authors at more prestigious institutions (Figure SII 2).

Figure 12 depicts the correlation between the topical profile of institutions and authors' identities for papers published in the Social Sciences, Humanities and Professional Fields. Two identity groups—Black women and White men—are presented as examples. HBCUs' topics are positively correlated with the topical profile of Black women across institutions (Spearman correlation, ρ =0.29), and negatively correlated with the topical profile of White men (ρ =-0.39). The same pattern can be observed in WCs and HSIs, which demonstrate positive correlations with the topical distribution of Black women (ρ =0.37, ρ =0.22, respectively), and a negative correlation with the topics of White men (ρ = -0.17; ρ = -0.27, respectively). The topical profile of Latinx women are more strongly correlated to HSIs (ρ =0.29) than White men (ρ =-0.27) (Figure SII 3). Although the composition of authors by demographic identity varies by institution in relative terms (Figure SII 2), the absolute proportion of authors by race and gender remains roughly stable across groups (see Figure SII 1), implying that topical profiles are not an artifact of author composition by institution. To validate, we controlled by the expected topical distribution of institutions given their demographics, and results remained the same.

The *perceived* prestige of institutions shows an even larger correlation with author's identities than mission- and enrollment-based institutional classifications. Specifically, there is a strong positive correlation between the topical profile of the Top 10 institutions and the topics of White men authors (ρ=0.66), and a strong negative correlation with the topical profile of Black women (ρ=-0.58) (2 12) and Latinx women (ρ=-.50) (Figure SII 3). The correlations are weaker when compared to the topical profiles of the Top 100 institutions, where we observe a positive alignment with White men's topical profile (ρ=0.23) and negative relationships for both Black women (ρ=-0.23) (Figure 12) and Latinx women (ρ=-0.17) (Figure SII 3). The pattern shifts for lower ranked institutions (Not Top), for which we observe a positive relation with Black women (ρ=0.47) (Figure 12) and Latinx women (ρ=0.4) (Figure SII 3), and a negative relation with White men *(*ρ=-0.52). In Health, we observe similar patterns, with lower alignment between institutions and researchers' race and gender (Figure SII 4). These results suggest that the topical profile of prestigious institutions is patterned in ways that disproportionately reflect White men's research profiles.

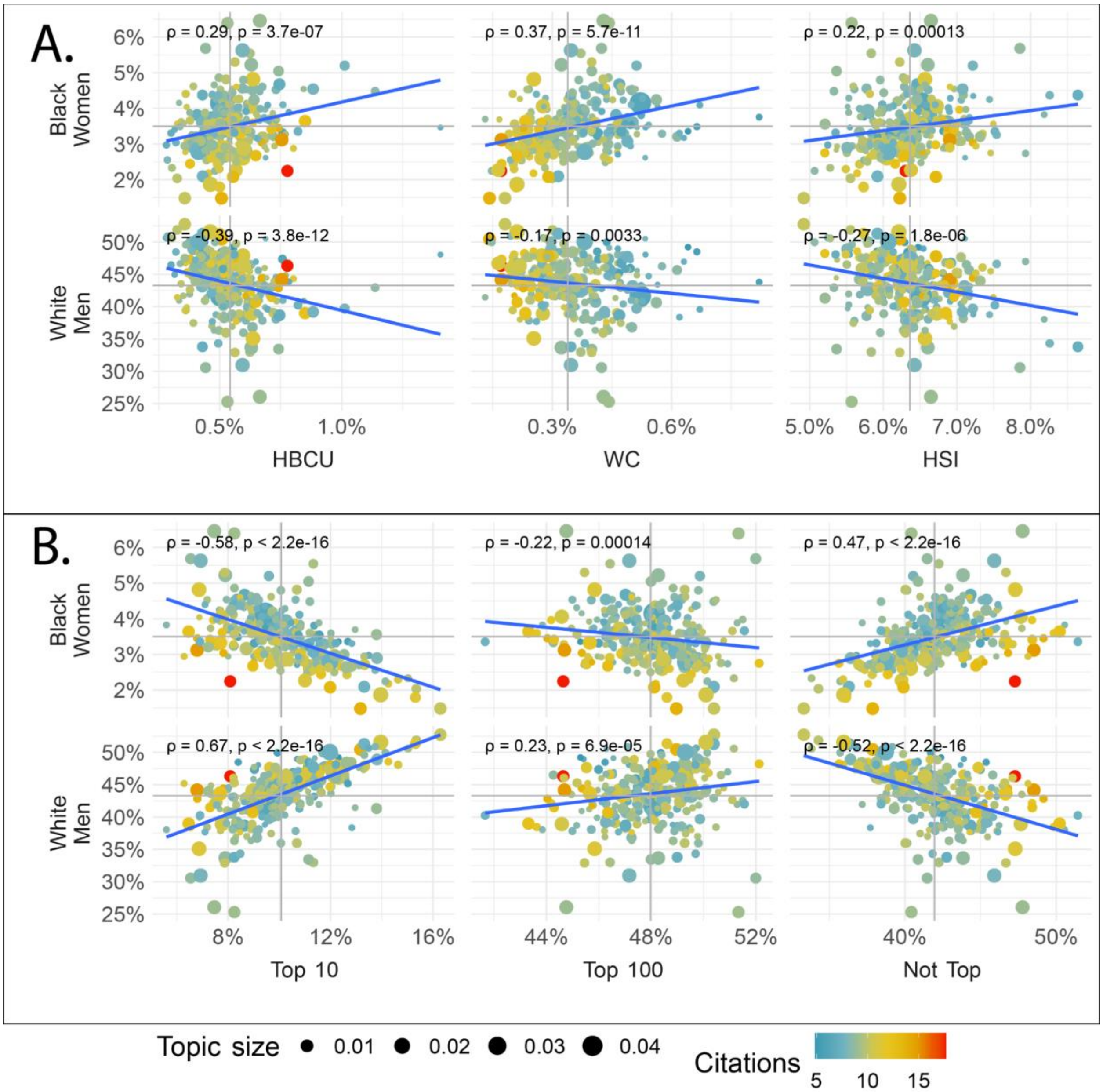

Figure 12: Relationship between topic representation of authors by race and gender, and topic representation of institutional groups, for papers in the Social Sciences, Humanities and Professional Fields. The figures provide Spearman correlations between the proportion of papers in different topics authored by Black Women and White Men (vertical axis) and the percentage of those papers authored by different institutional groups (horizontal axis). Panel (A) provides correlations for institutions that serve specific groups: Historically Black Colleges and Universities (HBCU), Hispanic Serving Institutions (HSI), and Women's colleges (WC). Panel (B) splits institutions into three categories of perceived prestige based on the US News and World report ranking: Top 10 institutions, Top 100 institutions (without the Top 10) and institutions not in the Top 100. Dot size represents the size of the topic in the corpus associated with the topic, while the dot color represents the average number of citations for that topic. For each subplot, ρ indicates the Spearman correlation with its p-value, and the blue line is the simple linear regression between the two variables.

Figure 13 provides correlations between author identity and institutional topical profiles for all institutional types (mission- and enrollment-driven classifications as well as all three prestige indicators) for Social Sciences, Humanities and Professional Fields (for Health see Figure SII 5). The topical profile associated with Black, White, and Latinx women positively correlates with that of HBCUs, WCs, and HSIs (panel A). The topical profile of Asian women is positively correlated with HBCUs (ρ=0.27) and HSIs (ρ=0.2), but negatively correlated with WCs (ρ=-0.31). The topical profile of White, Black, Latinx, and Asian men are all negatively correlated with HBCUs, WCs, and HSIs. Conversely, the topical space occupied by the highest prestige institutions (*perceived*) is positively correlated with all men, and negatively correlated with all women (panel B). The strongest positive relationship is between the topic profile of White men and Top 10 institutions (ρ=0.67); the strongest negative relationship is between Black women and Top 10 institutions (ρ=-0.56). *Research* (panel C) and *selectivity* (panel D) prestige reflect similar patterns; with positive association with men's topical profiles and negative with women's (with White men having the strongest positive relationship (ρ=0.62; ρ=0.65, respectively) and Black women the strongest negative correlation (ρ=-0.51; ρ=-0.56, respectively).

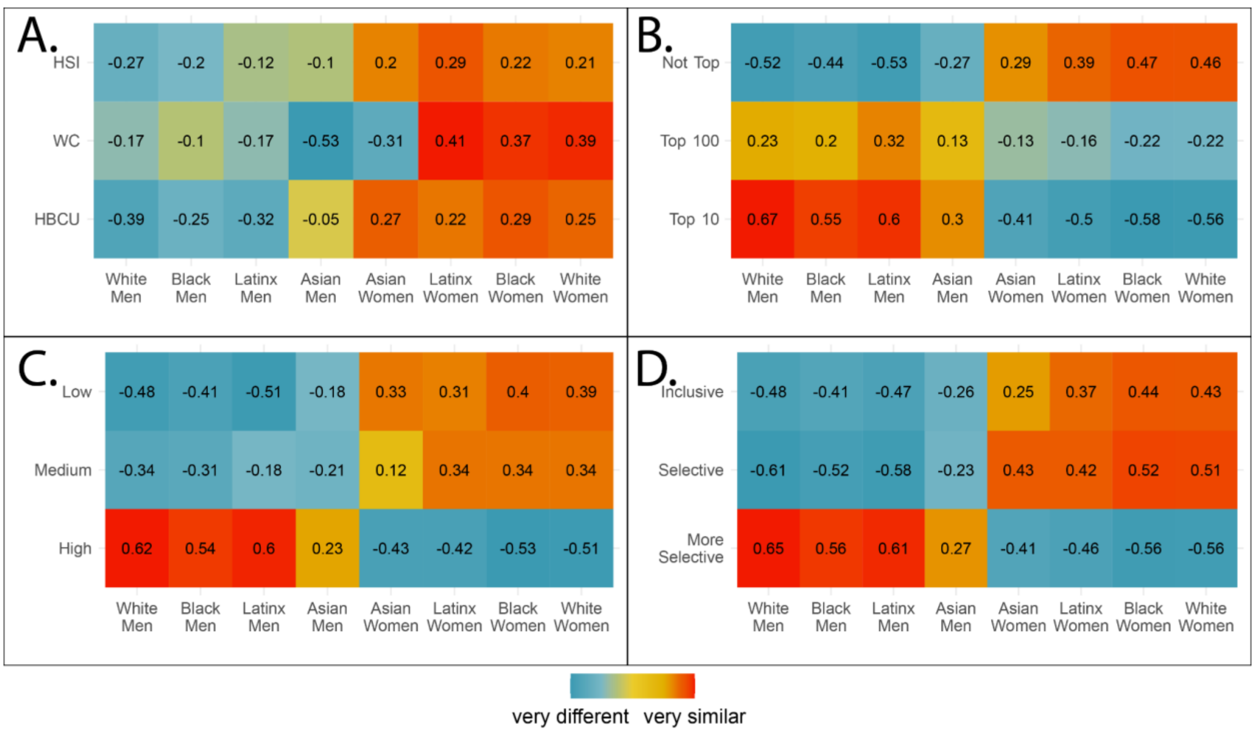

Figure 13. Spearman correlations between the topic profiles of each author identity and the topical profile of institutional categories for Social Sciences, Humanities and Professional Fields. Panel (A) provides correlations for institutions that serve specific groups: Historically Black Colleges and Universities (HBCU), Hispanic Serving Institutions (HSI), and Women's colleges (WC). Panel (B) provides correlations for institutions divided according to *Perceived* prestige from US News & World Report: Top 10 institutions, Top 100 institutions (without the Top 10), and institutions not in the Top 100. Panel (C) provides correlations according to institutions ranked by their average number of citations (*Research* prestige): Low (0.1, 1.47), Medium (1.48, 1.74), and High (1.77, 4.07); and Panel (D) provides correlations according to institutions according to *Selectivity* prestige: Carnegie Selectivity Index based on admissions rates.

These analyses focused on the correlation between all authors of a given identity and all authors associated with an institutional category. To validate and expand this analysis, we explored the correlation between the topical profile of all authors of an identity group within the institutional category, compared to the topical profile of the identity group overall (i.e., within *race and gender)* (Figure SII 6) and compared to all authors from that institutional category (i.e., within *institution)* (Figure SII 7) for Social Sciences, Humanities and Professional Fields. Important nuances emerge: e.g., White men at HBCUs have topical profiles that are negatively associated (ρ=-0.08) with the general portfolio of White men (within *race and gender* comparison*)*; whereas Black men at HBCUs have a positive association (ρ=0.1) compared to Black men overall (Figure SII 6). The positive correlations at HSIs across all identity groups suggests that identity groups at these institutions construct topical profiles that reflect their general identity portfolio (Figure SII 6). All women at Top 10 institutions tend to have profiles that are *less* similar to their general identity portfolio than men at these institutions (Figure SII 6). The effect is amplified when one compares with the population of those institutions (Figure SII 7) (*within institution* comparison): e.g., White men at Top 10 institutions are nearly perfectly correlated with the topical profile of the institutions (ρ=0.95); whereas Latinx, White, and Black women have a much weaker correlation (ρ=0.22, ρ=0.21, ρ=0.11). Asian women differ from other women in this regard, demonstrating a stronger profile alignment to Top 10 institutions (ρ=0.53). Similar effects for all identities can be observed in Health (Figs. SII 8-SII 9).

Taken together, correlations of topical profiles create a map of the US higher education landscape in which White men and Black Women represent polar ends of a spectrum (Figure SII 10). Placing the topical profile of two example institutions on this dimension (i.e., Howard University and Harvard University) illustrates the effect of institutions on science, wherein there is a concentration of prestige for topical profiles focused on historical exclusion (i.e., predominantly white institutions, research-intensive institutions, men, selective institutions), and another cluster focused on diversification (i.e., HBCUs, HSIs, WCs, teaching-oriented institutions, women, and inclusive institutions).

5.3.2 Institutions, identities, and impact

We built a series of linear models to analyze how institutions and topics may differentially mediate the scientific impact of authors by varying identities. Two impact indicators are included: citations and JIF, with topic and field normalization applied. We use the three institutional prestige indicators (i.e., *perceived* (US News & World Report), *research* (average citations), and *selectivity* (Carnegie Selectivity Index), placing the lowest prestige category of each indicator as the reference group. The first author's race and gender identity are included as co-variables, with career age of the first author, and total number of co-authors as controls.

The models illustrate the strong effect of institutional prestige on impact and provide evidence that race and gender affects impact, even when controlling for institution type (Figure 14). Specifically, if we examine *research* prestige (i.e., avg_citations); we find that Black and Latinx men (β=-.08, p<.01 ; β=-.10, p<.001, respectively) and women (β=-.15, p<.001; β=-.13, p<.001) respectively) receive fewer citations, on average, and publish in journals with lower JIFs than White men (Black women: β=-.09, p<.001; Black men: β=-.05, p<.001; Latinx women β=-.06, p<.001; and Latinx men: β=-.03, p<.001). Notably, the negative effect of author race and gender for both citations and JIF is most pronounced for Black and Latinx women. Asian men and women publish in journals with higher JIFs than White men (β=.05, p<.001; β=.05, p<.001, respectively), and Asian men receive higher average citations (β=.09, p<.001). White, Latinx, and Black women receive fewer citations (β=-.06, p<.001; β=-.13, p<.001; β=-.15, p<.001; respectively), and publish in journals with lower JIFs than White men (β=-.03, p<.001; β=-.06, p<.001; β=-.09, p<.001; respectively).

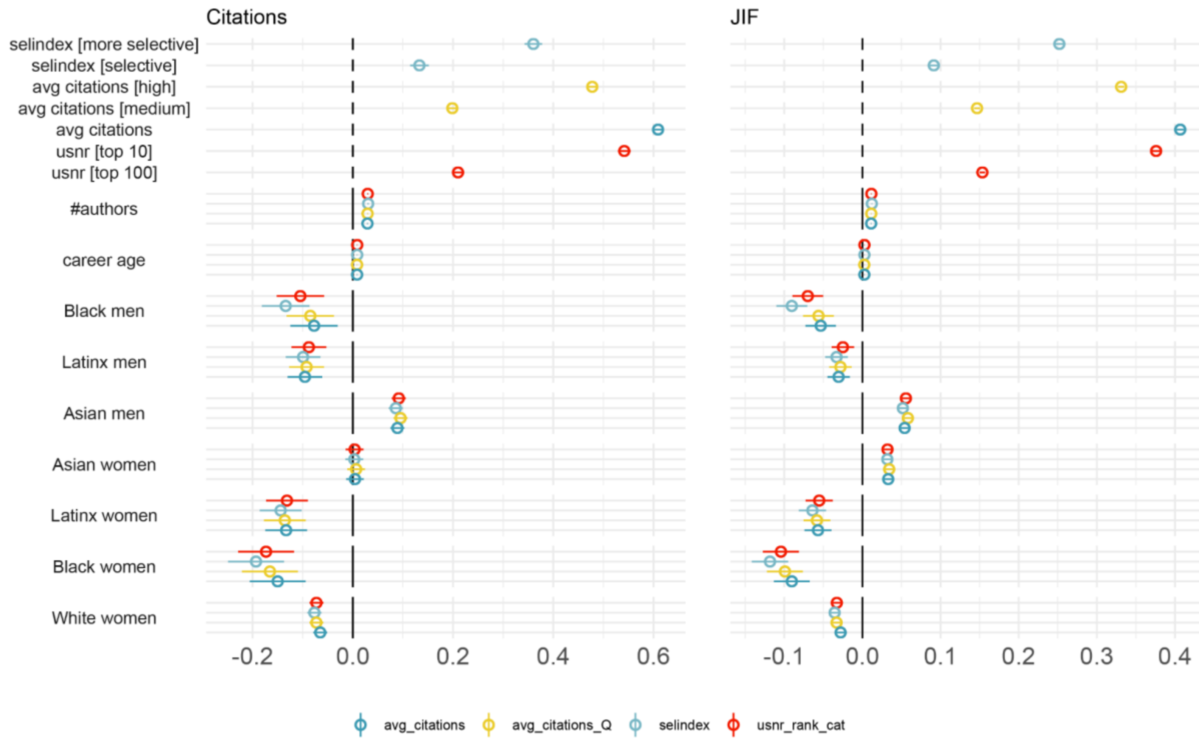

Figure 14. Parameters of linear regression models predicting topic and year normalized citations and JIF. The reference group for our intersectional race by gender identity variables is White men, with the number of co-authors and career age serving as controls. Each model was run with a different prestige indicator: perceived (US News & World Report): Top 10 institutions, Top 100 institutions (without the Top 10) and institutions not in the Top 100; research (institutions' historical average number of citations, both as a continuous, and categorical variable: Low (0.1, 1.47), Medium (1.48, 1.74), and High (1.77, 4.07); and selective (Carnegie Selectivity Index which is based on undergraduate admissions rates).

In order to measure the effect of topical profiles on research impact, we compare the models with both field- and topic- normalized impact indicators (Figure SII 11). If we restrict normalization of citations of JIF to field, we observe a larger positive effect for prestige co-variables and a larger negative effect for minoritized and marginalized authors (i.e., Black and Latinx men and women, and White women). Computing the difference in coefficients between each co-variable for the field and topic normalized models provides an indication of the effect of topic on the disparities observed (Figure SII 12). Here we observe a positive effect of topical profile on impact indicators for Asian men and women and a penalizing effect for Black and Latinx men and women, and White women. That is, the topics in which Black and Latinx scholars and White women are disproportionately associated are cited at lower rates.

To understand how institutional prestige affects scientific impact at the intersection of race and gender, we ran additional models omitting institutional covariables and compared the effects across groups. As shown in Figure 15, there is a larger effect of author race and gender in the most prestigious institutions; specifically for Latinx, Black, and White women. These identities have lower citations, on average, and publish in journals with lower JIF at all institutions, but the effect is most pronounced at institutions with higher *research* prestige groups (i.e., average citations rank). Asian women experience a negative effect in citation rates at high prestige institutions ($\beta=-.04$, $p<.05$), a nonsignificant effect in medium prestige institutions ($p>.05$, ns), and a positive effect at low prestige institutions ($\beta=.04$, $p<.001$). Alternatively, for JIFs, Asian authors experience a positive effect across all institution types (Asian Women: Low: $\beta=.05$, $p<.001$; Medium: $\beta=.03$, $p<.001$; High: $\beta=.01$, $p>.5$, ns; Asian Men: Low: $\beta=.06$, $p<.001$; Medium: $\beta=.04$, $p<.001$; High: $\beta=.06$, $p<.001$). There is relatively little institutional effect on citation impact for White women; however, they observe stronger penalties in publishing, where they publish in journals of lower JIF in the most prestigious institutions (Low: $\beta=-.01$, $p>.05$, ns; Medium: $\beta=-.02$, $p<.001$; High: $\beta=-.08$, $p<.001$).

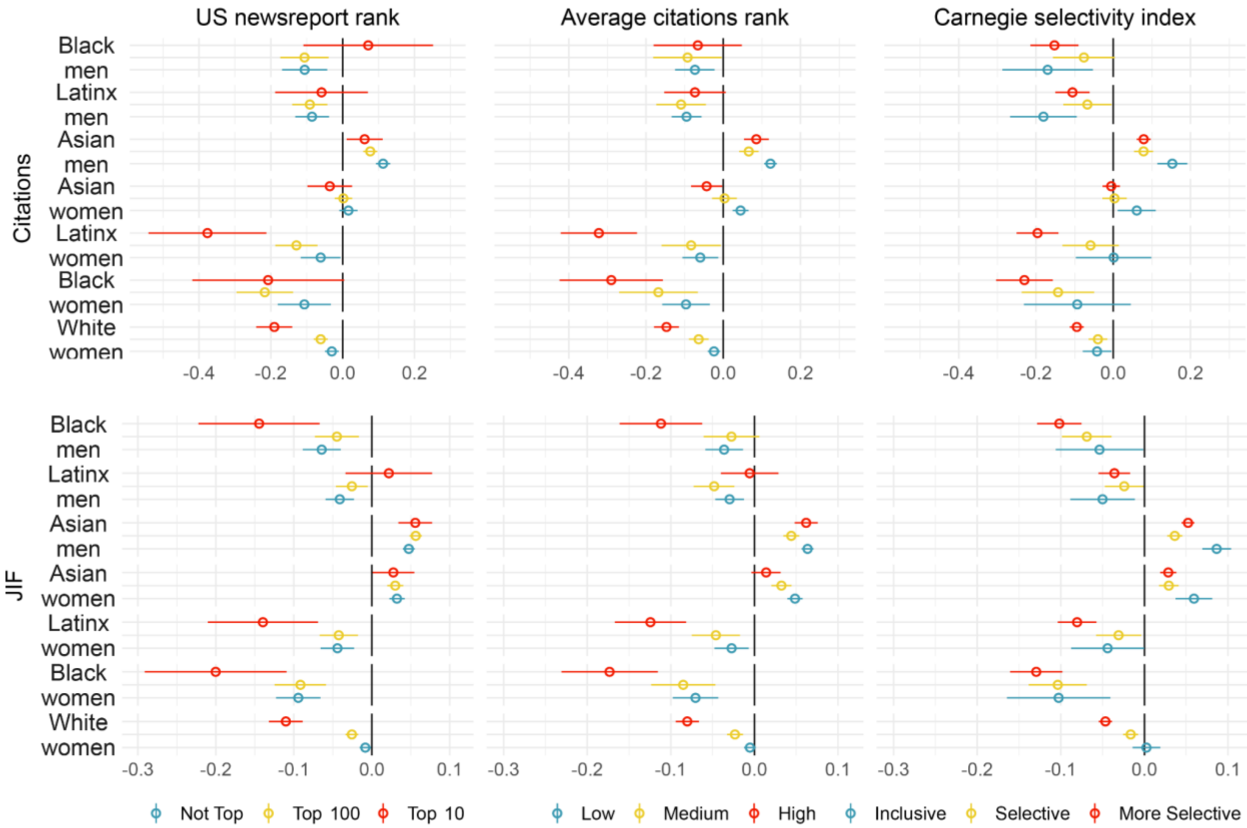

Figure 15. Parameters of linear regression models predicting the topic and year normalized citations and JIF, for subsets of institutions. The reference group for our intersectional race and gender identity variables is White men, with the number of co-authors and career age serving as controls. Each model was run with a different prestige indicator: perceived (US News & World Report): Top 10 institutions, Top 100 institutions (without the Top 10) and institutions not in the Top 100; research (institutions' historical average number of citations, both as a continuous, and categorical variable: Low (0.1, 1.47), Medium (1.48, 1.74), and High (1.77, 4.07); and selective (Carnegie Selectivity Index which is based on undergraduate admissions rates).

To analyze the intersectional disparities in scientific impact at prestigious institutions, we compare, for each identity, the difference in citations and JIFs in high and low prestige institutions, with respect to the middle group (Figure SII 13). Overall, men authors experience greater positive and negative effects based on their institutional affiliation than women authors across each prestige indicator (i.e., *perceived*, *research*, and *selective*) for both citations and JIF. If we examine *perceived* prestige for example, relative to Top 100 institutions; Black men experience a 42.4% citation gain, and 23.3% JIF gain at Top 10 institutions; while Black men at Not Top institutions experience a 25.8% citation loss, and 17.7% JIF loss. Similar patterns emerge for Latinx women but the gains and losses are not as substantial. Examining *perceived* prestige again relative to Top 100 institutions; Latinx women experience a 21.7% citation gain, and 17.5% JIF gain at Top 10 institutions; and a 20.5% citation loss, and 16.1% JIF loss at Not Top institutions.

Citation gaps between White men and other intersectional identities demonstrate a trend towards increased marginalization: increasing institutional prestige is associated with increasing inequalities in citations (Tables SII 2) and JIFs (Tables SII 3). For example, Latinx women have a difference of 12.6 percentage points in the citation gap between Not Top institutions (-7.7% citation penalty), and Top 10 institutions (-20.3% citation penalty) (Tables SII 2). The difference is smaller for White women (-6.8% and -15.1% in Not Top and Top 10 institutions respectively) and Black women (-9.0% and -15.7% in Not Top and Top 10 institutions respectively). This disparity holds for JIF, where we see in Not Top institutions a gap of -3.8%, -3.0%, -1.9% for Black, Latinx and White women, respectively, and of -9.5%, -8.8% and -8.4% on Top 10 institutions for those same groups (Table SII 3). The results imply that for Black, Latinx and White women, the differences in citations and JIF between institutions are not as substantial between institutional groups as they are for White men (Figure SII 13). Similar patterns emerge for Field normalized citations (Tables SII 4 & SII 5). This model provides clear evidence that being affiliated with a prestigious university has a positive impact on the citations and JIFs of all authors; however, this advantage is larger for White men.

5.4 **Discussion**

Institutions of higher education are increasingly being scrutinized for their role in reproducing inequalities in science (Clauset et al., 2015; Wapman et al., 2022). Economic and symbolic capital are highly concentrated in these institutions (Sugimoto, 2022; Whitford, 2022): few institutions control the production of faculty (Wapman et al., 2022), with research from these institutions having outsized scientific impact (Way et al., 2019). Policy interventions at prestigious institutions, therefore, have the opportunity to significantly alter the scientific landscape. This study provides an intersectional analysis of the relationship between the prestige of institutions and scientific impact. We provide evidence that institutions amplify the racialized and gendered stratification process in science and that the disparities in topic and scientific impact are most pronounced at institutions with highest prestige.

In our previous work, we found that the topical profile of authors have a proportionally greater focus on issues of direct relevance to their racialized and gendered identities —e.g., racial discrimination, migration, and gender-based violence (Kozlowski, Larivière, et al., 2022a). In the present work, we find that HBCUs, HSIs and WCs have research profiles that are closely related to the topical profiles of Black, Latinx, and White women. However, as we climb the ladder of institutional prestige[10], we observe a sharp decline in the relative importance of these topics. Far from being a consequence of the composition of their respective authors, this patterns reflects a more complex phenomenon: not only do authors from historically minoritized groups—particularly those at prestigious institutions—have a topical profile that differs from the dominant topical profile at their home institutions (i.e., within *institutional* difference), they also have a topical profile that differs from the dominant topical profile of other authors within their own racialized and gendered identity group across institutions (i.e., within *race and gender* difference).

[10] Three HSIs rank within the top 100 of US News & World Report 2021 rankings (University of California, Santa Barbara; University of California, Riverside; and Texas A&M University-College Station); just one HBCU meets this threshold (Howard University); and there are no Women's Colleges within this list.

Prestigious institutions are thereby exacerbating the gendered and racialized marginalization of scientific topics.

Disparities in citation by topic are particularly disadvantageous for Black and Latinx men and women and White women. However, even when controlling for topic (Figure 14), these populations receive fewer citations and publish in journals of lower JIF. This suggests that topic selection alone does not fully explain disparities in citations. We reinforce the strong relationship between impact and prestige (Hagstrom, 1971) and note that authors from all identities affiliated with prestigious institutions receive an impact advantage. However, these advantages are not distributed equally. It is at the institutions of highest prestige that we observe the largest disparities in impact, particularly for Black, Latinx, and White women. This suggests that, even when controlling for topic choice and institutional placement, there remains a disparity in impact for Black, Latinx, and White women and, to a lesser extent, Black and Latinx men. One possible explanation for the smaller impact gap between men and women authors at less prestigious institutions is the relative under-placement of women in faculty positions (Clauset et al., 2015). Similar employment mechanisms could be driving other trends observed, such as the topic misalignment between Asian men and women in HBCUs (Betsey, 2007). Regardless of the explanation, the disproportionate advantage for White men at prestigious institutions further codifies stratification at the intersection of prestige and identity.

To promote topical diversity in science, we need strategic shifts at institutional and federal levels. Federal agencies are the largest supporters of academic R&D in the US (i.e., 53%, ~ $45 billion); however, more than 20% of research funding is also derived from within academic institutions themselves (~ $21 billion) (NCSES, 2019). There is tremendous variation in the degree to which academic R&D is institutionally and federally supported. For example, Howard University, the only HBCU to be ranked in the top 100 of US News & World Report, had nearly $45 million in R&D expenditures in 2021, of which 65% came from federal funding sources (~$30 million) and 24% from internal sources (~$11 million) (NCSES, 2020a; USNWR, 2021). By comparison, Harvard University, ranked second in US News & World Report, had approximately $1.2 billion in R&D expenditures in 2021, of which 49% (~$601 million) originated from federal sources, and 32% (~$390 million) from internal sources (NCSES, 2020b; USNWR, 2021). In relative terms, Harvard is less reliant on federal funding for research than Howard University, suggesting that the institution has greater ability to strategically organize funding towards marginalized topics and to support the work of minoritized scholars (through funding, hiring, promotion, amplification, and mentorship policies). Institutions with higher reliance on federal funding should advocate for change within these agencies; acknowledging systemic disparities in funding (Chen et al., 2022; Hoppe et al., 2019) and recommending new practices for more equitable evaluation (Hunt et al., 2022).

Editors, journals, and publishers are also pivotal actors in this space. There is a nontrivial and reinforcing relationship between funding and publishing (Győrffy et al., 2020; Jacob & Lefgren, 2011). Therefore, journals' broader acceptance of topics of salience to marginalized communities is likely to have effects on both who and what is funded. Editors can ensure that they are reflexive in considering the ways in which they may promote sexist or racist discourse and imagery in their coverage of work (Nature, 2022) and work to mitigate bias through the selection of more diverse teams of reviewers (Murray et al., 2019b). These actions may also have a cascading effect in promoting other aspects of reflective and robust scientific practices that serve to elevate the work of minoritized scholars (Dworkin et al., 2020; Kwon, 2022).

The Matthew-Matilda effect refers to cumulative advantages (Merton, 1968) and disadvantages (Rossiter, 1993) in science. At the institutional level, we observe a Howard-Harvard effect, in which mission-driven institutions *support* and other prestigious institutions *suppress* the topical profile and impact of minoritized scholars. The US higher education system, and the actors that support it, are called to reduce the systemic marginalization of particular identities and topics of greatest salience for these populations.

5.5 Appendix II: Supplementary information for chapter 4

5.5.1 Materials and methods

5.5.1.1 Data

Our dataset consists of 5,431,451 articles published between 2008 and 2020 and indexed in the Web of Science (WOS), for which the first author carries a U.S. affiliation, and the distinct 4,713,444 first authors affiliated with these articles. These articles were associated with 261,336 distinct institution name strings, which were cleaned to assign papers to specific universities. The cleaning process for institutions consisted of two tasks: first, normalizing the multiple strings by which the name of the same university appears in WOS; and, second, building a crosswalk between institutions' names as they appear in WOS and in the Carnegie list of institutions. Both tasks were first conducted algorithmically, and then checked manually. The institutions selected for the manual cleaning followed a double criterion: first, we considered all institutions names in WOS that appeared 500 times or more. Given that this work also focuses on HBCUs, HSIs, and Women's Colleges, we did a second round of manual cleaning for names in WOS that partially matched those of the institutions in Carnegie from these groups, with a smaller threshold of 25 instances. This latter step allows us to triple our coverage of these institutions. After cleaning, the final dataset consists of 4,553,335 articles, 3,441,264 U.S. first authors, and 685 universities, which covers 84% of articles and 73% of authors contained in the original dataset. Out of the 685 colleges and universities analyzed, 62 are HBCUs (out of 100 in Carnegie), 127 are HSIs (out of 803), and 25 are WC (out of 34). The lack of coverage of all institutions may in part be due to a low signal in WoS for many HBCUs, WCs, and HSIs. In addition, we took a manual approach to retrieving all articles with Tribal Colleges, which are also mission-driven institutions categorized by the Carnegie classification. However, the low volume of articles retrieved (500) for those institutions—which is a finding in itself—did not allow us to perform further analyses. This is an acknowledged limitation of the present work. It is important to note also that within these institutional categories, the imbalance in the number of publications across institutions means that the results are driven by the leading institutions of each category. For example, the Top 10 most productive HBCUs published 70% of the articles of the group, while the 40 least productive accounts for less than 9% of the articles. For HSIs, the Top 10 institutions account for 73% of the papers, while the remaining 117 account for only 27%. In Women's colleges, the Top 10 institutions published 90% of the articles, while the remaining 18 published 10%.

Institutional prestige is a key variable of this analysis. We rely on three different indicators of institutional prestige: US News & World Report ranking, the historical average of field-normalized numbers of citations of institutions, and Carnegie's selectivity index. For each of these, we split the institutions into three groups: high, middle and low prestige.

US News & World report use a compound of factors such as graduation rates, faculty resources, and undergraduate academic reputation to determine the ranking of the—in their terms—best colleges in US[11]. We used the 2022 edition of the report and search their website[12] to match the Top 100 institutions with our curated WOS database. With this information we split the universities between those in the Top 10 of the ranking (11 universities, given ties), those between the Top 10 and Top 100 (89 universities) and those that fall outside the Top 100 (584 universities). Research production remains uneven within this group, with Top 10 institutions accounting for 17% of articles, and the Top 100 accounting for 47% of articles. Given the widespread use of this ranking by society to form expectations about institutions, we consider this to be a classification of *perceived prestige*.

We also used the historical average of field-normalized number of citations (Waltman & van Eck, 2019) by institution. For this, we use all WOS-indexed articles published by universities between 1980 and 2019, and the field- and year-normalized citations. To build the high/medium/low average citations groups we used a weighted version of quantiles that considers the number of publications, in order to build groups of similar size. Highly cited institutions (60 universities) have between 1.77 and 4.07 normalized citations per article. Medium cited institutions (78 universities) move between 1.48 and 1.74 normalized citations, while low cited institutions (547) have between 0.1 and 1.47 citations on average. Each of the three groups account for roughly 33% of articles each (see Table S1). This citation-based classification of prestige can be labeled as *research prestige*, as it is based on the research impact of papers from each university. We also build alternative classifications of impact, using the total number of citations, the proportion of paper an institution has in the top 1%, 5% and 10% most cited articles. All of these classifications yield similar results, and hence we decided to use the historical average number of normalized citations for simplicity.

As a third approach to the prestige of institutions, we used the Carnegie Selectivity index (Carnegie, 2022), a metric built by the Carnegie Classification of Institutions of Higher Education which can be retrieved on the official website[13], which divides universities according to their undergraduate admission rates. Those are divided as “inclusive” (196 universities), “selective” (206 universities) and “more selective” (187 universities). This perspective focuses on the elitism of the institution within the student population, and we call it *selectivity prestige*. We did not use Carnegies’ Basic Classification because R1 institutions account for a great majority of research papers, generating an imbalanced dataset that is unable to show differences within the R1 universities.

Each of these three operationalisations gives a partial view of prestige. US News & World report is a widely regarded ranking by the US society overall. It therefore affects the perception that the broader society has about the prestige of an institution. The historical average number of citations shows the impact that an institution has within the scientific community. The selectivity index shows the elitism of the student population. The similarity of the outcomes on these three levels

[11]https://www.usnews.com/education/best-colleges/articles/how-us-news-calculated-the-rankings (retrieved 29/08/2022)

[12] https://www.usnews.com/best-colleges/rankings/national-universities (retrieved 29/08/2022)

[13]http://carnegieclassifications.acenet.edu/downloads/CCIHE2021-PublicDataFile.xlsx Version 9, Accessed November 19, 2022)

gives robustness to the analysis. The size of the groups differs across classifications (see table S1), which has an impact on the behavior of the middle groups, as this depends on the thresholds that define them (see for example Fig. 2). The US News & World Ranking shows a narrower definition of top institution, including only 11 institutions and less than 1M papers, while the top group based on selectivity gathers more than 3M papers and is the biggest of the three groups. Conversely, the bottom group based on selectivity gathers 262,617 articles, while institutions not in the top 100 of US News & World report gather 1.9M articles. Given the nature of the indicator, the three groups based on the average number of citations retrieve between 1.75M and 1.83M articles. These thresholds are arbitrary cuts of the prestige dimension, and are simply heuristics for our analysis. The results show similar behaviors on the high and low prestige groups across categories, allowing a robust interpretation of the results.

Following (Kozlowski et al., 2022), authors of the selected papers were assigned a race based on the association between their family names and race found in the US census data (USBC, 2016). Gender was inferred using authors' given names, based on the method presented in Larivière et al. (2013). Gender is considered in a binary way, as other genders can only be assigned through self-identification. This is a clear limitation of the algorithmic approach. As shown in Kozlowski, Larivière et al. (2022a), the demographics of US authors have a different distribution than those of the 2010 US census, with an under-representation of Black and Latinx authors. Therefore, using the 2010 US as a source for the name-based racial inference can potentially overestimate these groups, as has been recently shown by (LaBerge et al., 2022). The reason for this is that Black and White identities often share family names, given the historical legacy of assigning names to human property during the hundreds of years of institutionalized chattel slavery in the U.S. As our results demonstrate, there are reasons to believe these methods hold face validity for a number of analyses but can nevertheless overestimate the proportion of Black and Latinx authors and, therefore, can be considered as an upper bound for their participation in research activities. Furthermore, this automatic inference method limits our ability to infer race for Native American scholars and individuals with more than one race.

5.5.1.2 Topics and indicators

The definition of fields used in this paper is based on a journal classification developed for the US NSF (Hamilton, 2003). The topic of articles is inferred using Latent Dirichlet Allocation models (LDA). Based on our previous work (see Kozlowski, Larivière, et al. (2022a), we train a model for Social Science, Humanities and Professional Fields with 300 topics, and a model with 200 topics for each of the other disciplines (including Health). Fig. 1-2 are based on the proportion of papers each group—race & gender identities or institutional groups—contributes to each topic. Race & gender are assigned probabilistically to each article and topic. To account for the proportion of papers that a researcher identity produces in a topic, we sum for all papers their probability associated to that topic multiplied by the probability of that paper being written by an author of that same identity. For institutional groups, which are categorical, we sum the probabilities associated with topics for each group separately, and then divide by the sum of probabilities for that topic across all groups. The result obtained is the proportion of papers each race, gender, and institutional group contributed to each topic. Then, the correlation between each group and participation in a given topic can be made for any institutional category. Fig. 2 shows the correlations between institutions and identities, Fig. S6 shows the correlation between authors from a given identity and institutional type with respect to all authors from their same identity, and Fig. S shows the relation between authors from a given identity and institutional type with respect to authors from their same institutional type. All possible combinations are available at: https://sciencebias.uni.lu/app/.

5.5.1.3 Linear models

A series of linear models were built to test the relation between researchers' identity and impact. We use as dependent variables the topic- and year-normalized citations and Journal Impact Factor (JIF) of the journal in which the paper was published. Topic normalization is needed, as research topics affect the number of citations (see Fig. S11). As each discipline has its own topic modeling, the topics are not comparable between disciplines, but can still be used for normalization, which allows a comparable dependent variable across fields.

The aggregated models show the following structure:

$$(1)\ y = \beta_0 + \beta_1 \#authors + \beta_2 career\ age + \sum_i \beta_i\ race\ \&\ gender + \sum_j \beta_j\ institution$$

where y is the year- and topic-normalized citations (or field normalized in Fig. S11) or JIF, $\#authors$ is the number of authors, $race\ \&\ gender$ is the first author probability of being from a specific race and gender group. Researchers' identities are computed as probabilities, and the sum of those probabilities adds to one. Therefore we exclude the *White men*'s group to avoid multicollinearity. This means that all the other values should be understood as the effect of being from a specific group in comparison to the White man category. For institutions, we build a model for each of the categories described above: US News & World report, average citations and Carnegie selectivity. For US News & World report and Carnegie selectivity—which are categorical variables—we build dummy variables excluding the low prestige group of each categorisation. For the average number of citations of the institution, we used a continuous variable. As explained above, the average number of citations by institution is different from the dependent variable (i.e. the mean impact of papers in that topic from that identity at that institution). The first—the institutions' classification—uses historical data between 1980 and 2019 of field-normalized citations at the institution level, the dependent variable is the topic- and year-normalized citations on the article level. There is a strong relation between these two variables, but is on the same order of magnitude as for the other institutional categorisations.

In order to understand how race and gender inequalities affect different types of institutions, we build a second group of models with the subset of data that correspond to each level of prestige (see Fig. 4):

$$(2)\ y = \beta_0 + \beta_1 \#authors + \beta_2 career\ age + \sum_i \beta_i\ race\ \&\ gender$$

where j is each of the three groups—low, middle and high prestige—of each of the institutional categorisations—US News & World report, average citations, and Carnegie selectivity index.

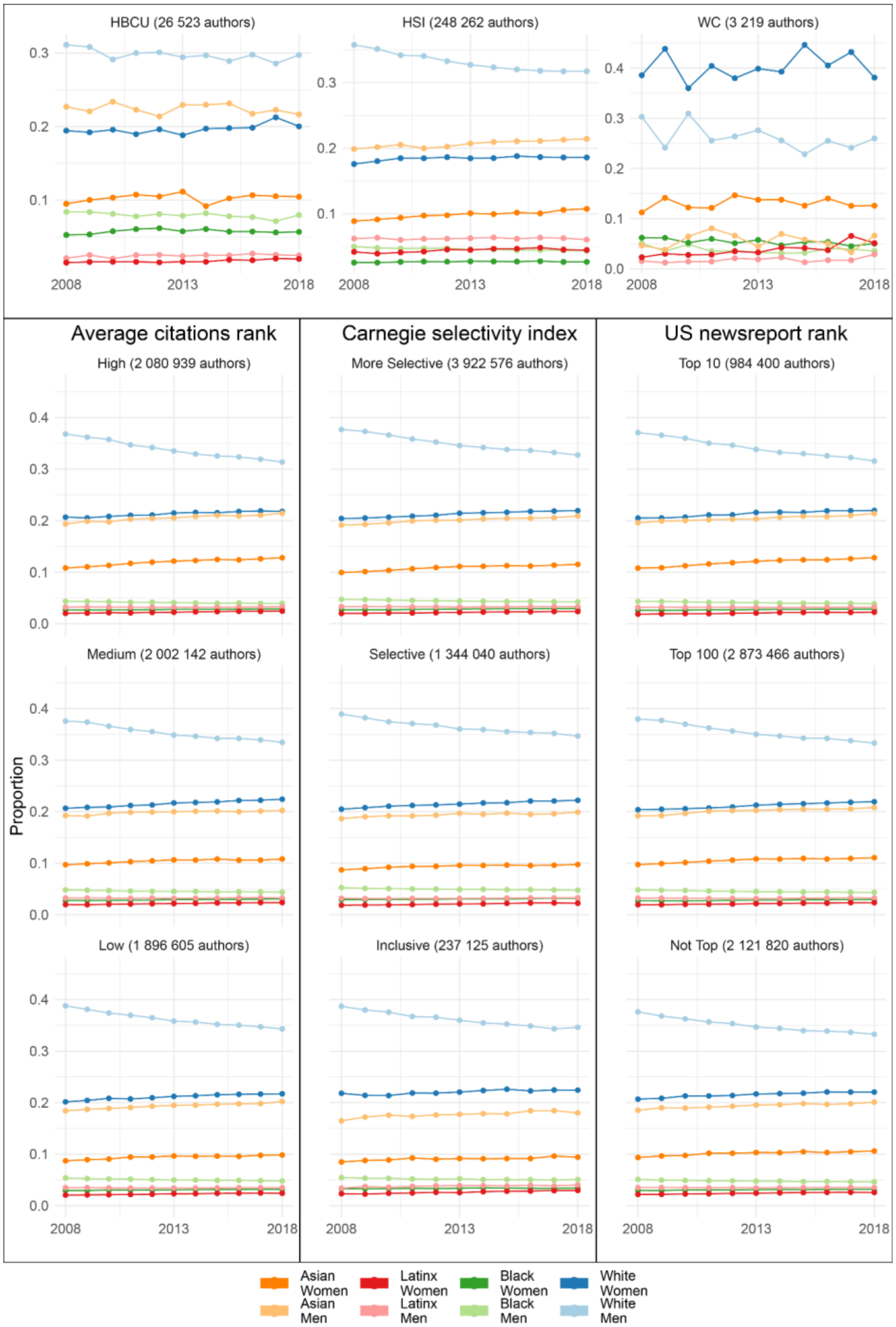

Figure S II 1. White men are still largely overrepresented with respect to their proportion in the US Census across all institution types. Proportion of groups by race and gender, for the number of authors. HBCU: Historically Black Colleges and Universities, HSI: Hispanic Serving Institutions, and WC: Women's colleges. Institutions sorted by their average number of citations: Low (0.1, 1.47), Medium (1.48, 1.74), and High (1.77, 4.07). Carnegie Selectivity Index based on admissions rates. US News & World ranking: Top 10 institutions, Top 100 institutions (without the Top 10) and institutions not in the Top 100. Total number of authors between parentheses.

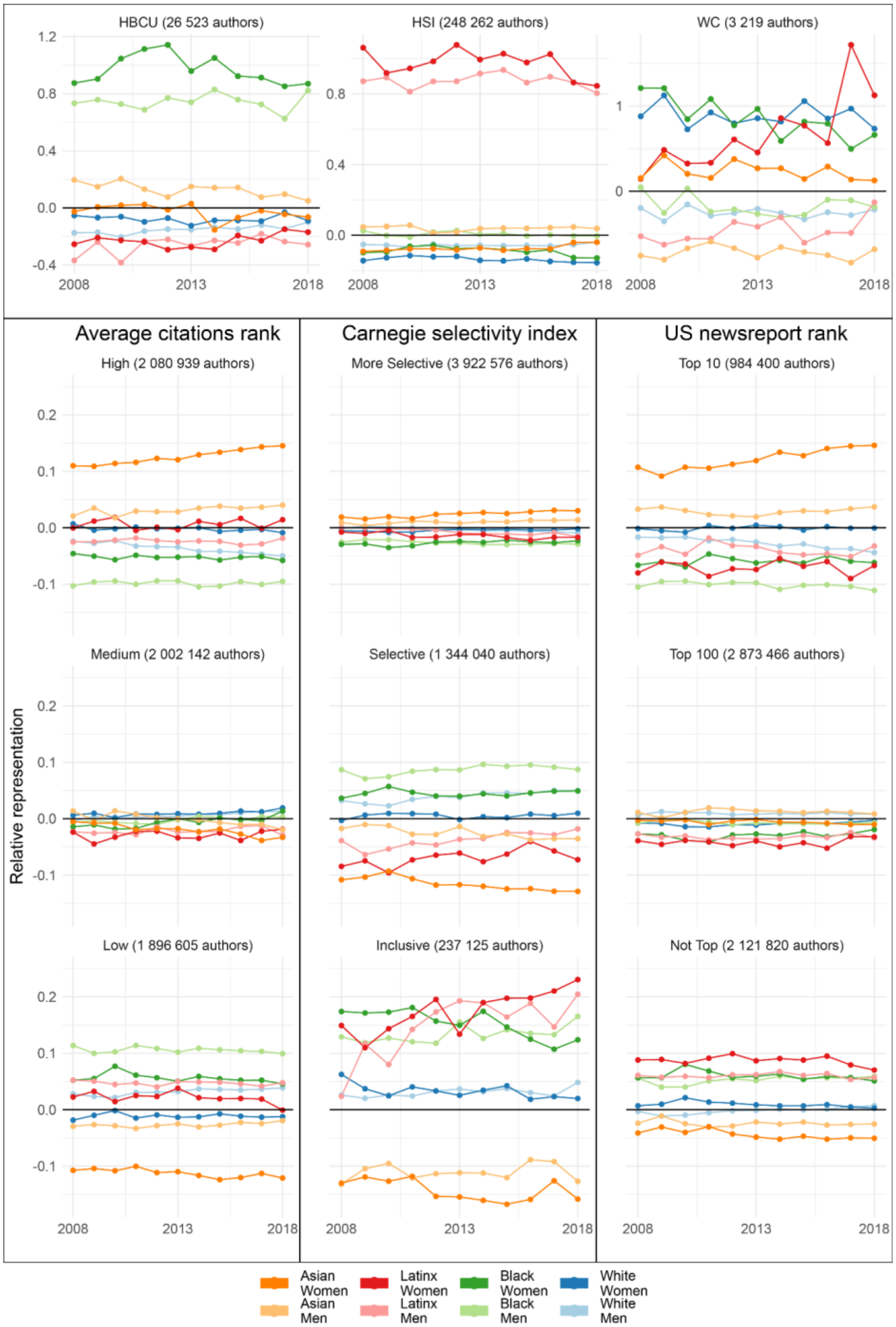

Figure S II 2. Institutions serving specific groups show a larger authorship from those groups, while low prestige institutions show a larger proportion of Black and Latinx authors. Relative over/under representation of groups by race and gender, relative to their participation in the overall dataset, for the number of authors. HBCU: Historically Black Colleges and Universities, HSI: Hispanic Serving Institutions, and WC: Women's colleges. Institutions sorted by their average number of citations: Low (0.1, 1.47), Medium (1.48, 1.74), and High (1.77, 4.07). Carnegie Selectivity Index based on admissions rates. US News & World Report ranking: Top 10 institutions, Top 100 institutions (without the Top 10) and institutions not in the Top 100. Total number of authors between parentheses.

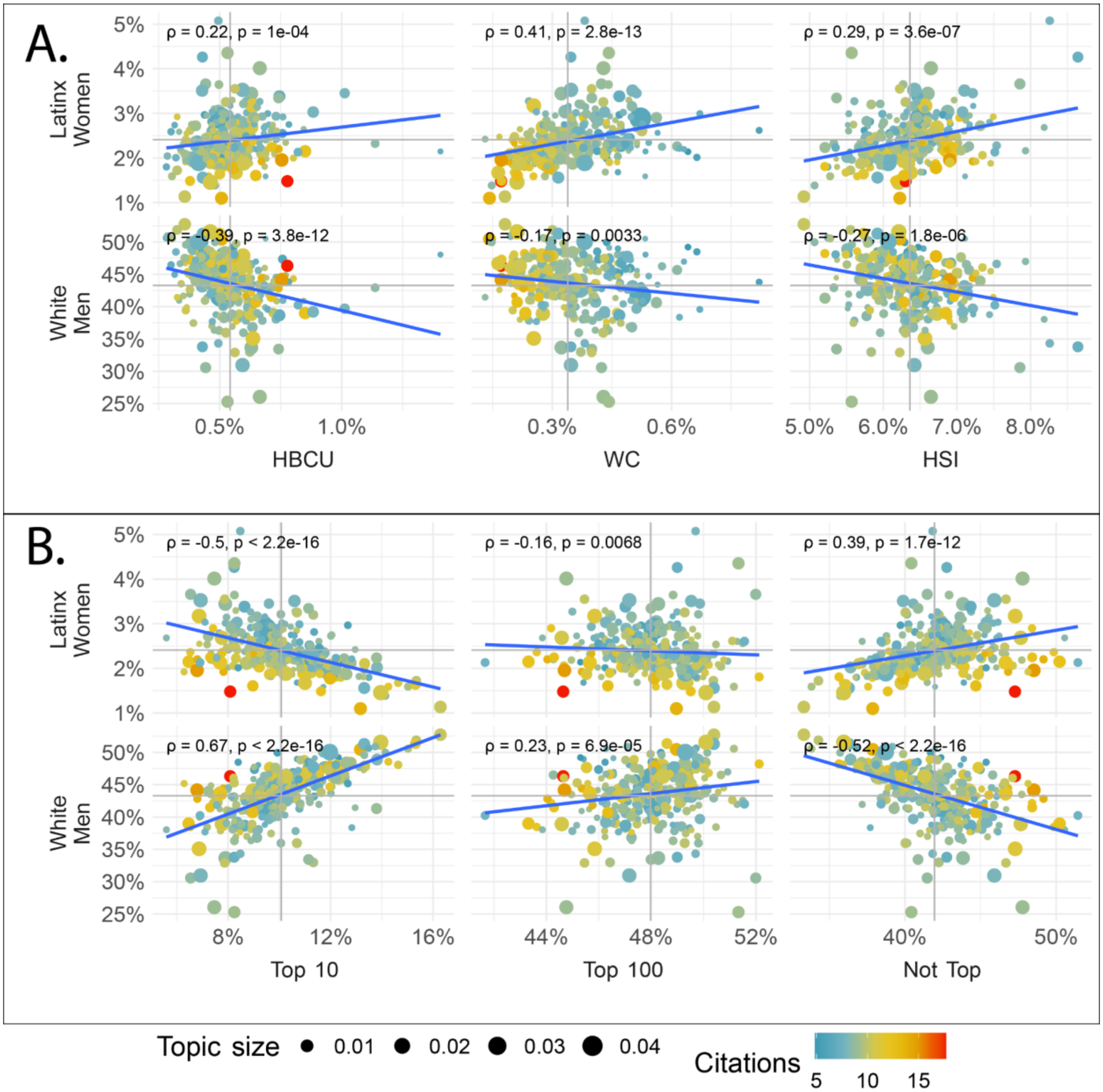

Figure S II 3. Relationship between topic representation of authors by race and gender, and topic representation of institutional groups, for papers in the Social Sciences, Humanities and Professional Fields. The figures provide Spearman correlations between the proportion of papers in different topics authored by Latinx Women and White Men (vertical axis) and the percentage of those papers authored by different institutional groups (horizontal axis). Panel (A) provides correlations for institutions that serve specific groups: Historically Black Colleges and Universities (HBCU), Hispanic Serving Institutions (HSI), and Women's colleges (WC). Panel (B) splits institutions into three categories of perceived prestige based on the US News and World report ranking: Top 10 institutions, Top 100 institutions (without the Top 10) and institutions not in the Top 100. Dot size represents the size of the topic in the corpus associated with the topic, while the dot color represents the average number of citations for that topic. For each subplot, ρ indicates the Spearman correlation with its p-value, and the blue line is the linear smooth of the scatterplot.

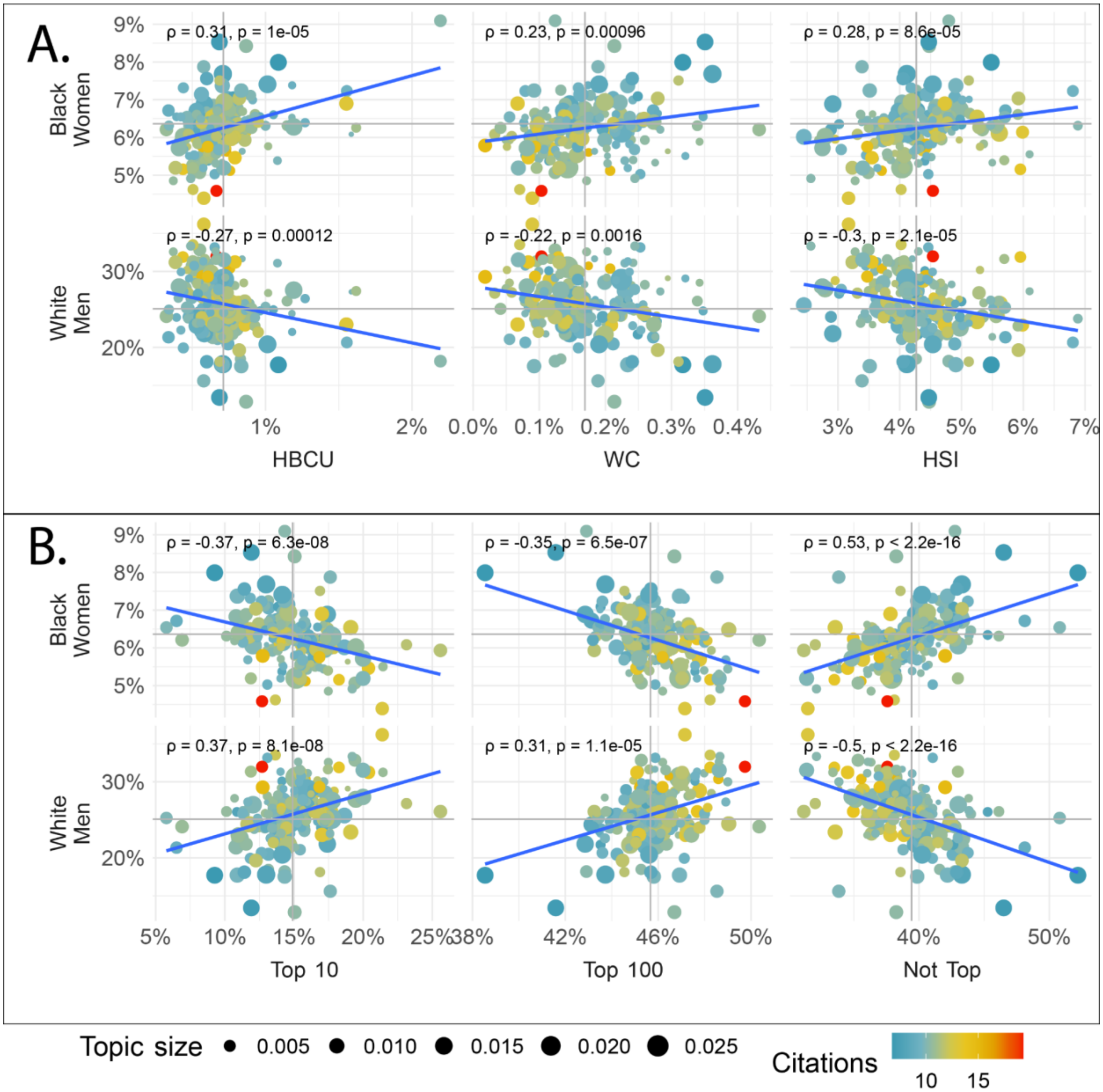

Figure S II 4. Relationship between topic representation of authors by race and gender, and topic representation of institutional groups, for papers in Health. The figures provide Spearman correlations between the proportion of papers in different topics authored by Black Women and White Men (vertical axis) and the percentage of those papers authored by different institutional groups (horizontal axis). Panel (A) provides correlations for institutions that serve specific groups: Historically Black Colleges and Universities (HBCU), Hispanic Serving Institutions (HSI), and Women's colleges (WC). Panel (B) splits institutions into three categories of perceived prestige based on the US News and World report ranking: Top 10 institutions, Top 100 institutions (without the Top 10) and institutions not in the Top 100. Dot size represents the size of the topic in the corpus associated with the topic, while the dot color represents the average number of citations for that topic. For each subplot, ρ indicates the Spearman correlation with its p-value, and the blue line is the linear smooth of the scatterplot.

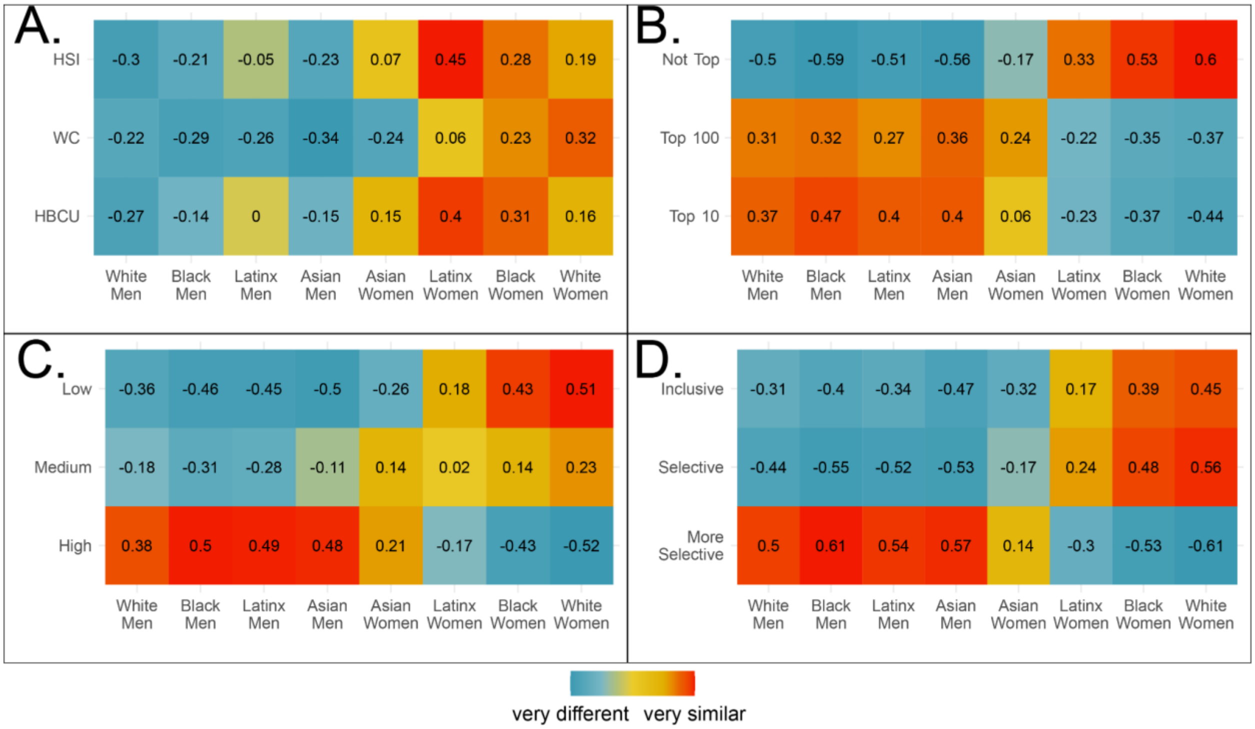

Figure S II 5. Spearman correlations between the topic profiles of each author identity and the topical profile of institutional categories for Health. Panel (A) provides correlations for institutions that serve specific groups: Historically Black Colleges and Universities (HBCU), Hispanic Serving Institutions (HSI), and Women's colleges (WC). Panel (B) provides correlations for institutions divided according to Perceived prestige from US News & World Report: Top 10 institutions, Top 100 institutions (without the Top 10), and institutions not in the Top 100. Panel (C) provides correlations according to institutions ranked by their average number of citations (Research prestige): Low (0.1, 1.47), Medium (1.48, 1.74), and High (1.77, 4.07); and Panel (D) provides correlations according to institutions according to Selectivity prestige: Carnegie Selectivity Index based on admissions rates.

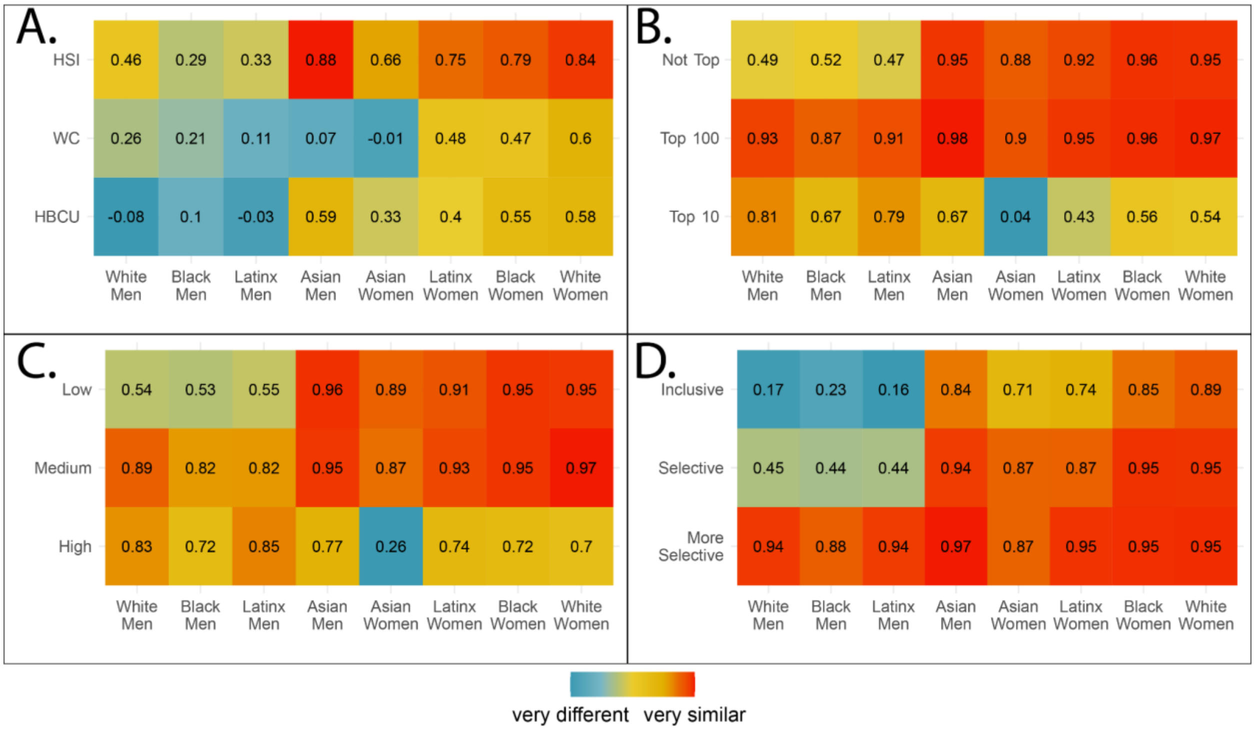

Figure S II 6. Spearman correlations between the topic profile of each author identity within an institutional category and the topic profiles of each author identity across all institutional categories for Social Sciences, Humanities and Professional Fields. Panel (A) provides correlations for institutions that serve specific groups: Historically Black Colleges and Universities (HBCU), Hispanic Serving Institutions (HSI), and Women's colleges (WC). Panel (B) provides correlations for institutions divided according to Perceived prestige from US News & World Report: Top 10 institutions, Top 100 institutions (without the Top 10), and institutions not in the Top 100. Panel (C) provides correlations according to institutions ranked by their average number of citations (Research prestige): Low (0.1, 1.47), Medium (1.48, 1.74), and High (1.77, 4.07); and Panel (D) provides correlations according to institutions according to Selectivity prestige: Carnegie Selectivity Index based on admissions rates.

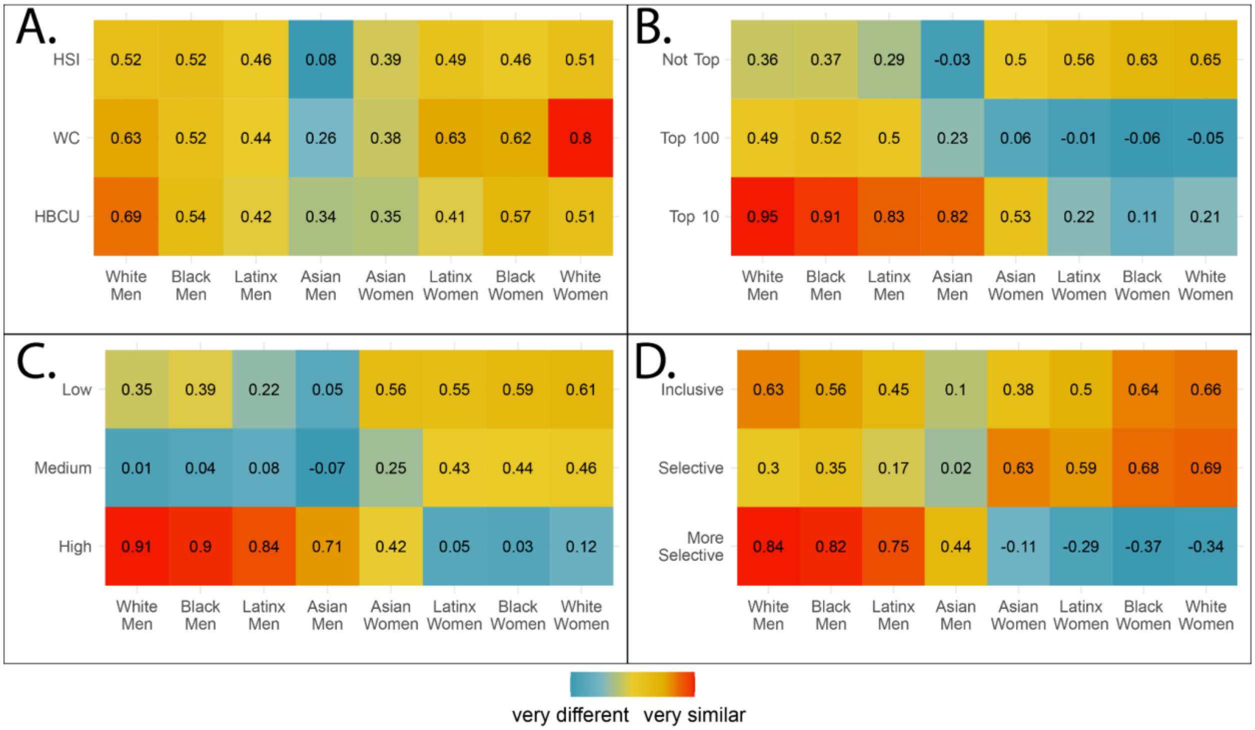

Figure S II 7. Spearman correlations between the topic profile of each author identity within an institutional category and the topic profiles of all authors from that institutional category for Social Sciences, Humanities and Professional Fields. Panel (A) provides correlations for institutions that serve specific groups: Historically Black Colleges and Universities (HBCU), Hispanic Serving Institutions (HSI), and Women's colleges (WC). Panel (B) provides correlations for institutions divided according to Perceived prestige from US News & World Report: Top 10 institutions, Top 100 institutions (without the Top 10), and institutions not in the Top 100. Panel (C) provides correlations according to institutions ranked by their average number of citations (Research prestige): Low (0.1, 1.47), Medium (1.48, 1.74), and High (1.77, 4.07); and Panel (D) provides correlations according to institutions according to Selectivity prestige: Carnegie Selectivity Index based on admissions rates.

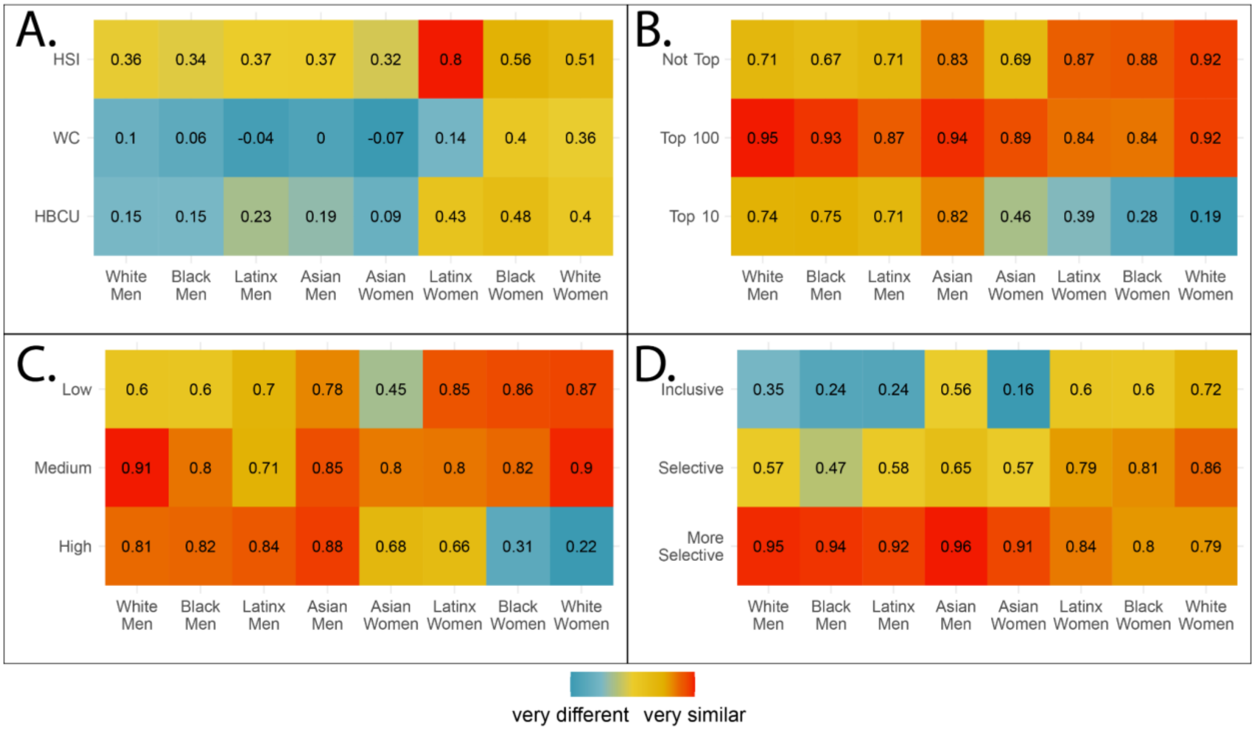

Figure S II 8. Spearman correlations between the topic profile of each author identity within an institutional category and the topic profiles of each author identity across all institutional categories for Health. Panel (A) provides correlations for institutions that serve specific groups: Historically Black Colleges and Universities (HBCU), Hispanic Serving Institutions (HSI), and Women's colleges (WC). Panel (B) provides correlations for institutions divided according to Perceived prestige from US News & World Report: Top 10 institutions, Top 100 institutions (without the Top 10), and institutions not in the Top 100. Panel (C) provides correlations according to institutions ranked by their average number of citations (Research prestige): Low (0.1, 1.47), Medium (1.48, 1.74), and High (1.77, 4.07); and Panel (D) provides correlations according to institutions according to Selectivity prestige: Carnegie Selectivity Index based on admissions rates.

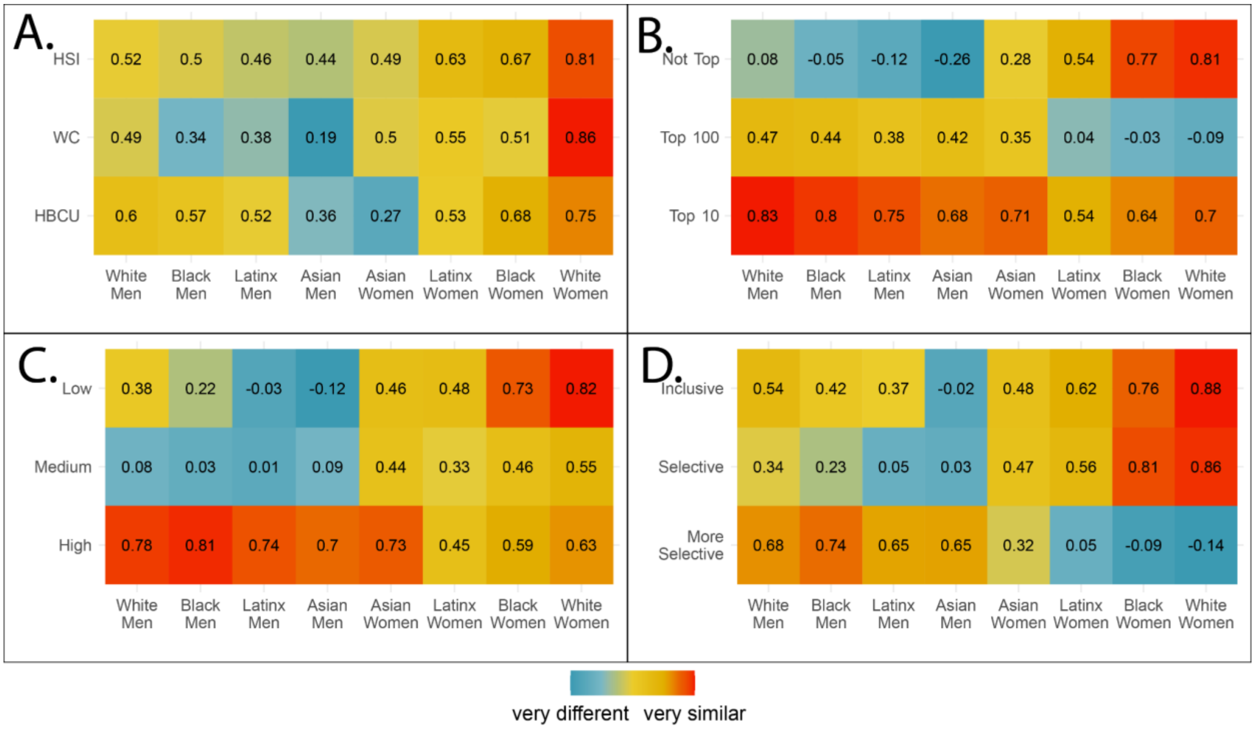

Figure S II 9. Spearman correlations between the topic profile of each author identity within an institutional category and the topic profiles of all authors from that institutional category for Health. Panel (A) provides correlations for institutions that serve specific groups: Historically Black Colleges and Universities (HBCU), Hispanic Serving Institutions (HSI), and Women's colleges (WC). Panel (B) provides correlations for institutions divided according to Perceived prestige from US News & World Report: Top 10 institutions, Top 100 institutions (without the Top 10), and institutions not in the Top 100. Panel (C) provides correlations according to institutions ranked by their average number of citations (Research prestige): Low (0.1, 1.47), Medium (1.48, 1.74), and High (1.77, 4.07); and Panel (D) provides correlations according to institutions according to Selectivity prestige: Carnegie Selectivity Index based on admissions rates.

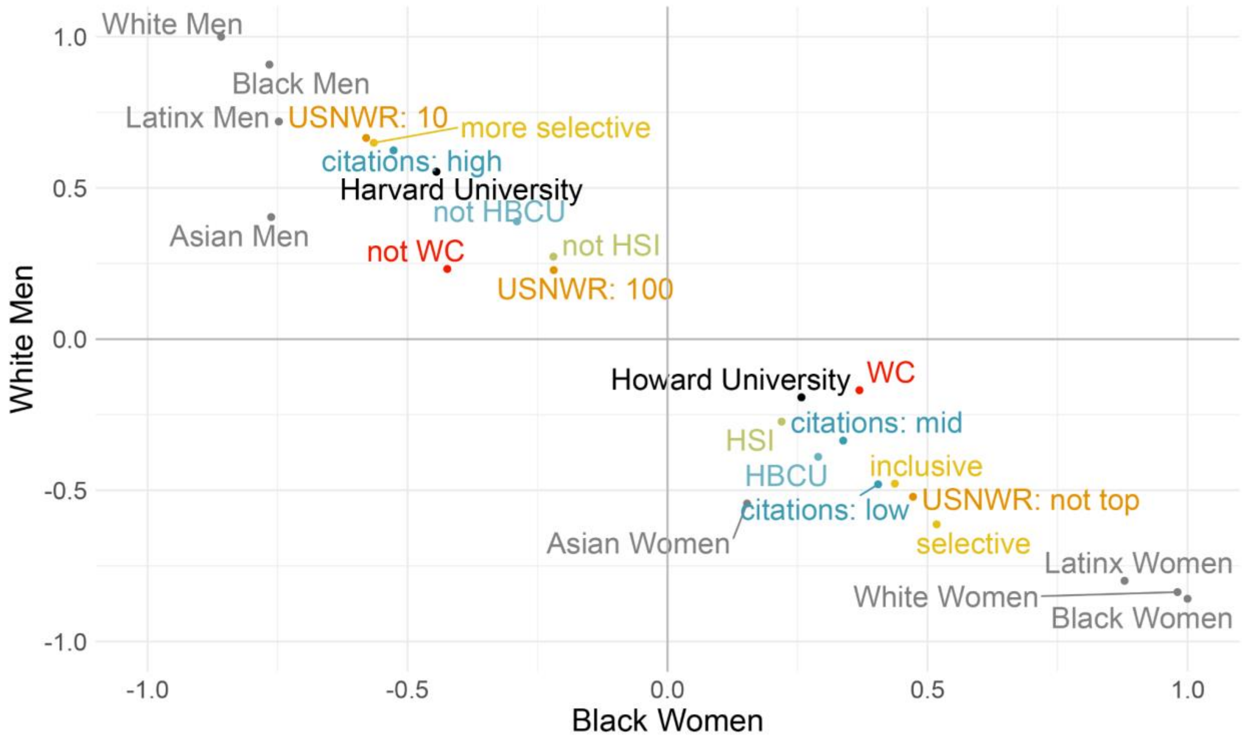

Figure S II 10. Scatterplot of Spearman correlations between the topic profiles of each author identity and the topical profile of institutional groups, for Black Women (horizontal axis) and White men (vertical axis). Institutional groups are: Historically Black Colleges and Universities (HBCU), Hispanic Serving Institutions (HSI), and Women's colleges (WC); US News & World Report: Top 10 institutions (USNWR: 10), Top 100 institutions (without the Top 10) (USNWR: 100), and institutions not in the Top 100 (USNWR: Not Top); Institutions ranked by their average number of citations: Low (0.1, 1.47) (citations: low), Medium (1.48, 1.74) (citations: mid), and High (1.77, 4.07) (citations: high); Institutions according to Selectivity: Carnegie Selectivity Index based on admissions rates (inclusive, selective and more selective).

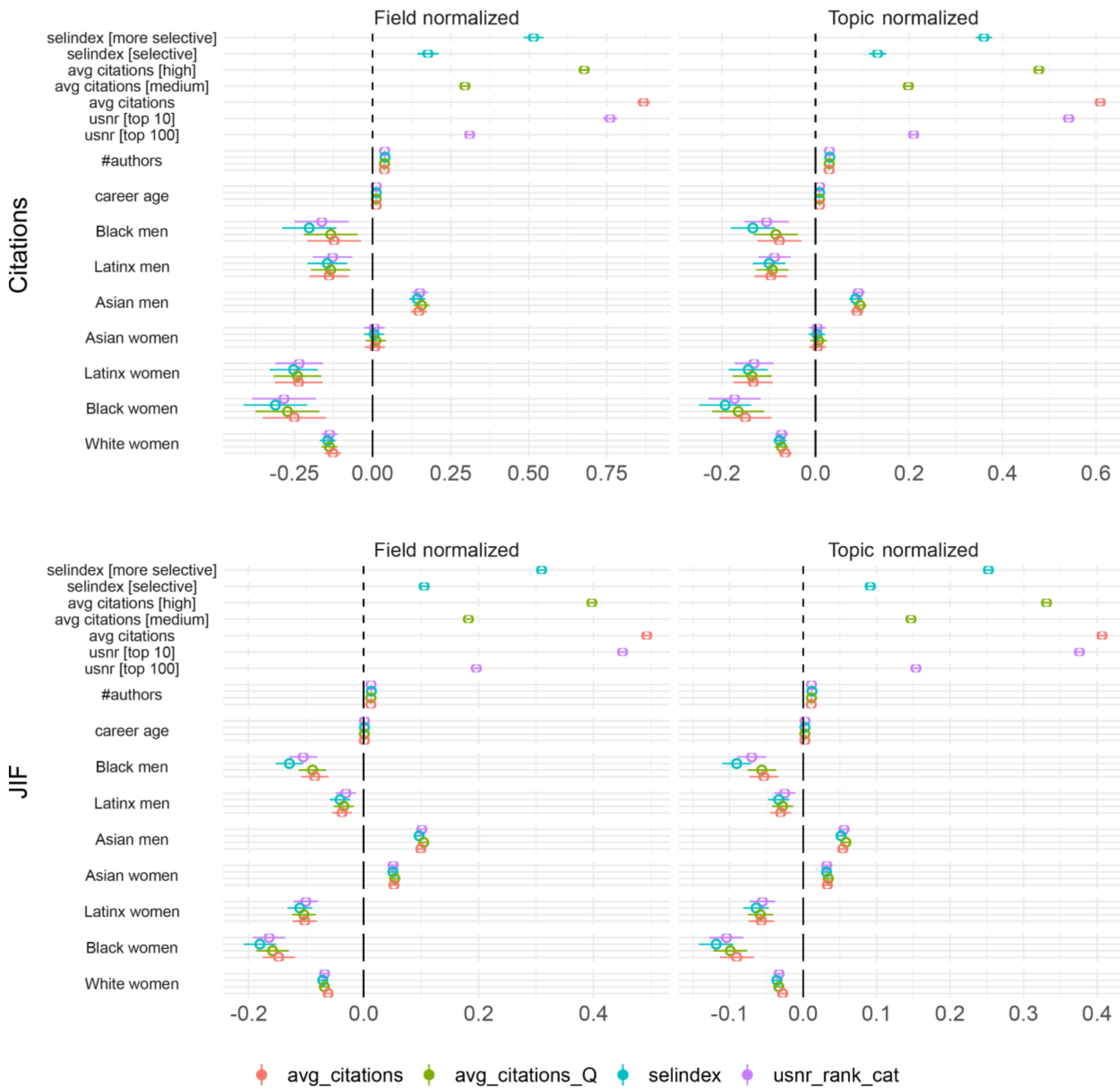

Figure S II 11. Parameters of linear regression models predicting citations and JIF, with and without topic normalization. The reference group for our intersectional race by gender identity variables is White men, with the number of co-authors and career age serving as controls. Parameters of linear regression models predicting the two-year citations and JIF both with and without topic normalization. The unnormalized models scale the dependent variables (citations and JIF) by the average over the full dataset, while the normalized models scale the dependent variables by the average of the topic. The normalized version controls the effect of topics on impact. Each model was run with a different prestige indicator: perceived (US News & World Report): Top 10 institutions, Top 100 institutions (without the Top 10) and institutions not in the Top 100; research (institutions' historical average number of citations, both as a continuous, and categorical variable: Low (0.1, 1.47), Medium (1.48, 1.74), and High (1.77, 4.07); and selective (Carnegie Selectivity Index which is based on undergraduate admissions rates).

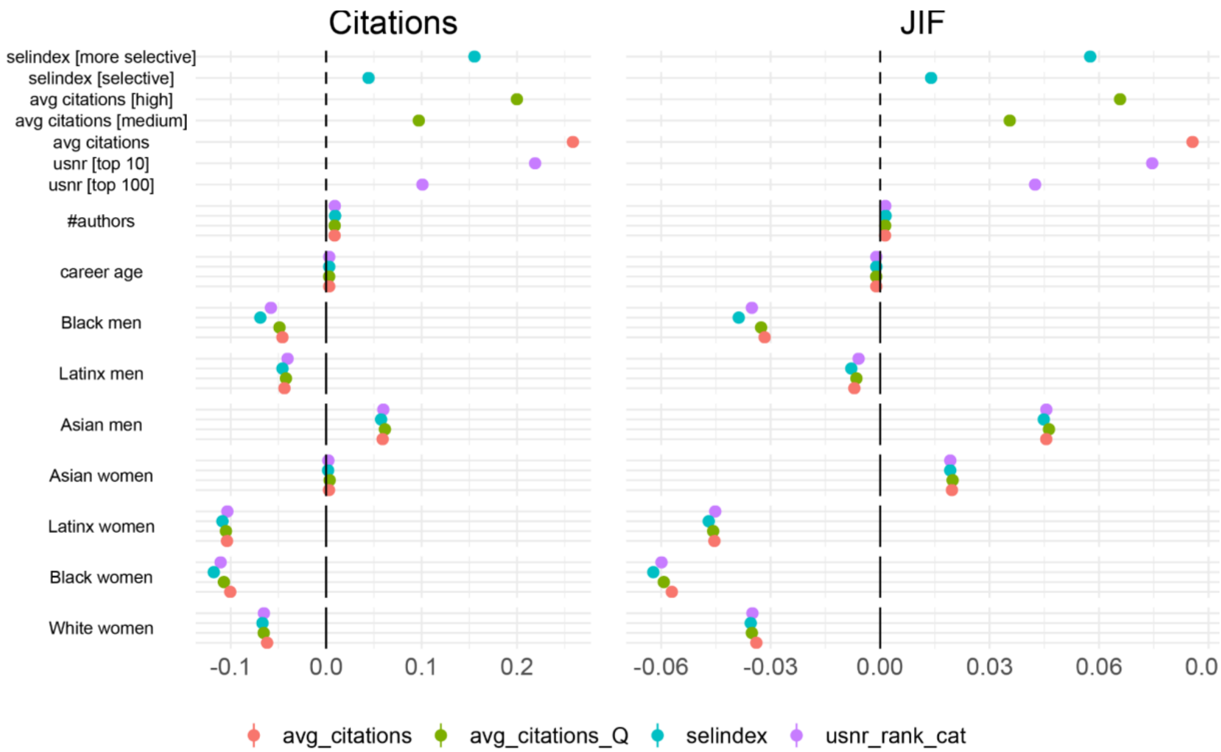

Figure S II 12. Difference between the parameters of linear regression models predicting citations and JIF, with and without topic normalization. The reference group for our intersectional race by gender identity variables is White men, with the number of co-authors and career age serving as controls. Parameters of linear regression models predicting the two-year citations and JIF both with and without topic normalization. The unnormalized models scale the dependent variables (citations and JIF) by the average over the full dataset, while the normalized models scale the dependent variables by the average of the topic. The normalized version controls the effect of topics on impact. Each model was run with a different prestige indicator: perceived (US News & World Report): Top 10 institutions, Top 100 institutions (without the Top 10) and institutions not in the Top 100; research (institutions' historical average number of citations, both as a continuous, and categorical variable: Low (0.1, 1.47), Medium (1.48, 1.74), and High (1.77, 4.07); and selective (Carnegie Selectivity Index which is based on undergraduate admissions rates).

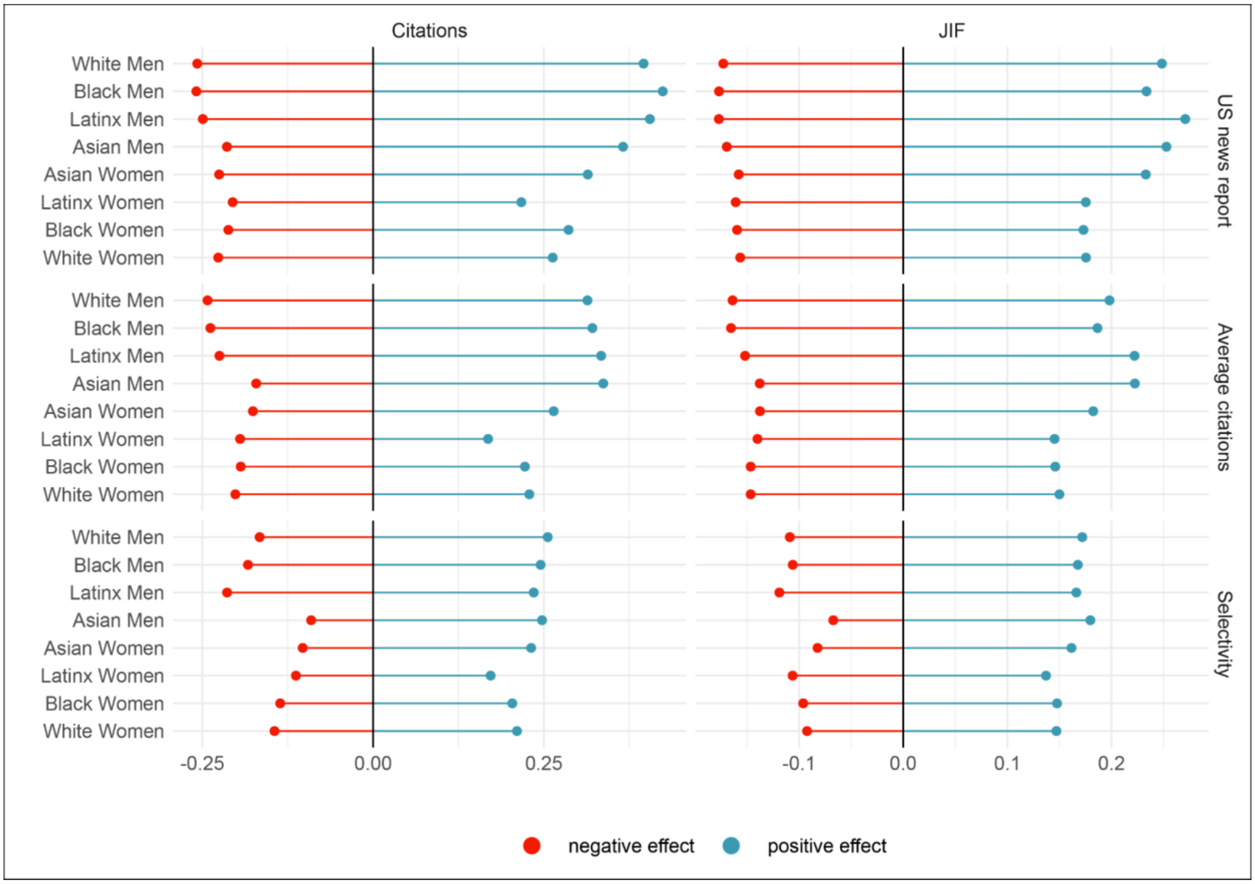

Figure S II 13. Negative and positive effects on citations and JIF, by race and gender between, across institutional groups. For each institutional classification, we compute the increase in citations and JIF between the top and middle group, and the decrease in citations and JIF between the low prestige and middle group. Citations and JIF are topic and year normalized. US News & World ranking: Top 10 institutions and not in the Top 100 with respect the top 100; institutions sorted by their average number of citations: Low (0.1, 1.47), and High (1.77, 4.07) respect to Medium (1.48, 1.74); and Carnegie Selectivity Index, Inclusive and More selective with respect to Selective.

Table S II 1. Number of papers, distinct authors and institutions, by institutional group.

Group	# papers	# authors	# institutions
Carnegie Selectivity Index			
more selective	3264304	2280454	187
selective	1283167	833853	206
inclusive	262617	168731	196
not indexed	428957	168731	96
Average citations of institutions			
High (1.77, 4.07)	1826346	1215155	60
Medium (1.48, 1.74)	1815227	1189355	78
Low (0.1, 1.47)	1746770	1204592	547
US News & World ranking			
Top 10	935931	579559	11
Top 100	2517913	1684950	89
Not in top	1901865	1330966	584
Women and Minority Serving Institutions			
HBCU	35518	24829	62
HSI	278109	169469	127
WC	8710	5320	25

Table S II 2. Citation gap compared to White men, by identity and institutional group, normalized by topic.

Group	Black Men	Latinx Men	Asian Men	Asian Women	Latinx Women	Black Women	White Women
US News & World Report							
Not Top	-3.26%	-5.02%	9.28%	-2.23%	-7.72%	-8.98%	-6.78%
Top 100	-2.32%	-4.56%	2.76%	-4.78%	-10.83%	-11.15%	-8.07%
Top 10	0.28%	-2.65%	-0.10%	-9.17%	-20.35%	-15.74%	-15.14%
Carnegie Selectivity Index							
inclusive	-5.68%	-11.77%	17.04%	4.02%	-2.66%	-8.69%	-6.69%
selective	-2.53%	-3.78%	4.71%	-4.27%	-8.44%	-10.56%	-7.96%
more selective	-2.90%	-4.77%	2.85%	-5.49%	-14.10%	-12.83%	-10.21%
Average citations of institutions							
Low (0.1, 1.47)	-2.41%	-5.43%	10.63%	1.04%	-6.62%	-7.92%	-5.87%
Medium (1.48, 1.74)	-2.25%	-5.85%	0.98%	-5.83%	-9.76%	-10.85%	-8.51%
High (1.77, 4.07)	-1.17%	-2.94%	2.50%	-8.19%	-18.47%	-15.22%	-12.94%

Table S II 3. JIF gap compared to White men, by identity and institutional group, normalized by topic.

Group	Black Men	Latinx Men	Asian Men	Asian Women	Latinx Women	Black Women	White Women
US News & World Report							
Not Top	-1.56%	-1.88%	4.41%	2.25%	-3.04%	-3.77%	-1.92%
Top 100	-0.88%	-1.14%	3.33%	0.40%	-3.70%	-4.44%	-3.20%
Top 10	-1.89%	0.87%	3.02%	-0.90%	-8.77%	-9.54%	-8.35%
Carnegie Selectivity Index							
inclusive	-1.47%	-2.39%	8.90%	5.23%	-2.83%	-3.45%	-0.92%
selective	-1.61%	-0.95%	3.06%	1.56%	-2.78%	-4.48%	-2.68%
more selective	-1.75%	-1.34%	3.30%	0.32%	-5.64%	-6.05%	-4.60%
Average citations of institutions							
Low (0.1, 1.47)	-0.95%	-1.31%	5.70%	3.56%	-1.94%	-3.11%	-1.67%
Medium (1.48, 1.74)	-0.65%	-2.30%	2.14%	0.33%	-4.03%	-4.35%	-3.14%
High (1.77, 4.07)	-1.50%	0.10%	3.83%	-1.04%	-7.79%	-7.99%	-6.66%

Table S II 4. Citation gap compared to White men, by identity and institutional group, normalized by field.

Group	Black Men	Latinx Men	Asian Men	Asian Women	Latinx Women	Black Women	White Women
US news report ranking							
Not Top	-3.24%	-4.75%	11.17%	-2.52%	-8.51%	-10.33%	-7.99%
Top 100	-2.30%	-4.60%	3.92%	-5.45%	-14.52%	-14.02%	-10.97%
Top 10	-0.38%	-2.84%	0.59%	-9.70%	-22.55%	-17.90%	-17.38%
Carnegie Selectivity Index							
inclusive	-6.28%	-11.28%	15.71%	1.51%	-2.84%	-9.90%	-8.56%
selective	-2.53%	-3.72%	7.09%	-3.59%	-10.16%	-11.46%	-9.23%
more selective	-3.01%	-4.81%	3.87%	-6.31%	-17.13%	-15.66%	-12.86%
Average citations of institutions							
Low (0.1, 1.47)	-2.56%	-4.93%	12.53%	1.08%	-7.79%	-9.39%	-7.00%
Medium (1.48, 1.74)	-1.94%	-5.78%	1.71%	-6.55%	-13.26%	-13.68%	-11.51%
High (1.77, 4.07)	-1.61%	-3.29%	3.79%	-8.99%	-21.48%	-17.85%	-15.61%

Table S II 5. JIF gap compared to White men, by identity and institutional group, normalized by field.

Group	Black Men	Latinx Men	Asian Men	Asian Women	Latinx Women	Black Women	White Women
US news report ranking							
Not Top	-1.46%	-1.02%	7.13%	3.42%	-3.97%	-5.04%	-3.11%
Top 100	-1.04%	-0.76%	5.91%	1.15%	-5.53%	-6.12%	-5.02%
Top 10	-1.84%	0.97%	4.55%	-0.90%	-9.96%	-10.91%	-9.79%
Carnegie Selectivity Index							
inclusive	-1.88%	-1.34%	9.60%	4.74%	-3.60%	-5.56%	-2.60%
selective	-1.63%	-0.52%	6.13%	3.18%	-3.78%	-5.47%	-3.75%
more selective	-1.73%	-0.91%	5.63%	0.84%	-7.24%	-7.62%	-6.28%
Average citations of institutions							
Low (0.1, 1.47)	-1.00%	-0.14%	8.61%	4.93%	-3.10%	-4.79%	-3.03%
Medium (1.48, 1.74)	-0.76%	-1.93%	4.74%	1.06%	-5.77%	-5.71%	-4.85%
High (1.77, 4.07)	-1.52%	0.05%	5.66%	-0.88%	-9.22%	-9.49%	-8.27%

CHAPTER 6. SUMMARY AND OUTLOOK

6.1 Summary of results

The general goal of this thesis is to develop a case study—geographically and timely delimited— of race and gender inequalities in publications and impact of authors, crossed by topics and institutions.

This goal is fulfilled through bibliometric analysis. Given the data available on Web of Science, I first needed a way to curate this database to infer the identities of authors. Chapter 3 presents the potential biases when inferring racial categories from names using several different methods and proposes the use of fractional counting as the tool that minimizes those potential biases. This chapter also warns about the use of census averages for imputation of missing names. The most important contribution of chapter 3 is that it shows empirically how the lack of contextualization of data can create new inequalities. This first step sets the technical basis for the analyses that follows and develops a framework that can potentially be used—with the appropriate modifications— on other countries.

With the expanded database, chapter 4 studies the publications of US first authors between 2008 and 2019. This chapter shows the underrepresentation of Black, Latinx and women authors in US science. It defines relative over and underrepresentation to understand how people from different identities distribute across topics and founds that there is a relative underrepresentation of women in fields like Physics and Engineering. The analysis by major disciplines was largely covered by previous literature, but this chapter considers that there is a relevant dimension of analysis on the distribution of authors across topics. To inquire this line of research, this chapter builds a topic modeling representation of articles to infer what is their object of study. The results show the distribution by topic, race and gender in Social Sciences, Humanities and Professional fields, and Health, and found an alignment between intersectional identities and research topics that concern those populations. On impact, the chapter shows the distribution of citations across topics to find an alignment between the proportion of White men and number of citations of topics. Together with the previous results, this means that those topics that are related with the experience of the marginalized populations receive less attention than other topics, which contributes to the inequality in citations.

Also, the within topics' citations distributions by race and gender show that regardless the topic, men —and especially White and Asian men— tend to receive more citations. This shows that the citation bias is only partially explained by the topical interest.

The schema presented at the introductory chapter 2 shows the centrality of institutions in the reproduction of inequalities. Chapter 5 is devoted to study the relation between institutions, topics, and intersectional discrimination on science. For this, I semi automatically disambiguated names of institutions—with further human validation—. The chapter uses these institutional names to match them with Carnegie classification and build a series of institutional categories for the analysis. It focuses on mission- and threshold-driven classifications such as HBCUs, WCs and HSIs; and on three proxies of prestige: *perceived* prestige (US News & World report ranking), *research* prestige (by historical citations) and *selectivity* prestige (Carnegie Selectivity Index).

The results show that there is a correlation between institutional type and topical profile. Following the results from the previous chapter, as has been showed that intersectional identities have a characteristic topical profile, these intersectional identities are used as pivots to infer the topical profile of institutions. Mission-driven institutions show a correlation with the topical profile of Black women, which implies that their mission is fulfilled beyond the promotion of Black and Women students in undergraduate programs, as they also promote a more diverse scientific landscape.

The three categorizations of prestige give a robust result conclusion: More prestigious institutions show a relative underrepresentation of Black and Latinx authors. Top institutions also show a topical profile aligned with the topical profile of men, while less prestigious institutions show a topical profile that is closer to the one of women. This result is not the product of the different representation of identities in different types of institutions, as it sustains after controlling for this factor.

Authors from marginalized intersectional identities in top institutions show a topical profile that is not aligned with that of their home institution. Nevertheless, these authors also seem to be less aligned with the topical profile of their identity across institutions. This shows hints of a very complex relation between institutions, authors, and topics. There is a clear alignment between the topical profile of top institutions and men's topical profile. Authors from marginalized intersectional identities that work on top institutions bring diversity to their institutions, but at the same time have a less characteristic topical profile as other authors from their same identity.

This chapter also aims to understand how all these elements come to play in the distribution of impact. For this, this work builds a series of linear models to partially control for different aspects. First, the comparison of models shows that the topical profile has a deep effect on citations, even after controls for institution's prestige. This is shown by the larger effects observed on the model that only accounts for a field-based normalization of citations and JIF instead of topic-based normalization. Institutional prestige has a large explanation of the differences observed in impact measures. Black and Latinx and women authors have a penalty on their impact, even after controlling for the institutional effect. To understand the experience of authors from marginalized populations across institutions, subsets of models are built for each institutional type. This shows a larger impact gap for marginalized intersectional identities on top institutions. The citation and JIF gap are larger for top institutions than for less prestigious ones.

6.2 Discussion

This thesis is grounded in the premise that the scientific enterprise is a branch of capitalist production, where the scientific community operates as a massive collective worker. Consequently, the relations among researchers, as well as between researchers and their employing institutions, must be viewed as complex and often conflicting labor relations that involve both collaboration and competition. As scientific workers, we engage in the scientific labor market with the primary aim of securing our livelihoods. The process of scientific inquiry demands a collaborative and innovative work, which needs individual motivations that extend beyond the mere adversarial relation that characterizes other labor relations. Nonetheless, this inherent antagonism persists, and plays a pivotal role in understanding the inequalities that exist within the scientific community.

The first source of antagonism within the scientific community lies at the entry level, where the highly skilled nature of the profession limits access to a privileged minority of the workforce. Only 1% of the population holds a PhD (OECD, 2022b), and even among those who do, securing a research career is a fiercely competitive process. The inequalities that exist within the scientific community are merely one facet of a broader system of labor stratification, in which a small group of the working class can access highly skilled and well-compensated job, while the vast majority of workers are relegated to low-paying insecure jobs. The process of stratification is often reproduced across generations, with economic background playing a central role in defining access to education and the cultural capital necessary for becoming a highly skilled worker. This process unfolds across time and space, and gender and racial markers (among other factors) reinforce and reproduce the division of labor within specific countries. As Foucault has argued, systemic racism serves as an ideological justification for labor stratification (Foucault, 1998), while gender norms perpetuate the sexual division of labor. These mechanisms are also contextual and have evolved over time. For example, the original capital accumulation in America was based on forced labor, ideologically and legally sustained in racial segregation. Historical legal structures like Latin America's *mita* and *yanaconazgo* systems, and African slavery in the United States have been followed by other forms of legal discrimination, such as the Jim Crow laws. The alleged racial blindness of current legal systems still reproduces material inequalities by denying the role of this racist legacy. People of Native American and African American descent continue to be overrepresented in low-skilled and low-paid work.

The differentiation process extends beyond national boundaries, as the new international division of labor allows for the fragmentation of the production process across multiple countries. Highly skilled and well-compensated work is allocated in Europe and the United States, while low-skilled work is outsourced to countries with lower labor costs. Science and technology are integral to this global value chain, which in turn helps to understand the subjacent role of the stark disparities in research resources between countries. Conversely, when jobs requiring lower levels of qualification cannot be outsourced from countries with a highly skilled labor force, such vacancies are often filled by migrant workers, many of whom lack the legal protections afforded to the domestic workers by their citizenship status. This establishes the migrant condition as another dimension of structural discrimination.

This stratification process of the labor force determines the competition to enter and thrive in the scientific field, where privileges and disadvantages hold a central role. Individual-level markers such as race, gender, economic status, nationality, and migrant status define the possibilities of entering science and are also part of the stratification process that occurs within the scientific community. Underrepresentation not only exists at a general level —there are fewer authors from marginalized communities— but is also reinforced and multiplied within the hierarchical structure of science, through factors such as seniority, institutional affiliation, and individual prestige.

Going back to science as a specific productive branch, there is also the question of who benefits from the product of the scientific endeavor? Grant reviews, strategic planning, and research evaluation are mechanisms to organize the directions of scientific work. While these reviews are primarily conducted by other scientists, they are heavily influenced by the gatekeepers' attitudes and values, which reflect the dominant culture and power dynamics within the field. On other cases, reviews are based on impact metrics that automatize the perpetuation and amplification the field's inequalities. Strategic planning for funding allocation goes beyond peer review by scientists and it is ultimately in the hands of agencies and enterprises that determine what research get funded and who benefits from its results. With the rise of New Public Management, and the increased participation of private companies in research funding, the decision of who benefits the most from science is further removed from scientists themselves, in what Bourdieu called the heteronomy of science.

In sum, the mechanism that perpetuates inequalities follows a vicious cycle. Firstly, the stratification of the labor force results in the exclusion of specific race and gender identities from science. This exclusion leads to minoritization of these groups in science, even though they constitute a significant proportion of the population. Secondly, resources in science are not allocated according to the general needs of the population, but are based on the norms and values of the dominant groups in science, and the interests of profit-driven companies. The stratification process of the population by their race, gender, class, or nationality also implies that those with marginalized identities have less power in the struggle to allocate resources towards research questions that are most relevant to their communities. These mechanisms are intertwined, as the benefits of science tend to accrue disproportionately to privileged groups, further reinforcing their privileged position.

Bourdieu's theory of habitus can shed light on another challenge that marginalized authors face. The field habitus is a product of scientists across generations and, in a context of systemic inequalities, it is shaped in the image of privileged groups that dominate the field. While the training process for acquiring the field habitus may relate to the traditional familial habitus of dominant groups, authors with marginalized identities entering the field can face a clash between their familial habitus and that proposed by the field. In those cases, authors will have to find a coping mechanism, which may involve rejecting their personal habitus in favor of the field habitus (adaptation), embracing their original habitus (confrontation), or negotiating between both (switching) (Ingram, 2018). But any of these strategies can come at a cost. While adapting to the new habitus may help marginalized authors meet the expectations and values of the field, it can lead to personal consequences (such as feeling like an outsider or impostor syndrome). On the other hand, embracing one’s own habitus affect career development if the work does not align with the dominant values of the field. This conflict is expanded on elite institutions, which play a key role in the conformation of the field habitus given their accumulation of academic capital.

The topical choice can be thought as one of the expressions of authors’ habitus. This thesis shows how authors from marginalized identities publish more on topics that relates with their intersectional identities. This is an expression of a different habitus. But the analysis of institutions can show with more detail how the conflict develops on elite institutions. The results show how marginalized authors are both less aligned with the rest of the authors in their institutions, and less aligned with other authors that share their intersectional identities. On the other hand, White men from top institutions show a large alignment in both dimensions. This means that the habitus conflict is indeed in place for marginalized identities, and that both mechanisms (adaptation and confrontation) are in place.

Despite the persistent and widespread nature of inequalities in science, there have been some positive changes observed in recent years within the US context. It is important to understand the context of these changes, their reach, and limitations. Critical race theory provides a useful framework for this, specifically with Derrick Bell’s interest convergence dilemma. Bell argued that progress towards racial desegregation in US schools, as exemplified by the Brown v. Board of Education case, occurred because it was also in the interest of White people to improve the public image of the US in the context of the Cold War. Similarly, the current promotion of

Diversity, Equity, and Inclusion (DEI) policies by several higher education institutions can also be understood in the context of the interest convergence dilemma (Bhopal & Myers, 2023). Public expectations of equality have changed, and institutions are now expected to have better representation of the population. While this opens possibilities, it also highlights the limitations of some DEI policies, as tokenization can be used as a mechanism to adapt to the public expectations without changing the structural problems. In this way, privileged groups can showcase diversity without truly redistributing power within the field. To change the power distribution in the field it is necessary to transform the field's habitus to include alternative class habitus. These alternative habitus are often reflected in research topics, especially in Social Sciences, Humanities, Professional Fields, and Health, where authors' identities may inform their research. This falls beyond the public sphere where the interest convergence takes place. It is therefore possible to see improvements in the public dimension —representation— while the value assigned to topics, together with other private forms of the power struggle like division of labor (Larivière et al., 2021), remain unchanged.

In the context of this thesis, the extended results (see https://sciencebias.uni.lu/app/) show a steady decrease of White men authors, from 38% to 33% between 2008 and 2018 among all authors, and from 43% to 39% for authors with more than one publication. Although this is arguably too little and too slow in terms of changes, it goes in line with the interest convergence hypothesis. The analysis of topical profiles allows to shed light over the part of the problem that do not receive as much attention and measurement, and where therefore there is no interest convergence. What that analysis showed was a complete alignment between White men's and elite institutions' topical profiles. In this sense, by using computational methods and secondary sources of information, this thesis contributes to shedding light on what escapes the common public sphere of systemic inequalities in science. This could also be a step towards forcing an extension of the space of interest convergence.

The impact of research and researchers is heavily conditioned by the factors discussed above. Discrimination based on race and gender identity can directly affect the assessment of research quality, but there are also indirect mechanisms that create impact biases. The different value assigned to research topics, the journals in which research is published, and the institutional affiliation of authors, all powered by the cumulative nature of prestige, are mechanisms that can undermine the impact of research made by marginalized scholars. The selection of research topics is not a free will individual decision, but it is defined by structural determinants. The lived experiences on the communities of marginalized scholars promote their interests on topics that reflect on the needs of their communities. This is not an absolute determination, where an author identity automatically creates a specific interest, but an underlying structural mechanism, which will reflect on the phenomena observed in this thesis: that statistically, authors from marginalized communities tend to work more on some specific topics. The reason why those topics are undervalued and understudied is also structural. The marginalization of identities and topics is the mechanism through which deeper social structures operates to undermine those topics. The underlying problem is that, given the general labor force stratification, the capitalist accumulation process that fuels the scientific practice has no interest in devoting more resources into the wellbeing of the population that has the low paid, insecure, and unqualified jobs. This interest takes form in the scientific community through the dual mechanism of heteronomy and the underrepresentation of marginalized identities among scientists.

Discrimination of scientists based on their individual identities appears in this way as part of a bigger problem. The inequalities in science are framed by the power struggle for the benefits of scientific production, and by the general stratification of the labor force, in which scientists are part of a high skilled minority.

Together, these results bring new empirical evidence to the study of race and gender inequalities in science, putting a number to many previous qualitative studies. The use of computational methods such as the race and gender inference and the topic modelling allow a deeper examination some of the mechanisms of discrimination in science. The proposed methodology allows to find which are the specific research topics that are related with specific identities. This opens the possibility of direct public policy interventions to promote research on these topics. This thesis also shows the effects of topical choice on impact, which deepens our understanding on why impact metrics should be used with caution on research assessment. The incommensurability between most quantitative and qualitative analysis affects the credibility of much research made on this subject, given its qualitative nature. Although I do believe that qualitative analysis is valuable and its results should be considered, there is still a need for quantitative research that reinforces conclusions previously made through other approaches. This thesis contributes to this need.

Diversity, Equity, and Inclusion policies have been mostly focused on the representation of women and racialized authors in science, and especially in STEM. The evidence presented in this thesis supports the need for those actions, but also highlights the need of other types of interventions. Research topics are an important driver of inequality in science, and many topics that are relevant to marginalized communities are understudied. There is a need to empower those topics through funding and recognition of their relevance. Also, this work founds that elite universities are less diverse in terms of composition and topical profile and show the highest impact gaps. These institutions have the means to implement positive changes and promote diversity of authors and topics. On the other hand, HBCU, WC and HSI show more diversity not only in their students —their main goal—, but also in their research. Mission-driven institutions represent role models of how to promote diversity in science. For this reason, this thesis proposes the 'Howard-Harvard effect', where elite institutions hinder diversity, and mission-driven institutions promote it. Researchers from elite institutions need to demand change in the research agendas of their institutions together with better representation of marginalized identities, and the scientific community overall needs to empower mission-driven institutions, through better funding to support their efforts.

6.3 Competing explanations

The presented discussion and interpretation of results is informed by my epistemic and ontological stand. As mentioned in the literature review, my positionality in this regard is opposed to the mainstream trends, namely positivism and postmodernism. Given this, in this section I will briefly discuss how the empirical results presented in this thesis could be differently interpreted by this other points of view.

A positivist point of view on a similar phenomenon was presented by Judea Pearl (2018) as the 'Berkley admission paradox', where women were observed to have a lower admission rate, because they were applying to departments that had the lowest acceptance. From this point of view, there might be reasons for women to choose certain departments over other, which can be based on society's general sexism, but this is not a responsibility of the University, and therefore there is no relevant bias or discrimination after controlling for department, solely a statistical difference. There is no questioning on why certain departments have more funds than others, which results in higher acceptance rates. By considering the different mechanisms of systemic inequality as things that should be controlled in a model, this point of view is only able to consider as a problem the direct explicit discrimination based on the identity of authors and disregard all the elements that constitute the identity as a way of structuring the labor force stratification. Therefore, the political implications of this approach are limited, as it is impeded to transform any mechanism beyond direct discrimination. Extrapolated to the subject of this thesis, the research topics are a decision of the individual researchers, that may or may not be affected by general social patterns, but it is ultimately out of the scope of action of science.

6.4 Research questions

At the introduction a series of research questions were presented, that can be now answered:

> **RQ1**. Is it possible to operationalize the racial identities of authors from the information available in bibliometric databases?
>
> With the information available for US, it is possible to operationalize authors' racial identity based on their family names. Any extrapolation of this results to other countries needs to consider the data availability and the historical development of racial categories and naming practices in that country.
>
> **RQ2**. Is it correct to use thresholding for individual-level classification of authors' race?
>
> In the case of US thresholding is a pernicious method, as it underestimates Black authors. Using full distributions is a better practice, although differences in the US census population and the authors population may lead to an overestimation of some groups.
>
> **RQ3**. How is the composition of the US scientific labor force by race and gender?
>
> The composition of the US scientists is biased with respect of the census, with an over representation of White men. Asian authors are also overrepresented, but this population also shows a large proportion of migrant authors, which indicates that the census is not a proper benchmark for this group.
>
> **RQ4**. How does this composition vary by discipline?

Latinx, Black and White women are relatively more present in disciplines such as Health and Psychology, and especially underrepresented in Physics, Mathematics and Engineering & Technology. Asian women are underrepresented in Arts, Humanities, and Social Sciences, and more present in Biomedical Research. Asian men show a similar underrepresentation to Asian women, but they are overrepresented in Engineering and Technology and Physics. Latinx men are underrepresented in Health, Psychology, and Professional Fields, and are more present in Mathematics. Black and White men are relatively underrepresented in Health and Biomedical Research, and overrepresented in Humanities and Social Sciences. Fields such as Biology, Clinical Medicine and Earth & Space Sciences show the lowest relative over/underrepresentation of groups, which means that they follow the general composition of science—i.e., absolute overrepresentation of White men—.

RQ5. Which is the relation, if any, between race and gender identities and research topics?

I found strong relations between race and gender identities and topical interest. In social Science and Health, although a large group of topics is unrelated with authors' identities, there is a considerable number of research topics where racialized and women authors publish more, which are aligned with their identity communal interests. Women publish more on topics related to gender violence, Latinx authors publish more on topics related to migration, Black authors publish more on topic related with racial discrimination.

RQ6. What is the relation between research topics and citations?

I found a two-sided relation between topics and citations: There is a between-topic bias, where topics with more presence of White and Asian men receive more citations; and an intra-topic bias, where White and Asian men receive more citations across topics.

RQ7. How would the research space look like if the authors composition by race and gender would match the census distribution?

Using contrafactual scenarios, an authors' composition that matches the census would shield 29% more articles on public health, 26% more on gender-based violence, 25% more in gynecology and gerontology, 20% more research on immigrants and minorities, and 18% more in mental health. This is the knowledge gap that the underrepresentation of women and racialize authors in science produced.

RQ8. What is the representation of marginalized scholars in institutions, given their mission and prestige?

In absolute terms, the representation by race and gender is stable across institutional types, following RQ3. White men are overrepresented across all types of institutions, except for Women's Colleges (WC), where they are the second largest group, following White women. Nevertheless, the compositions relative to each race and gender group's size shows variation. Black men and women are more present in HBCUs, Latinx authors in HIS and Women across races are more present in WC. Latinx and Black authors are relatively underrepresented in more prestigious institutions, and correspondingly overrepresented in less prestigious institutions.

RQ9. How women and minority serving institutions reflect their mission on their topical profile?

These institutions show a topical profile that is partially aligned with the topical interests of the marginalized populations they serve. HSI, WC and HBCU have a positive correlation with the topical profiles of Latinx, Black and White women. HSI show a larger relation with Latinx women than any other group, and although negatively correlated with Latinx men's topical profile, this correlation is smaller than White and Black men. Correspondingly, HBCU show more correlation with Black women, and a smaller negative correlation with Black men than with White and Latinx men.

RQ10. How does prestige relate to the topical profile of institutions?

I found an alignment between prestige of institutions and gender. Elite universities show a strong positive correlation with men's topical profiles, and a negative correlation with women's topical profiles, and the opposite happens with less prestigious institutions.

RQ11. Are marginalized authors from top institutions more topically aligned with other marginalized authors or with other authors from top institutions?

Women authors that work on prestigious universities show less relation with the topical profile of their institutions than men from those same institutions, but at the same time show a less alignment with other women than men from top institutions with respect to other men. This implies that women bring more diversity to top institution, but at the same time those women that work on top institution are not fully aligned with the topical interests of women in other institutions.

RQ12. How does institutional prestige and topical profile relate to impact?

The topics distribution affects the expected citations and JIF. Institutional prestige has a strong effect on both citations and the JIF of the journal in which the articles are published.

RQ13. What is the impact gap of marginalized scholars and how this relates with topics and institutional prestige?

Across institutions, there exists a citation and JIF penalty against women and racialized authors, with Latinx and Black women receiving the largest penalty. More prestigious institutions show a larger gap for both citations and JIF.

6.5 Limitations and future directions of analysis

The analysis suffers from some serious limitations. The race and gender inferences are limited to the data availability and fail to account for non-binary authors, Native Americans and Two or more races' authors. Also, the shared family names between Black and White population in US makes it hard to disambiguate both groups, and therefore given the method used there might be an overestimation of Black authors, and an overestimation of the alignment between the two groups in terms of disciplines and topics. Therefore, these results can only be considered as the lower bar of inequalities, as we would expect a higher underrepresentation and a more characteristic topical profile for Black authors. There is a need for alternative methods that rely on self-identification of authors' race and gender identities to correct these problems. Self-identification would also allow to study discrimination of authors that go beyond the cis-hetero norm.

The scope of analysis is also limited: I focus on US between 2008 and 2020, and give particular attention to Social Science, Humanities, Professional Fields, and Health. Given this, the results can be considered a large-scale case study.

This thesis is focused on the US because race and gender identities need to be properly contextualized. Nevertheless, other case studies could be made to see how much the results of this work sustain on other societies with a different racial and gendered history. This would be particularly interesting on countries such as South Africa, where most of the population belongs to the oppressed race(s). Also, societies with a high proportion of mixed-race population, like Brazil or other Latin-American countries, might show different results. Even when this type of analysis needs to be regionally contextualized, it is important to move beyond US and Europe for this type of research to avoid assuming that the rest of the world works in the same way as these regions. Beside the multiple possible case studies, the international distribution of resources in science is a major factor of inequalities that was omitted from the present work. Future lines of work should integrate the international dimension that crosses all national realities. The economic background is a very important dimension of inequality that given the data limitations was excluded from the present analysis. Alternative sources that allow to include this dimension would be key for a broader understanding of systemic inequalities. The study of collaborations is also important and can be incorporated to the present analysis by studying co-authorship and its relation to race, gender, and topics. Mobility necessarily goes beyond national boundaries, but it is important to understand the relation between mobility and changes in topical profiles. Awards and funding were also excluded from this analysis but could be included by including other data sources. The role of founders in the promotion of specific topics, and the relation between those topics and race and gender identities would give light to a very important mechanism of inequalities in science.

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