March 7, 2025 Please click here for the latest version.

The cyclicality of hiring discrimination[*]

A meta-reanalysis of correspondence experiments

Louis Lippens

Ghent University

Stijn Baert

Ghent University, University of Antwerp, Université catholique de Louvain, IZA Institute of Labor Economics

ABSTRACT Hiring discrimination persists despite decades of policy interventions aimed at ensuring equitable employment opportunities. While economic theory predicts competition could reduce discriminatory practices by raising costs for discriminating employers, empirical findings remain inconclusive on whether labour market conditions affect employer biases. The cyclical nature of hiring discrimination remains poorly understood. Here, we bring preliminary results of a meta-reanalysis of correspondence experiments spanning multiple discrimination grounds, countries, industries, occupations. We also introduce a novel method, which we coin the meta-analytic event study. Our results suggest that discrimination against racial and ethnic minorities is countercyclical. Specifically, higher unemployment rates correspond with significantly fewer callbacks for minority applicants, while occupation-level competition similarly reduces hiring biases. Gender discrimination appears less responsive to market fluctuations, whereas age discrimination intensifies during economic downturns, particularly affecting the oldest workers. Future analyses will comprise more discrimination grounds as well as additional robustness checks and publication bias corrections.

Keywords: Competition, Business cycle, Hiring discrimination, Correspondence experiments, Meta-analysis
JEL Codes: J14, J15, J16, J23, J71

[*]**Corresponding author.** Louis Lippens (louis.lippens@ugent.be). **Acknowledgements.** We thank Louise Devos, Helena Peters, and Femke Timmerman for their research assistance. **Funding.** This research received funding from FWO (Research Foundation – Flanders) under grant number 12AM824N and the patronage of the National Bank of Belgium. **Disclaimer.** This preprint may contain analyses or findings subject to revision. Readers are encouraged to provide comments and feedback. **Please keep confidential and do not (re)distribute.**

1 Introduction

Discrimination in the labour market is a well-documented and enduring phenomenon (Batinovic et al., 2023; Flage, 2020; Lippens et al., 2023; 2025; Quillian et al., 2017; Quillian & Lee, 2023; Schaerer et al., 2023). It occurs when employers treat equally productive individuals differently due to (biased) preferences or inferences. Hiring discrimination based on characteristics such as race, gender, or age reduces opportunities for affected groups and contributes to persistent penalties in employment outcomes (Quillian et al., 2020; Zwysen et al., 2021). Globally, meta-research shows little reduction in hiring discrimination in the past decades (Lippens, Baert, & Neyt, 2025; Quillian, Pager, Hexel, & Midtbøen, 2017; Quillian & Lee, 2023). Notwithstanding the many (trans-)national anti-discrimination measures taken, public policies appear largely ineffective in combating hiring discrimination (OECD, 2020).

One channel through which discrimination may decline is market competition. Economic theory provides a framework for understanding how competition might influence discriminatory practices. On the one hand, (Becker, 1971) taste-based discrimination theory posits that employers with a taste for discrimination incur higher costs in competitive markets. Their preferences lead them to forgo qualified candidates, reducing firm profitability and potentially pushing them out of the market (Lang & Lehmann, 2012). However, when employers react to the preferences of their coworkers or customers, it can make economic sense to refrain from hiring minority candidates because otherwise, employers could lose valuable personnel or business (Borjas, 2020; Coleman, 2004). Competition should not reduce discrimination in those cases. On the other hand, statistical discrimination theory suggests that employers rely on group-level statistics as proxies for individual productivity in the absence of complete information (Arrow, 1972; 1973; Phelps, 1972). This type of discrimination can perpetuate biases even in competitive markets. Employers who at least believe their proxies are correct will be less inclined to hire from the least productive group, negating competition effects (Bohren et al., 2023; Ruzzier & Woo, 2023). However, employers who do not update their beliefs timely will face more negative consequences of discrimination when competition for scarce talent is high.

This paper uses a meta-reanalysis approach to examine the link between competition and hiring discrimination. By matching competition measures from administrative data sources with discrimination outcomes from dozens of correspondence experiments across occupations, industries, locations, and time, we assess whether competitive pressures in the labour market reduce discriminatory hiring practices. Our study systematically evaluates this relationship for various vulnerable groups, contributing to the broader discussion on the cyclicality of discrimination.[2]

Prior research has investigated the role of competition in reducing discrimination using both theoretical models and empirical studies. Based on this literature, the impact of competition on hiring discrimination appears mixed, yet the consensus leans towards a counter-cyclical effect, where more competition (i.e., a tighter labour market) leads to decreased discrimination. Some studies, for example, have examined occupational differences, comparing discrimination levels in shortage versus non-shortage occupations (Baert et al., 2015; Carlsson et al., 2018). A different

[2]The approach of our systematic review and meta-reanalysis was preregistered on the Open Science Framework (OSF) using the generalized systematic review registration template (van den Akker et al., 2023).

approach relies on linking changes in unemployment to differences in callback and employment outcomes (Dahl & Knepper, 2023; Kuhn & Chanci, 2024). Others have exploited external market shocks, such as the Great Recession or the COVID-19 crisis, to assess how recessionary conditions affect hiring biases (Challe, 2017; Challe et al., 2023; Neumark & Button, 2014). While these studies provide valuable insights, they often rely on single-country analyses, particular vulnerable groups, or measurement-specific contexts, limiting their generalisability.

Our study builds on this literature in several ways. First, we leverage a meta-analytic framework to compare the cyclicality of transnational discrimination estimates in time. Through this framework, we introduce the concept of a *meta-analytic event study*. This novel method takes advantage of temporal labour market dynamics to explain the heterogeneity in hiring discrimination between audit studies. Second, capitalising on our extensive metadataset, we can offer a more systematic perspective on the relationship between competition and discrimination across diverse labour market settings. Third, we consider multiple discrimination grounds concurrently and bring more clarity on the economic mechanisms at play for each of the impacted groups. Compared to existing studies, our approach provides a more comprehensive understanding of the competition–discrimination relationship, helping to reconcile the mixed findings in the literature.

The preliminary findings of our meta-reanalysis suggest that hiring discrimination based on both race, ethnic identity, and national origin and age follows a counter-cyclical movement. Although discrimination decreases with increased labour market competition, our analyses indicate that discrimination does not disappear. These results highlight the complexity of market-based solutions to discrimination, which cannot solve the issue on their own.

The remainder of the paper is structured as follows. Section 2 outlines our data collection, while Section 3 describes our methodological approach. Section 4 presents our key findings and discusses some of their implications. Section 5 concludes with a preliminary summary, limitations, and plans for future research.

2 Data

2.1 Labour market competition

2.2 Hiring discrimination

Besides labour market competition measures, we gathered conditional average treatment effects (CATEs) of hiring discrimination from a large register of correspondence audit studies. These CATEs consist of discrimination estimates by occupation, industry, country, and region. We retrieved the estimates based on a systematic and extensive search for field experiments that examine hiring discrimination through an audit approach. Following this search for studies, we screened these studies for eligibility based on a predefined set of criteria and extracted the necessary metadata. Our approach was essential to conducting a meta-reanalysis—a term coined by Galos & Coppock (2023) in their re-evaluation of the relationship between occupational gender composition and hiring bias. While we slightly deviated from their method, the general idea of retrieving CATEs at different measurement levels, which are subsequently plugged into meta-regression analyses, remains.

2.2.1 Study search

Our literature search strategy involved systematically querying several academic databases and repositories to identify relevant audit studies. Specifically, we consulted the following databases: Web of Science (including the Web of Science Core Collection and ProQuest™ Dissertations & Theses Citation Index), PsycINFO, Scopus, JSTOR, SSRN, IZA Discussion Papers, NBER Working Papers, CEPR Discussion Papers, ArXiv, PsyArXiv, and SocArXiv. Searching these databases using their respective interfaces ensured comprehensive coverage of both peer-reviewed literature and grey literature, such as preprints, working papers, discussion papers, and theses.

We applied a structured inclusion and exclusion framework based on an adapted version of the PICO criteria (see Table 1). Eligible studies were correspondence experiments, characterised by applications from fictitious applicants responding to genuine job postings. Included studies specifically measured outcomes indicative of unequal treatment prohibited by anti-discrimination legislation. The context of the included studies encompassed discriminatory practices across sixteen legally prohibited grounds. The review period covered studies published from 2000 through 2024. We explicitly ignored studies that reused datasets previously covered in other correspondence experiments already included in our register.

Table 1: PICO eligibility criteria for inclusion and exclusion

Criterion	Definition
Study type	Correspondence experiment in which applications of fictitious applicants are sent in response to genuine vacancies through (e-)mail or (online) job platforms.
Population	Fictitious applicants from minority groups and their majority counterparts.
Outcome	Unequal treatment forbidden by law in the hiring and selection process (i.e., hiring discrimination).
Comparison	Positive responses (or callbacks or interview invitations) of minority applicants compared with those of majority applicants.
Context	Hiring discrimination related to sixteen discrimination grounds upon which unequal treatment is forbidden (i.e., race, ethnic identity, and national origin, sex and gender, age, physical appearance, parenthood and fertility, health and disability, sexual orientation, religion, wealth, civil status, union affiliation, political orientation, military affiliation, genetic information, citizenship status, and criminal record).
Timing	Studies published from 2000 to 2024 (including).

Notes. The framework used to define the eligibility criteria is based on the PICO (Population, Intervention, Comparison, Outcome) framework first coined by (Richardson et al., 1995).

We tailored the search queries to each database's specific interface. They were formulated to reflect our inclusion criteria, emphasising hiring discrimination, protected applicant characteristics, hiring contexts, and the correspondence audit method. For instance, the query for Web of Science combined detailed search terms relating to discriminatory treatment, specific characteristics subject to discrimination, and the labour and work context. Other databases were searched using simpler yet broad keyword searches, reflecting the technical constraints of their respective interfaces.

To ensure comprehensiveness and validity, we cross-validated our initial search results against references listed in a recent comprehensive meta-analysis by Lippens, Vermeiren, & Baert (2023). We expected and found substantial overlap between our identified studies and those included in this meta-analysis. Additionally, we complemented our database searches by examining references cited in previous systematic reviews and meta-analyses on hiring discrimination using correspondence experiments (Bartkoski et al., 2018; Batinovic, Howe, Sinclair, & Carlsson, 2023; Flage, 2020; Gaddis et al., 2021; Galos & Coppock, 2023; Galvan et al., 2022; Heath & Di Stasio, 2019; Park & Oh, 2025; Quillian, Pager, Hexel, & Midtbøen, 2017, Quillian et al. (2019); Quillian, Lee, & Oliver, 2020; Schaerer, du Plessis, Nguyen, van Aert, Tiokhin, Lakens, Giulia Clemente, Pfeiffer, Dreber, Johannesson, Clark, & Luis Uhlmann, 2023; Thijssen et al., 2021; Zschirnt & Ruedin, 2016).[3]

2.2.2 Study screening

Study screening was conducted through a structured, multi-stage process. Initially, articles identified through the database searches underwent a first-round screening based primarily on titles and abstracts. At least two independent human reviewers conducted this step.[4] Following this initial round, eligible studies underwent full-text screening in a second stage. The same approach applied here, with the lead screener verifying and resolving discrepancies between their classifications and those of other screeners.

During the screening process, we did not blind bibliographic information. Instead, fields such as authors, publication years, journal titles, abstracts, and full-text content remained visible to screeners, facilitating quick decision-making and reducing the necessity for extensive full-text assessments. We implemented deduplication at the outset of screening by systematically removing duplicate records identified across different databases.

All studies that successfully met the criteria were retained for inclusion in subsequent analyses. Studies were included based on the following explicit inclusion criteria: studies employing the correspondence audit method; those using genuine vacancies or responses from real employers; studies with majority or control group comparisons; studies addressing discrimination based on of the sixteen predetermined legally prohibited categories; and studies published between 2000 and 2024.[5]

[3]While most relevant studies have been identified at the time of writing, several studies have not yet been processed. For multiple studies, notably recent correspondence experiments, metadata are missing. These data will be included in future iterations. We further intend to contact corresponding authors of included studies through an 'open call for data' to enhance the comprehensiveness of our dataset.

[4]We plan to complement this strategy with the assistance of a large language model (LLM) as a zero-shot classifier. We will provide the LLM with clear inclusion and exclusion criteria via the system prompt, asking the model to classify studies accordingly. Human reviewers will always retain the authority to make the final inclusion or exclusion decision.

[5]The resulting dataset will be made available as part of the associated OSF project, hosted via GitHub. These data will remain under embargo until the publication of the first preprint derived from this systematic review.

2.2.3 Data extraction

Data extraction involved at least two independent human extractors. Initially, each extractor independently retrieved relevant metadata and detailed study characteristics from included sources, ensuring comprehensive coverage and accuracy. The extracted metadata encompassed general bibliographic information, such as author names, DOIs, peer-review status, and precise locations of relevant data within each study (e.g., page numbers, table identifiers, appendices).

Extracted methodological information included candidate demographics (i.e., gender, median age, education level, employment status), details of the experimental design, including occupation, sector, country, and the matching strategy (i.e., whether authors evaluated employer discrimination multiple times with different applicant profiles). Additionally, we documented the definitions of callbacks, prioritising broader measures of positive employer responses over narrower definitions, such as interview invitations, to maximise informational value. Data concerning discriminatory treatment included the specific grounds of discrimination, names and descriptions of both treatment and control groups, and the number of applications sent in each condition. Extractors followed predefined instructions detailed in a standardised data dictionary to ensure consistency.

After initial extraction, extractors cross-verified each other's work to identify and resolve discrepancies. This verification process involved revisiting the original study sources to validate the accuracy of data entries, especially callback counts and categorisation decisions. When disagreements arose, these were resolved through discussion and mutual consensus between the extractors.[6]

3 Methods

3.1 Empirical framework

3.1.1 Identification

The causal identification strategy of this meta-reanalysis rests partly on the experimental nature of correspondence audit studies, which generate internally valid estimates of hiring discrimination. By submitting fictitious job applications differing solely by the discrimination ground under study (e.g., ethnicity, gender, or age), these experiments directly capture the causal effects of discrimination at the initial hiring stage. Consequently, the derived CATEs are causal in their interpretation regarding employer callbacks.

However, identifying the causal relationship between employer competition—the main moderator of interest—and hiring discrimination is more complex. Competition measures were derived from administrative data at the occupation, sector, country, or regional levels, introducing observational variation into the meta-regression. While the experimental design guarantees causality in estimates of hiring discrimination, the association between competition measures and these CATEs remains inherently correlational. We applied several procedures to ensure a causal interpretation, which we detail below.

[6]We plan to contact corresponding authors in case crucial metadata remain unclear or are missing from the original manuscripts or supplementary materials.

First, in the analyses centred on unemployment and vacancy rates, we accounted for several potential confounders. Specifically, we controlled for design-related variables, such as whether researchers used a matched design and how callback was recorded. In addition, we controlled for candidate characteristics, including education level, employment status, gender, and occupation.

Second, to address causality more robustly, we incorporated a novel meta-analytic event study approach exploiting labour market shocks (i.e., sudden, exogenous changes in the business cycle). By examining changes in discrimination for different occupations around and during such shocks, this approach strengthens our causal identification. The specific approach relied on identifying occupations for which demand was high. We considered these the treated occupations. Next, we used the global financial crisis as the event time, with 2009 as the reference year, to implement a standard difference-in-difference estimator with country fixed effects. This strategy allowed us to estimate the causal impact of competition at the occupation level across the business cycle.

3.1.2 Estimation

We estimate the effects of labour market competition on hiring discrimination using an unrestricted weighted least squares meta-regression (UWLS-MRA) framework. UWLS-MRA offers several advantages over traditional random-effects meta-regression (RE-MRA). In random effects models, the weight multiplicative constant is fixed at one, and the between-study variance (τ^2) must be estimated. This procedure can be sensitive to publication or small-sample bias. In contrast, UWLS-MRA estimates this multiplicative constant directly from the data via the mean squared error. Even if the true variance structure is misspecified, UWLS-MRA produces unbiased estimates with robust confidence intervals.

Through simulation and empirically, Stanley & Doucouliagos (2017), Stanley et al. (2022), Stanley et al. (2023) show that UWLS-MRA performs comparably better than RE-MRA when their assumptions hold and often outperforms the latter when excess heterogeneity or publication selection bias is present. In our analysis, this robustness is crucial, given the variation in study-level precision and the potential for unobserved biases. By employing UWLS-MRA, we ensure that our meta-regression estimates of hiring discrimination on competition are more reliable and less prone to the distortions that can afflict conventional random effects approaches.

In our primary specification, the dependent variable is the natural logarithm of the positive response ratio, defined as:

$$\ln(\mathrm{PRR}_k) = \ln\left(\frac{t_k/n(t)_k}{c_k/n(c)_k}\right) \tag{1}$$

where t_k is the callback count for the treated group for effect k, $n(t)_k$ is the application count for the same group, c_k is the callback count for the control group, and $n(c)_k$ is the application count for that group.

The standard error of this discrimination measure is:

$$\mathrm{SE}_{\ln(\mathrm{PRR}_k)} = \sqrt{\left(\frac{1}{t_k} + \frac{1}{c_k} - \frac{1}{n(t)_k} - \frac{1}{n(c)_k}\right)} \tag{2}$$

We define the precision as:

$$p_k = \frac{1}{SE_{\ln(PRR_k)}} \tag{3}$$

and use its square as the the weight in our inverse-variance weighted meta-regression:

$$w_k = \frac{1}{(SE_{\ln(PRR_k)})^2)} = p_k^2 \tag{4}$$

To obtain a pooled log-effect of hiring discrimination, we compute a weighted average of the study-specific log-effects, adjusting for random error and unobserved heterogeneity:

$$PRR_{pooled} = \frac{\Sigma_{k=1}^{K}\left(\ln(PRR_k) + \epsilon_k + \zeta_k\right) w_k}{\Sigma_{k=1}^{K} w_k} \tag{5}$$

where ϵ_k and ζ_k capture sampling error and residual heterogeneity, respectively.

We then estimate our primary meta-regression model by regressing $\ln(PRR_k)$ on PRR_{pooled}, the study precision p_k, a set of covariates $X_k B$ (including study-level controls such as candidate gender, age, education, and employment status). We iterate over competition measure C_k to assess their main effect. Standard errors are clustered at the study level with small sample adjustment. This meta-regression model is represented as:

$$\ln(PRR_k) = PRR_{pooled} + \beta_p\, p_k + \beta_c\, C_k + X_k B + \epsilon_k + \zeta_k \tag{6}$$

where β_p quantifies the association between study precision and the reported effect and β_c denotes the effect of the competition measure on the $\ln(PRR_k)$.

To assess the dynamic impact of competition 'shocks' on hiring discrimination, we extend the UWLS approach with a meta-analytic event study specification. In this framework, we incorporate a treatment indicator with a set of dummies for event time (relative to a chosen reference period). The resulting model is:

$$\begin{aligned} \ln(PRR_k) =& PRR_{pooled} + \sum_{\tau \neq 0} \beta_\tau\, 1\,(\text{event} = \tau) \times \text{treated}_k \\ &+ \beta_p\, p_k + X_k\, B + \delta_{\text{country }(k)} + \epsilon_k + \zeta_k \end{aligned} \tag{7}$$

In Equation (7) , $\delta_{\text{country }(k)}$ explicitly captures country-level fixed effects. The summation term models the event study dynamics by estimating separate coefficients β_τ for each non-reference time τ, interacted with the treatment indicator treated_k. As before, the precision p_k is included with coefficient β_p and the model accounts for additional moderators X_k with coefficient vector B. Cluster-robust standard errors at the study level are used to account for potential within-study correlation.

Following the recommendation of Borenstein et al. (2011), we conducted analyses only when the number of studies (or clusters) equalled or exceeded the number of covariates in the specified meta-regressions. This ensures that we could compute the effects for the specified regressions.

However, this strategy has the disadvantage that, given the current dataset, we could not compute competition effects for many of the discrimination grounds in the scope of our meta-reanalysis.

3.2 Limitations

The current analysis has three clear limitations. First, while we have gathered hiring discrimination estimates for many different groups, we focus exclusively on race, ethnic identity, and national origin, sex and gender, and age. This self-imposed limitation is due to ongoing data collection, resulting in sufficient data points to produce preliminary analyses based on the three aforementioned discrimination grounds but not the others.

Second, while we have planned many analyses the UWLS-MRA approach with heterogeneity bias correction, we present none in this version of the manuscript. The idea is to conduct these once the data collection is finalised. Additional analyses include multilevel random effects meta-regression and hierarchical Bayesian meta-regression to account for the multilevel structure of our metadataset. Following Irsova et al. (2023), Harrer et al. (2021), and Havránek et al. (2020), we will also conduct several analyses to correct for publication biases—best-practices include:

- funnel approaches, such as:
  - the funnel plot and Egger's funnel plot asymmetry test;
  - precision-effect test (PET) and precision-effect estimate with standard error (PEESE);
  - limit meta-analysis;
  - meta-analysis instrumental variable estimator (MAIVE);
- selection model approaches, such as:
  - three- and four-parameter selection models;
  - Andrews–Kasy selection models (Andrews & Kasy, 2019);
  - p-uniform* analysis;
- a bias assessment and correction approach for meta-regression:
  - robust Bayesian model averaging (RoBMA), combining six selection models and PET-PEESE to compute average, corrected estimates.

Third, given the ongoing data collection, we cannot use recent hiring discrimination estimates in our analyses. Notably, our current dataset has minimal discrimination metadata post-2020. This limitation is unfortunate given the negative COVID-19 'shock' and subsequent labour market boom starting in 2021 and still somewhat continuing to date. However, future iterations of this manuscript will include discrimination data from this period, which will prove to be very valuable in further uncovering the link between the business cycle and hiring discrimination.

4 Results

Here, we present the results from a preliminary meta-reanalysis of competition (i.e., business cycle measures) on hiring discrimination. We start by broadly discussing the link between country-level unemployment rates and positive response ratios based on the main specification Equation (6) for the three retained discrimination grounds: 'Race, ethnic identity, and national origin', 'Sex and gender', and 'Age'. We also evaluate the link between the occupation-level response rates and the positive response ratios as well as the findings of the meta-analytic event study approach—both for the discrimination ground 'Race, ethnic identity, and national origin', for which we have most estimates and empirical support using the current methods.

4.1 Country-level competition and hiring discrimination

Figure 1 shows the relationship between unemployment rates and positive response ratios. The regression slope is only statistically significant (at the conventional $\alpha = 0.05$) for 'Race, ethnic identity, and national origin' ($\hat{\beta} = -0.2899$, $p = 0.004$, see Table A.1). In our log-log models, slopes represent elasticities, meaning that a 1.00% increase in unemployment is associated with a decrease in positive responses for racial or ethnic minorities by about 0.29%. The alternative RE-MRA approach and country-level vacancy-to-unemployment rate measure affirm the notion that racial and ethnic discrimination in hiring is counter-cyclical (see Table A.2 and Table A.3).

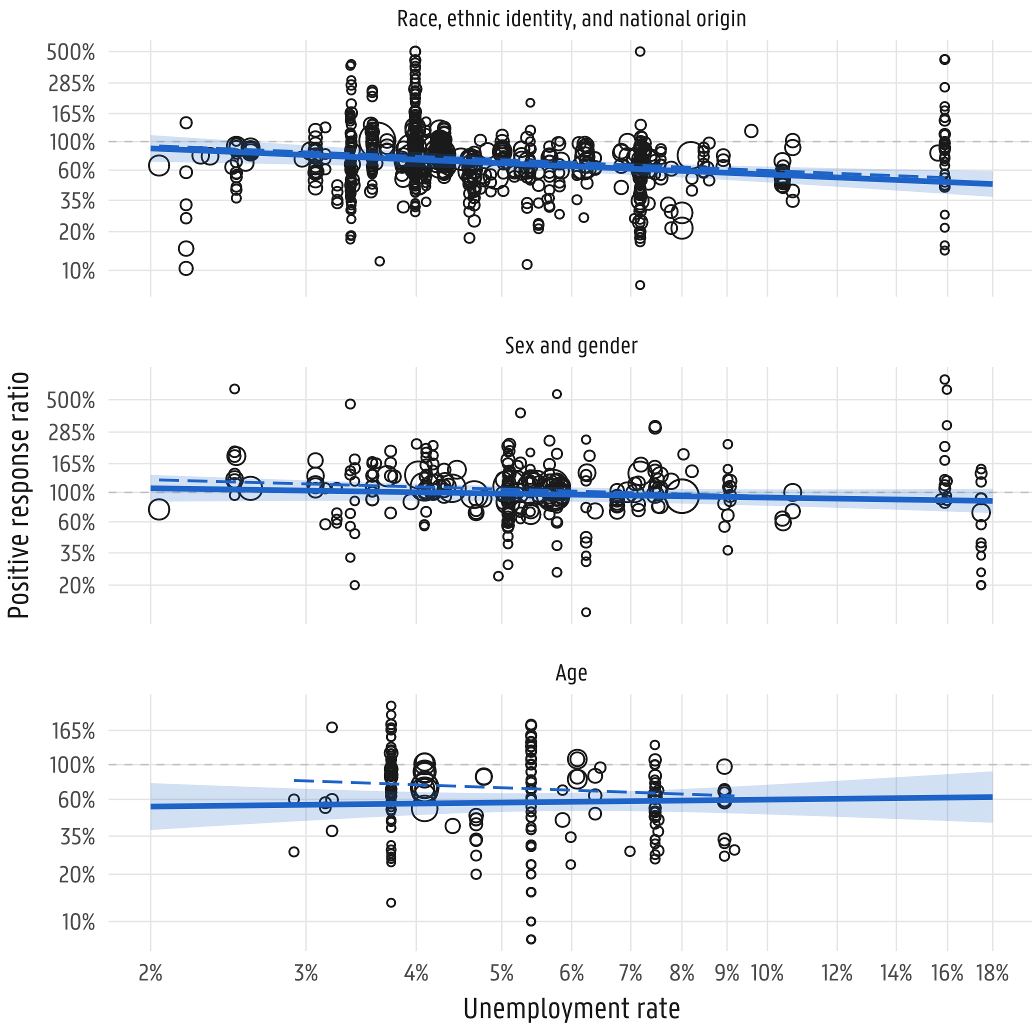

Figure 1: Association between unemployment and hiring discrimination. Dots are positive response ratios for each effect k; their sizes reflect their inverse variances or meta-analytic weights. Solid lines are predicted values based on Equation (6) . Predictions are calculated across a balanced grid of categories with continuous covariates held at their mean. Standard errors are clustered at the study level. Dashed lines are predicted values based on a simple inverse-variance weighted least squares model $\ln(\mathrm{PRR_k}) = \beta\,\mathrm{UR_k}$. Axes are on a logarithmic scale; tick labels display exponentiated (original) values.

The results of our meta-reanalysis also show that hiring discrimination based on sex or gender is relatively unresponsive to country-level unemployment ($\hat{\beta} = -0.1002$, $p = 0.246$, see Table A.1). This finding is unsurprising, given that there is little baseline sex or gender discrimination in hiring, on average, across occupations (Galos & Coppock, 2023; Lippens, Vermeiren, & Baert, 2023).[7]

[7]Sex or gender discrimination in hiring is mainly situated in particular occupations (Galos & Coppock, 2023; Schaerer, du Plessis, Nguyen, van Aert, Tiokhin, Lakens, Giulia Clemente, Pfeiffer, Dreber, Johannesson, Clark, & Luis Uhlmann, 2023). We are aware that using a multilevel meta-regression approach, allowing unemployment baseline values (i.e. intercepts) or slopes to vary by occupation, might reveal an effect of unemployment rates on positive response ratios. We have preliminary indications that sex and gender discrimination in hiring also

Furthermore, the results indicate that hiring discrimination based on age also does not vary by unemployment; the coefficient is even positive ($\hat{\beta}$ = 0.0635, p = 0.688, see Table A.1).

However, this general approach ignores that age discrimination in hiring increases with age (differences) (Batinovic, Howe, Sinclair, & Carlsson, 2023). The individual correspondence experiments included in our metadataset rely on various treatment and control groups in terms of age. Controlling for age in the control group (i.e., fixating the baseline age level), we see that positive response ratios decline curvilinearly as of 40 years (see Figure A.1). Using a moderated moderation approach, we find that age discrimination is responsive to the business cycle, with higher discrimination levels as levels of unemployment and age increase (see Figure 2). Somewhat surprisingly, our UWLS-MRA model also predicts that increased country-level unemployment is associated with more positive responses to applications of younger jobseekers.

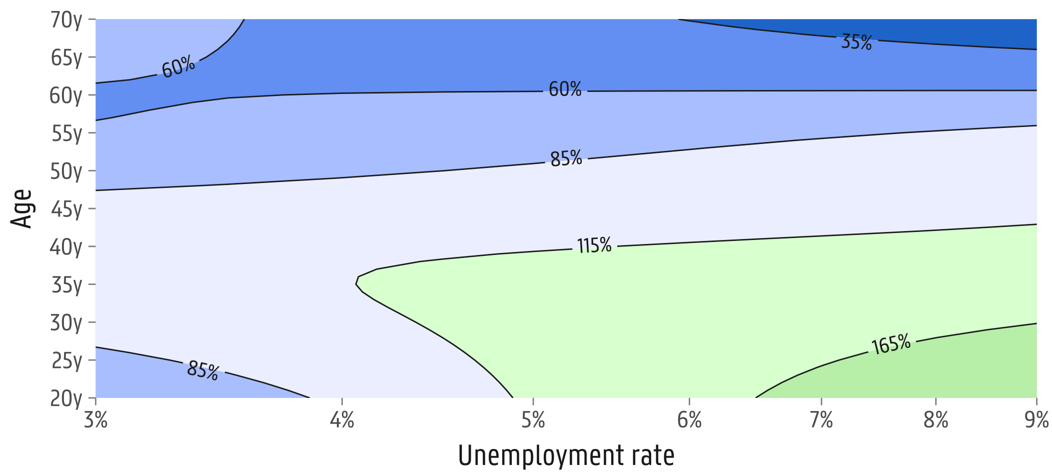

Figure 2: Association between unemployment, (age) discrimination in hiring, and age. The graph represents a contour plot with colour planes responding to prediced positive response ratio intervals based on Equation (6) . Predictions are calculated across a balanced grid of categories with continuous covariates held at their mean. The reference age is 35 years. Standard errors are clustered at the study level. Solid lines are interval boundaries. The x-axis is on a logarithmic scale; tick labels display exponentiated (original) values.

4.2 Occupation-level competition and hiring discrimination

Stepping away from the country-level measures of competition, we consider the association between occupation-level competition and hiring discrimination. Specifically, we evaluate if positive response rates increase with rising response rates—higher rates indicate more demand and, thus, a scarcer talent pool. Figure 3 shows this association for 'Race, ethnic identity, and national origin'. We indeed find that higher demand at the occupation level is associated with lower hiring discrimination for ethnic minorities ($\hat{\beta}$ = 0.4785, p = 0.02, see Table A.4). A 1pp. increase in employer response is linked to a 0.4785% increase in positive responses. In line with the country-

responds to country-level unemployment in the expected direction (following taste-based discrimination). We will report in more detail on this multilevel association in future iterations.

level results, we do not find a similar trend for 'Sex and gender' ($\hat{\beta} = -0.2544$, $p = 0.018$) or 'Age' ($\hat{\beta} = 1.7911$, $p = 0.28$).[8]

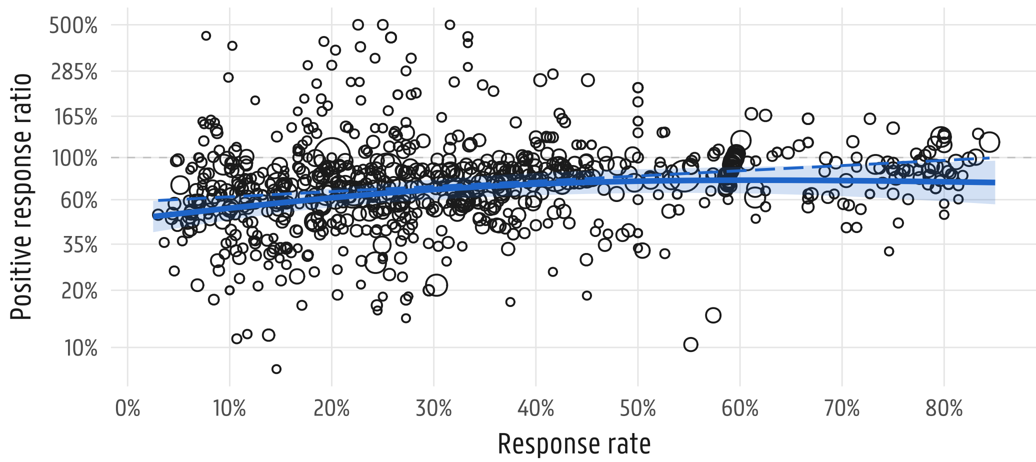

Figure 3: Association between employer response and hiring discrimination—Race, ethnic identity, and national origin. Dots are positive response ratios for each effect k; their sizes reflect their inverse variances or meta-analytic weights. The solid line represents predicted values based on Equation (6) . Predictions are calculated across a balanced grid of categories with continuous covariates held at their mean. Standard errors are clustered at the study level. The dashed line depicts predicted values based on a simple inverse-variance weighted least squares model $\ln(PRR_k) = \beta\, RR_k$. The y-axis is on a logarithmic scale; tick labels display exponentiated (original) values.

4.3 Meta-analytic event study

In this section, we briefly present the findings of our meta-analytic event study approach. Our event study estimates indicates hiring discrimination related to race, ethnic identity, and national origin is responsive to a negative labour market shock, notably the global financial crisis, relying on occupation-level discrimination estimates (see Figure 4). Using 2009 as the reference year, we observe that minority applicants applying for occupations facing higher employer competition (in terms of higher response rates) experienced marked increases in positive response ratios, with notable peaks just before and after the reference year. This finding suggests that, in a slacker labour market, employers temporarily exhibit more discriminatory behaviour in hiring, most likely due to decreased competitive pressures from other employers and increased labour supply. Estimates remain significantly positive in the years after the crisis. Fluctuations in the estimates across time hint at enduring sensitivity of occupational-level ethnic discrimination in hiring to business cycle conditions.

[8] Again, we note that sex or gender discrimination in hiring most likely depends on the specific occupation and that a multilevel approach makes more sense here. Also, age discrimination is sensitive to age (differences). We will reassess these associations in future iterations.

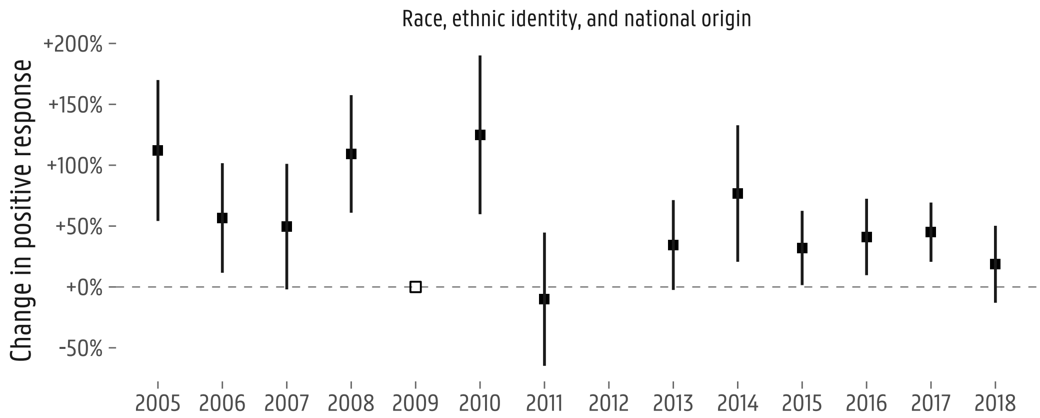

Figure 4: Meta-analytic event study plot of changes in employer responses to high-demand occupations—Race, ethnic identity, and national origin. Filled squares are average changes in positive response ratios—comparing ethnic minority to majority applications—for high-demand occupations (with average response rates exceeding 35%) based on (7) . The unfilled square is the baseline value for the reference year 2009. Vertical lines represent 95%-confidence intervals. Boostrapped standard errors are clustered at the study level (1,000 iterations).

5 Conclusion

The results of our meta-reanalysis indicate that hiring discrimination based on race, ethnic identity, and national origin is counter-cyclical, with higher country-level unemployment rates associated with significantly fewer positive responses for ethnic minority applicants. Conversely, our preliminary findings suggest discrimination based on sex or gender is largely unaffected by fluctuations in country-level unemployment, consistent with low and stable overall sex and gender discrimination in hiring. Age-based hiring discrimination is more complex, showing no association with overall unemployment rates, yet moderation analyses reveal increased discrimination with increasing age during economic downturns and, somewhat unexpectedly, improved outcomes for young applicants. Occupation-level analyses support the main effect for ethnic minorities, with higher occupation-specific demand reducing ethnic hiring discrimination. Last, our novel meta-analytic event study approach confirms the counter-cyclicality of ethnic hiring discrimination, notably intensifying around the global financial crisis, implying employers temporarily exhibit increased discriminatory behaviour in slacker labour markets.

The present analysis faces three primary limitations. First, it examines hiring discrimination exclusively regarding race, ethnic identity, and national origin, sex and gender, and age due to ongoing data collection efforts that currently restrict the inclusion of other discrimination grounds. Second, despite planning several multilevel analyses—such as multilevel random effects or hierarchical Bayesian meta-regressions—and advanced publication bias corrections—such as funnel approaches (e.g., Egger's tests, PET-PEESE), selection models (e.g., Andrews–Kasy, p-uniform*), and robust Bayesian model averaging (i.e., RoBMA)—this preliminary analysis relies heavily on the unrestricted weighted least squares approach with heterogeneity bias correction. Thus, a more comprehensive multilevel and publication bias assessment is delayed until data collection is complete. Third, the dataset presently lacks substantial discrimination estimates dated 2020 and later, limiting insights into discrimination dynamics during the COVID-19 crisis and subsequent labour market recovery. Future iterations incorporating these recent data will significantly enrich our understanding of (counter-)cyclical discrimination patterns.

Appendix

A Supplementary materials

A.1 Supplementary figures

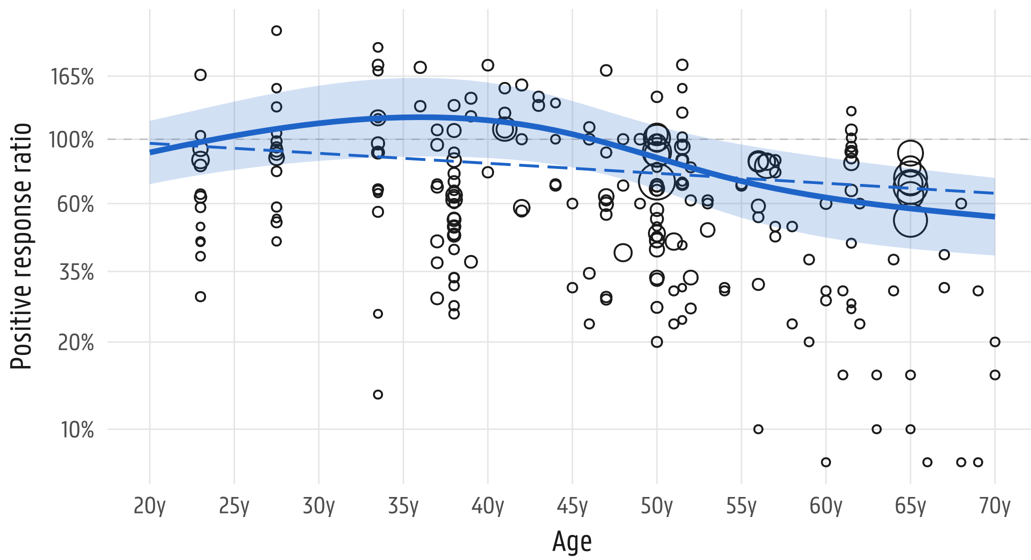

Figure A.1: Association between age and (age) discrimination in hiring. Dots are positive response ratios for each effect k; their sizes reflect their inverse variances or meta-analytic weights. Solid lines are predicted values based on UWLS-MRA regression with natural (cubic) splines of age differences with 3 degrees of freedom. The reference age is 35 years. Predictions are calculated across a balanced grid of categories with continuous covariates held at their mean. Standard errors are clustered at the study level. The dashed line represents predicted values based on a simple inverse-variance weighted least squares model $\ln(\mathrm{PRR}_k) = \beta\,\Delta\,\mathrm{Age}_k$. The y-axis is on a logarithmic scale; tick labels display exponentiated (original) values.

A.2 Supplementary tables

Table A.1: UWLS-MRA of PRR (log) on UR (log) by discrimination ground

	Race, ethnic identity, and national origin	Sex and gender	Age
Unemployment rate (log)	−0.2899 (0.0970)	−0.1002 (0.0856)	0.0635 (0.1559)
Precision (1/SE)	0.0088 (0.0052)	0.0013 (0.0034)	0.0040 (0.0115)
N	750	282	223
R^2	0.330	0.159	0.345
Adj. R^2	0.309	0.094	0.280

Notes. Acronyms used: UWLS-MRA (unrestricted weighted least squares meta-regression), PRR (positive response ratio), UR (unemployment rate). Statistics are coefficient estimates (with standard errors between brackets) controlled for candidate education, employment status, gender, and occupation, except for 'Sex and gender', which is not controlled for candidate gender. In addition, estimates are controlled for using a matched design and callback type, except for 'Age', which is only controlled for using a matched design due to a spurious correlation between the ages used in the audits and callback type. Standard errors are clustered at the study level.

Table A.2: RE-MRA of PRR (log) on UR (log) by discrimination ground

	Race, ethnic identity, and national origin	Sex and gender	Age
Unemployment rate (log)	−0.1944 (0.0791)	−0.1626 (0.0801)	−0.0817 (0.2047)
N	750	282	223

Notes. Acronyms used: RE-MRA (random effects meta-regression), PRR (positive response ratio), UR (unemployment rate). Statistics are coefficient estimates (with standard errors between brackets) controlled for candidate education, employment status, and gender, except for 'Sex and gender', which is not controlled for candidate gender. In addition, estimates are controlled for using a matched design and callback type, except for 'Age', which is only controlled for using a matched design due to a spurious correlation between the ages used in the audits and callback type. Standard errors are clustered at the study level.

Table A.3: UWLS-MRA of PRR (log) on VU (log) by discrimination ground

	Race, ethnic identity, and national origin	Sex and gender	Age
Vacancy rate (log)	0.0892 (0.0333)	0.0146 (0.0405)	0.0898 (0.0799)
Precision (1/SE)	0.0071 (0.0058)	−0.0050 (0.0059)	0.0112 (0.0142)
N	568	189	217
R^2	0.324	0.188	0.362
Adj. R^2	0.297	0.102	0.297

Notes. Acronyms used: UWLS-MRA (unrestricted weighted least squares meta-regression), PRR (positive response ratio), VU (vacancy-to-unemployment rate). Statistics are coefficient estimates (with standard errors between brackets) controlled for candidate education, employment status, gender, and occupation, except for 'Sex and gender', which is not controlled for candidate gender. In addition, estimates are controlled for using a matched design and callback type, except for 'Age', which is only controlled for using a matched design due to a spurious correlation between the ages used in the audits and callback type. Standard errors are clustered at the study level.

Table A.4: UWLS-MRA of PRR (log) on RR by discrimination ground

	Race, ethnic identity, and national origin	Sex and gender	Age
Response rate	0.4785 (0.2015)	−0.2544 (0.1058)	1.7911 (1.6147)
Precision (1/SE)	0.0083 (0.0052)	0.0017 (0.0033)	0.0039 (0.0111)
N	774	312	226
R^2	0.296	0.179	0.376
Adj. R^2	0.274	0.123	0.315

Notes. Acronyms used: UWLS-MRA (unrestricted weighted least squares meta-regression), PRR (positive response ratio), RR (response rate). Statistics are coefficient estimates (with standard errors between brackets) controlled for candidate education, employment status, gender, and occupation, except for 'Sex and gender', which is not controlled for candidate gender. In addition, estimates are controlled for using a matched design and callback type, except for 'Age', which is only controlled for using a matched design due to a spurious correlation between the ages used in the audits and callback type. Standard errors are clustered at the study level.

References

Andrews, I., & Kasy, M. (2019). Identification of and correction for publication bias. *American Economic Review*, *109*(8), 2766–2794. https://doi.org/10.1257/aer.20180310

Arrow, K. J. (1972). Some Mathematical Models of Race Discrimination in the Labor Market. In A. H. Pascal (Ed.), *Racial Discrimination in Economic Life* (pp. 187–204). D.C. Heath.

Arrow, K. J. (1973). The Theory of Discrimination. In O. Aschenfelter & A. Rees (Eds.), *Discrimination in Labor Markets*. Princeton University Press.

Baert, S., Cockx, B., Gheyle, N., & Vandamme, C. (2015). Is There Less Discrimination in Occupations Where Recruitment Is Difficult?. *ILR Review*, *68*(3), 467–500. https://doi.org/10.1177/0019793915570873

Bartkoski, T., Lynch, E., Witt, C., & Rudolph, C. (2018). A meta-analysis of hiring discrimination against Muslims and Arabs. *Personnel Assessment and Decisions*, *4*(2), 1–16. https://doi.org/10.25035/pad.2018.02.001

Batinovic, L., Howe, M., Sinclair, S., & Carlsson, R. (2023). Ageism in Hiring: A Systematic Review and Meta-analysis of Age Discrimination. *Collabra: Psychology*, *9*(1). https://doi.org/10.1525/collabra.82194

Becker, G. (1971). *The Economics of Discrimination* (2nd ed.). University of Chicago Press.

Bohren, J. A., Haggag, K., Imas, A., & Pope, D. G. (2023). Inaccurate Statistical Discrimination: An Identification Problem. *Review of Economics and Statistics*. https://doi.org/10.1162/rest_a_01367

Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2011). Meta-regression. In M. Borenstein, L. V. Hedges, J. P. T. Higgins, & H. R. Rothstein (Eds.), *Introduction to Meta-Analysis* (pp. 187–203). John Wiley & Sons. https://doi.org/10.1002/9780470743386.ch20

Borjas, G. (2020). Labor market discrimination. In G. Borjas (Ed.), *Labor Economics* (8th ed., pp. 299–340). McGraw-Hill Education.

Carlsson, M., Fumarco, L., & Rooth, D.-O. (2018). Ethnic discrimination in hiring, labour market tightness and the business cycle – Evidence from field experiments. *Applied Economics*, *50*(24), 2652–2663. https://doi.org/10.1080/00036846.2017.1406653

Challe, L. (2017). Ageism and the business cycle: An exploratory approach. *The European Journal of Comparative Economics*, *14*(2), 221–264. https://doi.org/10.25428/1824-2979/201702-221-264

Challe, L., L'Horty, Y., Petit, P., & Wolff, F.-C. (2023). Cyclical behavior of hiring discrimination: Evidence from repeated experiments in France. *The Annals of Regional Science*, *72*(3), 711–733. https://doi.org/10.1007/s00168-023-01217-2

Coleman, M. G. (2004). Racial discrimination in the workplace: Does market structure make a difference?. *Industrial Relations*, *43*(3), 660–689. https://doi.org/10.1111/j.0019-8676.2004.00354.x

Dahl, G. B., & Knepper, M. (2023). Age Discrimination across the Business Cycle. *American Economic Journal: Economic Policy*, *15*(4), 75–112. https://doi.org/10.1257/pol.20210169

Flage, A. (2020). Discrimination against gays and lesbians in hiring decisions: A meta-analysis. *International Journal of Manpower*, *41*(6), 671–691. https://doi.org/10.1108/ijm-08-2018-0239

Gaddis, S. M., Larsen, E., Crabtree, C., & Holbein, J. (2021). *Discrimination against Black and Hispanic Americans is highest in hiring and housing contexts: A meta-analysis of correspondence audits*. https://doi.org/10.2139/ssrn.3975770

Galos, D. R., & Coppock, A. (2023). Gender composition predicts gender bias: A meta-reanalysis of hiring discrimination audit experiments. *Science Advances*, *9*(18). https://doi.org/10.1126/sciadv.ade7979

Galvan, M. J., Alvarez, G. M., Cipolli, W. I., Cooley, E., Muscatell, K., & Payne, K. (2022). *Is Discrimination Widespread or Concentrated? Evaluating the Distribution of Hiring and Housing Discrimination Against Black Americans*. https://doi.org/10.31234/osf.io/sxeg4

Harrer, M., Cuijpers, P., Furukawa, T. A., & Ebert, D. D. (2021). *Doing Meta-Analysis with R*. https://doi.org/10.1201/9781003107347

Havránek, T., Stanley, T. D., Doucouliagos, H., Bom, P., Geyer-Klingeberg, J., Iwasaki, I., Reed, W. R., Rost, K., & van Aert, R. C. M. (2020). Reporting guidelines for meta-analysis in economics. *Journal of Economic Surveys*, *34*(3), 469–475. https://doi.org/10.1111/joes.12363

Heath, A. F., & Di Stasio, V. (2019). Racial discrimination in Britain, 1969–2017: A meta-analysis of field experiments on racial discrimination in the British labour market. *The British Journal of Sociology*, *70*(5), 1774–1798. https://doi.org/10.1111/1468-4446.12676

Irsova, Z., Doucouliagos, H., Havranek, T., & Stanley, T. D. (2023). Meta-analysis of social science research: A practitioner's guide. *Journal of Economic Surveys*, *38*(5), 1547–1566. https://doi.org/10.1111/joes.12595

Kuhn, F., & Chanci, L. (2024). Racial disparities in labor outcomes: The effects of hiring discrimination over the business cycle. *Economic Analysis and Policy*, *81*, 801–817. https://doi.org/10.1016/j.eap.2023.12.027

Lang, K., & Lehmann, J.-Y. K. (2012). Racial Discrimination in the Labor Market: Theory and Empirics. *Journal of Economic Literature*, *50*(4), 959–1006. https://doi.org/10.1257/jel.50.4.959

Lippens, L., Baert, S., & Neyt, B. (2025). Hiring discrimination across vulnerable groups. *IZA World of Labor*. https://doi.org/10.15185/izawol.515

Lippens, L., Vermeiren, S., & Baert, S. (2023). The state of hiring discrimination: A meta-analysis of (almost) all recent correspondence experiments. *European Economic Review*, *151*, 104315–104316. https://doi.org/10.1016/j.euroecorev.2022.104315

Neumark, D., & Button, P. (2014). Did Age Discrimination Protections Help Older Workers Weather the Great Recession?. *Journal of Policy Analysis and Management*, *33*(3), 566–601. https://doi.org/10.1002/pam.21762

OECD. (2020). *All Hands In? Making Diversity Work for All*. OECD Publishing. https://doi.org/10.1787/efb14583-en

Park, S. Y., & Oh, E. (2025). Getting a foot in the door: A meta-analysis of U.S. audit studies of gender bias in hiring. *Sociological Science*, *12*, 26–50. https://doi.org/10.15195/v12.a2

Phelps, E. S. (1972). The Statistical Theory of Racism and Sexism. *The American Economic Review*, *62*(4), 659–661.

Quillian, L., & Lee, J. J. (2023). Trends in racial and ethnic discrimination in hiring in six Western countries. *Proceedings of the National Academy of Sciences*, *120*(6). https://doi.org/10.1073/pnas.2212875120

Quillian, L., Heath, A., Pager, D., Midtbøen, A., Fleischmann, F., & Hexel, O. (2019). Do Some Countries Discriminate More than Others? Evidence from 97 Field Experiments of Racial Discrimination in Hiring. *Sociological Science*, *6*, 467–496. https://doi.org/10.15195/v6.a18

Quillian, L., Lee, J. J., & Oliver, M. (2020). Evidence from Field Experiments in Hiring Shows Substantial Additional Racial Discrimination after the Callback. *Social Forces*, *99*(2), 732–759. https://doi.org/10.1093/sf/soaa026

Quillian, L., Pager, D., Hexel, O., & Midtbøen, A. H. (2017). Meta-analysis of field experiments shows no change in racial discrimination in hiring over time. *Proceedings of the National Academy of Sciences*, *114*(41), 10870–10875. https://doi.org/10.1073/pnas.1706255114

Richardson, W. S., Wilson, M. C., Nishikawa, J., & Hayward, R. S. A. (1995). The well-built clinical question: A key to evidence-based decisions. *ACP Journal Club*, *123*(3), A12. https://doi.org/10.7326/acpjc-1995-123-3-a12

Ruzzier, C. A., & Woo, M. D. (2023). Discrimination with inaccurate beliefs and confirmation bias. *Journal of Economic Behavior & Organization*, *210*, 379–390. https://doi.org/10.1016/j.jebo.2023.04.018

Schaerer, M., du Plessis, C., Nguyen, M. H. B., van Aert, R. C. M., Tiokhin, L., Lakens, D., Giulia Clemente, E., Pfeiffer, T., Dreber, A., Johannesson, M., Clark, C. J., & Luis Uhlmann, E. (2023). On the trajectory of discrimination: A meta-analysis and forecasting survey capturing 44 years of field experiments on gender and hiring decisions. *Organizational Behavior and Human Decision Processes*, *179*, 104280–104281. https://doi.org/10.1016/j.obhdp.2023.104280

Stanley, T. D., & Doucouliagos, H. (2017). Neither fixed nor random: Weighted least squares meta-regression. *Research Synthesis Methods*, *8*(1), 19–42. https://doi.org/10.1002/jrsm.1211

Stanley, T. D., Doucouliagos, H., & Ioannidis, J. P. A. (2022). Beyond Random Effects: When Small-Study Findings Are More Heterogeneous. *Advances in Methods and Practices in Psychological Science*, *5*(4), 251524592211204. https://doi.org/10.1177/25152459221120427

Stanley, T. D., Ioannidis, J. P. A., Maier, M., Doucouliagos, H., Otte, W. M., & Bartoš, F. (2023). Unrestricted weighted least squares represent medical research better than random effects in

67,308 Cochrane meta-analyses. *Journal of Clinical Epidemiology*, *157*, 53–58. https://doi.org/10.1016/j.jclinepi.2023.03.004

Thijssen, L., van Tubergen, F., Coenders, M., Hellpap, R., & Jak, S. (2021). Discrimination of Black and Muslim Minority Groups in Western Societies: Evidence From a Meta-Analysis of Field Experiments. *International Migration Review*, *56*(3), 843–880. https://doi.org/10.1177/01979183211045044

van den Akker, O. R., Peters, G.-J. Y., Bakker, C. J., Carlsson, R., Coles, N. A., Corker, K. S., Feldman, G., Moreau, D., Nordström, T., Pickering, J. S., Riegelman, A., Topor, M. K., van Veggel, N., Yeung, S. K., Call, M., Mellor, D. T., & Pfeiffer, N. (2023). Increasing the transparency of systematic reviews: Presenting a generalized registration form. *Systematic Reviews*, *12*(1). https://doi.org/10.1186/s13643-023-02281-7

Zschirnt, E., & Ruedin, D. (2016). Ethnic discrimination in hiring decisions: A meta-analysis of correspondence tests, 1990–2015. *Journal of Ethnic and Migration Studies*, *42*(7), 1115–1134. https://doi.org/10.1080/1369183X.2015.1133279

Zwysen, W., Di Stasio, V., & Heath, A. (2021). Ethnic Penalties and Hiring Discrimination: Comparing Results from Observational Studies with Field Experiments in the UK. *Sociology*, *55*(2), 263–282. https://doi.org/10.1177/0038038520966947