Race-related Research in Economics: Volume, Content and Publication Incentives*

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Abstract

Issues of racial justice and economic inequalities across racial and ethnic groups have risen to the top of public debate. Economists' ability to contribute to these debates is based on the body of race-related research. We study the volume and content of race-related research in economics and examine the implicit incentives to produce such work. We do so for a corpus of 225,000 economics publications from 1960 to 2020 to which we apply an algorithmic approach to classify race-related work, and construct paths to publication for 22,000 NBER and 10,000 CEPR working papers posted over the last few decades. We present three new facts. First, since 1960 less than 2% of economics publications have been race-related, with such work being balkanized into a few fields and largely absent from many others. There is an uptick in such work in the mid 1990s. Among the top-5 journals this is driven by the *AER*, *QJE* and the *JPE*. *Econometrica* and the *REStud* have each cumulatively published fewer than 15 race-related articles since 1960. Second, on content, while over 50% of race-related publications in the 1970s focused on Black individuals, by the 2010s this had fallen to 20%. There has been a steady decline in the share of race-related research on discrimination since the 1980s, with a rise in the share of studies on identity. Finally, irrespective of field, race-related working papers do not have worse publication outcomes compared to non race-related working papers, in terms of publication likelihood, quality of publication, publication lags and citations. Hence conditional on working papers being produced, the publications process provides little disincentive to work on race-related issues. We discuss policy implications stemming from our findings on economists' ability to contribute to debates on race and ethnicity in the economy. *JEL: A11, B41*.

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1 Introduction

Economic ideas and concepts shape society through their impact on business, government and the media [Fourcade *et al.* 2015, Maesse *et al.* 2022]. Distinct features of economic methodology have enabled economists to tackle a widening array of subject matter, with a source of strength for economics being its diversity of subfields and the rise of empiricism, which has also led to economics increasingly influencing research in other disciplines [Lazear 2000, Angrist *et al.* 2020]. We study whether and how economists have leveraged this influence to contribute knowledge relevant to tackling a major social issue: large and persistent gaps in economic well-being across racial and ethnic groups. Using an array of newly matched bibliometric data from journal publications and working paper series, we provide novel evidence on the volume and content of race-related research that economists have produced, and the implicit incentives provided to economists to work on such topics via the publications process. Our finding raise multiple of issues of whether and how economists could do more on this topic.[1,2]

The spine of our analysis is built around the research content of academic journal publications in economics: these constitute the very subject matter of the discipline, laying the scientific foundation for economists to contribute to public debate. We identify race-related research by taking an algorithmic approach to classify such work from a corpus of 225,000 publications in over 200 economics journals from 1960 to 2020. Publications are also the key metric along which career success is defined – they carry career rewards in terms of hiring, promotion, pay and tenure. We thus analyze the implicit incentives to produce race-related work by tracking paths to journal publication for 22,000 NBER working papers and 10,000 CEPR working papers.

The first step in our analysis is to identify race-related research. We fully recognize there is no definitive way to approach this given there can be reasonable differences in normative views on what such a body of work should constitute. Given the volume of publications considered, it is also infeasible to codify race-related research by hand. We thus take an algorithmic approach to classify publications as race-related, using keywords along two dimensions: (i) the racial or ethnic group being studied; and, (ii) the issue being studied, with a focus on five topic areas: discrimination, inequality, diversity, identity and historical studies. Examples of the 35 (case-insensitive) group

[1] Maesse *et al.* [2022] discuss four channels that economists have used to expand their influence: expert discourse, modalities of government linking policy and science, economists in academic, political and media networks, and economics as a social field. Lazear [2000] describes three features of economic methodology driving economic imperialism: the modelling of rational agents engaging in maximizing behavior subject to constraints, the importance of equilibrium, and the defined concept of efficiency. Angrist *et al.* [2020] document the rising influence of economics among other disciplines. They show economics is now the most widely cited social science in 7 of 16 disciplines, partly because different disciplines cite economics papers from different fields.

[2] The meaning of race and ethnicity have been extensively discussed in the social sciences. Ethnic differences apply across measurable group categories, and racial inequalities reflect racialized processes attributed to visible differences, with there being overlap in how these terms are used [Platt 2019]. While there is no biological basis for dividing people into 'races', race retains a social meaning. Throughout, for expositional ease, we refer to race-related research as work relevant for understanding racial and ethnic inequalities in well-being.

keywords we use are *race*, *african-american, person of color*, and *ethnicity*. Examples of the 103 issue keywords we use are *discrimination*, *prejudice*, and *stereotype*. Our algorithm selects a publication as being race-related if: (i) at least one group keyword is in the title; or, (ii) at least one group keyword and at least one issue keyword are mentioned in the title or abstract (excluding the last line of the abstract).

Applying this algorithm to our corpus of publications, we reveal the following new facts on the volume and content of race-related research in economics. From nearly zero race-related publications in the early 1960s, the share of race-related publications rose to a peak of 2.9% in the mid 1970s, fell to 1.6% from the mid 1980s to the mid 1990s, and has risen steadily thereafter to around 2% today. This represents a cumulative body of knowledge of just over 4000 race-related publications in economics from 1960 to 2020. Accounting for changing journal influence over time, the *AER*-weighted share of race-related publications shows a more rapid rise, more than doubling since the mid-1990s. Hence although the share of publications studying issues of race has remained relatively flat since the mid 1990s, the prominence of such work has risen since the mid 1990s.

We zoom in on patterns of race-related research in the top-5 general interest journals in economics given these represent what is considered of broad interest to the discipline, reflect views of leading scholars, editors and referees, and are among the most highly cited publications [Heckman and Moktan 2020]. We document a major uptick in the share of race-related publications in the top-5 in the late 1990s, that has continued since – driven by increased numbers of such publications in the *AER*, *QJE* and *JPE*. In contrast, *Econometrica* and the *Review of Economic Studies* have each cumulatively published fewer than 15 race-related articles between 1960 and 2020.

Examining the evolution of content in race-related research, we find that in the 1970s race-related publications divided almost equally between those studying non-specific minority groups (so using keywords such as *ethnic minority* or *non-white*) and those focused on Black groups. By the 2010s the share of publications studying non-specific groups had risen to 75%, while those studying Blacks had fallen to 20%. Research studying Latinx groups emerged in the 1980s, but still only 3% of all race-related publications in the most recent years study this group. The study of other groups – including Asians and Native Americans – still comprises less than 2% of all race-related research. On topics, there has been a steady decline in the share of race-related research on discrimination since the 1980s, with a rise in the share of studies of identity.

To examine the distribution of race-related research across fields, we apply our algorithm to NBER working papers (WPs) posted from 1974 to 2015, where *JEL* classification codes are provided for each. Around 3% of NBER WPs have been race-related, but the shares vary tremendously across fields. We document a balkanization of race-related research into a few fields, and with such work being largely absent from many others. *Macroeconomics* (JEL Code E) – the most prominent field in the NBER series with 12% of all WPs – has the lowest share of race-related WPs (.35%). We do find some indication of positive time trends in the production of race-related research in fields in which it remains most scarce – such as *Macroeconomics* and *International*

Economics. Fields with among the highest shares of race-related WPs are *Labor Economics* (J), *Urban Economics* (R) and *Economic History* (N). These each have at least 7% of WPs being race-related – three times the disciplinary average. For CEPR WPs, around 2% have been race-related over the 2000s, with similar patterns across fields being observed as for the NBER series.

The remainder of our analysis exploits the classification of *individual* pieces of work to understand the implicit incentives researchers have to engage with such topics. We do so by examining paths to publication for WPs, merging data on NBER and CEPR WPs with data on published articles, and comparing race-related papers to various counterfactual WPs. This is a process where editors of leading journals have recently expressed concerns about difficulties in publishing race-related research [Omeokwe 2020].

Unconditionally, race-related NBER WPs are less likely to be published in an economics journal ($p = 0.28$). Those which are published in an economics journal, are published in journals with a substantially lower *AER*-weight ($p = .002$) – a metric of journal quality. At the top end of the distribution, conditional on being published in an economics journal, race-related publications are no less likely to be published in a top-5 journal ($p = .361$). However, once we condition on date of posting, *JEL* code, WP characteristics and author affiliation, race-related NBER WPs are not differentially likely to be published in an economics journal relative to not race-related NBER WPs, and are actually 3.9pp more likely to be published in a top-5 economics journal, all else equal ($p = .086$). They also experience no longer publication lags at the top-tier than other working papers. This is consistent with such papers not being held to a higher standard. Moreover, we see no difference in citations between race-related and non race-related WPs. This is consistent with such papers not being held to a lower standard of publication – a result robust to controlling for publication journal fixed effects.

Taken together, our results suggest that conditional on observables, there are few publication penalties for NBER working papers that are race-related. This conclusion is confirmed and extended in a series of further checks in which we consider: (i) text readability scores as more nuanced measures of whether race-related WPs are held to a differential standard in the publication process [Hengel 2022]; (ii) paths to publication for CEPR WPs, that are largely authored by economists based in Europe rather than US-based affiliates of the NBER.

A concern over the interpretation of these findings is that conditional on *JEL* code, WP characteristics and author affiliation, the style of race-related WPs might still differ from other work, for example in methodology, or policy relevance. A premium to these traits in the publication process might then mask any penalties that race-related work otherwise faces, leading to the null results found (with the opposite being the case if there are publication penalties for these other traits). We address this by considering two alternative sets of counterfactual WPs rather than all non race-related working papers: (i) WPs that have at least one of the topic keywords in their title and/or abstract – this counterfactual mostly includes WPs that study issues of inequality, just not through the lens of racial/ethnic differentials; (ii) using machine learning to classify the

topic of WPs and then control for these broad topics instead of controlling for *JEL* codes. In both comparisons our core results continue to hold.

In short, the evidence we provide from different angles all points to the same conclusion. If the publication process provides implicit incentives to work on certain topics, there is little evidence this process should discourage individuals from working on race-related research.

Our work sheds new light on the ability of academic economists to contribute on a scientific basis to public debates on racial justice and the causes, consequences and solutions to persistent economic inequalities across racial and ethnic groups. A preliminary version of the algorithm we use to identify race-related research was used in our earlier work [Advani *et al.* 2022], the focus of which was to describe the time series on race-related work in economics, compare these aggregate series to other disciplines, and use the *Social Science Prediction Platform* to examine whether economists were aware of trends in the publication of race-related research. In the current paper, we refine the algorithm, describe the content of race-related research in economics in more detail including variation across fields and the economics journals such work has published in, and consider how the entire pipeline from working papers to publications varies between race-related and other research. We extend the wider literature in two directions.

First, by placing the subject matter of economic research at the heart of our analysis, we add to a nascent literature classifying race-related research in economics, that does so either in terms of a specific area, such as discrimination [Bohren *et al.* 2020] or with regards to a specific journal, such as the *AER* [Horpendahl and Kling 2020]. In contrast, we take a disciplinary-wide perspective spanning a 60 year horizon of publications, to understand the content and publication outcomes of race-related research in economics. Our approach is thus more aligned to work describing corpi of work in economics [Angrist *et al.* 2017, 2020, Kleven 2018, Currie *et al.* 2020], or the representation of minorities in a large corpus of books [Adukia *et al.* 2023].[3]

Second, by studying the implicit incentives provided by the publications process to work on such ideas, we complement an existing literature that has focused on how elements of the publication process might be biased against *individuals* based on their traits – such as gender or race, that ultimately feed into the under-representation of minorities [Lundberg and Stearns 2019, Bayer and Rouse 2016, Bayer *et al.* 2020]. In contrast, we focus on the issue of whether the *subject matter* of research influences its path to publication. To be the best of our knowledge, there are no comparable estimates of this in the economics discipline.[4]

For both lines of inquiry above, we do not take a normative stance, but rather aim to lay out

[3]Bohren *et al.* [2020] study the miscategorization of types of discrimination in economics research. They find that between 1990-2018, 10 economics journals (including the top-5), published 105 empirical papers focused on topics such as discrimination, bias and disparities. Our algorithm identifies a broader set of topics for race-related research. Horpendahl and Kling [2020] document the rise in articles addressing issues of race in the *AER* (and in the *AEA Papers and Proceedings*) from 1991 to 2019.

[4]Studies of minorities in economics have focused on barriers to entry, promotion and publication processes [Collins 2000, Price 2009, Bayer and Rouse 2016, Bayer *et al.* 2020, Logan and Myers 2020, Slater 2020].

positive evidence that might usefully inform normative questions on how economists can contribute to important societal debates. Throughout as we present our analysis, we discuss avenues of need of greater research. We build on this in our concluding discussion by identifying areas of race-related research that might be relatively understudied in economics, discussing the role of information about the publications process, the allocation of research funds enabling the initial development of race-related working papers, and the entry of minorities into the economics academy and the production of race-related research.

The paper is organized as follows. Section 2 follows Advani *et al.* [2022] in describing how we identify race-related publications. Section 3 documents the volume and content of this body of work in the last six decades of publications in economics, and Section 4 does the same for working papers. Section 5 examines incentives to produce race-related research by considering the paths to publication of working papers. Section 6 draws together our findings to discuss policy implications for the discipline. The Appendix details data sources and robustness checks.

2 Identifying Race-Related Research

2.1 Corpus

Our corpus of academic publications is based on the *JSTOR* database, using journals classified under the discipline of economics from 1960 through 2020. We fill gaps in this source using the *Web of Science* and *Scopus* databases. For each publication we extract information on the journal it is published in, publication date, its title and full text of the abstract. Our working sample covers $224,524$ publications in 230 economics journals.[5]

2.2 Algorithm

Our intention is to identify work relevant for the study of the economic well-being of racial and ethnic groups, across countries and over time. Throughout, we refer to this body of work as 'race-related' research. Given the volume of publications considered, it is infeasible to codify race-related research by hand. We thus take an automated approach using an algorithm to classify each publication. We do so using keywords along two dimensions: (i) the racial or ethnic group being studied; and, (ii) the issue being studied. All keywords for classification purposes are considered in a case-insensitive manner and wildcards are used to capture different word spellings or forms. Examples of (case-insensitive) keywords for groups being studied are *race*, *african-american, person*

[5] *JSTOR* has gaps in its publication series (especially in more recent years) and is missing some prominent journals. We fill these gaps using data from *Web of Science* (`webofknowledge.org`) and *Scopus* (`scopus.com`). The Data Appendix describes the procedure through which we access these databases and gives additional details on the construction of the corpus, including the fact that we do not use publications from the *AER Papers and Proceedings* as these lack abstracts.

of color, and *ethnicity*. Examples of issue keywords are *discrimination*, *prejudice*, and *stereotype*.[6]

Our algorithm selects a publication as being race-related if: (i) at least one group keyword is in the title; or, (ii) at least one group keyword and at least one issue keyword are mentioned in the title or abstract – dropping the last sentence of the abstract to avoid false positives from publications that only mention race parenthetically; (iii) we declassify publications based on eliminating phrases such as *black market* and *horse race*.

The full lexicon of group keywords is in Table A1. We define alternative bands of group keywords that gradually expand the racial/ethnic groups picked up by the algorithm. Band 0 consists of 16 generic base keywords denoting racial and ethnic groups (e.g. *race*, *ethnic*, *under represented minority*). These non-specific keywords signify the study of minorities in general, rather than a specific group. Band 1 adds another 19 group base keywords relating to the main minority groups in the US (*African American*, *Latino* and *Native American*). Band 2 adds another 25 less salient group base keywords (e.g. *South Asian*, *Indian American*, *Japanese American*) and other minorities based on religious beliefs (e.g. *Muslim*, *Jewish*). Our core results are based on combining the 35 group keywords in Band 0 and Band 1, and we show how results vary using narrower and broader bands.

Table A2 shows the lexicon of issue keywords: the 103 base keywords are designed to cover five topics: discrimination, inequality, diversity, identity, and historical issues. For example, discrimination includes *prejudice* and *stereotypes*, while inequality includes *disparity* and *disadvantage*.

Finally, we declassify publications containing any of the eliminated phrases in Table A3 in either the title or abstract. We derived this list of phrases iteratively by comparing the produced classification of race-related research against a hand-checked sample of publications.

Our algorithm is not designed to capture the universe of all race-related research and inevitably some gray areas remain (for example in topics related to immigration). However our algorithm is easily replicable, and can be extended to cover other topics.[7]

Our algorithmic approach still leads to misclassification errors in the form of false negatives and false positives. To reduce the rate of false negatives (race-related publications that are missed by our algorithm), we are relatively inclusive in the construction of the lexicon. To avoid false positives, using the combination of group and issue keywords removes many instances of not race-related research that might otherwise match our lexicon patterns. Dropping the eliminated phrases before applying the algorithm reduces false positives, where a term, e.g. race, is used with a different meaning. Dropping the last sentence of abstracts before applying the algorithm reduces

[6] For example, the group wildcard rac* captures race, races, racial, racist, and racism. Wildcard issue keywords include discriminat*, prejudi*, and stereotyp*. The wildcards allow for both American and British English spellings.

[7] Our algorithm is not designed to capture two classes of work that could still be relevant for the study of racial/ethnic inequalities. First, papers that do not mention group keywords but refer to, say, 'blue' and 'red' groups instead. Second, research that is not specifically about race but could potentially be applied to understand racial inequalities – for instance, minorities might be more impacted by minimum wages [Derenoncourt and Montialoux 2021], polices with urban biases [Cook and Logan 2020], or through distributional effects of monetary policy [Bartscher *et al.* 2022].

false positives by excluding papers where race/ethnicity is not the primary focus, but mentioned parenthetically, often as a piece of heterogeneity analysis or robustness check.

2.3 False Positives and False Negatives

To quantify potential rates of false negatives and false positives, we hand code publications as being race-related in a validation sample from our original corpus. We construct this validation sample by first extracting a complete list of publications mentioning a group keyword in their title or abstract (excluding the final sentence, and not considering topic keywords and eliminated phrases) from the top-5 general interest journals from 1960 to 2020. This comprises 179 publications, which we then manually classify as being race-related or not. We find 81% of them to actually be race-related. Around one in five publications that contain a group keyword, but where no other restrictions are applied, is therefore *not* race-related.[8]

We compare the hand-coded classification in the validation sample to that generated by our algorithm to compute rates of false positives and false negatives. Following this approach, the rate of false positives is:

$$\frac{\text{\#Non race-related publications labeled as race-related (False Positive)}}{\text{\#False Positive} + \text{\#True Negative}} = 15.2\%, \tag{1}$$

and the rate of false negatives is:

$$\frac{\text{\#Race-related publications labeled as not race-related (False Negative)}}{\text{\#False Negative} + \text{\#True Positive}} = 5.5\%. \tag{2}$$

Combining both forms of misclassification error, the implied ratio of true race-related research to identified race-related research is:

$$\frac{\text{\#Race-related publications}}{\text{\#Publications labeled as race-related}} = \frac{\text{\#False Negative} + \text{\#True Positive}}{\text{\#False Positive} + \text{\#True Positive}} = 102\%, \tag{3}$$

To apply these rates of false positives and negatives to our full corpus of publications we need to assume: (i) no race-related research is conducted in these journals that excludes group keywords; and, (ii) misclassification rates found in the top-5 general interest journals apply equally to other journals. We underpin both assumptions in the next subsection, and later show how results vary by worst- and best-case scenarios for misclassification error.

[8] An alternative approach to constructing a validation sample would be to take a random sample of all publications and hand code them as race-related or not. We do not follow this approach because race-related research comprises a small fraction of all publications (even in a hand coded sample of 1000 random articles we only expect 20 or so to be truly race-related). Hence an infeasibly large sample would either require to be hand-coded, or inferred rates of false positives and false negatives would be very imprecise.

2.4 Validation Using Chat-GPT

An alternative approach to classify whether publications are race-related or not is to use Chat GPT-3.5, a Generative Large Language Model created by OpenAI. We do so using the same validation sample described above, and then compare GPT's classification to our algorithm's. The Appendix describes the GPT prompt used. We summarize the contrast in approaches in Panels A and B of Figure A1. The confusion matrices demonstrate: (i) both approaches classify publications at around 90% accuracy, as shown in the diagonal matrix entries; (ii) as shown in the off-diagonal entries, GPT tends to falsely assign more publications into the not race-related category (false negatives), while our algorithm produces a more equal number of false positives and negatives. Of the 18 misclassified research publications using GPT, our algorithm makes similar errors in four of them.

Given the overall similarity in performance between our algorithm and GPT, we use GPT to: (i) show that the classification of publications as being race-related is not sensitive to using additional information from the introduction of papers (as well as the title and abstract); (ii) underpin the earlier assumptions needed to calculate rates of false positive and negatives in our complete corpus of publications.[9]

2.5 Journal Weights

We construct counts of race-related research based on the classification of individual publications. These counts make no adjustment for the quality of journals that work is published in. Given our 60-year study period has witnessed changing journal influence, to consider both the quantity and quality of race-related research we adjust for journal quality using the journal weighting scheme employed by Angrist *et al.* [2020] in their study of the intermural influence of economics. Journal weights are given by the relative frequency with which the journal is cited by the top 'trunk' journal in the economics discipline: the *American Economic Review*. Hence the weight of journal

[9] On (i), we select 44 publications from the validation sample across all publication years. We have to reduce the sample because most introductions of publications are contained in a separate PDF file on *JSTOR*, which presents challenges for easy access. Moreover, given our validation sample covers publications over a long time period and across journals, there is considerable variation in their structure. We manually extract introductions, disregarding tables and figures. This resulting classification using GPT based on title, abstract and introductions is shown in the confusion matrix in Panel C of Figure A1. The classifications coincide for 89% of publications, but GPT's classification still exhibits a higher rate of false negatives, even when incorporating additional information from introductions. On (ii), we use two approaches. First, we note that to apply the rates of false positives and negatives to our full corpus of publications we assumed no race-related research in the top-5 journals excludes group keywords from its title and abstract. To test this we take a random sample of publications from the top-5 journals from 1960 to 2020 that were not in our validation sample but have a group keyword in their title or abstract, and use GPT to identify race-related papers within this group: none of these publications are classified as race-related. Second, we compare the classification of race-related research in non top-5 journals between our algorithm and using GPT based on a second validation sample, taking 86 random articles from the non top-5 that include group keywords in their abstracts or titles. This comparison is shown in the confusion matrices in Panels D and E of Figure A1. Both approaches yield a similar classification.

j in year t is given by:

$$w_j^t = \frac{\text{\#Citations to journal } j \text{ by trunk journal in year } t}{\text{\#Citations to all journals in the same discipline by trunk journal in year } t}. \tag{4}$$

These time-varying weights capture the rise and fall of the importance of journals in our corpus over time. Following Kleven [2018] and Angrist *et al.* [2020], when presenting time series evidence we plot five year moving averages to smooth variation but still pick up trends.[10]

3 Race-Related Journal Publications

3.1 Aggregate Trends

Mirroring Advani *et al.* [2022], Panel A of Figure 1 shows the time series of race-related publications in economics from 1960 to 2020. While there are close to zero race-related publications in the early 1960s, there is a rapid growth in the share of race-related publications through the 1960s, so that by the end of the decade, close to 2% of all publications in economics were race-related. The share rises to a peak of 2.9% in the mid 1970s, falls to 1.5% by the mid 1990s, and rises slightly thereafter to around 2% today. Panel B shows the corresponding number of publications: there is a steadily rising number of race-related publications each year, amounting to almost 120 publications annually from 2010 onwards. In 2020, the cumulative number of race-related publications in economics since 1960 stands at 4211.[11]

Moving beyond our earlier work, Panel C repeats the analysis using *AER*-weighted publications. Accounting for journal influence, the solid line shows the weighted-share of race-related publications replicates the pattern of rising race-related publications from the 1960s to mid 1970s and a decline until the mid 1990s. However the weighted-share reveals a more rapid rise in race-related publications since the mid-1990s – a trend masked in Panel A when we do not account for journal quality. This is not because of changing weights for journals where race-related research is published, but rather because race-related research has been published in higher quality journals over time. To see this, the dashed line in Panel C fixes journal weights to their 2020 values, and shows similar trends since the 1980s as when we allow for time-varying journal weights.

Panel D shows the weighted number of race-related publications has risen steadily over time, reaching the equivalent of 1.5 *AER* publications annually since the mid-2010s. Hence although the share of all publications studying issues of race has remained relatively flat since the mid 1990s,

[10] From the 1980s onwards, the set of journals in our sample is relatively stable. It is not the case that progressively higher or lower ranked journals over time are selected into the corpus. All economics journals that are not covered in Angrist *et al.* [2020] are given a zero weight.

[11] The total number of annual publications across all economics journals has risen from 1000 in the mid 1970s to over 7000 in the mid 2010s. The lower coverage of *JSTOR, WoS* and *Scopus* in the most recent years explains the slight downturn in the number of race-related publications in Panel B – so the actual cumulative number of race-related publications in economics until 2020 is likely closer to 4500.

the prominence of such work – as measured by the journals in it published in – has risen steadily since the mid 1990s.

Figure A2 confirms these time trends in the share and weighted-share of race-related research are similar when: (i) we drop the requirement of not using the final sentence of abstracts in our algorithm; (ii) we use alternative Bands for the group keywords. For example, utilizing the broadest set of all 60 group keywords (Bands 0, 1 and 2) we see that the share of race-related research lies around 2.5% since the 2000s.

3.2 Journals

Top-5 Journals It is useful to separately consider publications in the top-5 general interest economics journals: the *AER*, *Econometrica*, *QJE*, *JPE* and *Review of Economic Studies*. These represent what is considered of broad interest to the discipline, reflects views of leading editors and referees, and are among the most highly cited publications [Heckman and Moktan 2020]. Panel A of Figure 2 shows the share of race-related research in top-5 journals has lagged behind publication shares in other economics journals for most of our study period. However, we see a major uptick in the share of race-related publications in the top-5 from the mid-1990s, that has continued since. As a result, since the early 2000s there has been a convergence in the share of race-related research in top-5 and non top-5 journals.

Panel B shows the rise of race-related research in the top-5 journals has been driven by the *AER*, *QJE* and *JPE*. In nearly all years since 1960, the *QJE* has published a higher number of race-related articles than other top-5 journals, although there has been a rapid rise in the number of race-related publications in the *AER* since 2010, overtaking the *QJE* in the most recent years. In contrast, *Econometrica* and the *Review of Economic Studies* have each cumulatively published fewer than 15 race-related articles since 1960.[12]

All Journals Figure A3 shows a broader set of journals publishing race-related research. General interest journals are at the top of the figure, with more specialized journals then ranked below by the share of race-related articles published from 1960 to 2020. Three points are of note. First, among general interest journals, the *Review of Economics and Statistics* has published the highest share of race-related articles in the 2000s, at just under 4%, with the *QJE* publishing the highest share in the 2010s, at just over 4%. Second, there is not much to suggest that European-based general interest journals – such as the *Review of Economic Studies*, *JEEA* or the *Economic Journal* – have published higher shares of race-related articles. Third, outside of general interest journals,

[12] The rise in publications addressing issues of race in the *AER* (and *AEA Papers and Proceedings*) from 1991 to 2019 is documented in Horpendahl and Kling [2020]. Their classification of such articles is based initially on those with *JEL* codes *J15* and *J71*, and then hand-checking each identified article. They report 56 articles on race were published in the *AER* and *AER P&P* between 1991 to 2018 – closely matching our estimate only for the *AER* over this period of 48.

the *JUE*, *JHR* and *JoLE* have all been traditional homes to race-related research. In the last decade, *EDCC*, the *Journal of Legal Studies* and the *AEJ: Applied* are some of the journals having 5% or more of their articles being race-related, double the disciplinary average.

Review of Black Political Economy The most prominent economics journal specialized in race-related research is the *Review of Black Political Economy* (*RBPE*) – that was indeed launched in response to concerns that mainstream economics journals were not open to publishing research on the political economy of race [Alexis *et al.* 2008]. The final bars at the foot of Figure A3 show race-related publication rates for the *RBPE* – that are measured on a different x-axis scale to all other journals. Our algorithm assigns 77% of publications in the *RBPE* to be race-related in the 2000s, and 67% to be race-related in the 2010s. That this is not 100% partly reflects that our algorithm uses topic keywords that are not exhaustive of all potential race-related research of interest to economists – a point we return to in our concluding discussion.

3.3 Groups and Topics Studied

Groups For each publication the algorithm classifies as race-related, we can use the group keywords to pinpoint which minority groups are studied.[13] Panel A of Figure 3 shows that in every year since 1975, the majority of race-related publications have covered non-specific groups (those in band 0 in our algorithm): today such work comprises around 75% of all race-related research in economics. While close to 50% of race-related publications in economics during the 1970s focused on Blacks, by the 2010s this had fallen to less than 20%. Research studying Latinx groups emerged in the 1980s, yet still only 3% of all race-related research in the most recent years has focused on this group. Research on other groups – including Asians or Native Americans – remains almost non-existent, that might be due to a lack of data, or inconsistent coding of disaggregated data for such groups. Hence, current trends still reflect a long-standing concern about the lack of research on smaller minorities (and on interactions between minority groups) [Altonji and Blank 1999].

Topics We can use the topic keywords used by our algorithm to pinpoint the issue studied, divided into the five areas covered: discrimination, inequality, diversity, identity, and historical issues.[14] Panel B of Figure 3 shows the majority of race-related research relates to inequality, comprising 59% of all race-related publications today. There has been a steady decline in the share of race-related research on discrimination since the 1980s with a rise in the share of studies

[13] Publications can of course be classified as studying multiple groups: this occurs in 6.5% of cases (Black and Latinx groups are the groups most commonly studied together). When a publication mentions more than one group, we split the publication equally across groups.

[14] The algorithm identifies when publications study multiple topics: this occurs in 28% of cases. The most commonly combined topics are discrimination and diversity, while identity tends to be studied separately. When a publication mentions more than one topic, we split the weight of the publication equally across topics.

on identity. Race-related historic research has increased slightly over time, while the share of race-related publications examining issues of diversity has remained relatively constant over our long study period.

3.4 Benchmarks

While we make no normative claim as to whether the share of race-related articles in economics is too high or too low, it remains useful to construct some benchmark comparisons. We approach this in two ways, making comparisons within and across disciplines.

Within Discipline: Using Machine Learning to Classify Topics We use machine learning to classify study areas in our corpus, and use this to measure the extent to which race and ethnicity has been studied relative to other identified topics in economics. To do so, we use Latent Dirichlet Allocation (LDA) modeling as an analytical tool to uncover hidden thematic structures of publications from their abstracts. LDA is a latent factor model that probabilistically assigns words in a document to one or more underlying topics, which are represented as distributions over words. LDA iteratively uncovers these hidden topics and their prevalence in each document. We would like the LDA model to learn the broadest possible set of social science topics, that may or may not be prevalent in economics. Hence, we build a broad corpus of $500,000$ publications across social science disciplines: economics, sociology, political science, law, management, public policy, and history. Our benchmark model then identifies 30 distinct topics that are studied in this body of work. Figure A4 displays word clouds for the topics generated and we label each of the topics as shown in the lower part of Figure A4. One of the identified topics – Topic 8 – is labelled as 'race and ethnicity' where the most prominent keywords comprising this topic including *group*, *black*, *ethnic*, *white* and *racial*.[15]

We then use the LDA model to predict the topic of any given publication in our corpus of economics publications only. Panel A of Figure 4 shows the distribution of LDA topics across publications in economics: 1% of them are classified under the race and ethnicity topic, which is less prevalent than nearly all other topics. Panel B shows the time series of the share of race and ethnicity topic papers, overlaid with the time series for the share of race-related research that our algorithm identified. Two points are of note. First, in most years since the early 1970s, our algorithm identifies a higher share of race-related research than is picked out by the LDA model.

[15] To implement LDA modeling, we use the `Gensim` library in Python, using its built-in tools to perform pre-processing tasks, such as removing punctuation and eliminating stopwords. During this process, we construct a dictionary, which is refined by excluding the 5% most and least frequent words. To determine the optimal number of topics, we analyze a combination of coherence score and perplexity measures across models with different numbers of topics. We also manually inspect the word distribution for each topic in each model. Two of the LDA topics are comprised of non-English words because some publications in English language journals still include non-English terms. The LDA model identifies these as separate groups, and we refer to them as Miscellaneous topics. These topics still also include English language words

Second, trends in both time series both show an uptick in research on race/ethnicity in the mid 1990s that has continued until today. This is another reassuring validation of the real information picked up by our algorithmic classification of race-related research.[16]

Across Disciplines: Comparison to Sociology An alternative approach to benchmarking is to compare across disciplines, as discussed in Advani *et al.* [2022]. We do so by applying our algorithm to publications in sociology, noting that we likely under count race-related research in sociology given our use of economics-focused topic keywords. We find that: (i) in each year between 1960 and 2020, sociology journals have published a greater share of race-related research than economics journals – throughout the 2010s at least 12% of sociology publications have been race-related; (ii) more than 500 race-related articles have been published annually in sociology journals in the most recent years, and the cumulative number of race-related articles in sociology from 1960 to 2020 is $14,718$, more than three times the cumulative number in economics; (iii) accounting for journal influence, the weighted-share of race-related research has risen from the mid 1990s, reaching the equivalent of seven or more *ASR* publications annually since 2010.

4 Race-Related Working Papers

Having described trends in the aggregate volume and content of race-related publications in economics, we consider the implicit incentives scholars have to produce such work. We do so by investigating an earlier stage of the research process: the production of working papers (WPs). We use working papers to further detail the production of race-related work by fields, and in the next Section, we examine paths to publication from working papers to journal articles.

4.1 Corpus

We build a corpus of the two most prominent WP series in economics, from the NBER and CEPR. Our sample covers $22,056$ NBER WPs first posted from 1974 to 2015, and $10,306$ CEPR WPs first posted from 1984 to 2015. The Data Appendix further details each series. We apply our algorithm to this corpus to establish the extent to which WPs are race-related.[17]

[16] Cihak *et al.* [2020] also compare the extent to which topics have been studied in economics. They compile data on every race-related publication in the top-10 economics journals for the last decade, although the set of keywords they use to identify race-related research is far narrower than ours. They report .2% of those $7,920$ articles cover issues of race, racial inequality, and racism. This is lower than what they find in terms of the share of articles devoted to monetary policy (7.4%), income distribution (2%), poverty (1.4%) and gender (.8%).

[17] The NBER and CEPR represent prominent networks for US- and Europe-based research economists respectively. The NBER was founded in 1920, currently has around 1600 members organized around 20 research programs and 13 working groups. Each year the NBER holds around 125 meetings and publishes over 1100 WPs. The CEPR was founded in 1983, has over 1700 members in 14 research programmes, organizes around 250 meetings and publishes over 1000 discussion papers annually.

4.2 Aggregate Trends

Panel A of Figure 5 shows the time series of race-related NBER and CEPR WPs. In each year, NBER WPs are more likely to be race-related than CEPR WPs. While both series show upward trends in the share of race-related WPs, the gap between them has remained relatively constant over time. Over the last decade, 3.5% of NBER WPs have been race-related, while the corresponding figure for CEPR WPs is closer to 2%. Comparing these to discipline wide time trends in journal publications, we see that: (i) NBER WPs have nearly always had a higher share of race-related research than journal publications in any given year since the 1980s (either across all journals or among the top-5); (ii) the uptick in the share of race-related research in the NBER and CEPR WP series – that occurs in the early 1990s – slightly predates the uptick previously documented in the weighted-share of such journal publications, that was noticeable from the mid-1990s.

4.3 Fields

Both series contain *JEL* classifications for each WP, unlike journal publications where such classifications are not consistently available. This allows us to examine the differential production of race-related WPs across subfields of economics. Aggregating over the available time period for each WP series, Panel B of Figure 5 shows for each high-level *JEL* code: (i) the share of all WPs which list this *JEL* code (gray bars); (ii) the share of WPs that are race-related for each *JEL* code (blue/red bars). In both panels, we order *JEL* codes in increasing shares of race-related research among NBER WPs.[18]

For both WP series, we observe a balkanization of race-related research into a few fields, with such work being largely absent from many other fields.[19]

Starting with NBER WPs, the share of race-related working papers vary from .35% to 13% across *JEL* codes. *Macroeconomics* (JEL Code E) has the lowest share of race-related WPs from 1973 to 2019 (.35%). *Financial Economics* (G) is the next field where race-related working papers are most scarce. These two fields are among the most prominent in the NBER series, comprising nearly a quarter of all WPs. Hence the low rates of race-related WPs in these fields has knock-on effects for the aggregate share of all NBER WPs that are race-related.

The field with the highest share of race-related research is *Other Special Topics* (Z), at 13%. This is not surprising given that stratification economics is listed under this category.[20] The

[18] When a working paper has multiple *JEL* codes, we split the assignment equally across all listed codes. The ranking across fields helps to further validate our algorithm. For example, we see that our algorithm classifies fewer than 3% of NBER WPs in *Economic Development* (O) as being race-related.

[19] These patterns across fields are reminiscent of the balkanization of women in economics into subfields, as documented by Fortin *et al.* [2021] at the time of PhD graduation, and Chari and Goldsmith-Pinkham [2018] in terms of conferences. Using data on NBER SI submissions by program, Chari and Goldsmith-Pinkham [2018] find that over 2016-8, the share of women authors was 18% in programs related to finance and macro, and 31% in programs related to applied micro.

[20] Stratification economics views inter-group inequality as the long term result of historic factors. The field draws

pattern across other fields closely matches the field journals in economics that have published the highest shares of race-related research: the *JUE*, *JHR, JoLE* and *EEH* – the other fields with the highest shares of race-related WPs are *Labor Economics* (J), *Urban Economics* (R) and *Economic History* (N). These each have at least 7% of WPs being race-related, three times the disciplinary average. There is some gap to the next field, *Public Economics* (H) – that has 3% of WPs being race-related. This is noteworthy given wealth inequalities across groups can be more extreme than for labor market outcomes [Darity and Mullen 2020, Mirza and Warwick 2023].[21]

The right hand panel shows that very similar patterns on the production of race-related research across fields are observed for CEPR WPs.

The Relevance of Race-related Research Across Fields To narrow the interpretation of these field differences, we first consider whether they reflect that issues of race and ethnicity are just far less relevant for core research questions in some fields, or whether such issues are harder to study given data constraints.

We start to examine the issue by first restricting attention to WPs that have at least one of the topic keywords (Table A2) in their title and/or abstract. For example, this includes all WPs studying inequality, just not necessarily through the lens of racial/ethnic differentials. Panel A of Figure 6 then repeats the analysis by fields for this subset of WPs.

Although the share of race-related WPs increases in each field – ranging from 2% in *Macroeconomics* to 24% in *Urban Economics* in the NBER series, overall the ranking across fields in the share of race-related WPs remains largely unchanged. For example, macroeconomics papers that have at least one topic keyword in their title and/or abstract constitute 7% of all NBER WPs, and 2% of this subset are identified to be race-related. Among CEPR WPs the same patterns emerge when we restrict WPs to those that have at least one of the topic keywords in their title and/or abstract.

A second potential explanation for cross field differences in the study of race-related issues is data constraints [Adjaye-Gbewonyo *et al.* 2014, Cronin *et al.* 2023, Heller *et al.* 2024]. For research questions focused on individuals/households, survey data on race and ethnicity can sometimes be lacking or overly aggregated, or racial-ethnic gaps in well-being are not studied due to small sample sizes. To the extent that such constraints are gradually being eased over time, we might pick this up in the share of race-related research WPs by field and decade. Panel B of Figure 6 shows

on economics, sociology, and social psychology and was crystallized in Darity [2005]. It was assigned *JEL* category Z13 (*Economic Sociology, Economic Anthropology, Language, Social and Economic Stratification*) and is cross-listed with D31 (*Personal Income, Wealth and Their Distributions*).

[21] For the US, Darity and Mullen [2020] document that the median net worth of Whites in the bottom 20% of the income distribution is higher than the median net worth of all Black households. For the UK, Mirza and Warwick [2023] document that all ethnic minority groups are under-represented in the top 20% of the wealth distribution. Types of wealth also differ dramatically: while the median White British household has £115,000 in property wealth, the median Black household has none, while Pakistani and Indian households have median property wealth greater than for White British households.

how the production of race-related WPs has changed over the last three decades (still limited to those WPs that mention at least one topic keyword). Among the NBER series, we see steady increases in the share of such work over time in fields such as *International Economics*, *Industrial Organization*, and *Economic History*. This suggests data constraints might slowly being eased to allow for the study of group differences in some fields of economics, although patterns by decade are less clear within field for the CEPR WP series.

5 Race-Related Research and the Publication Process

Having so far considered the supply of race-related research, we now exploit the classification of *individual* publications to understand how demand-side factors shape the production of race-related research in economics. We first examine publication outcomes for NBER WPs posted from 1974 to 2015, merging the NBER series with data on published articles from *Web of Science* and *Scopus* up to 2020. The fuzzy matching process used is detailed further in the Data Appendix. This linkage allows us to assess whether paths from working paper to publication differ for race-related work. In so doing, we address a common refrain in economics, that the publication process is unduly cautious – an issue where editors of leading journals have also recently expressed concerns [Omeokwe 2020]. We focus primarily on the NBER series because this is the most prominent WP series, and produces more race-related content than the CEPR series. Results for the CEPR series are later presented as a robustness check.

5.1 Descriptives

Table 1 presents descriptive evidence comparing race-related NBER WPs to non race-related NBER WPs. We identify 888 WPs posted between 1974 and 2015 to be race-related. Panel A focuses on publication outcomes. 63% of non race-related WPs are published in an academic journal within the *Web of Science* or *Scopus* catalogs, and this likelihood is 3pp lower for race-related WPs ($p = .081$). Moreover, race-related WPs are 4pp less likely to be published in an economics journal, rather than in a journal from another discipline ($p = .028$), and this remains true even conditional on them being published in a journal in any discipline ($p = .007$). The two types of WP however have similar publication lags, of around 2.4 years ($p = .473$).

Panel B presents descriptives on publication quality. Using the *AER*-weight of the economics journal of publication as a measure of quality we see that: (i) race-related publications are less likely to be published in a journal with zero *AER*-weight ($p = .017$); (ii) the average *AER*-weight of journals published in is significantly lower for race-related WPs ($p = .002$); (iii) race-related publications are no more likely to be published in a top-5 journal ($p = .361$). Figure A6 probes further how the likelihood of publication of race-related and non race-related research varies by journal quality. We plot the unconditional difference between the likelihood that race-related and

non race-related WPs are published in journals: (i) in the top-5; (ii) in the top, middle and lower terciles of journals with positive *AER*-weight; (iii) in a zero *AER*-weight journal. For the NBER WP series there is a bimodal distribution of publication quality, where relative to non race-related WPs, race-related WPs are more likely to be published in low *AER*-weight journals, but also more likely to be published in the top-5. Race-related WPs from the CEPR series differ: they are more likely to publish in zero or low *AER*-weight journals, and are less likely to publish in higher weight journals or in the top-5.

The final rows in Panel B of Table 1 consider citations as a measure of publication quality. While the *AER*-weight reflects the decisions of editors and referees, citations are determined by the discipline as a whole. Despite the bimodal distribution of journal quality where race-related NBER WPs are published, such research is not differentially cited from other WPs ($p = .635$).

5.2 Estimation

To establish whether these unconditional differences are robust, we estimate the following OLS specification for publication outcome y for NBER WP a first posted in year t:

$$y_{at} = \beta RR_a + \theta X_a + \alpha_t + \sum_{j \in J(a)} \alpha_j + \sum_{s \in S(a)} \alpha_s + \varepsilon_{at}, \tag{5}$$

where RR_a is a dummy for whether the WP is classified as race-related, X_a are characteristics of the WP, α_t are year fixed effects corresponding to the year in which the WP is first posted, α_j are *JEL* codes the WP refers to (so $J(a)$ refers to the set of *JEL* codes for WP a), α_s are dummies for the institution affiliation of each author on the WP (the set $S(a)$ is the affiliations of all co-authors), and ε_{at} is an error term. We treat outcomes for WPs to be independent and report robust standard errors.[22]

The parameter of interest is β: the differential in publication outcome y_{at} for race-related NBER WPs relative to those that are not race-related, conditional on WP characteristics, publication time, field and author affiliations. The counterfactual working papers considered are those in the same field (as measured by WP *JEL* classifications), so studying similar research topics but just not through the lens of race or ethnicity. We consider alternative sets of counterfactual papers as

[22] The WP characteristics in X_a are the number of pages (and its quadratic), the length of its title (and its quadratic), the number of authors, and the number of *JEL* codes covered. There are 20 unique top-level *JEL* codes, α_j. Information on institutional affiliation is derived from the *Scopus* database, using first and last names. For each author-year combination we observe in the NBER data, we retrieve the affiliation of the author in the *Scopus* database with an economics publication who shares the same first and last name as the author in the NBER WP dataset. Moreover, the selected author should have a publication that is closest in time to the author being analyzed. When we identify multiple matches, we break ties randomly. To account for possible measurement error in this procedure, we also control for the average number of matches found for each author of an article (and its quadratic). Affiliations of NBER working paper authors are found in two thirds of cases. We define the α_s dummies to cover the 100 most frequent institutions in our data set, a dummy for other affiliations and a dummy for no matched affiliation.

part of our robustness checks below.

To understand selection into the production of WPs, Table A4 presents further descriptives comparing race-related working papers to other WPs. In Panel A we see there are statistically significant differences in the length, titles and number of *JEL* classifications of race-related WPs relative to others. However the magnitude of these differences are small. These differences translate into features of race-related publications. Panel B examines the group and topic content of race-related WPs. As expected, non race-related WPs rarely mention any of the group keywords, and rarely relate to the topics our algorithm is based on. An exception is the topic of inequality, where 24% of non race-related working papers mention some of the keywords under this broad heading (shown in Table A2).

5.3 Results

5.3.1 Publication Outcomes

We first consider publication outcomes. Columns 1 to 3 in Table 2 show that once we condition on date of posting, *JEL* codes, WP characteristics and author affiliation dummies, the unconditional differences in publication outcomes between race-related NBER WPs and not race-related WPs disappear: race-related NBER WPs are not differentially likely to be published in any journal, published in a economics journal, or differ in their publication lag in economics journals (Columns 1 to 3). These null impacts are precisely estimated. For example, the 95% confidence interval for $\widehat{\beta}$ rules out the publication lag for such work being .14 years longer than for other work (relative to a baseline lag of 2.7 years).

The remaining Columns of Table 2 focus on publication quality, conditional on the WP being published in an economics journal. The results are broadly in line with the earlier unconditional estimates. More precisely, race-related NBER WPs are: (i) significantly less likely to be published in a journal with zero *AER*-weight (Column 4); (ii) not published in journals of differential quality as measured by their *AER*-weight, including zero weights (Column 5); (iii) are significantly more likely to be published in a top-5 journal (Column 6, $p = .086$). The magnitude of this last effect is 3.9pp, corresponding to a 16% increase over the baseline likelihood of non race-related NBER WPs being published in top-5 journals conditional on them being published in an economics journal.[23]

Column 7 shows publication lags for WPs published in top-5 journals are not different between race-related and other WPs. This is in line with such papers not being held to a higher standard as proxied by longer refereeing processes for example.[24]

The final margin considered is citations for published WPs (where citations accumulate over

[23] The probability of an NBER WP being published in a top-5 journal is therefore .734 x .988 x .244 = 17.7%.

[24] Publication lags in economics are longer than in the natural sciences, other social sciences and finance. Hadavand *et al.* [2021] show using data from the top-5 economics journals, that these stem from longer periods over which authors revise their work. Hence longer lags could be indicative of papers being held to a higher standard.

both WP and published versions). Citations matter for reputation, and decisions related to hiring, promotion and grant awards [Ellison 2013, Koffi 2021]. Race-related NBER WPs are 1.1pp more likely to be cited (although this is a last-mile issue given 98% of non race-related WPs are ever cited). More substantively, we see no difference in total citations between race-related and non race-related WPs. This is in line with such work not being held to a lower standard of publication. This final result is robust to controlling for journal fixed effects (Column 10).[25]

This set of results suggests there are few publication penalties for NBER WPs that are race-related, conditional on those papers being produced. If the publication process provides implicit incentives to scholars to work on certain topics [Heckman and Moktan 2020], and individuals are perfectly informed of these features of the path to publication of NBER WPs, then our results provide little evidence that demand-side process should discourage NBER-affiliated researchers from working on race-related research. If however researchers are imperfectly informed, they might be more swayed by the unconditional higher probability of race-related WPs being significantly less likely to publish in an economics journal (Table 1), or publish in a low *AER*-weight journal even for those that are published in an economics journal. They might also perceive such work faces higher risks of achieving good publication outcomes, that ultimately matter for academic career progression.

The general set of null impacts might also reflect differential selection in an earlier stage of the publications process: the step from ideas to the formation of working papers in the first place. If researchers believe that race-related work is either less likely to be published in an economics journal, then a more positively selected sample of race-related working papers will be produced to begin with. However, the results show that race-related WPs are not differentially subject to publication lags nor do they receive differential rates of citation – both pieces of evidence against differential selection into the production of race-related WPs. We return to this issue below in our robustness checks, and in our concluding discussion.

5.3.2 Groups and Topics Studied

We delve deeper to examine whether paths to publication for race-related WPs vary by the group or topic studied. To do so we estimate heterogeneous effects of race-related NBER WPs for the outcomes considered above. Table 3 presents the results on groups, where the omitted category is non race-related WPs. On the whole, there are relatively few differences in publication outcomes

[25] Results in Table 2 are robust to small changes in specification such as dropping the dummies for author affiliation (α_s). Moreover, allowing for changing trends across journals by including a series of journal x year fixed effects, the outcomes for *AER*-adjusted journal quality and log citations remain unchanged. One concern is that our results are biased if NBER WPs are only posted once they are accepted for publication. To check for this, we repeat the analysis restricting the sample to those WPs with a publication lag of at least one year. We find the differential likelihood of being published in a zero *AER*-weight journal becomes smaller (but still statistically significant at the 10% level) and the differential likelihood of being published in a top-5 journal is 3.1pp but not significantly different between race-related and non race-related working papers.

for race-related NBER WPs focused on different groups. However, two notable results emerge.

First, NBER WPs focused on Black groups are more likely to be published in an academic journal relative to non race-related WPs ($p = .033$), and relative to race-related research on non-specific groups ($p = .072$) and all other groups ($p = .016$). Second, the likelihood of being published in a top-5 journal (conditional on being published in an economics journal) differs depending on the minority group being studied. As Column 6 shows, WPs studying Blacks are 20pp significantly more likely to be published in the top-5 than those studying all Other groups ($p = .071$). This differential might help explain the relatively slow progress in the study of Other groups.

Table 4 conducts a similar analysis for race-related NBER WPs based on their topic of study, using the five-way classification: discrimination, inequality, diversity, identity, and historical issues. Overall, topics of study matter more for publication outcomes (Columns 1 to 3) than for publication quality (Columns 4 to 10).

More specifically, Column 1 shows how the likelihood to be published in an academic journal varies by topic. Comparing race-related research to non race-related work, no race-related topic is significantly less likely to be published than non race-related WPs. Race-related studies on discrimination and identity are more likely to be published than non race-related WPs. Within race-related topics, studies on inequality are less likely to be published than studies on discrimination ($p = .046$). As the majority of race-related papers study inequality, this can reinforce a misperception among researchers that race-related research is generally less likely to publish well. In contrast, studies of discrimination are 11.4pp more likely to be published than non race-related WPs, although these constitute a steadily smaller share of race-related research over time.

Column 2 shows the likelihood of being published in an economics journal does not differ much over topics with the exception of race-related studies of identity: these are 8.4pp more likely to be published than non race-related WPs ($p = .014$) and significantly more likely to be published in an economics journal than studies on discrimination ($p = .011$), inequality ($p = .013$), or diversity ($p = .069$). Race-related studies on inequality and identity also have significantly shorter publication lags than non race-related WPs (Column 3).

Finally, narrowing in on race-related research on discrimination, we see little evidence of differential paths to publication with other race-related topics. The evidence does not suggest such studies are less likely to be published in an economics journals, or be held to systematically higher or lower standards, as proxied by publication lags and citations, in the pathway from working paper to publication. This is important given the concern that studies of discrimination in economics are hard to publish because of the conventional null of there being no discrimination, and hence the onus being to show the existence of discrimination.

5.3.3 Fields

Finally, we consider how paths to publication vary by field, and how this correlates to the actual supply of race-related WPs. We first consider the likelihood of a race-related WP being published in a top-5 journal, and estimate (5) for each *JEL* code separately. We thus obtain estimates $\widehat{\beta}_j$ for *JEL*-code j. Panel A of Figure 7 then plots for each *JEL* code: (i) the unconditional probability of a race-related NBER WP being published in the top-5; (ii) the conditional estimate, $\widehat{\beta}_j$. We overlay this with a histogram showing the share of WPs in the *JEL*-code that are race-related, where we order the fields in increasing share of race-related WPs.

Three points are of note. First, across *JEL*-codes, the unconditional probability of a race-related NBER WP being published in the top-5 does not vary substantially; nor does the conditional estimate, $\widehat{\beta}_j$. Second, there is only a weak relationship between either probability and the share of race-related research actually produced under any given *JEL*-code. Hence there is little responsiveness to these conditional publication probabilities on the supply of race-related research by field. Third, the same very weak relationship exists in terms of the *AER*-weighted quality of journal publications, as shown in Panel B.

Whether this equilibrium outcome reflects imperfect information of researchers is unclear. We saw earlier how unconditionally, race-related WPs are likely to be published in an economics journal, and there is a bimodal distribution in the quality of journals where race-related research from NBER WPs is published. If these unconditional differences are more salient for researchers, this could drive down the production of race-related work.

5.4 Robustness

We examine the robustness of our main findings in three directions – these checks are discussed in more detail in the Appendix.

Readability Scores We follow Hengel [2022] in considering readability scores as more nuanced measures of whether race-related WPs are held to a differential standard in the publication process. We find evidence that readability scores of race-related NBER WPs are significantly higher than for non race-related WPs. This pattern of higher readability scores is less robust among published versions of the same WPs. In other words, the evidence suggests readability scores do not change differentially between working paper and published versions of race-related work versus other work. This reinforces the idea that the publication process from working paper submission to acceptance at a journal, does not hold race-related work to a differential standard. Rather, if readability scores are a good metric for selection, then researchers publishing in the NBER WP series appear to be more selective in posting race-related WPs than non race-related WPs, conditional on other characteristics of the WP.

CEPR Working Papers We tackle the concern that drawing inferences about the publications process for race-related research using the NBER WP series might be misleading because such work is produced by a group of non-randomly selected academics [Kleemans and Thornton 2021, Koffi and Wantchekon 2022].[26] We do so by considering paths to publication for CEPR WPs. As described earlier, CEPR WPs are less likely to be race-related, and their publication outcomes are generally slightly worse than for NBER WPs. For example, 18% of all NBER WPs are eventually published in the top-5 journals, while the corresponding figure for CEPR WPs is 8%. The comparison for paths to publication of CEPR and NBER WPs is therefore informative of how race-related research from different tiers of the discipline fares in the publication process. We find a generally similar pattern of null results for CEPR WPs' paths to publication as we found for NBER WPs, both for publication outcomes and publication quality. Hence our results on paths to publication for race-related research does not appear driven by the set of researchers that can post WPs in either series.

Counterfactual Working Papers We have so far been comparing race-related WPs to non race-related WPs, conditional on date of WP posting, *JEL* code, WP characteristics and author affiliation. A concern might be that even within such bands, the style of race-related WPs differs – for example in methodology, or policy relevance. A premium to these traits in the publication process might then mask any penalties that race-related work otherwise faces, leading to the null results found. To address this concern over omitted variables bias, we consider two alternative approaches to identifying counterfactual WPs: (i) not race-related WPs that have at least one of the topic keywords (Table A2) in their title and/or abstract – this counterfactual mostly includes WPs that study issues of inequality, just not through the lens of racial/ethnic differentials; (ii) using machine learning to classify the topic of WPs and then controlling for these broad topics instead of controlling for *JEL* codes. On most margins of the path to publication, for both NBER and CEPR WPs, we continue to find either null or positive impacts for race-related papers irrespective of the set of counterfactual WPs considered.

6 Discussion

Economists typically – and rightly – view themselves as having an important role to play in informing societal debates [Fourcade *et al.* 2015, Spriggs 2020, Maesse *et al.* 2022]. This should

[26] Kleemans and Thornton [2021] study the selection of economists into the NBER. They find that while, on average, men and women have similar membership rates, the hazard of becoming an NBER member is 14 percent lower for men once they control for rank of PhD granting institution, first job, and research productivity. NBER membership is heavily dependent on top-5 publications, rather than total publications or citations. Koffi and Wantchekon [2022] study the under representation of minorities (especially African scholars) in the NBER political economy and development groups. They highlight that the institutional concentration of affiliates (70% are graduates from six programs) can lead to the persistent under-representation of minorities.

include debates on gaps in economic well-being across racial and ethnic groups. Our ability to do so depends on the scientific foundation of race-related research that economists have collectively produced. We quantify the volume and content of such work over the last six decades, and shed light on demand for such work as measured by paths to publication from working papers to journals. We document that since 1960 less than 2% of economics publications have been race-related, with an uptick in work in the mid 1990s. There have also been changes over time in the groups and topics studied within race-related work. Across subfields of economics, we find that race-related research is balkanized into a few fields, with such work being largely absent from many others. However, irrespective of field, the publications process provides little disincentive to produce race-related working papers: such work has no worse publication outcomes than non race-related research.

In comparison to sociology, our approach suggests the discipline has something like a 20-30 year lag in the production of race-related research. This difference might just reflect valid disciplinary differences in subject matter. If this is not the case however, then it is useful to see what evidence can be brought to bear to understand the economics-specific factors that can narrow this gap. We consider: (i) understudied race-related topic areas in economics; (ii) the role of economics journals; (iii) funding; (iv) the selection and retention of minority faculty in the economics academy.

6.1 Understudied Race-related Topics in Economics

As emphasized throughout, our algorithm is designed to identify race-related research partly on the basis of topic keywords orientated towards economic issues. To shed light on the kinds of race-related work that might be missed, we examine topics that are studied in journals or disciplines focused on race and ethnicity, but that our algorithm does not pick up. To be clear, the explicit inclusion of these topics into our algorithm might well lead to more false positives, but they are still informative of race-related topics that are relatively understudied in economics.

Figure 8 shows the topics studied from three sources: (i) the *Review of Black Political Economy*; (ii) journals in the discipline of African American and American Indian Studies; (iii) sociology. In each case we show the share of race-related research in the five topics picked up by our algorithm, and a residual category – labelled 'other topics' for the *RBPE* and labelled 'not economics orientated' for the other two sources. The right hand side of each Figure then picks out example keywords from this residual category.[27]

Examining race-related research in the *RBPE* we see that, as expected, the share of other topics publications is relatively small – comprising around 10% of publications in the last decade. Example keywords from this work include *inner-city*, *minority-owned*, *enterprises*, *finance* and

[27]The corpus of *RBPE* publications considered are from 1977, publications in any journal in the discipline of African American and American Indian Studies since 1986 (as classified by *JSTOR*), and race-related research in sociology from 1960 onwards. For sociology publications, we also condition on the requirement that a least one group keyword is in the title or abstract, excluding the final sentence of the abstract.

married. This is of note because we saw earlier in the context of NBER working papers, *Financial Economics* (G) is a field where race-related working papers are scarce. For journals in African American and American Indian Studies we actually find the economics-focused topics comprise the majority of race-related research since the mid 1980s. Since the 1990s the share of not economics orientated publications has steadily risen to comprise around 30% of all publications in this discipline. Example keywords from this work include *curriculum*, *languages*, *teachers* and *art*. Finally, among publications in sociology with a least one group keyword in the title or abstract, around 75% relate to topics not captured by our algorithm. This share has remained relatively stable over our entire study period. Example keywords from this work include *couples*, *church*, *adolescents*, *husbands*, *happiness*, *personality*, *art*, and *religiosity*.

These findings complement existing work emphasizing that the lens through which economists study discrimination can be broadened [Small and Pager 2020, Spriggs 2020]. Others have argued a lack of recognition for minority economists has led to their perspective on mainstream topics being ignored – an example being within the economics of crime the lack of attention given to racial profiling, mass incarceration, and police use of force [Mason *et al.* 2022], or the design and impacts of public policy more broadly [Francis *et al.* 2022]. Stratification economics, that emphasizes competition and collaboration across groups to attain and maintain relative position in social hierarchies, has yet to enter mainstream areas of economic study [Darity 2022]. Finally, earlier work has suggested the discipline move away from the idea of race as exogenous, and build on the idea that racial self-classification may be endogenous to economic outcomes [Saperstein and Penner 2010, Charles and Guryan 2011, Spriggs 2020], or might reflect choices of identity [Darity *et al.* 2006, Akerlof and Kranton 2000].

6.2 Journals

We have documented that conditional on observables, race-related working papers face few penalties in their paths to publication. Our findings have three important implications.

First, across fields, we document a weak relationship between the probability of race-related research being published in the top-5 and the supply of such work by field. This might reflect researcher misperceptions, who are more aware of the unconditional distribution of publication outcomes for race-related working papers – that as we shown is bimodal, with such work being both slightly more likely to be published in the top-5, but also more likely to be published in low or zero *AER*-weight journals. Correcting such misperceptions about paths to publication for race-related research could encourage the production of such work in the first place. Such misperceptions would not be altogether surprising. In our earlier work [Advani *et al.* 2022], we used the *Social Science Prediction Platform* to examine whether economists were aware of trends in the publication of race-related research. Based on 300 responses of economists, we found they: (i) overestimate the share of race-related research in economics five-fold; (ii) overestimate the growth of race-related

research in economics; (iii) incorrectly predict that the top-5 journals currently have lower shares of race-related publications than the discipline as a whole.

Second is the issue of having more economics journals specialized in race-related research. Such journals exist to a great extent in sociology, and the entry of such journals might well be partly responsible for the rise in the share of race-related research in sociology from the 1980s. However, a key issue that remains for future research is understanding whether such specialization would lead to an even greater balkanization of race-related research, because publications in specialized journals are more likely to cite such work, and the broader ideas from race-related work then do not filter through to other parts of the academy.

Finally, the set of null impacts on paths to publication might also reflect differential selection in an earlier stage of the publications process: the step from ideas to the formation of working papers in the first place. If researchers misperceive that race-related work is either held to a higher standard or less likely to be published, then a more positively selected sample of race-related working papers will be produced to begin with. On the one hand, our results show that race-related WPs are not differentially subject to publication lags, nor do they receive differential rates of citation – all pieces of evidence against differential selection into the production of race-related WPs. On the other hand, readability scores of race-related WPs – at least for the NBER series – are higher than for non race-related working papers, suggesting more potential for differential selection into such work.

6.3 Funding

Another approach to identify the differential selection of race-related work is to consider the process of research funding. Along these lines, Cruz-Castro *et al.* [2022] review the evidence on gender, race and ethnicity differentials in research funding in the US and Europe – so focusing on how the identity of individual researchers impacts funding outcomes (not the subject matter of funding proposals). While they find that gender gaps in funding have closed at the NSF, NIH and in Europe, for the US minorities remain far less likely to receive research funding than White individuals. There remain multiple possible explanations for this such as differences in applicant behavior, research productivity, peer review processes, and other inherent biases. Irrespective of the cause, the result might be the differential selection into the production of race-related working papers vis-à-vis non race-related work, that can partly reconcile our null findings for paths to publication for race-related work. This remains an important topic for future work.[28]

[28] We have tried to pursue this line of inquiry by collecting data on NSF funding applications. However, declined grant proposals are not made available for research purposes due to the Privacy Act, which limits what information NSF is authorized to disclose.

6.4 Faculty

Differential outcomes in the process of research funding based on the race and ethnicity of researchers can lead to differential selection into race-related research *if* there is a link between the racial/ethnic identity of researchers and the areas they study. While such links have been documented in the context of inventors [Einiö *et al.* 2023] and individuals working in medical research [Dossi 2024], our findings lead naturally to the study of the relationship between the production of race-related research and the entry of minorities into the economics academy. The lack of entry of minorities – the pipeline problem – is well recognized, and this is a margin along which many of the initiatives of economic associations, such as the *AER*, *EEA* and *RES* are heavily directed [Bayer and Rouse 2016, Bayer *et al.* 2020].[29]

In ongoing work, we study the nexus between the racial and ethnic identity of individual faculty and the production of race-related research. We thus extend a line of work linking the subject matter of economic research and the subject matter studied by Black economists [Price and Sharpe 2020], most notably in relation to stratification economics and the economics of race, but also Black economists' distinct approaches and contributions to the study of areas of public policy – as discussed in a recent *JEL* symposium [Darity 2022, Francis *et al.* 2022, Mason *et al.* 2022]. Moreover, the documented balkanization of race-related research across fields might have knock-on effects for the formation of professional networks, that are so important for career progression in academia [Fourcade *et al.* 2015, Zinovyeva and Bagues 2015].[30]

Tackling this wider agenda, of understudied topics in economics, information on the publishing process, and the entry and retention of minority faculty in the economics academy, can potentially all contribute in important ways to underpin the ability of academic economists to contribute to societal debates on the causes and consequences of large and persistent gaps in economic well-being across racial and ethnic groups.

[29] The under representation of minorities in the profession has long been recognized – the *AEA* established its *Committee on the Status of Minority Groups in the Economics Profession* over 50 years ago. More recently the *AEA*, *EEA* and *RES* have all been taken steps to promote inclusivity by establishing new initiatives, formalizing codes of conduct and surveying members. The 2019 *AEA* member survey found that 3% of economists identified as Black, 47% of Black respondents reported experiences of discrimination, and only 45% of all respondents (regardless of race) believed non-White economists are respected.

[30] Mason *et al.* [2005] shows that papers with at least one Black author are more likely to report a finding of racial discrimination than papers with no Black authors. Freeman and Huang [2015] show that papers by ethnically diverse coauthor teams receive more citations than papers written by same ethnic group teams. The link between selection and research has been documented more along lines of gender than race. For example, in a survey of 143 *AEA* members, men and women economists are found to differ on views on economic outcomes and policies, even after controlling for PhD vintage and employment type [May *et al.* 2014].

A Appendix

A.1 Data Sources

JSTOR We use *JSTOR* as our primary data source on academic publications. To classify journals to disciplines, we use *JSTOR*'s disciplinary definition for each journal except when Angrist *et al.* [2020] provide an alternative classification. For journals classified to be cross-disciplinary, we assign equal weights to journal publications across disciplines. For each *JSTOR* publication, we extract metadata such as the *JSTOR* ID, journal name, year, abstracts, and titles. *JEL* codes are not available for the metadata from *JSTOR* (while some publications do contain *JEL* codes, they are embedded within the PDF versions of publications and not published on *JSTOR*'s website).

Web of Science and Scopus The *JSTOR* publication series still has gaps, especially in recent years. These gaps relate to missing data for some journals in particular years, and also because the *JSTOR* publications series does not include certain journals, such as the *Journal of Public Economics* and the *Review of Black Political Economy*. To address these issues, we utilize data from the *Web of Science* (*WOS*) and *Scopus* publications series. The *WOS* dataset consists of articles published between 1970 and 2015. By employing ISSN numbers, we map articles to their respective disciplines. Within the *WOS* series there can still be missing abstracts (because the *WOS* API does not provide abstracts), that we then fill in using information from *Scopus*. We employ the Scopus API to retrieve publications from a specific journal and publication year. A matching process is then subsequently conducted to find similar titles between the *WOS* and *Scopus* series. For each ISSN and year combination, we compare all possible pairs of indices from the two datasets using fuzzy string matching. Pairs with a partial ratio above a threshold (.95) were considered matches and stored in a dictionary. We utilized the matching dictionary to map indices from the *WOS* dataset to their corresponding indices in the *Scopus* dataset. Abstracts from the *Scopus* dataset were added to the *WOS* dataset based on the matched indices.

Throughout, we exclude publications that do have missing abstracts that cannot be recovered using *Scopus* data. Additionally, our corpus does not include publications from *Paper and Proceedings* series, as these typically do not contain abstracts. We also note that certain journals, such as the *Economic Journal* prior to 1994, did not require abstracts and so those journal-years are not included in our final corpus.

Foreign Languages We drop all non-English language parts of abstracts, using an automated Python language detection method. We retain those journals that have paper titles and abstracts in both English and another language because our algorithm can be applied to such papers.

Deduplication Since we construct our corpus by combining different data sources, we face an issue that multiple versions of the same publication might exist. To address this issue we com-

pare the titles of articles within each discipline, journal, and year to identify potential duplicates. The procedure utilizes string similarity measures to calculate the pairwise distance between article titles. If the distance exceeds a predefined threshold (.90), the publications are considered duplicates. All duplicates are dropped from the analysis.

Cleaning Abstracts Scraped abstracts from *JSTOR, WOS* and *Scopus* have varying formats. A challenge is that abstracts often contain copyright sentences or additional information. As our algorithm to identify race-related work relies on penalization based on the last sentence of abstracts, it is crucial to ensure abstracts are cleaned and standardized across platforms. Through manual inspection, we identified approximately twenty different patterns of copyright sentences used. Using string matching algorithms, we cleaned all abstracts for analysis to remove such extraneous information.

Working Papers For the NBER series, we construct a corpus starting from 28,206 NBER WPs first posted from 1974 to 2019. Dropping articles published as WPs after 2015 for publication delay considerations, we are left with 22,056 observations. For the CEPR series, we construct our corpus based on WPs first posted from 1984 to 2019. We start with 15,137 WPs, and dropping articles published from WPs after 2015, we are left with 10,306 WPs. WPs and their metadata are scraped using a publicly available API. In a few cases, multiple versions of WPs are posted over time. We use the first posted versions throughout, and also verify that almost no WPs change classification from race-related to non race-related (or *vice versa*) across posted versions.

When a WP lists multiple *JEL* codes, we split the assignment equally across codes. We omit WPs with no *JEL* classification and *JEL Code Y* (*Miscellaneous Categories*) because it is not represented in the NBER corpus and is associated with only eight papers in the CEPR series, among which none are race-related. 4722 (589) NBER (CEPR) papers do have not *JEL* codes.

Constructing Readability Scores We use the `Textatistic` library, a Python package for estimating readability metrics [Hengel 2022]. `Textatistic` employs a combination of algorithms to first count the number of sentences, characters, syllables, words, words with three or more syllables, and words not on a predefined list of easy words. Using these counts, it calculates a variety of readability indices, including the Flesch Reading Ease Score, Gunning Fog Index, and the Simple Measure of Gobbledygook (SMOG) score.

The Flesch Reading Ease test assigns higher scores to materials that are easier to read and lower scores to passages that are more challenging to comprehend. The Gunning Fog Index also estimates the reading level required to understand a piece of writing. It measures the complexity of sentences and words in the text, with higher scores indicating more complex and challenging content. The SMOG measures the complexity of written content by analyzing the number of words

with three or more syllables in a sample text. The higher the SMOG score, the more advanced the reading level required to understand the text.

As the scores have different scales and signs, to compare scores, the Gunning Fog and SMOG measures are inverted. For all measures a higher score thus corresponds to easier to read and comprehend texts. We standardize each measure to have mean zero and standard deviation one.

Matching Working Papers to Publications For each WP we find all articles in the *WoS* and *Scopus* databases with the same coauthors published after the WP release date, and then compute the string distance between this set of published papers and the WP (so retrieving titles similar to both the WP and published article). To ensure we capture all possible matches between WPs and published articles, we intentionally set the match similarity threshold to 50 score points. This helps avoid missing potentially true matches caused by spelling errors in names/titles. A single WP may have multiple matches above the set threshold. When multiple matches are found, we retain the WP-publication pair with the highest similarity. Although we have implemented a conservative approach to enhance the efficiency of the matching process, we note that more than 90% of all matched pairs have a similarity score above 95, and approximately 80% of all matches have a perfect score of 100 points. Panel A of Figure A5 presents the distribution of string similarity among matched NBER and CEPR WPs, and this histogram provides evidence of highly accurate matches between WPs in each series and published articles. Panel B of Figure A5 shows how match rates vary by publication years using progressively stricter thresholds for the NBER and CEPR series.

A.2 Robustness Checks

Chat GPT The system prompt given to GPT-3.5 Turbo was based on our experience with similar tasks. The benchmark prompt was: *you are a helpful assistant. Determine in the most accurate way if the academic paper is related to race and/or ethnicity based on the given title and abstract. Respond with one word: Yes, No, or Unclear.* We set the temperature parameter to zero to ensure replicability. The output of GPT's classification was manually reviewed to check for hallucinations from the language model (i.e. where GPT provides answers that are not among our identified choices). We did not encounter any hallucinations. In one instance GPT provided an answer that included an additional explanation of its choice: 'Unclear. The paper discusses various economic topics, but it is not clear if it specifically relates to race and/or ethnicity.'

Readability Scores We follow Hengel [2022] and construct readability scores for each NBER WP abstract. For each WP we derive three readability scores based on the Flesch Reading Ease, Gunning Fog and Simple Measure of Gobbledygook (SMOG) metrics. We code each metric so that higher values correspond to material that is easier to read. All scores are then standardized

so coefficients can be interpreted in effect sizes. We then consider these as outcomes in (5).

The results are in Table A5. Columns 1 to 3 show that for all three measures, readability scores of race-related NBER WPs are significantly higher than for non race-related NBER WPs. Columns 4 to 6 repeat the analysis but based on the readability score of the publication (not the original WP): here we find a weaker pattern as for the original WPs. Columns 7 to 9 then check whether readability scores of race-related NBER WPs change moving from original working papers to published articles. The estimate on each change in readability score is never statistically significant. In short, we find suggestive evidence that there is differential selection into the original production of NBER WPs for race-related work, but consistent with other measures of work being held to higher standards (publication lags, citations), we find no evidence that race-related working papers go through a different process on the path to publication conditional on working papers being produced.[31]

CEPR Working Papers The results for paths to publication for CEPR WPs are in Table A6. To begin with, as reported at the foot of each Column, publication outcomes for non race-related CEPR WPs are slightly worse than for non race-related NBER WPs on most margins: they are less likely to be published in any journal, less likely to be published in an economics journal, have slightly longer publication lags, are noticeably less likely to be published in the top-5 (so that 8% of all CEPR working papers are published in the top-5), and have lower citations. In line with our main results for NBER WPs, on nearly all margins, paths to publication for race-related CEPR WPs do not differ to those from those of non race-related CEPR WPs. The exception is the *AER*-weight of the journal published in, that is significantly lower for race-related CEPR WPs.

Table A7 confirms that on the readability metrics, we find no differences between race-related CEPR WPs and non race-related CEPR WPs, and changes in readability from WP to published versions of work are again all not statistically different from zero.

Counterfactual Working Papers Our core results compare race-related working papers to non race-related working papers (conditional on date of WP posting, *JEL* code, WP characteristics and author affiliation). A concern might be that even within such bands, the style of race-related WPs differs – for example in methodology, or policy relevance – and any differences detected are due to such omitted variables rather than the work being race-related. We address the issue using alternative groups of counterfactual working paper.

First, we consider not race-related WPs that have at least one of the topic keywords (Table A2) in their title and/or abstract. As Panel B of Table A4 shows, this counterfactual mostly includes WPs that study issues of inequality, just not through the lens of racial/ethnic differentials. Second,

[31] We also examined whether the actual classification of research as being race-related or not changes between working papers and published versions of articles. We find almost no examples of such changes in classification - and this is the case irrespective of which band of group keywords we use for our algorithmic approach.

we use machine learning to classify the topic of WPs and then control for these broad topics instead of controlling for *JEL* codes. We again use the LDA model to identify topics. To determine the optimal number of topics, we analyze a combination of coherence score and perplexity measures across a range of models with different numbers of topics. Additionally, we manually inspect the word distribution for each topic in each model. For our benchmark model, we choose 30 topics. Figure A7 displays word clouds for these 30 topics generated based on our benchmark model, using a dataset comprising NBER working papers.

For NBER WPs, the results from both approaches to defining alternative groups of counterfactual working paper are in Table A8. For each outcome, we show results for race-related working papers relative to these two groups of counterfactual paper. We find evidence that race-related papers are less likely to be published in journals with a zero *AER*-weight, but on no other margin do we find significantly worse outcomes for race-related papers. Table A9 repeats the robustness check for paths to publication for CEPR working papers. For all margins considered we find no evidence of statistically significant worse outcomes for race-related papers at the 5% level.

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Table 1: Race-related NBER Working Papers

Means, standard deviation in parentheses, p-values in brackets

	(1) Race-related	(2) Not Race-related	Test of Equality [p-value]
A. Publication Outcomes			
Published in any journal	.603	.634	[.081]
Published in an economics journal	.587	.628	[.028]
Published in an economics journal | published in any journal	.973	.988	[.007]
Publication lag (years)	2.36	2.44	[.473]
	(2.42)	(2.95)	
Publication lag (years) | published in an economics journal	2.54	2.65	[.486]
	(2.67)	(3.11)	
B. Publication Quality			
Published in AER weight zero journal | published in an economics journal	.136	.182	[.017]
Journal quality (AER-weight) | published in an economics journal	.050	.067	[.002]
Published in Top-5 | published in an economics journal	.264	.244	[.361]
Total citations | published in an economics journal	96.2	102.3	[.635]
	(154)	(256)	

Notes: The sample is based on NBER working papers first posted between 1974 and 2015. Columns 1 and 2 show means and standard deviations in parentheses for working papers classified as race-related and not race-related respectively. Column 3 shows the p-values from a t-test of equality of means between race-related and not race-related articles, based on a regression with robust standard errors. In Panel A, published working papers are published in any outlet, published in any journal is if the working paper can be matched to a journal article in *Web of Science* or *Scopus*. The publication lag is the number of years between when the NBER working paper is first posted and its year of publication. In Panel B, journal quality is based on the weighting scheme used in Angrist *et al.* [2020]. Total citations are the number of citations received by an article in either the *Web of Science* or *Scopus*.

Table 2: Paths to Publication for NBER Working Papers

OLS estimates, robust standard errors in parentheses

	Published in any Journal	Published in an Economics Journal	Publication lag (years)	Published in AER zero weight journal	Journal Quality (AER-Weighted)	Published in Top-5	Publication Lag (years) | Published in Top-5	Any Citations (dummy)	Log (citations)	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Race-related	-.001	-.011	-.145	-.049***	.004	.039*	-.026	.011	.098	.029
	(.020)	(.008)	(.142)	(.018)	(.004)	(.022)	(.191)	(.006)	(.063)	(.057)
Outcome mean (sd)	.734	.988	2.65 (3.10)	.181	.066 (.104)	.244	2.28 (2.24)	.978	3.64 (1.46)	3.65 (1.46)
Year FE	X	X	X	X	X	X	X	X	X	X
JEL Code FE	X	X	X	X	X	X	X	X	X	X
WP Characteristics	X	X	X	X	X	X	X	X	X	X
Author Affiliation FE	X	X	X	X	X	X	X	X	X	X
Journal FE										X
Sample	All Published NBER WPs (N=19,070)	All NBER WPs Published in Any Journal (N=13,995)	NBER WPs Published in Econ Journal (N=13,822)	NBER WPs Published in Econ Journal (N=13,822)			NBER WPs Published in Top 5 (N=3,377)	NBER WPs Published in Econ Journal (N=13,822)	NBER WPs Published in Econ Journal (N=13,511)	NBER WPs Published in Econ Journal (N=13,416)

Notes: *** denotes significance at the 1%, ** at the 5%, * at the 10% level. The sample is based on NBER working papers first posted between 1974 and 2015. In Column 1 the outcome is a dummy for whether the working paper is published in any journal. In Column 2 the outcome is a dummy for whether the working paper is published in an economics journal. In Column 3 the publication lag is the number of years between when the NBER working paper is first posted and its year of publication. In Column 4 the outcome is whether the AER-weighted measure of journal quality constructed in Angrist *et al.* [2020] is zero. In Column 5 the outcome is the *AER*-weighted measure of journal quality constructed in Angrist et al. [2020] (including zeroes). In Column 6 the outcome is a dummy for whether the working paper is published in a top-5 economics journal. In Column 7 the outcome is the publication lag is the number of years between when the NBER working paper is first posted and its year of publication in a top-5 economics journal. In Column 8 the outcome is whether the publication receives any citations, as measured from the *Web of Science* or *Scopus*. In Columns 9 and 10 the outcome is the total number of citations received by an article since publication, as measured from the *Web of Science* or *Scopus*. All specifications include fixed effects for the year in which the working paper is first posted, and its JEL codes. Working paper characteristics include a linear and quadratic in page counts, linear and quadratic terms for the title length, dummies for the number of authors and for the number of unique JEL codes. Author affiliation fixed effects are derived from *Scopus*. Information on institutional affiliation is derived from the *Scopus* database, using first and last names. For each author-year combination we observe in the NBER data, we retrieve the affiliation of the author in the *Scopus* database with an economics publication who shares the same first and last name as the author in the NBER WP dataset. Moreover, the selected author should have a publication that is closest in time to the author being analyzed. When we identify multiple matches, we break ties randomly. We also control for the average number of matches found for each author of an article (and its quadratic). Affiliations of NBER working paper authors are found in two thirds of cases. The author affiliation dummies to cover the 100 most frequent institutions in our data set, a dummy for other affiliations and a dummy for no matched affiliation. In Column 10 we additionally control for journal of publication fixed effects. Robust standard errors are reported throughout.

Table 3: Paths to Publication for NBER Working Papers, Group Studied

OLS estimates, robust standard errors in parentheses

	Published in any Journal	Published in an Economics Journal	Publication lag (years)	Published in AER Zero weight journal	Journal Quality (AER-Weighted)	Published in Top-5	Publication Lag (years) | Published in Top-5	Any Citations	Log (citations)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Race-related x Black	.134**	-.008	.004	-.026	-.008	.029	.028	.006	.135	.203
	(.058)	(.013)	(.362)	(.053)	(.014)	(.064)	(.642)	(.023)	(.181)	(.163)
Race-related x All other groups	-.132	.043	.676	.122	-.014	-.186*	.474	-.009	-.257	-.119
	(.091)	(.041)	(.47)	(.092)	(.018)	(.096)	(.703)	(.012)	(.279)	(.273)
Race-related x Non-specific	.007	.034	-.712	.026	.003	-.006	-.593	.022	-.166	-.061
	(.057)	(.022)	(.473)	(.053)	(.012)	(.066)	(.565)	(.023)	(.187)	(.175)
Outcome mean (sd)	.734	.988	2.65 (3.10)	.181 (.385)	.066 (.104)	.244	2.28 (2.24)	.978	3.64 (1.46)	3.65 (1.45)
p-values, within race-related research										
Black = All other groups	[.016]	[.251]	[.269]	[.166]	[.812]	[.071]	[.671]	[.608]	[.270]	[.345]
Black = Non-specific	[.072]	[.098]	[.220]	[.432]	[.507]	[.647]	[.366]	[.606]	[.152]	[.169]
All other groups = Non-specific	[.188]	[.844]	[.019]	[.346]	[.448]	[.121]	[.246]	[.209]	[.792]	[.861]
Year FE	X	X	X	X	X	X	X	X	X	X
JEL Code FE	X	X	X	X	X	X	X	X	X	X
WP Characteristics	X	X	X	X	X	X	X	X	X	X
Author Affiliation FE	X	X	X	X	X	X	X	X	X	X
Journal FE										X
Sample	All Published NBER WPs (N=19,070)	All NBER WPs Published in Any Journal (N=13,995)	NBER WPs Published in Econ Journal (N=13,822)	NBER WPs Published in Econ Journal (N=13,822)			NBER WPs Published in Top 5 (N=3,377)	NBER WPs Published in Econ Journal (N=13,822)	NBER WPs Published in Econ Journal (N=13,511)	NBER WPs Published in Econ Journal (N=13,416)

Notes: *** denotes significance at the 1%, ** at the 5%, * at the 10% level. The sample is based on NBER working papers first posted between 1974 and 2015. In Column 1 the outcome is a dummy for whether the working paper is published in any journal. In Column 2 the outcome is a dummy for whether the working paper is published in an economics journal. In Column 3 the publication lag is the number of years between when the NBER working paper is first posted and its year of publication. In Column 4 the outcome is whether the *AER* -weighted measure of journal quality constructed in Angrist et al. [2020] is zero. In Column 5 the outcome is the *AER* -weighted measure of journal quality constructed in Angrist *et al.* [2020] (including zeroes). In Column 6 the outcome is a dummy for whether the working paper is published in a top-5 economics journal. In Column 7 the outcome is the publication lag is the number of years between when the NBER working paper is first posted and its year of publication in a top-5 economics journal. In Column 8 the outcome is whether the publication receives any citations, as measured from the *Web of Science* or *Scopus* . In Columns 9 and 10 the outcome is the total number of citations received by an article since publication, as measured from the *Web of Science* or *Scopus* . All specifications include fixed effects for the year in which the working paper is first posted, and its JEL codes. Working paper characteristics include a linear and quadratic in page counts, linear and quadratic terms for the title length, dummies for the number of authors and for the number of unique JEL codes. Author affiliation fixed effects are derived from *Scopus* . Information on institutional affiliation is derived from the *Scopus* database, using first and last names. For each author-year combination we observe in the NBER data, we retrieve the affiliation of the author in the *Scopus* database with an economics publication who shares the same first and last name as the author in the NBER WP dataset. Moreover, the selected author should have a publication that is closest in time to the author being analyzed. When we identify multiple matches, we break ties randomly. We also control for the average number of matches found for each author of an article (and its quadratic). Affiliations of NBER working paper authors are found in two thirds of cases. The author affiliation dummies to cover the 100 most frequent institutions in our data set, a dummy for other affiliations and a dummy for no matched affiliation. In Column 10 we additionally control for journal of publication fixed effects. At the foot of each Column we report the p-value on the null that the interactions of race-related articles with the group under study (black, all other groups, non-specific groups) are equal. Robust standard errors are reported throughout.

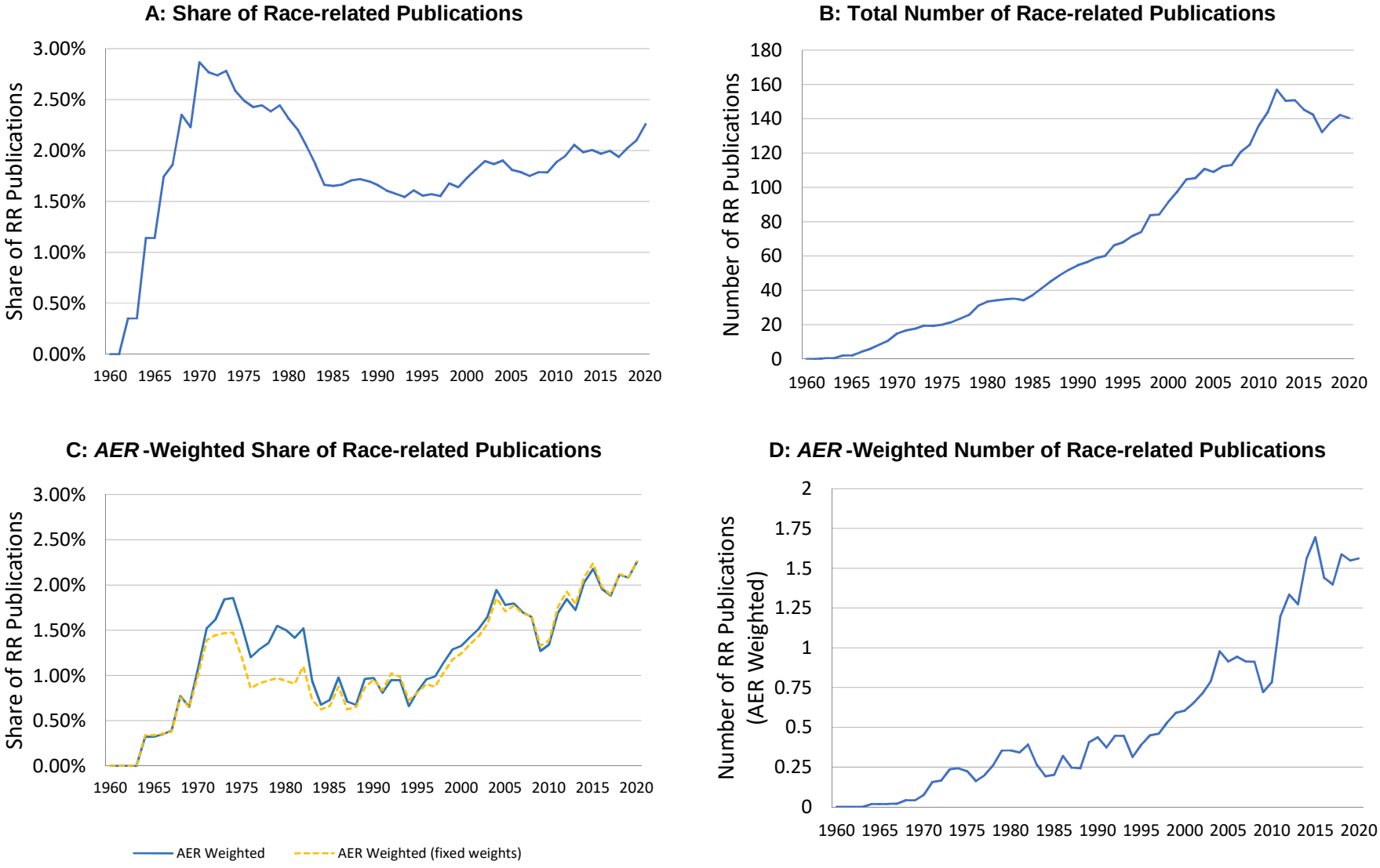
Table 4: Paths to Publication for NBER Working Papers, Topic Studied

OLS estimates, robust standard errors in parentheses

	Published in any Journal	Published in an Economics Journal	Publication lag (years)	Published in AER Zero weight journal	Journal Quality (AER-Weighted)	Published in Top-5	Publication Lag (years) | Published in Top-5	Any Citations	Log (citations)	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Race-related x Discrimination	.114**	-.038	.225	-.038	.016	.085	.688	.004	.252	.197
	(.053)	(.028)	(.448)	(.052)	(.011)	(.069)	(.508)	(.025)	(.174)	(.161)
Race-related x Inequality	-.007	-.012	-.748*	.019	.005	-.013	.182	.021	.046	.028
	(.047)	(.018)	(.402)	(.044)	(.009)	(.057)	(.458)	(.020)	(.141)	(.126)
Race-related x Diversity	.065	.020*	.270	-.058	.026**	.098	-.466	.014	-.149	-.243
	(.059)	(.012)	(.421)	(.057)	(.011)	(.068)	(.429)	(.021)	(.181)	(.162)
Race-related x Identity	.158*	.084**	-1.61**	.050	-.011	-.000	-1.07	-.005	-.163	-.046
	(.093)	(.036)	(.691)	(.111)	(.023)	(.138)	(.826)	(.018)	(.347)	(.325)
Race-related x Historic	.016	-.063	.047	-.126	.011	-.004	-1.03	.001	-.106	-.399
	(.087)	(.075)	(1.14)	(.095)	(.020)	(.106)	(1.37)	(.051)	(.333)	(.303)
Outcome mean (sd)	.734	.988	2.65 (3.10)	.181 (.385)	.066 (.104)	.244	2.28 (2.24)	.978	3.64 (1.46)	3.65 (1.45)
p-values, within race-related research										
Discrimination=Inequality	[.046]	[.336]	[.119]	[.248]	[.382]	[.196]	[.489]	[.557]	[.287]	[.338]
Discrimination=Diversity	[.516]	[.070]	[.930]	[.783]	[.536]	[.898]	[.086]	[.745]	[.113]	[.056]
Discrimination=Identity	[.679]	[.011]	[.040]	[.462]	[.291]	[.587]	[.111]	[.780]	[.317]	[.526]
Discrimination=Historical	[.336]	[.759]	[.864]	[.412]	[.809]	[.488]	[.252]	[.958]	[.349]	[.078]
Inequality=Diversity	[.288]	[.103]	[.059]	[.295]	[.093]	[.153]	[.249]	[.763]	[.372]	[.161]
Inequality=Identity	[.070]	[.013]	[.193]	[.782]	[.492]	[.927]	[.137]	[.153]	[.576]	[.832]
Inequality=Historic	[.805]	[.546]	[.533]	[.172]	[.787]	[.940]	[.375]	[.716]	[.668]	[.174]
Diversity=Identity	[.362]	[.069]	[.020]	[.392]	[.144]	[.517]	[.472]	[.458]	[.971]	[.588]
Diversity=Historic	[.642]	[.301]	[.823]	[.531]	[.507]	[.420]	[.677]	[.787]	[.910]	[.650]
Identity=Historic	[.259]	[.099]	[.250]	[.238]	[.475]	[.981]	[.982]	[.911]	[.905]	[.434]
Year FE	X	X	X	X	X	X	X	X	X	X
JEL Code FE	X	X	X	X	X	X	X	X	X	X
WP Characteristics	X	X	X	X	X	X	X	X	X	X
Author Affiliation FE	X	X	X	X	X	X	X	X	X	X
Journal FE										X
Sample	All Published NBER WPs (N=19,070)	All NBER WPs Published in Any Journal (N=13,995)	NBER WPs Published in Econ Journal (N=13,822)	NBER WPs Published in Econ Journal (N=13,822)			NBER WPs Published in Top 5 (N=3,377)	NBER WPs Published in Econ Journal (N=13,822)	NBER WPs Published in Econ Journal (N=13,511)	NBER WPs Published in Econ Journal (N=13,416)

Notes: *** denotes significance at the 1%, ** at the 5%, * at the 10% level. The sample is based on NBER working papers first posted between 1974 and 2015. In Column 1 the outcome is a dummy for whether the working paper is published in any journal. In Column 2 the outcome is a dummy for whether the working paper is published in an economics journal. In Column 3 the publication lag is the number of years between when the NBER working paper is first posted and its year of publication. In Column 4 the outcome is whether the *AER*-weighted measure of journal quality constructed in Angrist *et al.* [2020] is zero. In Column 5 the outcome is the *AER*-weighted measure of journal quality constructed in Angrist *et al.* [2020] (including zeroes). In Column 6 the outcome is a dummy for whether the working paper is published in a top-5 economics journal. In Column 7 the outcome is the publication lag is the number of years between when the NBER working paper is first posted and its year of publication in a top-5 economics journal. In Column 8 the outcome is whether the publication receives any citations, as measured from the Web of Science or Scopus. In Columns 9 and 10 the outcome is the total number of citations received by an article since publication, as measured from the Web of Science or Scopus. All specifications include fixed effects for the year in which the working paper is first posted, and its JEL codes. Working paper characteristics include a linear and quadratic in page counts, linear and quadratic terms for the title length, dummies for the number of authors and for the number of unique JEL codes. Author affiliation fixed effects are derived from Scopus. Information on institutional affiliation is derived from the Scopus database, using first and last names. For each author-year combination we observe in the NBER data, we retrieve the affiliation of the author in the Scopus database with an economics publication who shares the same first and last name as the author in the NBER WP dataset. Moreover, the selected author should have a publication that is closest in time to the author being analyzed. When we identify multiple matches, we break ties randomly. We also control for the average number of matches found for each author of an article (and its quadratic). Affiliations of NBER working paper authors are found in two thirds of cases. The author affiliation dummies to cover the 100 most frequent institutions in our data set, a dummy for other affiliations and a dummy for no matched affiliation. In Column 10 we additionally control for journal of publication fixed effects. At the foot of each Column we report the p-value on the null that the interactions of race related articles with their topic under study (discrimination, inequality, diversity, identity historic) are equal across pairs of topics. Robust standard errors are reported throughout.

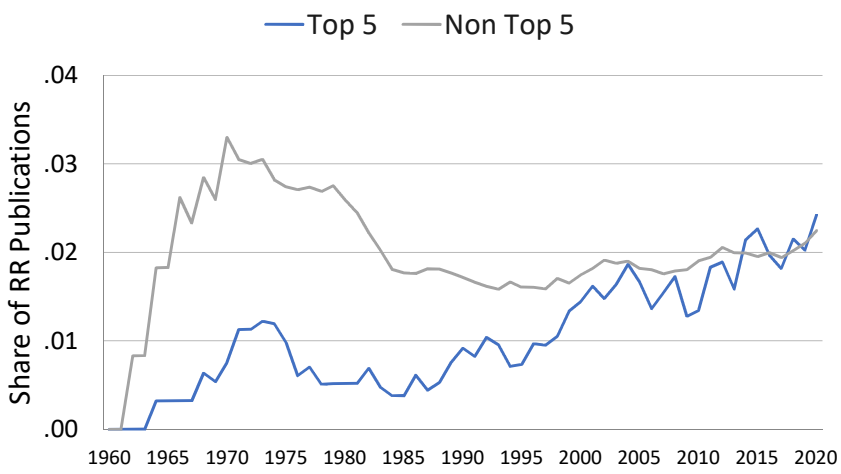
Figure 1: Race-related Publications in Economics, by Year



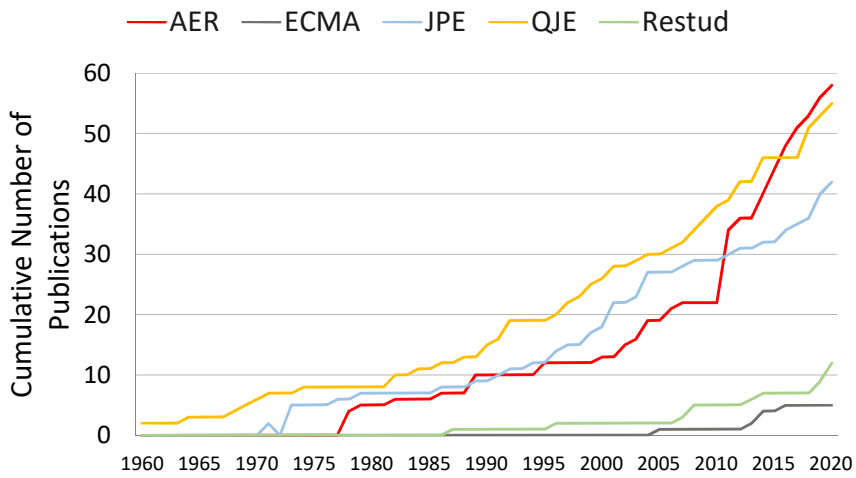
Notes: We use a corpus of publications in economics journals, based on data from *JSTOR*, *Web of Science* and *Scopus*. When a journal is assigned to multiple disciplines, we split the number of publications in that journal equally across disciplines. We report five-year moving averages throughout. Panel A reports the share of total publications identified to be race-related by year of publication. Panel B reports the number of race-related publications by year of publication. Panels C and D report *AER*-weighted versions of Panels A and B, using the journal weights constructed in Angrist *et al.* [2020].

Figure 2: Race-related Publications, Top-5 Journals

A: Share of Race-related Publications, Top-5 vs. Other Journals



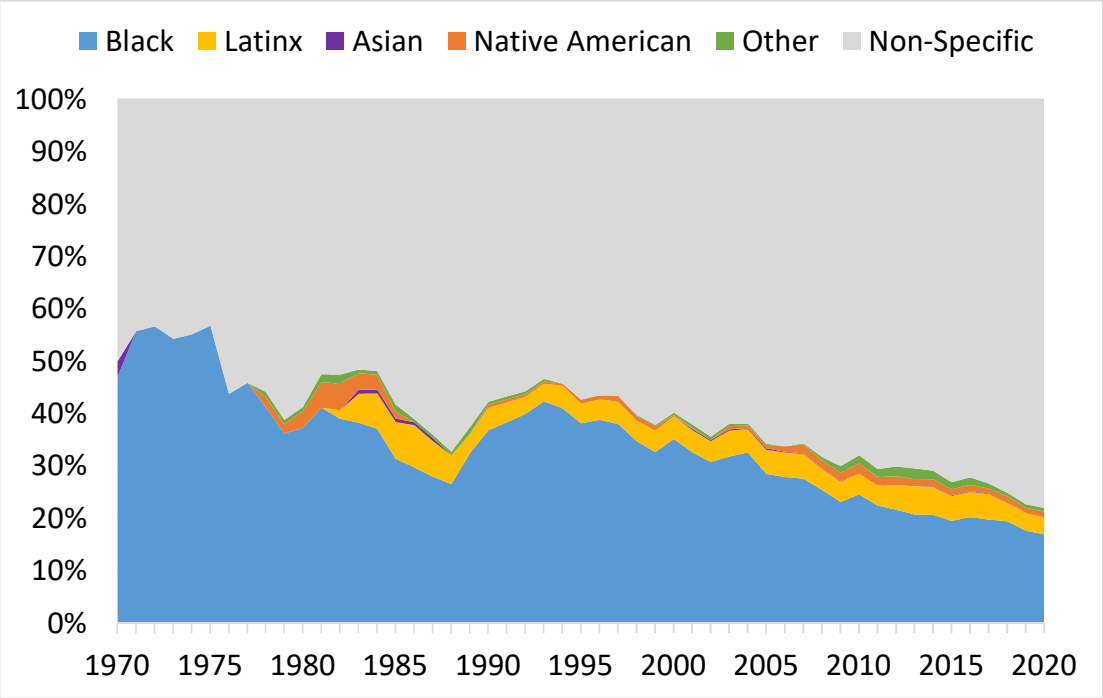
B: Cumulative Number of Race-related Publications, Top-5



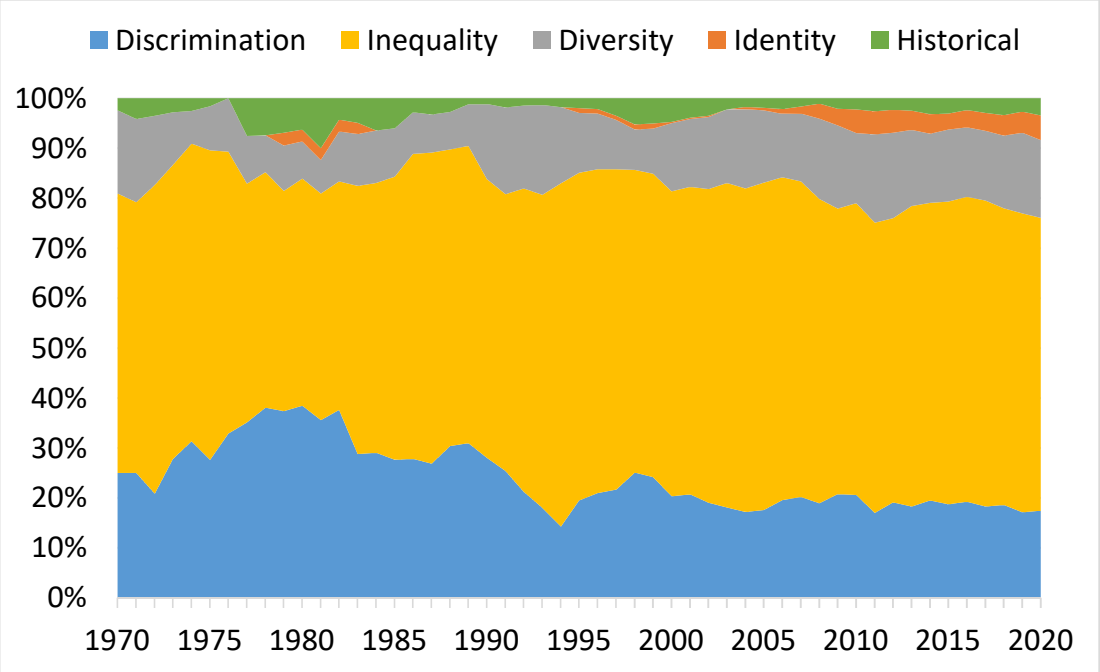
Notes: The top-5 general interest journals in economics are the *American Economic Review*, *Econometrica*, the *Journal of Political Economy*, the *Quarterly Journal of Economics*, and the *Review of Economic Studies*. For non-top 5 journals, we use a corpus of publications in economics journals, based on data from *JSTOR*, *Web of Science* and *Scopus*. When a journal is assigned to multiple disciplines, we split the number of publications in that journal equally across disciplines. In Panel A we report five-year moving averages.

Figure 3: Race-related Publications in Economics

A. Groups Studied



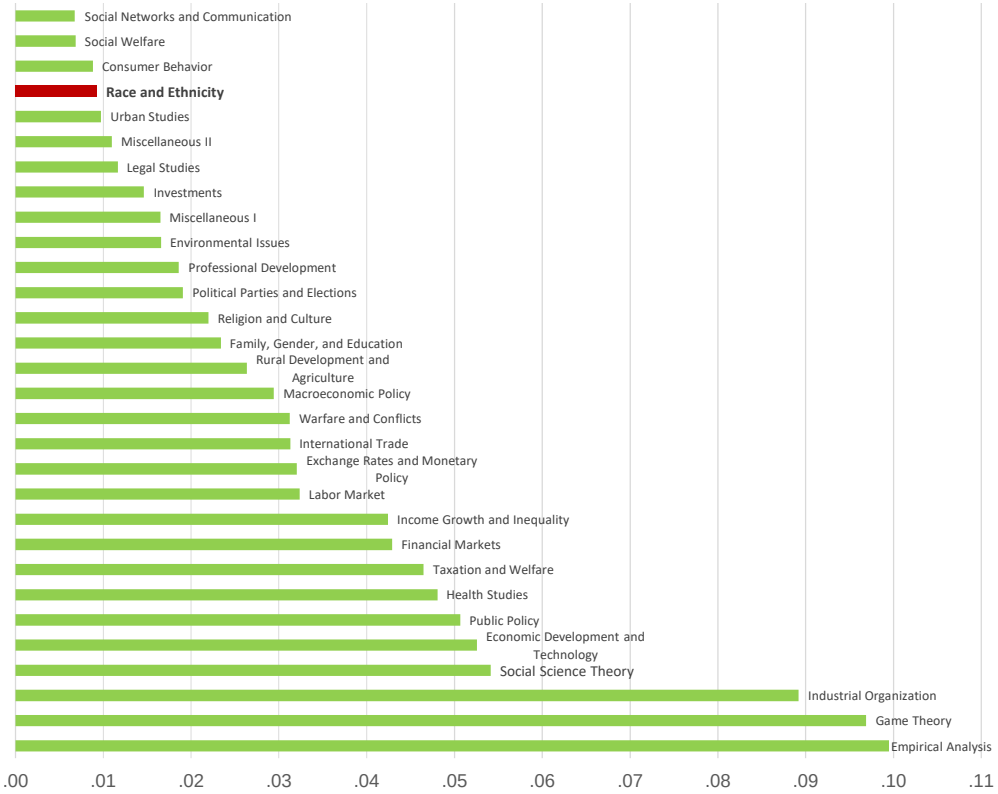
B. Topics Studied



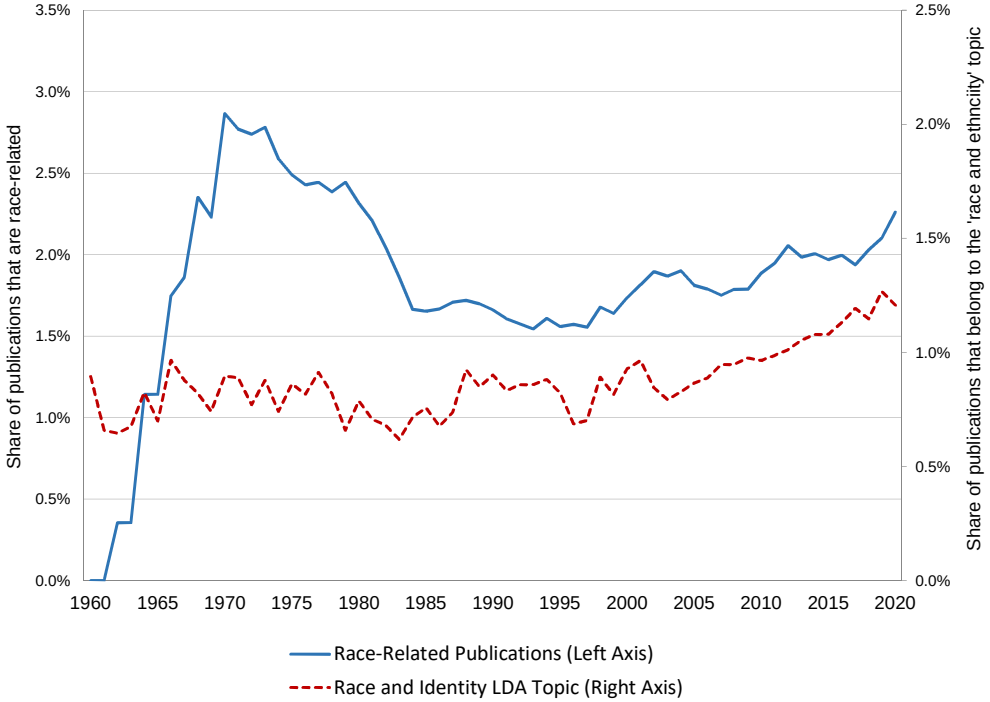
Notes: We use a corpus of publications in economics journals, based on data from *JSTOR*, *Web of Science* and *Scopus*. When a journal is assigned to multiple disciplines, we split the number of publications in that journal equally across disciplines. We report five-year moving averages throughout. To construct the groups studies series in Panel A, for each year, we calculate the publications among all race-related ones that mention at least one group. When a publication mentions more than one group, we split the weight of the publication equally across those different groups. In Panel B, we make an analogous construction for publications that mention more than one race-related topic.

Figure 4: LDA Topic Model on Corpus of Economics Publications 1960-2020

A. Share of Publications by Topic



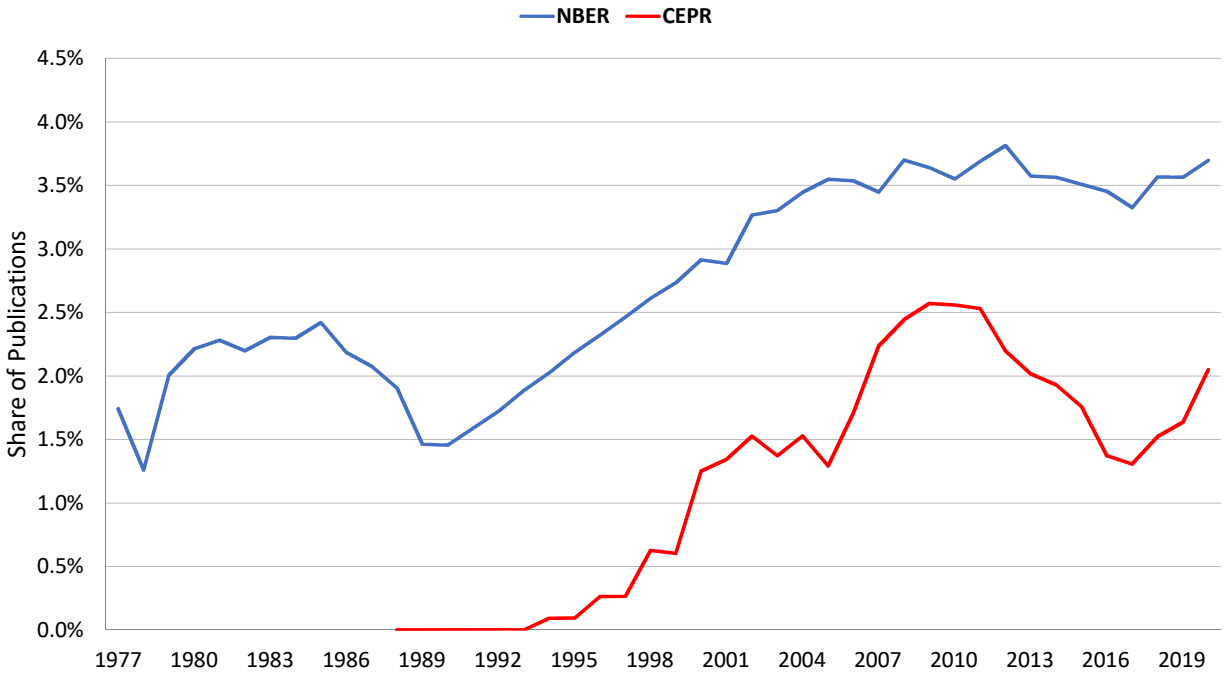
B. *AER*-Weighted Share of Race-related Publications and Share of Publications by Race and Identity Topic, by Year



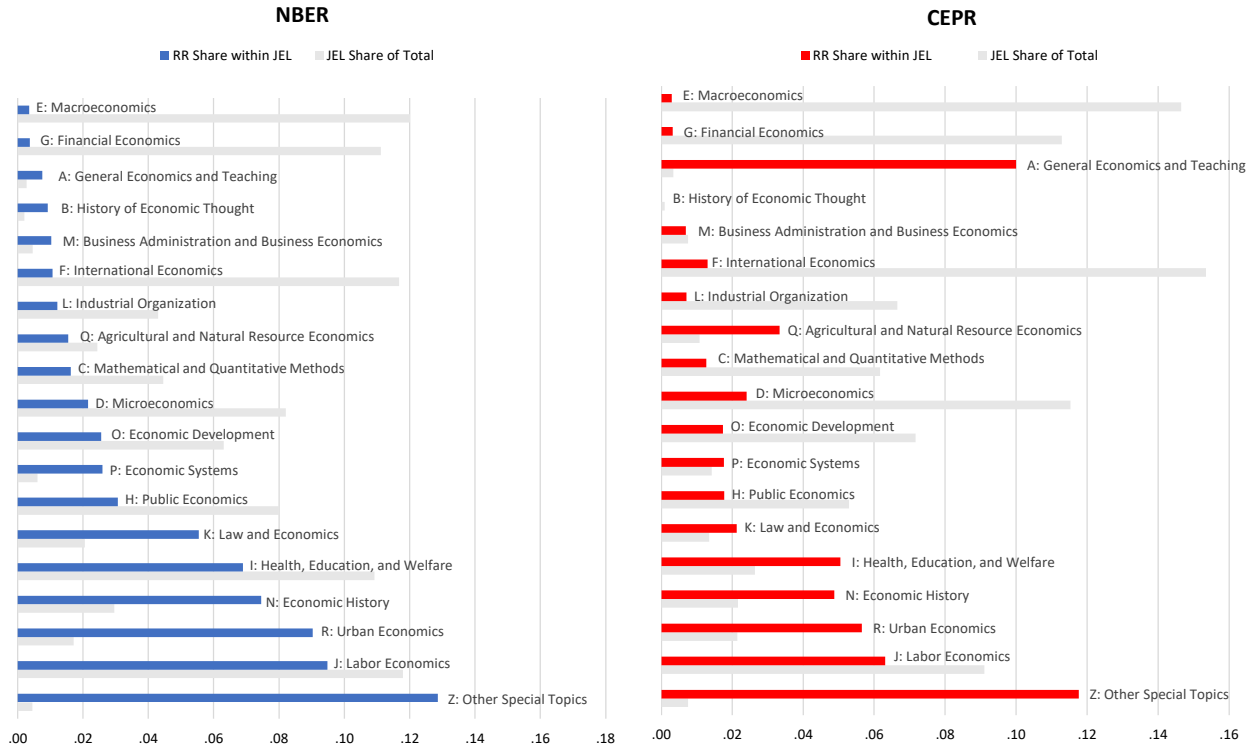
Notes: Panel A shows the share of publications in economics by topic, based on the 30 topics derived from the LDA model. The model is run on a corpus of 493,972 publications in economics, sociology, political science, law, management, public policy and history, based on data from *JSTOR Web of Science*, and *Scopus*. When a journal is assigned to multiple disciplines, we split the number of publications in that journal equally across disciplines. In Panel A we then use predicted topic probabilities on our corpus of publications in economics from 1960. Panel B reports five-year moving averages for the share of all economics publications that are identified by our algorithm as race-related. This series is measured on the left-hand axis. On the right-hand axis we show the share of economics publications that are assigned the LDA topic of 'race and ethnicity'.

Figure 5: NBER and CEPR Working Papers

A. Share of Race-related Working Papers



B. Share of Race-related Working Papers by JEL Category and JEL Share of Total

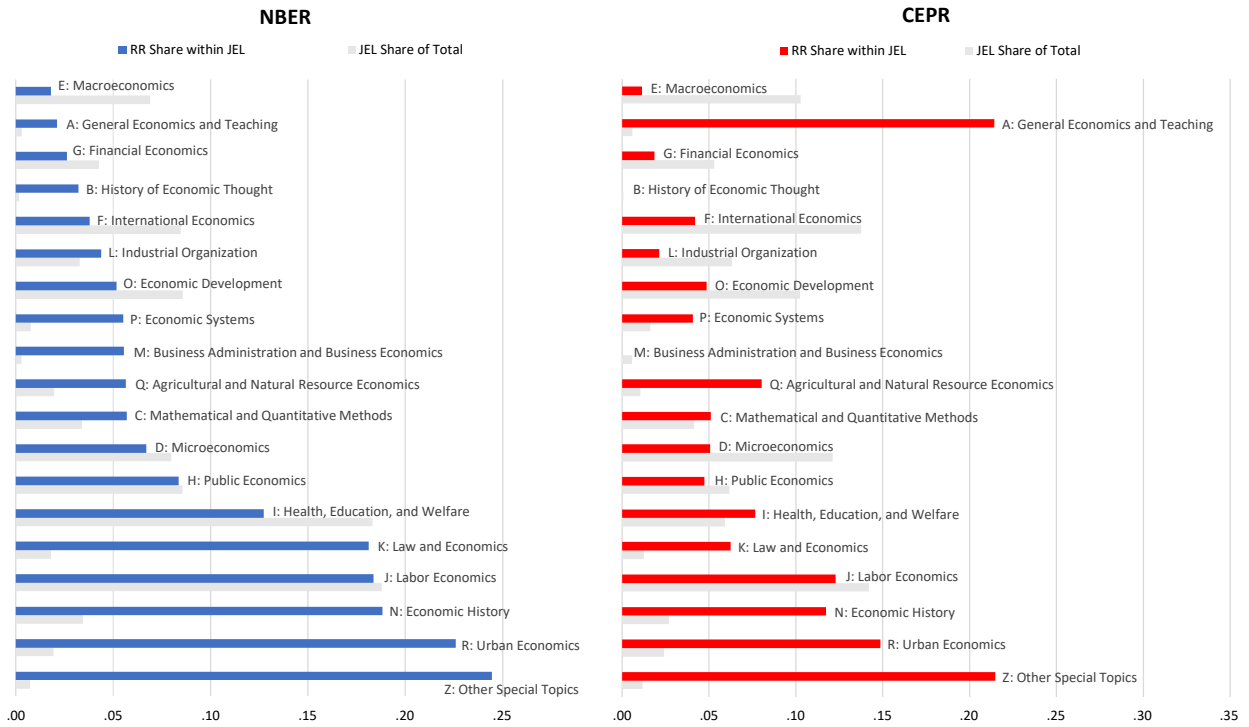


Notes: The sample is based on NBER working papers first released between 1974 and 2019, and CEPR working papers released between 1984 and 2019. Panel A shows the shares of working papers identified to be race-related in each series, in five-year moving averages - with the NBER (CEPR) series starting in 1977 (1987). Panel B shows the fraction of working papers that are identified to be race-related by JEL classification, as well as the share of all working papers in that series by JEL code. When a working paper has multiple JEL codes, we split the assignment article equally across all codes. We omit working papers with no JEL classification and JEL code Y, *Miscellaneous Categories* because this is not represented in the NBER corpus and is associated with eight papers in the CEPR series, among which none are race-related.

Figure 6: The Relevance of Race-related Research by Field

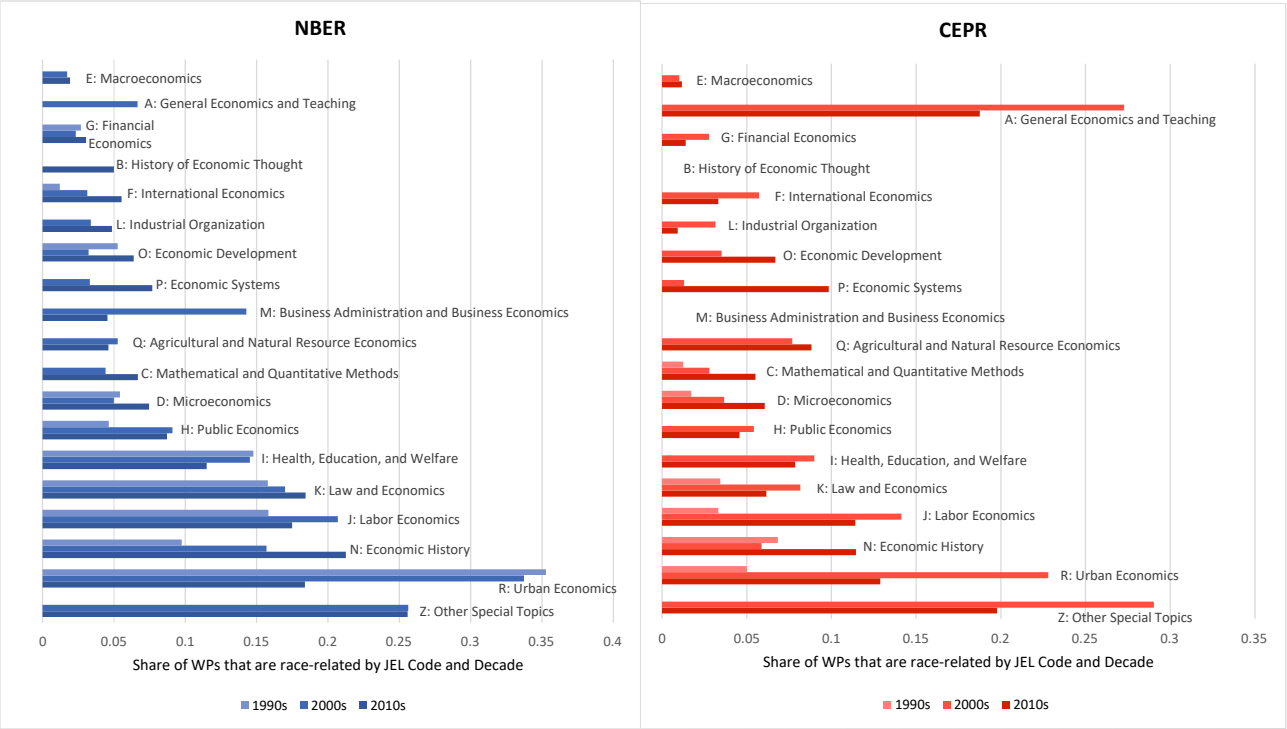
A. Share of Race-related Working Papers by JEL Category

Sample: Working papers with topic keywords



B. Share of Race-related Working Papers by JEL Category and Decade

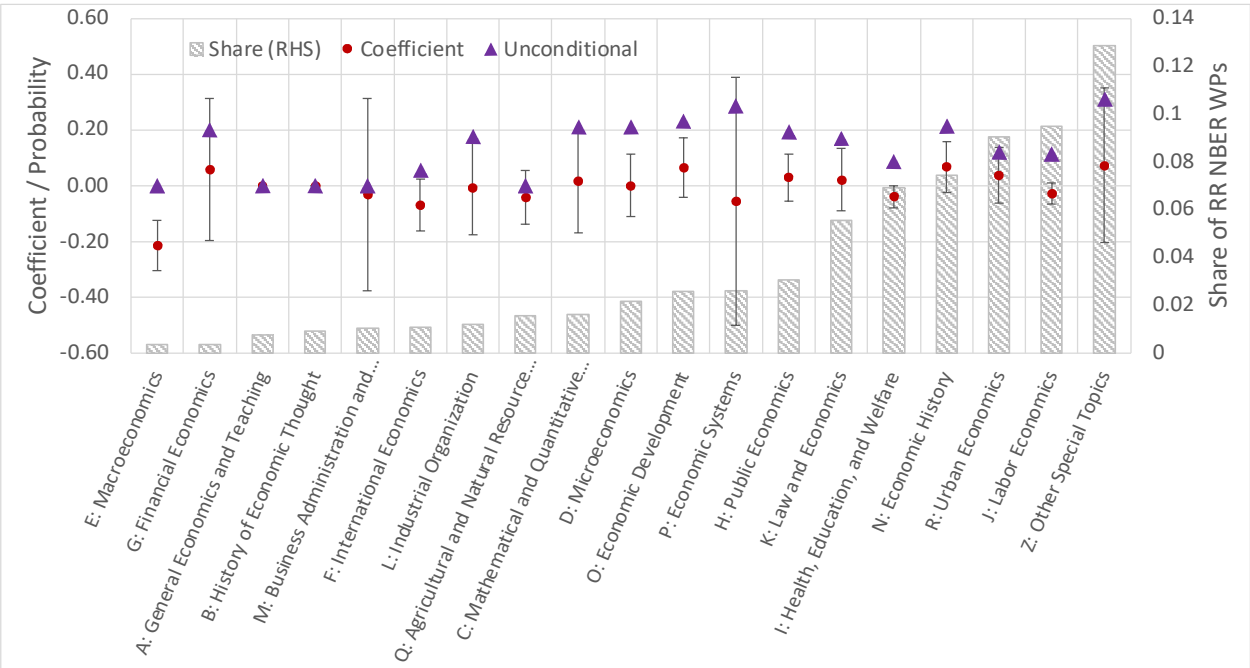
Sample: Working papers with topic keywords



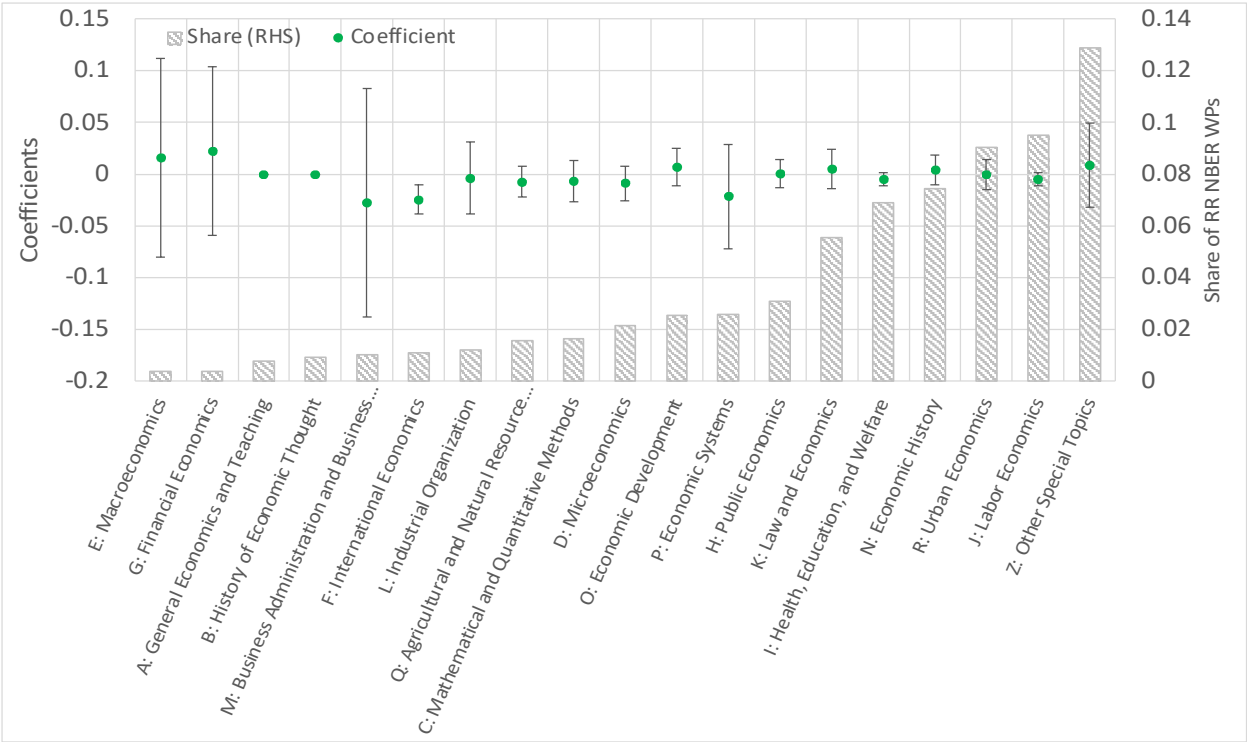
Notes: The sample is based on NBER working papers first released between 1974 and 2019, and CEPR working papers released between 1984 and 2019. In both cases we only consider working papers that mention at least one topic keyword in their title and abstract. Panel A shows the fraction of working papers that are identified to be race-related by JEL classification, as well as the share of all working papers in that series by JEL code. When a working paper has multiple JEL codes, we split the assignment article equally across all codes. We omit working papers with no JEL classification and JEL code Y, *Miscellaneous Categories* because this is not represented in the NBER corpus and is associated with eight papers in the CEPR series, among which none are race-related. Panel B shows the same information split by decade of posting.

Figure 7: Paths to Publication by Field

A. Publications in a Top-5 Journal

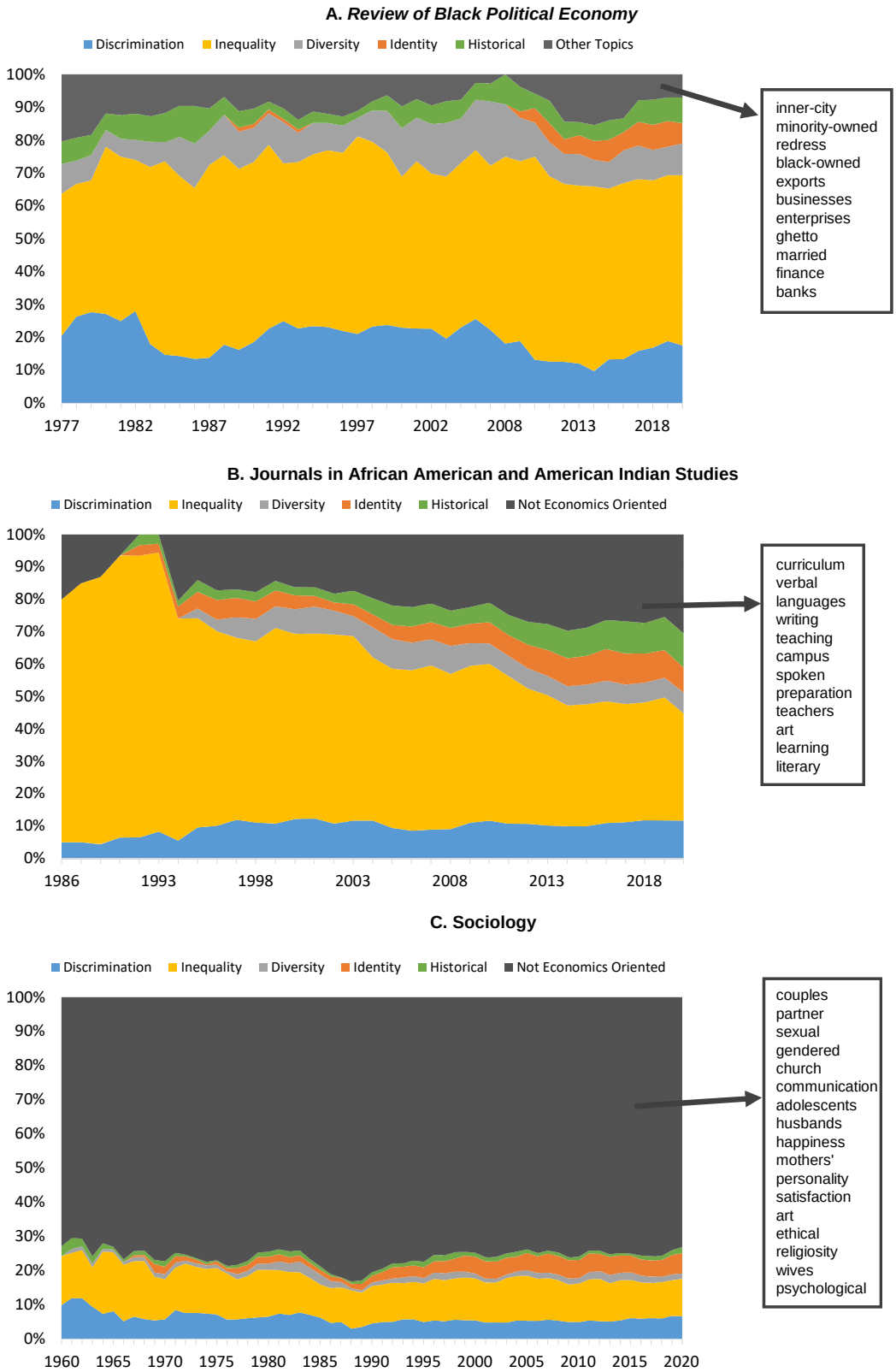


B. AER-Weighted Quality of Journal Publication



Notes: The sample is based on NBER working papers first released between 1974 and 2015. Panel A of Figure 7 then plots for each JEL code: (i) the unconditional probability of a race-related NBER WP being published in the top-5; (ii) the conditional estimate, that include fixed effects for the year in which the working paper is first posted, working paper characteristics (a linear and quadratic in page counts, linear and quadratic terms for the title length, dummies for the number of authors and for the number of unique JEL codes). Author affiliation fixed effects are derived from Scopus. We also control for the average number of matches found for each author of an article (and its square). We overlay this with a histogram showing the share of WPs in the JEL-code that are race-related, where we order the fields in increasing share of race-related WPs. Panel B repeats the analysis where the outcomes is the *AER*-weight of the journal publication. In both Panels results for JEL codes A and B are omitted due to multicollinearity issues. 95% confidence intervals are shown throughout.

Figure 8: Race-related Topics Studied in Minority Journals, Minority Disciplines



Notes: We use a corpus of publications in based on data from *JSTOR*, *Web of Science* and *Scopus*. When a journal is assigned to multiple disciplines, we split the number of publications in that journal equally across disciplines. We report five-year moving averages throughout. Panel A focuses on publications in the *Review of Black Political Economy*. Panel B focuses on journals from the discipline of African American and American Indian studies (as defined by *JSTOR*). Panel C focuses on journals in sociology. In Panels A and B, we assume all published articles are race-related, decomposing them into the broad topic areas and hence identifying those not covered by any topic area. We then select some prominent keywords in these other topic publications. For Panel C we start by restricting to publications with some group related keywords in the title and/or abstract.

Table A1: Group Keywords with Regular Expression Patterns

Non-Specific - Band 0	Decomposition Group
aboriginal	Non-Specific
advantaged[-]?group[a-zA-Z]{0,1}	Non-Specific
caste[a-zA-Z]{0,1}	Non-Specific
colou?red[a-zA-Z]{0,1}	Non-Specific
disadvantaged[-]?minor[a-zA-Z]{0,5}	Non-Specific
dominant[-]?group[a-zA-Z]{0,1}	Non-Specific
ethnic minorit[a-zA-Z]{0,3}	Non-Specific
ethnic[a-zA-Z]{0,4}	Non-Specific
indigenous	Non-Specific
natives	Non-Specific
non[-]?western[a-zA-Z]{0,1}	Non-Specific
non[-]?white[a-zA-Z]{0,1}	Non-Specific
people[-]?of[-]?colou?r	Non-Specific
person[a-zA-Z]{0,1}[-]?of[-]?colou?r	Non-Specific
rac[a-zA-Z]{0,3}	Non-Specific
underrepresented[-]?minorit[a-zA-Z]{0,3}	Non-Specific
Main Minority Groups - Band 1	**Decomposition Group**
african[-]?american[a-zA-Z]{0,1}	Black
afro[-]?american[a-zA-Z]{0,1}	Black
black[-]?american[a-zA-Z]{0,1}	Black
black[a-zA-Z]{0,1}	Black
negro[a-zA-Z]{0,2}	Black
hispanic[-]?american[a-zA-Z]{0,1}	Hispanic
hispanic[a-zA-Z]{0,1}	Hispanic
latino[-]?american[a-zA-Z]{0,1}	Hispanic
latino[a-zA-Z]{0,1}	Hispanic
mexican[-]?american[a-zA-Z]	Hispanic
spanish[-]?american[a-zA-Z]	Hispanic
american[-]?indian[a-zA-Z]{0,1}	Native American
cherokee[a-zA-Z]{0,6}	Native American
chippewa[a-zA-Z]{0,3}	Native American
choctaw[a-zA-Z]{0,3}	Native American
native[-]?american[a-zA-Z]{0,1}	Native American
navajo[a-zA-Z]{0,3}	Native American
siouan	Native American
sioux	Native American
Less Prominent Groups - Band 2	**Decomposition Group**
asian[-]?american[a-zA-Z]	Asian
chinese[-]?american[a-zA-Z]	Asian
indian[-]?american[a-zA-Z]	Asian
indo[-]?american[a-zA-Z]	Asian
japanese[-]?american[a-zA-Z]	Asian
korean[-]?american[a-zA-Z]	Asian
oriental[a-zA-Z]{0,1}	Asian
south[-]?asian[a-zA-Z]{0,1}	Asian
vietnamese[-]?american[a-zA-Z]	Asian
arab	Other
arab[-]?american[a-zA-Z]	Other
arab[-]?american[a-zA-Z]	Other
caucasian[a-zA-Z]{0,1}	Other
cuban[-]?american[a-zA-Z]	Other
ethiopian[-]?american[a-zA-Z]	Other
filipino[-]?american[a-zA-Z]	Other
hebrew[a-zA-Z]{0,1}	Other
islam[a-zA-Z]	Other
jew[a-zA-Z]{0,3}	Other
jewish[-]?american[a-zA-Z]	Other
muslim[-]?american[a-zA-Z]	Other
muslim[a-zA-Z]	Other
palestinian[-]?american[a-zA-Z]	Other
portuguese[-]?american[a-zA-Z]	Other
yiddish	Other

Notes: [a-zA-Z]{0,k} indicates that we allow any number of 0 to 'k' lowercase or uppercase characters to be matched. [-]? allows for an optional hyphen or space. We also account for American and British English spellings, for instance, in colou?red[a-zA-Z]{0,1}.

Table A2: Topic Keywords with Regular Expression Patterns

Discrimination (41)	Inequality (23)	Diversity (18)	Identity (4)	Historical (17)
-group bias	black youth[a-zA-Z]{0,1}	affirmative[-]?action[a-zA-Z]{0,1}	rac[a-zA-Z]{0,3} identit[a-zA-Z]{0,3}	black vot[a-zA-Z]{0,3}
animosit[a-zA-Z]{0,3}	black-white	desegregat[a-zA-Z]{0,3}	acting white	civil rights
animus	development	ethnic composition[a-zA-Z]{0,3}	identity	emancipat[a-zA-Z]{0,3}
anti[-]?black	disadvantage	ethnic[-]?diversity	identities	eugenics
anti[-]?discrimination	disadvantaged	ethnic[-]?fragmentation[a-zA-Z]{0,1}		jim crow
anti[-]?semitic	educat[a-zA-Z]{0,5}	ethnic heterogene[a-zA-Z]{0,5}		lynch[a-zA-Z]{0,5}
antisemitism	ethnic differen[a-zA-Z]{0,4}	ethnic integration[a-zA-Z]{0,1}		political disenfranchisement
apartheid	ethnic disparit[a-zA-Z]{0,3}	rac[a-zA-Z]{0,3} composition[a-zA-Z]{0,1}		postbellum
attitude[a-zA-Z]{0,1}	ethnic gap[a-zA-Z]{0,1}	rac[a-zA-Z]{0,3} integration[a-zA-Z]{0,1}		race relation[a-zA-Z]{0,1}
discriminat[a-zA-Z]{0,5}	ethnic inequalit[a-zA-Z]{0,3}	racial[-]?diversity		race riot[a-zA-Z]{0,3}
ethnic bias[a-zA-Z]{0,3}	gap[a-zA-Z]{0,1}	racial[-]?fragmentation[a-zA-Z]{0,1}		reconstruction[a-zA-Z]{0,1}
ethnic division[a-zA-Z]{0,1}	inequality	racial heterogene[a-zA-Z]{0,5}		slave[a-zA-Z]{0,2}
ethnic exclusion[a-zA-Z]{0,1}	living standard	representation		social[-]?activis[a-zA-Z]{0,1}
ethnic interact[a-zA-Z]{0,4}	standard of living	segregat[a-zA-Z]{0,3}		southern farm
ethnic stereotyp[a-zA-Z]{0,3}	negro-white	social[-]?diversity		the great migration
ethnic[-]?division[a-zA-Z]{0,1}	poverty	social[-]?fragmentation[a-zA-Z]{0,1}		tuskegee
ethnic[-]?exclusion[a-zA-Z]{0,1}	rac[a-zA-Z]{0,3} differen[a-zA-Z]{0,4}	tipping point		whitecapping
exploitation	rac[a-zA-Z]{0,3} disparit[a-zA-Z]{0,4}	underrepresent[a-zA-Z]{0,3}		
hatred	rac[a-zA-Z]{0,3} gap[a-zA-Z]{0,1}			
implicit bias[a-zA-Z]{0,4}	rac[a-zA-Z]{0,3} inequalit[a-zA-Z]{0,3}			
in-group	school[a-zA-Z]{0,3}			
ingroup	stratification			
institutional discrimination	welfare			
institutional racism				
inter-group				
intergroup				
oppress[a-zA-Z]{0,3}				
out-group				
outgroup				
prejudi[a-zA-Z]{0,4}				
rac[a-zA-Z]{0,3} bias[a-zA-Z]{0,4}				
rac[a-zA-Z]{0,3} interact[a-zA-Z]{0,4}				
rac[a-zA-Z]{0,3} profiling				
rac[a-zA-Z]{0,3} stereotyp[a-zA-Z]{0,3}				
racial[-]?division[a-zA-Z]{0,1}				
racial[-]?exclusion[a-zA-Z]{0,1}				
social[-]?division[a-zA-Z]{0,1}				
social[-]?exclusion[a-zA-Z]{0,1}				
statistical discrimination[a-zA-Z]{0,1}				
structural discrimination				
systemic racism				

Notes: [a-zA-Z]{0,k} indicates that we allow any number of 0 to 'k' lowercase or uppercase characters to be matched. [-]? allows for an optional hyphen or space.

Table A3: Eliminated Phrases with Regular Expression Patterns

arms.{0,3}rac.{0,3}
black swan[a-zA-Z-]{0,1}
black.{0,3}box.{0,3}
black.{0,3}card[a-zA-Z]{0,1}
black.{0,3}economy
black.{0,3}market[a-zA-Z-]{0,3}
black.{0,3}scholes
electoral.{0,3}rac.{0,3}
horse.*rac.{0,3}
patent.{0,3}rac.{0,3}
priority.{0,3}rac.{0,3}
prize.*rac.{0,3}
r d.{0,3}rac.{0,3}
rac.*horse.{0,3}
rac.*prize.{0,3}
rac.*winner{0,3}
race[s]{0,1} between
rat.{0,3}.{0,3}rac.{0,3}
rd.{0,3}rac.{0,3}
rival
white.{0,3}collar
white.{0,3}noise
winner.*rac.{0,3}

Notes: [a-zA-Z]{0,k} indicates that we allow any number of 0 to 'k' lowercase or uppercase characters to be matched. [-]? allows for an optional hyphen or space.

Table A4: Race-Related NBER Working Papers

Means, standard deviation in parentheses, p-values in brackets

	(1) Race-related	(2) Not Race-related	Test of Equality [p-value]
A. Working Paper Characteristics			
Number of authors	2.12	2.11	[.733]
	(.931)	(.928)	
Number of pages	47.5	44.7	[.000]
	(16.3)	(16.7)	
Title length (letter count)	69.3	64.7	[.000]
	(27.3)	(26.2)	
Number of JEL codes	1.58	1.42	[.000]
	(1.03)	(1.07)	
B. Groups and Topics Studied			
Group: Black	.538	.007	[.000]
Group: All Other Groups	.145	.002	[.000]
Group: Non-Specified	.717	.009	[.000]
Topic: Discrimination	.176	.019	[.000]
Topic: Inequality	.765	.238	[.000]
Topic: Diversity	.215	.009	[.000]
Topic: Identity	.027	.003	[.000]
Topic: Historic	.058	.003	[.000]

Notes: The sample is based on NBER working papers first posted between 1974 and 2015. Columns 1 and 2 show means and standard deviations in parentheses for working papers classified as race-related and not race-related respectively. Column 3 shows the p-values from a t-test of equality of means between race-related and not race-related articles, based on a regression with robust standard errors. In Panel B all other groups refers to Latinx, Asian, Native American and Other groups.

Table A5: Readability Scores, NBER Working Papers

OLS estimates, robust standard errors in parentheses

	Working Paper Version			Published Version			Change Across Versions		
	Flesch Reading Ease Score	Gunning Fog Score	Simple Measure of Gobbledygook Score	Flesch Reading Ease Score	Gunning Fog Score	Simple Measure of Gobbledygook Score	Flesch Reading Ease Score	Gunning Fog Score	Simple Measure of Gobbledygook Score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Race-related	.214***	.150***	.145***	.148***	.093	.094	-.066	-.062	-.058
	(.059)	(.060)	(.056)	(.064)	(.058)	(.059)	(.052)	(.053)	(.053)
Outcome mean (sd)	.004	.021	.007	.011	.020	.016	.008	.001	.011
Year FE	X	X	X	X	X	X	X	X	X
JEL Code FE	X	X	X	X	X	X	X	X	X
Article Characteristics	X	X	X	X	X	X	X	X	X
Author Affiliation FE	X	X	X	X	X	X	X	X	X
Sample	All NBER WPs Published in Any Journal with available SCOPUS/JSTOR abstracts (N=9,287)								

Notes:*** denotes significance at the 1%, ** at the 5%, * at the 10% level. The sample is based on NBER working papers first posted between 1974 and 2015 that are matched to publication abstracts from *JSTOR* or *Scopus*. We consider three readability indices. The Flesch Reading Ease test assigns higher scores to materials that are easier to read and lower scores to passages that are more challenging to comprehend. The Gunning Fog Index also estimates the reading level required to understand a piece of writing. It measures the complexity of sentences and words in the text, with higher scores indicating more complex and challenging content. The Simple Measure of Gobbledygook (SMOG) measures the complexity of written content by analyzing the number of words with three or more syllables in a sample text. The higher the SMOG score, the more advanced the reading level required to understand the text. As the scores have different scales and signs, to compare scores, the Gunning Fog and SMOG measures are inverted. For all measures a higher score thus corresponds to easier to read and comprehend texts. We standardize each measure to have mean zero and standard deviation one. In Columns 1 to 3, the outcomes are the readability scores of the NBER WP. In Columns 4 to 6, the outcomes are the readability scores of the published papers. In Columns 7 to 9 the outcomes are the change in readability scores between the published papers and their NBER WP version. Working paper characteristics include a linear and quadratic in page counts, linear and quadratic terms for the title length, dummies for the number of authors and for the number of unique JEL codes. Author affiliation fixed effects are derived from Scopus. Information on institutional affiliation is derived from the Scopus database, using first and last names. For each author-year combination we observe in the NBER data, we retrieve the affiliation of the author in the Scopus database with an economics publication who shares the same first and last name as the author in the NBER WP dataset. Moreover, the selected author should have a publication that is closest in time to the author being analyzed. When we identify multiple matches, we break ties randomly. We also control for the average number of matches found for each author of an article (and its quadratic). Affiliations of NBER working paper authors are found in two thirds of cases. The author affiliation dummies to cover the 100 most frequent institutions in our data set, a dummy for other affiliations and a dummy for no matched affiliation. Robust standard errors are reported throughout.

Table A6: Paths to Publication for Race-related CEPR Working Papers

OLS estimates, robust standard errors in parentheses

	Published in any Journal	Published in an Economics Journal	Publication lag (years)	Published in AER Zero weight journal	Journal Quality (AER-Weighted)	Published in Top-5	Publication Lag (years) | Published in Top-5	Any Citations	Log (citations)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Race-related	.002	-.039*	.134	.009	-.011**	-.036	-.269	.008	-.008	.154
	(.038)	(.020)	(.218)	(.047)	(.005)	(.030)	(.431)	(.015)	(.132)	(.115)
Outcome mean (sd)	.627	.993	2.75 (2.39)	.276 (.448)	.039 (.082)	.131	2.56 (1.79)	.971	3.20 (1.43)	3.21 (1.43)
Year FE	X	X	X	X	X	X	X	X	X	X
JEL Code FE	X	X	X	X	X	X	X	X	X	X
Article Characteristics	X	X	X	X	X	X	X	X	X	X
Author Affiliation FE	X	X	X	X	X	X	X	X	X	X
Journal FE										X
Sample	All published CEPR WPs (N=10,303)	All CEPR WPs Published in Any Journal (N=6,459)	All CEPR WPs Published in Econ Journal (N=6,419)	All CEPR WPs Published in Econ Journal (N=6,419)			CEPR WPs Published in Top 5 (N=831)	CEPR WPs Published in Econ Journal (N=6,419)	CEPR WPs Published in Econ Journal (N=6,233)	CEPR WPs Published in Econ Journal (N=6,158)

Notes: *** denotes significance at the 1%, ** at the 5%, * at the 10% level. The sample is based on CEPR working papers first posted between 1984 and 2015. In Column 1 the outcome is a dummy for whether the working paper is published in any journal. In Column 2 the outcome is a dummy for whether the working paper is published in an economics journal. In Column 3 the publication lag is the number of years between when the CEPR working paper is first posted and its year of publication. In Column 4 the outcome is whether the *AER*-weighted measure of journal quality constructed in Angrist *et al.* [2020] is zero. In Column 5 the outcome is the *AER*-weighted measure of journal quality constructed in Angrist et al. [2020] (including zeroes). In Column 6 the outcome is a dummy for whether the working paper is published in a top-5 economics journal. In Column 7 the outcome is the publication lag is the number of years between when the CEPR working paper is first posted and its year of publication in a top-5 economics journal. In Column 8 the outcome is whether the publication receives any citations, as measured from the *Web of Science* or *Scopus*. In Columns 9 and 10 the outcome is the total number of citations received by an article since publication, as measured from the *Web of Science* or *Scopus*. All specifications include fixed effects for the year in which the working paper is first posted, and its JEL codes. Working paper characteristics include a linear and quadratic terms for the title length, dummies for the number of authors and for the number of unique JEL codes (unlike for NBER WPs, page counts are unavailable for CEPR WPs). Author affiliation fixed effects are derived from Scopus. Information on institutional affiliation is derived from the Scopus database, using first and last names. For each author-year combination we observe in the CEPR data, we retrieve the affiliation of the author in the Scopus database with an economics publication who shares the same first and last name as the author in the CEPR WP dataset. Moreover, the selected author should have a publication that is closest in time to the author being analyzed. When we identify multiple matches, we break ties randomly. We also control for the average number of matches found for each author of an article (and its quadratic). Affiliations of CEPR working paper authors are found in two thirds of cases. The author affiliation dummies to cover the 100 most frequent institutions in our data set, a dummy for other affiliations and a dummy for no matched affiliation. In Column 10 we additionally control for journal of publication fixed effects. Robust standard errors are reported throughout.

Table A7: Readability Scores, CEPR Working Papers

OLS estimates, robust standard errors in parentheses

	Working Paper Version			Published Version			Change Across Versions		
	Flesch Reading Ease Score	Gunning Fog Score	Simple Measure of Gobbledygook Score	Flesch Reading Ease Score	Gunning Fog Score	Simple Measure of Gobbledygook Score	Flesch Reading Ease Score	Gunning Fog Score	Simple Measure of Gobbledygook Score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Race-related	.001	.069	.056	-.028	.040	.052	-.045	-.041	-.016
	(.100)	(.082)	(.089)	(.104)	(.093)	(.094)	(.073)	(.079)	(.079)
Outcome mean (sd)	.018	.026	.033	.000	.000	.000	-.018	-.025	-.022
Year FE	X	X	X	X	X	X	X	X	X
JEL Code FE	X	X	X	X	X	X	X	X	X
Article Characteristics	X	X	X	X	X	X	X	X	X
Author Affiliation FE	X	X	X	X	X	X	X	X	X
Sample	All CEPR WPs Published in Any Journal with available SCOPUS/JSTOR abstracts (N=6,097)								

Notes: *** denotes significance at the 1%, ** at the 5%, * at the 10% level. The sample is based on CEPR working papers first posted between 1984 and 2015 that are matched to publication abstracts from *JSTOR* or *Scopus*. We consider three readability indices. The Flesch Reading Ease test assigns higher scores to materials that are easier to read and lower scores to passages that are more challenging to comprehend. The Gunning Fog Index also estimates the reading level required to understand a piece of writing. It measures the complexity of sentences and words in the text, with higher scores indicating more complex and challenging content. The Simple Measure of Gobbledygook (SMOG) measures the complexity of written content by analyzing the number of words with three or more syllables in a sample text. The higher the SMOG score, the more advanced the reading level required to understand the text. As the scores have different scales and signs, to compare scores, the Gunning Fog and SMOG measures are inverted. For all measures a higher score thus corresponds to easier to read and comprehend texts. We standardize each measure to have mean zero and standard deviation one. In Columns 1 to 3, the outcomes are the readability scores of the CEPR WP. In Columns 4 to 6, the outcomes are the readability scores of the published papers. In Columns 7 to 9 the outcomes are the change in readability scores between the published papers and their CEPR WP version. Working paper characteristics include a linear and quadratic terms for the title length, dummies for the number of authors and for the number of unique JEL codes (unlike for NBER WPs, page counts are unavailable for CEPR WPs). Author affiliation fixed effects are derived from Scopus. Information on institutional affiliation is derived from the Scopus database, using first and last names. For each author-year combination we observe in the NBER data, we retrieve the affiliation of the author in the Scopus database with an economics publication who shares the same first and last name as the author in the CEPR WP dataset. Moreover, the selected author should have a publication that is closest in time to the author being analyzed. When we identify multiple matches, we break ties randomly. We also control for the average number of matches found for each author of an article (and its quadratic). Affiliations of CEPR working paper authors are found in two thirds of cases. The author affiliation dummies to cover the 100 most frequent institutions in our data set, a dummy for other affiliations and a dummy for no matched affiliation. Robust standard errors are reported throughout.

Table A8: Paths to Publication for Race-related NBER Working Papers
Alternative Counterfactuals

OLS estimates, robust standard errors in parentheses

	Published in an Economics Journal		Publication lag (years)		Published in AER zero weight journal		Journal Quality (AER-Weighted)		Published in Top-5		Any Citations		Log (citations)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Race-related	-.013	-.008	-.199	-.122	-.064***	-.029	.006	.005	.030	.013	.011	.008	-.033	-.051
	(.009)	(.009)	(.151)	(.145)	(.020)	(.019)	(.004)	(.004)	(.024)	(.023)	(.007)	(.007)	(.064)	(.059)
Outcome mean (sd)	.986 (.114)	.987 (.110)	2.65 (3.09)	2.69 (2.91)	.181 (.385)	.189 (.392)	.054 (.084)	.066 (.104)	.268 (.443)	.244 (.429)	.976 (.152)	.978 (.148)	3.66 (1.47)	3.65 (1.46)
Year FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
JEL Code FE	X		X		X		X		X		X		X	
Article Characteristics	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Author Affiliation FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Journal FE													X	X
LDA Topics		X		X		X		X		X		X		X
Counterfactual papers:	all not race-related, selected topic keywords	all not race-related, LDA topics as controls	all not race-related, selected topic keywords	all not race-related, LDA topics as controls	all not race-related, selected topic keywords	all not race-related, LDA topics as controls	all not race-related, selected topic keywords	all not race-related, LDA topics as controls	all not race-related, selected topic keywords	all not race-related, LDA topics as controls	all not race-related, selected topic keywords	all not race-related, LDA topics as controls	all not race-related, selected topic keywords	all not race-related, LDA topics as controls
Sample	All NBER WPs Published in Any Journal (N=3,935)	All NBER WPs Published in Any Journal (N=13,995)	NBER WPs Published in Econ Journal (N=3,883)	NBER WPs Published in Econ Journal (N=13,822)	NBER WPs Published in Econ Journal (N=3.883)	NBER WPs Published in Econ Journal (N=13,822)	NBER WPs Published in Econ Journal (N=3.883)	NBER WPs Published in Econ Journal (N=13,822)	NBER WPs Published in Econ Journal (N=3.883)	NBER WPs Published in Econ Journal (N=13,822)	NBER WPs Published in Econ Journal (N=3.883)	NBER WPs Published in Econ Journal (N=13,822)	NBER WPs Published in Econ Journal (N=3,726)	NBER WPs Published in Econ Journal (N=13,416)

Notes: *** denotes significance at the 1%, ** at the 5%, * at the 10% level. The sample is based on NBER working papers first posted between 1974 and 2015. In Columns 1 and 2 the outcome is a dummy for whether the working paper is published in an economics journal. In Columns 3 and 4 the publication lag is the number of years between when the NBER working paper is first posted and its year of publication. In Columns 5 and 6 the outcome is whether the *AER* -weighted measure of journal quality constructed in Angrist *et al.* [2020] is zero. In Columns 7 and 8 the outcome is the *AER* -weighted measure of journal quality constructed in Angrist et al. [2020] (including zeroes). In Columns 9 and 10 the outcome is a dummy for whether the working paper is published in a top-5 economics journal. In Columns 11 and 12 the outcome is whether the publication receives any citations, as measured from the Web of Science or Scopus. In Columns 13 and 14 the outcome is the total number of citations received by an article since publication, as measured from the *Web of Science* or *Scopus* . In Columns 1, 3, 5, 7, 9, 11 and 13, we restrict the sample of not race-related WPs to those which have at least one of the topic keywords in their title and/or abstract. In Columns 2, 4, 6, 8, 10, 12 and 14 we use machine learning to classify the topic of WPs and then control for these broad topics instead of controlling for JEL codes. All specifications include fixed effects for the year in which the working paper is first posted, and its JEL/topic model codes. Working paper characteristics include a linear and quadratic in page counts, linear and quadratic terms for the title length, dummies for the number of authors and for the number of unique JEL codes. Author affiliation fixed effects are derived from *Scopus* . Information on institutional affiliation is derived from the Scopus database, using first and last names. For each author-year combination we observe in the NBER data, we retrieve the affiliation of the author in the Scopus database with an economics publication who shares the same first and last name as the author in the NBER WP dataset. Moreover, the selected author should have a publication that is closest in time to the author being analyzed. When we identify multiple matches, we break ties randomly. We also control for the average number of matches found for each author of an article (and its quadratic). Affiliations of NBER working paper authors are found in two thirds of cases. The author affiliation dummies to cover the 100 most frequent institutions in our data set, a dummy for other affiliations and a dummy for no matched affiliation. Robust standard errors are reported throughout.

Table A9: Paths to Publication for Race-related CEPR Working Papers
Alternative Counterfactuals

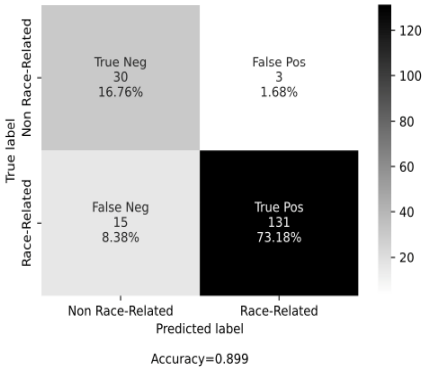
OLS estimates, robust standard errors in parentheses

	Published in an Economics Journal		Publication lag (years)		Published in AER Zero weight journal		Journal Quality (AER-Weighted)		Published in Top-5		Any Citations		Log (citations)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Race-related	-.042*	-.037*	-.076	.199	-.049	-.004	-.001	-.010*	-.026	-.038	.004	-.002	.153	.123
	(.023)	(.021)	(.233)	(.219)	(.052)	(.046)	(.006)	(.006)	(.039)	(.032)	(.019)	(.015)	(.134)	(.109)
Outcome mean (sd)	.993 (.081)	.994 (.078)	2.84 (2.31)	2.76 (2.39)	.281 (.449)	.276 (.448)	.032 (.062)	.039 (.082)	.159 (.366)	.131 (.338)	.968 (.176)	.971 (.168)	3.21 (1.45)	3.21 (1.43)
Year FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
JEL Code FE	X		X		X		X		X		X		X	
Article Characteristics	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Author Affiliation FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Journal FE													X	X
LDA Topics		X		X		X		X		X		X		X
Counterfactual papers:	all not race-related, selected topic keywords	all not race-related, LDA topics as controls	all not race-related, selected topic keywords	all not race-related, LDA topics as controls	all not race-related, selected topic keywords	all not race-related, LDA topics as controls	all not race-related, selected topic keywords	all not race-related, LDA topics as controls	all not race-related, selected topic keywords	all not race-related, LDA topics as controls	all not race-related, selected topic keywords	all not race-related, LDA topics as controls	all not race-related, selected topic keywords	all not race-related, LDA topics as controls
Sample	CEPR WPs Published in Econ Journal (N=1,797)	CEPR WPs Published in Econ Journal (N=6,459)	CEPR WPs Published in Econ Journal (N=1,785)	CEPR WPs Published in Econ Journal (N=6,419)	CEPR WPs Published in Econ Journal (N=1,785)	CEPR WPs Published in Econ Journal (N=6,419)	CEPR WPs Published in Econ Journal (N=1,785)	CEPR WPs Published in Econ Journal (N=6,419)	CEPR WPs Published in Econ Journal (N=1,785)	NBER WPs Published in Econ Journal (N=6,419)	CEPR WPs Published in Econ Journal (N=1,785)	NBER WPs Published in Econ Journal (N=6,419)	NBER WPs Published in Econ Journal (N=1,666)	NBER WPs Published in Econ Journal (N=6,158)

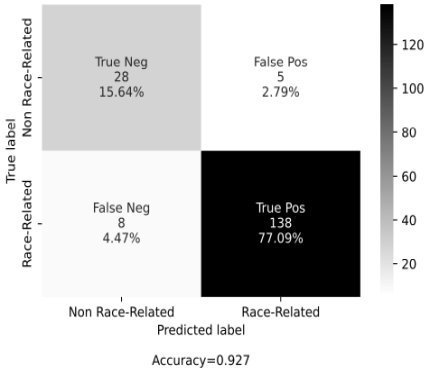
Notes: *** denotes significance at the 1%, ** at the 5%, * at the 10% level. The sample is based on CEPR working papers first posted between 1974 and 2015. In Columns 1 and 2 the outcome is a dummy for whether the working paper is published in an economics journal. In Columns 3 and 4 the publication lag is the number of years between when the CEPR working paper is first posted and its year of publication. In Columns 5 and 6 the outcome is whether the *AER*-weighted measure of journal quality constructed in Angrist *et al*. [2020] is zero. In Columns 7 and 8 the outcome is the *AER*-weighted measure of journal quality constructed in Angrist *et al.* [2020] (including zeroes). In Columns 9 and 10 the outcome is a dummy for whether the working paper is published in a top-5 economics journal. In Columns 11 and 12 the outcome is whether the publication receives any citations, as measured from the *Web of Science* or *Scopus*. In Columns 13 and 14 the outcome is the total number of citations received by an article since publication, as measured from the Web of Science or Scopus. In Columns 1, 3, 5, 7, 9, 11 and 13, we restrict the sample of not race-related WPs to those which have at least one of the topic keywords in their title and/or abstract. In Columns 2, 4, 6, 8, 10, 12 and 14 we use machine learning to classify the topic of WPs and then control for these broad topics instead of controlling for JEL codes. All specifications include fixed effects for the year in which the working paper is first posted, and its JEL/topic model codes. Working paper characteristics include a linear and quadratic terms for the title length, dummies for the number of authors and for the number of unique JEL codes (unlike for NBER WPs, page counts are unavailable for CEPR WPs). Author affiliation fixed effects are derived from *Scopus*. Information on institutional affiliation is derived from the Scopus database, using first and last names. For each author-year combination we observe in the NBER data, we retrieve the affiliation of the author in the Scopus database with an economics publication who shares the same first and last name as the author in the CEPR WP dataset. Moreover, the selected author should have a publication that is closest in time to the author being analyzed. When we identify multiple matches, we break ties randomly. We also control for the average number of matches found for each author of an article (and its quadratic). Affiliations of CEPR working paper authors are found in two thirds of cases. The author affiliation dummies to cover the 100 most frequent institutions in our data set, a dummy for other affiliations and a dummy for no matched affiliation. Robust standard errors are reported throughout.

Figure A1: Validation Using GPT-3.5

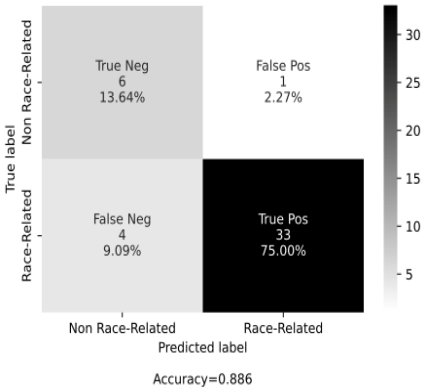
A. Confusion Matrix for GPT



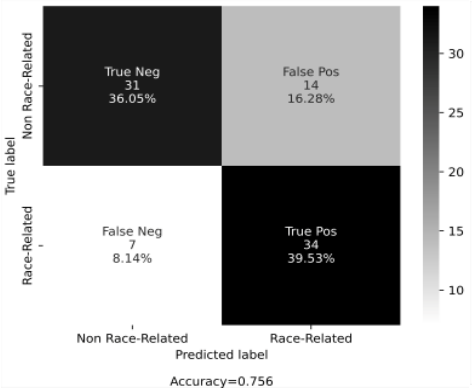
B. Confusion Matrix for Algorithm



C. Confusion Matrix for GPT (Sample with Inroductions included)



D. Confusion Matrix for GPT, Non top-5 Journals

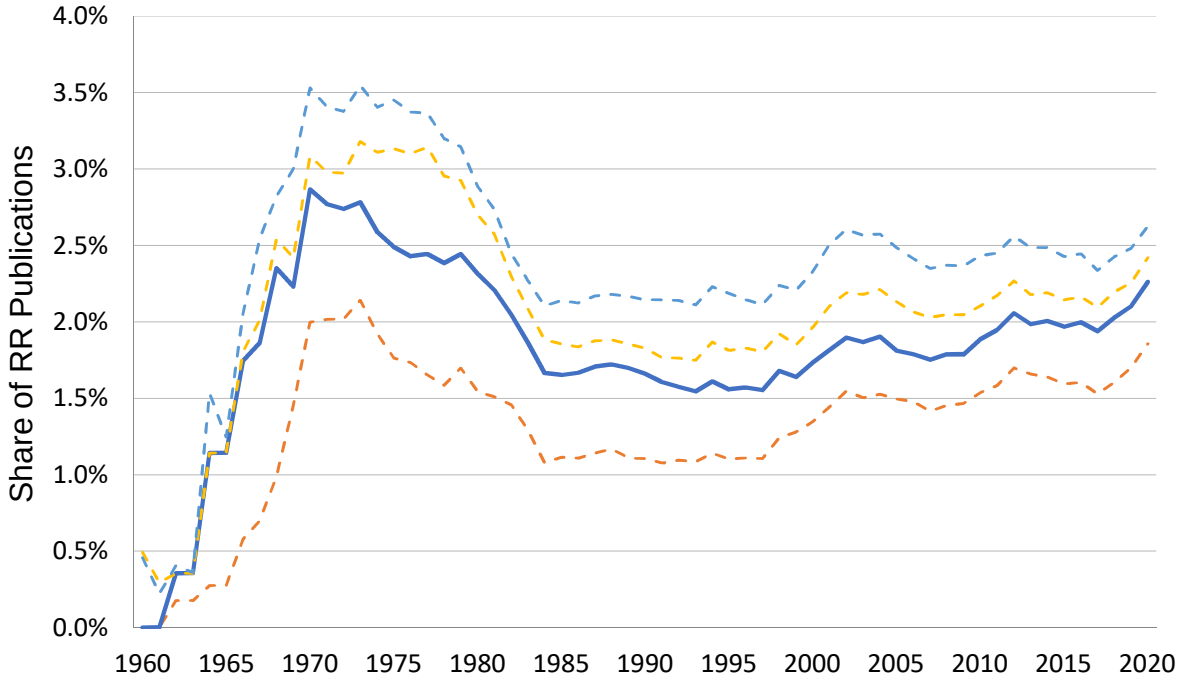


E. Confusion Matrix for Algorithm, Non top-5 Journals

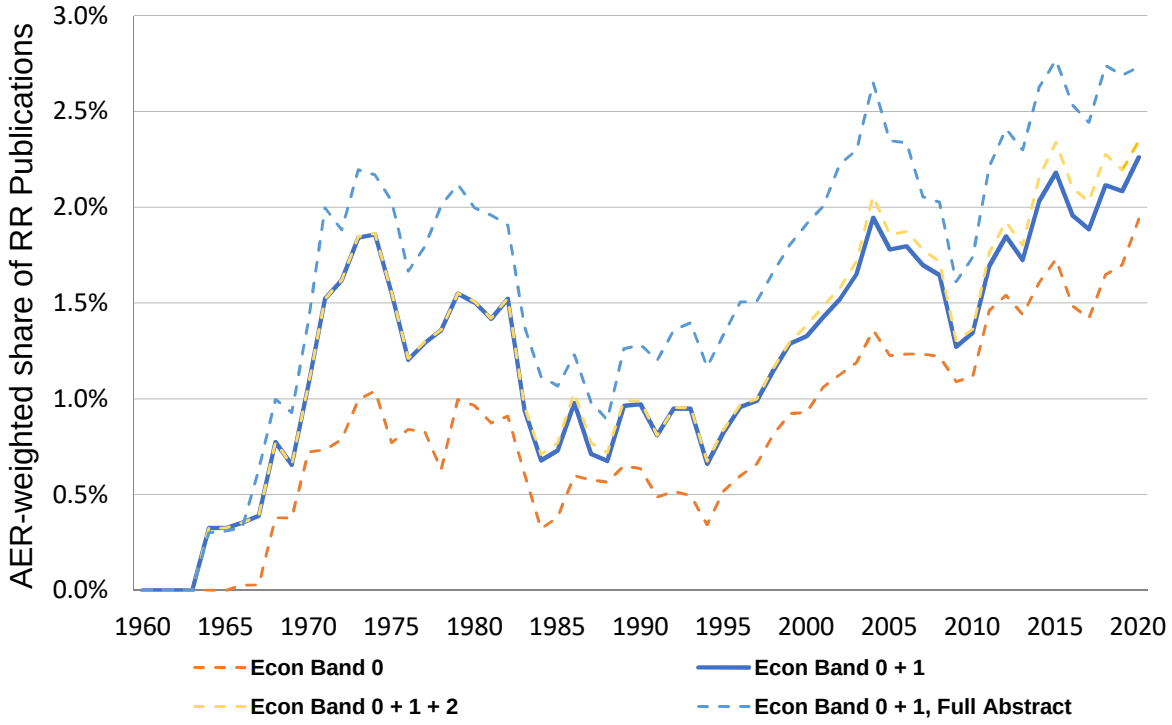
Notes: We use the OpenAI API to access GPT-3.5 for the validation exercise. Panels A and B show the output of classification of publications based on their titles and abstracts. The sample includes 179 publications mentioning a group keyword in their title or abstract (excluding the final sentence, and ignoring topic keywords and eliminated phrases) from the top-5 general interest journals from 1960 to 2020. We report confusion matrices for both the GPT classification output (Panel A) and the output obtained by implementing our algorithm on the same sample (Panel B), comparing them both to a hand-coded ground classification. These confusion matrices show the performance and efficacy of each classification model by summarizing the counts of true negatives (upper left quadrant), true positives (lower right quadrant), false positives (upper right quadrant), and false negatives (lower left quadrant). Panel C reports the confusion matrix for the GPT classification using additional information from the introduction of papers (as well as the title and abstract). This sample includes 44 publications selected from the validation sample described above. Panels D and E display confusion matrices for a random sample of 86 papers selected from non-top 5 economics journals. These papers specifically include group words in their abstracts or titles.

Figure A2: Bounds on Race-related Publications in Economics

A. Unweighted Share Bounds

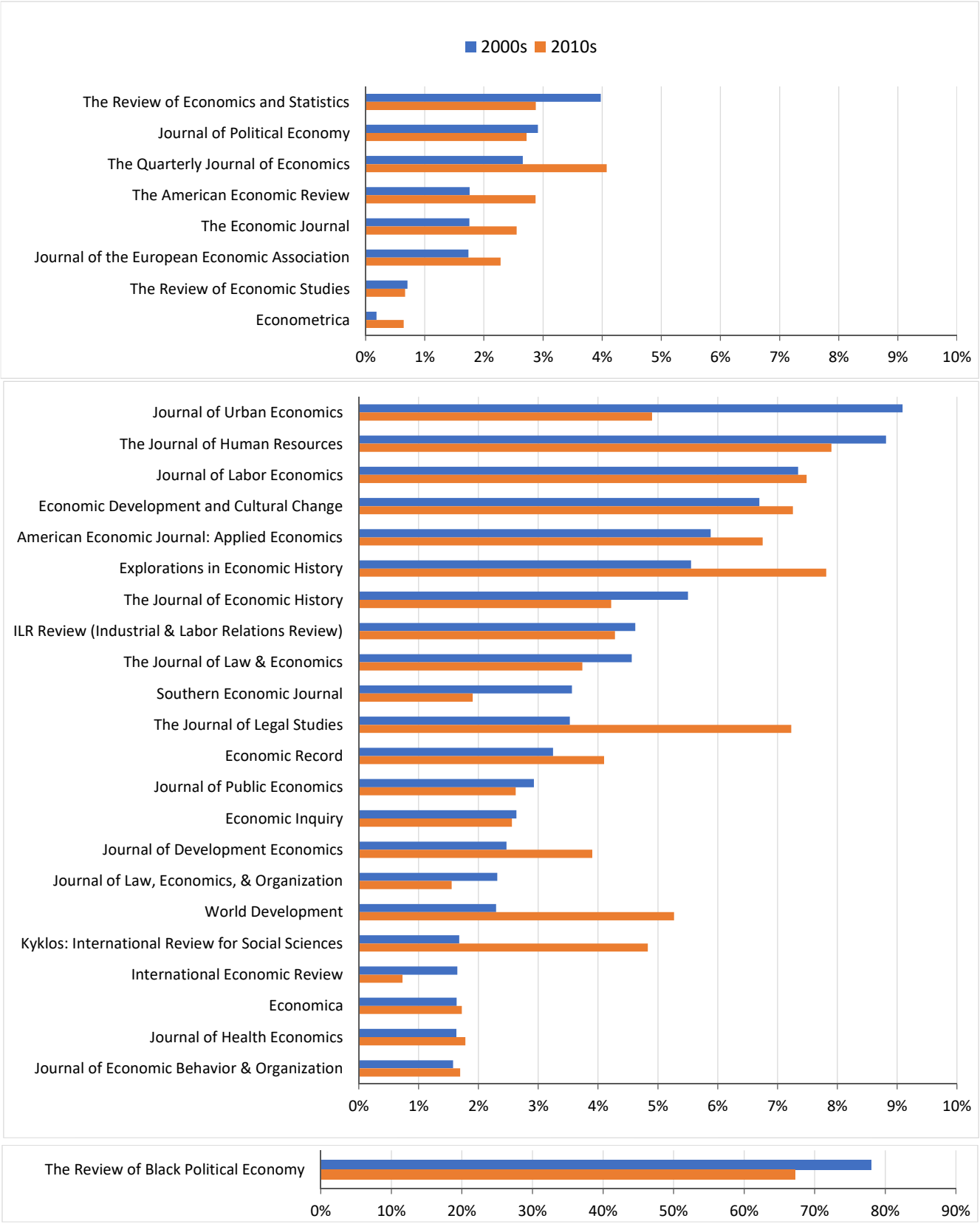


B. *AER* -Weighted Share Bounds



Notes: We use a corpus of publications in economics journals, based on data from *JSTOR*, *Web of Science* and *Scopus*. When a journal is assigned to multiple disciplines, we split the number of publications in that journal equally across disciplines. We report five-year moving averages throughout. Panel A reports the share of total publications identified to be race-related by year of publication. Panel B reports the *AER* -weighted version of Panel A, using the journal weights constructed in Angrist *et al*. [2020]. Each Panel shows the resulting time series using alternative group keyword bands (see Table A1), or by using bands 0 and 1 and also including the last line of the abstract.

Figure A3: Race-related Publications, by Economics Journal



Notes: Eight general interest journals in economics are ranked separately and placed at the top. Within these eight and the other economics journals shown, the panels are ordered according to the share of race-related articles in that journal from 1960 to 2020. Each bar then shows the share of publications in the journal that are race-related (as identified by our algorithm), for publications in the 2000s and for the 2010s. The final series of bars are for the *Review of Black Political Economy* , for which the scaling of the x-axis differs.

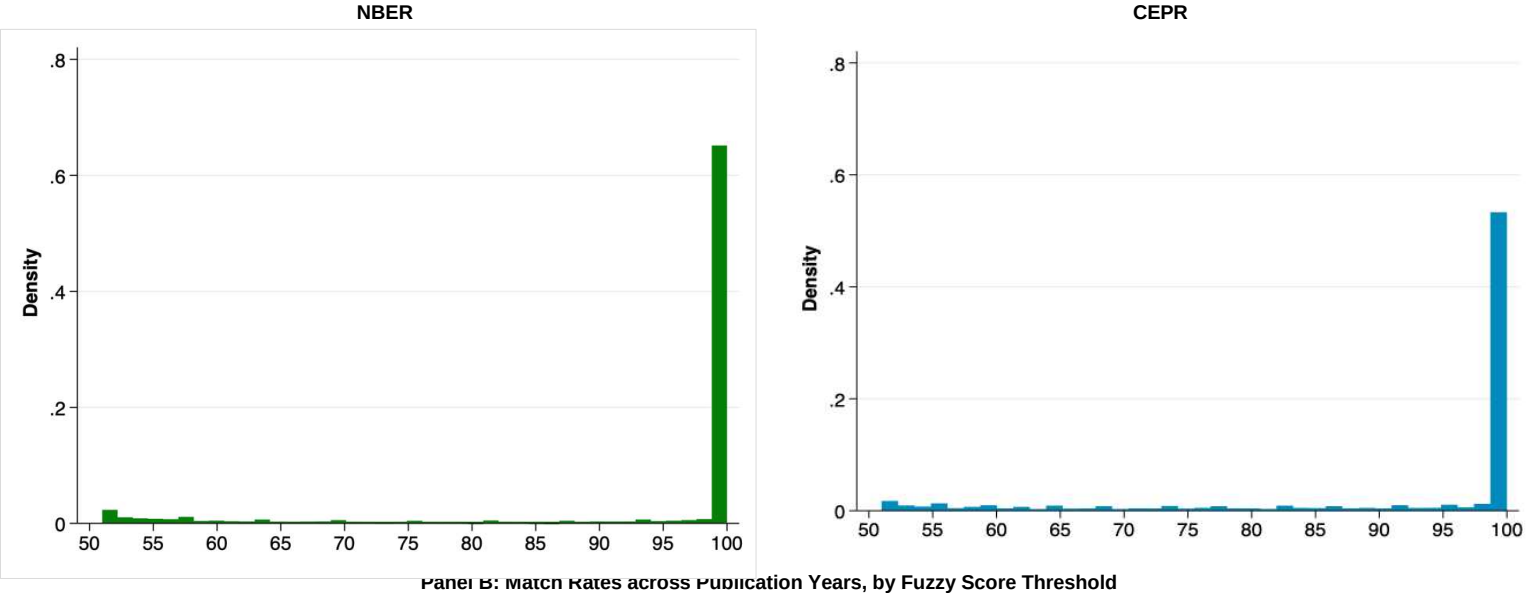
Figure A4: LDA Topics in the Full Corpus of Publications

Topic	Term1	Term2	Term3	Term4	Term5	Topic Label
1	model	firm	effect	datum	result	Industrial Organization
2	retirement	pension	french	plan	communist	Social Welfare
3	land	rural	resource	area	agricultural	Rural Development and Agriculture
4	model	test	method	paper	reserve	Empirical Analysis
5	country	trade	international	foreign	domestic	International Trade
6	law	right	court	legal	crime	Legal Studies
7	et	politique	les	ce	que	Miscellaneous I
8	group	black	white	ethnic	racial	Race and Ethnicity
9	long	run	shock	cycle	term	Macroeconomic Policy
10	network	social	trust	communication	medium	Social Networks and Communication
11	policy	public	government	reform	financial	Public Policy
12	war	conflict	year	state	more	Warfare and Conflicts
13	political	party	state	election	voter	Political Parties and Elections
14	economic	development	technology	new	research	Economic Development and Technology
15	datum	study	health	effect	measure	Health Studies
16	work	worker	job	more	organization	Professional Development
17	risk	market	asset	financial	insurance	Financial Markets
18	tax	income	welfare	government	household	Taxation and Welfare
19	city	urban	migration	migrant	housing	Urban Studies
20	environmental	cost	pollution	industry	plant	Environmental Issues
21	equilibrium	game	reserve	right	agent	Game Theory
22	capital	investment	energy	copyright	reserve	Investments
23	rate	exchange	price	monetary	inflation	Exchange Rates and Monetary Policy
24	labor	wage	employment	market	worker	Labor Market
25	que	et	este	por	article	Miscellaneous II
26	growth	income	inequality	population	increase	Income Growth and Inequality
27	food	climate	change	consumer	adaptation	Consumer Behavior
28	social	article	theory	research	approach	Social Science Theory
29	identity	class	cultural	society	culture	Religion and Culture
30	family	child	woman	gender	school	Family, Gender, and Education

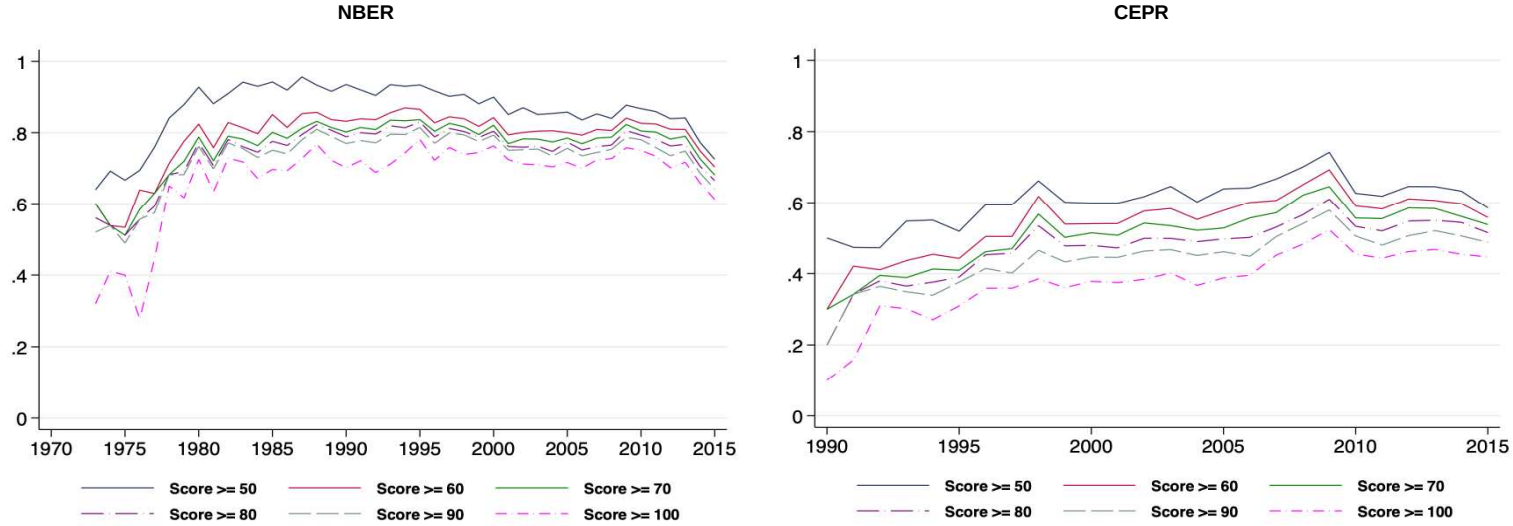
Notes: We use Latent Dirichlet Allocation (LDA) modeling to identify topics in the corpus of 493,972 publications in economics, sociology, political science, law, management, public policy and history, based on data from *JSTOR*, *Web of Science*, and *Scopus*. When a journal is assigned to multiple disciplines, we split the number of publications in that journal equally across disciplines. We retain those journals that have paper titles and abstracts in English because our algorithm can be applied to such papers (even if the main text is then in a non-English language). Our benchmark model then identifies 30 topics. The Figure displays word clouds for the topics generated and we label each of the topics as shown in the lower part of the Figure.

Figure A5: Matching Working Papers to Publications

Panel A: Distribution of String Similarity Measure Among Matched Working Papers

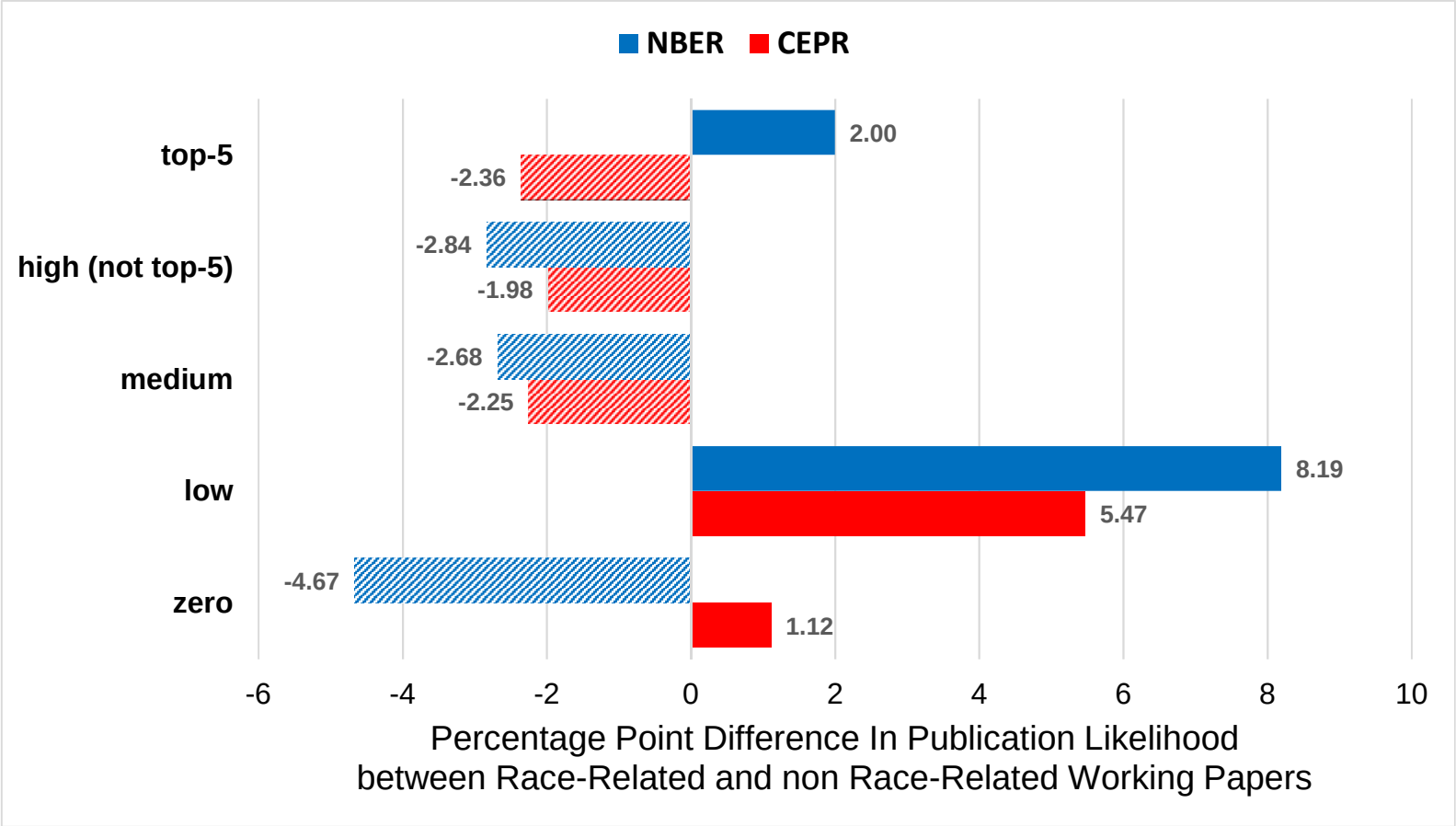


Panel B: Match Rates across Publication Years, by Fuzzy Score Threshold



Notes: Panels A and B report summary statistics from our matching process from NBER working papers to the *Web of Science* and *Scopus* databases. Panel A reports the distribution of the String Similarity measure between NBER working paper titles and matched titles from *Web of Science* or *Scopus*, conditional on finding a match. The similarity measure used is based on Levenshtein distance. A similarity of a 100 indicates a perfect match. The sample is based on all NBER (CEPR) working papers posted from 1974 to 2015 (1983 to 2015) and matched with a journal publication. Panel B reports the publication probability measured for NBER (CEPR) working papers first posted each year, and how it varies with our inclusion criteria. The six series shown correspond to gradually increasing the required threshold for matching on the String Similarity measure.

Figure A6: AER-Weighted Publications of NBER and CEPR Working Papers



Notes: The sample is based on NBER working papers first released between 1974 and 2019, and CEPR working papers released between 1984 and 2019. We then consider the set of working papers that are published in an economics journal. The outcome is the *AER*-weighted measure of journal quality constructed in Angrist et al. [2020], where we consider whether the working paper is published in a top-5 economics journal, in the top tercile of *AER*-weights (excluding the top-5 journals), in the middle tercile of *AER* weights, in the bottom tercile of *AER*-weights, or in a journal with zero *AER*-weight. The figure shows the unconditional differences in outcomes between race-related and not race-related working papers in the NBER and CEPR series in each of these outcomes.

Figure A7: LDA Topics in NBER Working Papers

Notes: We use Latent Dirichlet Allocation (LDA) modeling to identify topics in the corpus of NBER working papers posted from 1974 to 2019. Our benchmark model identifies 30 topics. The Figure displays word clouds for the topics generated.