Pre-Analysis Plan: Visibility as Vulnerability: Transgender Passing Privilege and Hiring Discrimination

Date: 5/13/2025

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Background

Transgender people—those whose gender identity differs from their sex assigned at birth— are a sizable and growing population (Brown, 2022; Bachmann et al., 2024). Research consistently shows that transgender people have worse labour market outcomes compared to cisgender peers, including lower employment rates, lower incomes, and higher poverty rates (Leppel 2016, 2021; Carpenter et al. 2020, 2022; Shannon 2022). Among this group, transgender women are uniquely disadvantaged: unlike transgender men, they experience a large and persistent earnings reduction post-transition (Carpenter et al., 2024; Geijtenbeek and Plug, 2018). Not "passing" as cisgender (i.e., not being perceived as cisgender by strangers) is associated with worse labor market outcomes (Shannon, 2022). Further, in self-reported terms, transgender women are less likely to pass than transgender men (James et al., 2016). However, it remains unclear whether passing directly improves employment prospects (e.g., by reducing discrimination) or if those with better job opportunities are more likely to pass (e.g., due to greater access to gender-affirming care which helps align gender expression with gender identity and facilitates passing). With a recent wave of legislation in the U.S. and elsewhere restricting access to such care (Trans Legislation Tracker, n.d.), understanding the role of passing in labor market outcomes is becoming increasingly relevant— yet little is currently known about its impact.

This study examines whether employers discriminate against transgender women job applicants compared to presumably cisgender applicants and explores the role of passing in hiring discrimination. To test this, I will conduct a field experiment in which fictitious applicants with A.I.-generated headshots apply to real job postings in Germany, where including a photo on one's CV is common. Each applicant's headshot will belong to a pair of "twin" images: one portraying someone who passes well as cisgender and the other portraying a woman who does not pass (the same image altered to enhance male features). Images have been generated using a process similar to Evysukova et al. (2025) involving A.I.-generated images from StyleGAN2 (Karras et al., 2020), image tagging and filtering using DeepFace (Taigman et al., 2014), and the development of male-to-female and female-to-male transformation vectors. Further, some applicants may indirectly disclose their transgender identity via a male-to-female name change ("Please note that some of my documents are still under the name [original name]; I now use the first name [new name].").

As such, there are three treatment arms and two control groups (where "MtF" denotes "Male-to-Female" and "FtF" denotes "Female-to-Female" name changes):

Table 1: Treatment and Control Groups

Group	Headshot	Name Change	Sent Alongside…
Treatment 1	Passes Poorly	MtF Name Change Disclosed	Control 1
Treatment 2	Passes Well	MtF Name Change Disclosed	Control 1
Treatment 3	Passes Poorly	No Name Change Disclosed	Control 2
Control 1	Passes Well	No Name Change Disclosed	Treatment 1, 2
Control 2	Passes Well	FtF Name Change Disclosed	Treatment 3

Study Timeline

Table 2: Field Study Timeline

Tasks	Start Date	Duration
Survey Experiment One	May 13-14, 2025	1-2 days
Survey Experiment Two	May 20-21, 2025	1-2 days
Field Experiment: Send fictitious resumes to job postings	May 19, 2025	Approx. 8 months
Field Experiment: Collect employer responses	May 18, 2025	Approx. 9 months
Preliminary analytics, power analysis update	July 14, 2025	Approx. 2 weeks

Timeline may be extended if target sample sized is not reached in 8 months.

Field Experiment Design

A. Geographies

Fictitious applications will be sent in 9 of 16 German states, and "Rank" is a ranking of the state's trans-progressiveness given the history and platforms of the listed parties. The ranking is a weighted average of the vote share (calculated as a percent of Green, Linke, SPD, Union, and AfD vote shares—omitting FDP since it is libertarian and does not achieve a large vote share in any area as well as BSW since it is a newly formed party with unclear trans-progressiveness) and a trans-progressiveness ranking per party (Green 10, Linke 9, SPD 8, Union 3, AfD 0).

Table 3: Experiment States

State	Green	Linke	SPD	Union	AfD	Rank	Population	Included
Baden-Württemberg	16%	8%	17%	37%	23%	4.72	11.2 M	X
Bavaria	14%	7%	14%	44%	22%	4.39	13.2 M	X
Berlin	20%	23%	18%	21%	18%	6.13	3.7 M	X
Hamburg	22%	16%	26%	24%	12%	6.44	1.9 M	X
Hesse	15%	10%	21%	33%	21%	5.07	6.3 M	X
North Rhine-Westphalia	14%	9%	23%	34%	19%	5.13	18.0 M	X
Rhineland-Palatinate	12%	8%	22%	35%	23%	4.68	4.1 M	X
Saxony	8%	14%	10%	24%	45%	3.53	4.1 M	X
Schleswig-Holstein	17%	9%	22%	32%	19%	5.30	3.0 M	X
Brandenburg	8%	13%	18%	22%	39%	4.05	2.6 M	
Bremen	18%	17%	26%	23%	17%	6.01	0.7 M	
Lower Saxony	13%	9%	26%	32%	20%	5.15	8.0 M	
Mecklenburg-Vorpommern	7%	15%	15%	22%	42%	3.81	1.6 M	
Saarland	8%	9%	26%	32%	25%	4.64	1.0 M	
Saxony-Anhalt	5%	13%	13%	23%	45%	3.48	2.1 M	
Thuringia	5%	18%	10%	22%	45%	3.57	2.1 M	

Fictitious applications will be sent in 25 cities within these 9 states, where a similar per-city "Rank" is generated:

Table 4: Experiment Cities

State	City	Green	Linke	SPD	Union	AfD	Rank	Population
Baden-Württemberg	Stuttgart	25%	13%	18%	31%	13%	6.03	626 K
Baden-Württemberg	Freiburg	30%	16%	17%	25%	12%	6.57	232 K
Bavaria	Munich	27%	10%	18%	34%	11%	6.09	1,488 K
Bavaria	Augsburg	19%	12%	16%	33%	20%	5.24	296 K
Berlin	Berlin	20%	23%	18%	21%	18%	6.13	3,677 K
Hamburg	Hamburg	22%	16%	26%	24%	12%	6.44	1,906 K
Hesse	Frankfurt	23%	17%	20%	28%	12%	6.28	759 K
Hesse	Wiesbaden	19%	13%	20%	31%	16%	5.64	279 K
North Rhine-Westphalia	Cologne	25%	15%	22%	28%	11%	6.38	1,073 K
North Rhine-Westphalia	Dusseldorf	21%	12%	21%	33%	13%	5.85	619 K
North Rhine-Westphalia	Dortmund	15%	13%	27%	26%	19%	5.60	587 K
North Rhine-Westphalia	Essen	14%	10%	26%	31%	19%	5.32	579 K
North Rhine-Westphalia	Duisburg	10%	12%	29%	25%	24%	5.19	495 K
North Rhine-Westphalia	Bochum	17%	14%	27%	27%	16%	5.89	363 K
North Rhine-Westphalia	Herne	10%	11%	29%	26%	24%	5.12	157 K
North Rhine-Westphalia	Wuppertal	14%	12%	23%	30%	21%	5.20	355 K
North Rhine-Westphalia	Bonn	26%	14%	20%	30%	10%	6.37	332 K
North Rhine-Westphalia	Munster	30%	14%	20%	29%	8%	6.69	318 K
North Rhine-Westphalia	Gelsenkirchen	7%	11%	28%	26%	28%	4.69	260 K
Rhineland-Palatinate	Mainz	24%	13%	21%	30%	12%	6.10	218 K
Saxony	Leipzig	16%	26%	13%	19%	26%	5.56	602 K
Saxony	Dresden	15%	18%	11%	23%	33%	4.67	555 K
Saxony	Chemnitz	8%	15%	14%	24%	40%	3.94	243 K
Schleswig-Holstein	Kiel	27%	16%	22%	23%	12%	6.55	246 K
Schleswig-Holstein	Lubeck	20%	12%	24%	26%	18%	5.81	216 K

Geographies may be added if feasible as the project progresses. Vote share information is sourced from The Federal Returning Officer (2025).

B. Occupations

Fictitious resumes will be sent to the following occupations, where "requirement level" denotes the most common requirement level associated with an occupation (i.e., the requirement level within which most workers reside):

Table 5: Experiment Occupations

KldB	Occupation	Requirement Level	Worker Composition			Category
			Headcount	% Female	% Male	
521	Truck Driver	2	865 K	5%	95%	Male-Dominated
251	Mechatronics Technician	2	965 K	10%	90%	Male-Dominated
513	Warehouse Worker	1	1,528 K	24%	76%	Male-Dominated
293	Cook	1	428 K	47%	53%	Mixed
633	Server	2	406 K	57%	43%	Mixed
621, 622	Retail Sales	2	1,339 K	63%	37%	Mixed
541	Cleaner	1	790 K	69%	31%	Female-Dominated
813	Nurse	2	823 K	75%	25%	Female-Dominated
714	Office Clerk	2	1,737 K	77%	23%	Female-Dominated

Headcount, requirement level, and worker composition information is sourced from the IAB Occupation Panel (Grienberger et al., 2022). Requirement level indicates what kind of education or training is required for the job; level one indicates no specific training is required, level two indicates vocational training is required—levels three and four are not considered in this study, and often require a University degree or advanced, specialized training.

Occupations will also be categorized based on the degree of customer-facing interaction and coworker interaction (sourced from O*NET). Occupations maybe added if feasible as the project progresses.

C. Names

The following names will be used in this study (the probability that a first name belongs to a female in Germany is reported in brackets):

Table 6: Experiment Names

First Name			Last Name
Original Male	Original Female	New Female	
Theodor (1%)	Theodora (99%)	Thea (99%)	Voigt
Christian (0%)	Christiane (99%)	Tina (99%)	Lehmann
Ludwig (0%)	Ludmilla (99%)	Milla (99%)	Maier
Johannes (0%)	Johanna (99%)	Hanna (98%)	Hoffmann
Markus (0%)	Martina (99%)	Mara (98%)	Neumann
Leonardo (1%)	Leonarda (98%)	Lena (97%)	Schmidt

In general, Original Male and Original Female are male and female versions of the same name (Theodor, Theodora) and the New Female name is a female name that is (1) a relatively common standalone legal name, (2) can be seen as a “nickname” or shortened version of the Original Female name, and (3) not so obviously a nickname as to warrant disclosure. If an applicant does not disclose a name change, they simply use the New Female name.

Last names were randomly selected from a list of the 100 most common surnames in Germany (Forebears, n.d.). The probability that a first name belongs to a female is sourced from genderize.io, specifying that this probability should be Germany-specific (genderize.io, n.d.).

Applicants who disclose a name change will have some documents in their original name:

- MtF: employer reference letter will be in their original name, vocational certificate will be a scan of a duplicate in their new name
- FtF: employer reference letter will be in their original name, vocational certificate will be a scan of an original in their original name

D. Application Design

A process for generating occupation-specific resumes has been developed using a program by Lahey and Beasley (2009). The characteristics over which resumes are randomized are equivalent across geographies, except for Work Experience where company names are city specific (position titles and descriptions are independent of geography). For all occupations and geographies, fictitious resumes are generated for an applicant born in either 1998 or 2002 (i.e., fictitious applicants are 27 or 23 in 2025 with either 8 or 4 years of work experience post-vocational training).

Applications are generated in pairs; within a characteristic, resumes can be matched same (i.e., if the first resume is randomly assigned characteristic A, then the matched pair will also be given characteristic A) or matched different (i.e., if the first resume is randomly assigned characteristic A, then the matched pair will be randomly assigned a characteristic aside from A).

Within an occupation and implied sex, applications are randomized across the following:

- Name: one of the six new first names (see Table 6 above)
  - Matched different
- Year of birth: either 1998 or 2002
  - Matched same
- Cover letter: randomly drawn from four cover letters
  - Matched different
- Treatment and Control Group: one of Treatment 1, 2, 3; Control 1, 2 (see Table 1 above)
  - Matched different: Treatment 1, 2 is matched with Control 1 / Treatment 3 is matched with Control 2
- Name Change Disclosure Timing: either in the introductory email or the cover letter
  - n/a, only applies to applicants who disclose a name change
- Summary: randomly drawn from a list of summaries or no summary
  - Matched different: two applicants can both have no summary, and two can have a summary—summary text is always different
- Vocational certificate: consistent with occupation requirements
  - Matched same: the actual certificate, grades (either average or good), prestige of company training is done at (either average or prestigious), achieved in Berlin

    - Matched different: scan style, actual company
- Work Experience: since archiving their vocational training
    - Matched same: applicants will have worked in the occupation of interest, applicants will have worked at two employers, applicants will attach a reference letter from their first employer, reference letter quality (either average or good), experience descriptions (either no description, or some bullets)
    - Matched different: one applicant will move to Hannover after finishing vocational training in Berlin and the other will move directly to the local area, reference letter formatting, reference letter text, company names, experience description text (if applicable)
- Skills: applicants list various skills
    - Matched same: English language skills (fluent or some practical ability)
    - Matched different: whether skills are listed and what skills are included—both for general competence and computer/technology-related skills
- Hobbies: randomly drawn from a list of hobbies or no hobbies
    - Matched different
- Formatting: applications are in one of two formats
    - Matched different
- Timing: either sent first or second
    - Matched different

E. Data Collection Process

Weekly, job posting data will be scraped from the major job posting website in Germany ([Bundesagentur für Arbeit]) in the occupations of interest, and a list of target job postings will be created (omitting companies we have applied for previously, omitting temporary work from employment agencies, omitting postings where the application occurs on an external job board or portal). A team of research assistants will aid in generating pairs of ficitious, randomized, matched applications to e-mail to employers and securing additional job posting information (like what e-mail to send applications to).

Employer response will be carefully tracked via phone and email. Upon contact, employers will be promptly contacted, where applicants will let them know they have recently found work and are therefore no longer interested in the position. The outcome of interest is whether the employer responds positively—that is, whether they offer the applicant an interview, request additional information about qualifications, request the applicant contacts them back, etc.

A version of the experiment may be conducted where trackable links are sent in place of PDF attachments in emails. Whether or not this occurs will depend on the results of a pilot test (will enough employers click on such links, especially in the context of Germany people are extremely vigilant about data protection and privacy).

Survey Experiment Design

A. Survey Experiment One

Survey Experiment One is aligned with Evysukova et al. (2025) and has two goals: (1) to confirm that A.I.-generated images are not detectable as such, and (2) to confirm that the "passing" signal is being communicated as intended.

Hence, a survey experiment, generated on Qualtrics, will be fielded via Prolific. In the first part of the experiment, from a grid of 20 images, respondents will be asked to select the images they think are A.I.-generated—and provided with a small bonus payment if they are entirely correct in their selection. In the second part of the experiment, respondents will be shown 11 images (10 images of interest, and one always included image of a woman wearing glasses), and asked to judge the person in the image: (a) their age, (b) the likelihood they were assigned male at birth on a 0-100 scale, (c) the likelihood they identify as a woman on a 0-100 scale, (d) whether they are wearing glasses (an attention check) on a 0-100 scale. Images of interest include "triplet" versions of each "twin" image pair potentially to be included in the field experiment—one image is presumably a cisgender woman (i.e., appears to be assigned female at birth and identifies as a woman; one of the field experiment "twins"), one image is presumably a transgender woman (i.e., appears to be assigned male at birth and identifies as a woman; one of the field experiment "twins"), and one image is presumably a cisgender man (i.e., appears to be assigned male at birth and identifies as a man; not one of the "twins").

Images are not identifiable as A.I.-generated if they are not meaningfully more likely to be selected as A.I.-generated by respondents when compared to images of real people. Images convey the passing signal as intended if the "passes well" twin is assumed to be assigned female at birth and the "does not pass well" twin is assumed to be assigned male at birth.

B. Survey Experiment Two

In Survey Experiment Two, the goal is to measure additional attributes associated with each image—for example, how approachable/competent/easy-going/confident/etc. an image seems on a 0-100 scale. Again, "triplet" images will be included in this experiment.

This can be used to consider the difference in attribute measures in general between presumably transgender woman and their cisgender counterparts—what attributes have the largest difference between transgender and cisgender ratings? It can also be used to consider the extent to which different attributes contribute to discrimination.

Analysis

A. Attribute Measurement (Survey Experiments)

Per image, I plan to measure attribute ratings as the average across all respondents.

I plan to measure the attribute "transgender gap" as follows:

$$a_{itnr} = \rho NP_i + \omega \mathrm{M_i} + \theta_t + \sigma_n + \eta_r + \varepsilon_{itr}$$

where a_{itr} is the attribute value given to image applicant i in triplet t with name n by respondent r; NP_i equals 1 if image i is a presumably transgender woman (i.e., she does not pass); M_i equals 1 if image i is a presumably cisgender man; and $\theta_t, \sigma_n, \eta_r$ are triplet, name, and respondent fixed effects.

To consider heterogeneity in ratings, I can add interaction terms to the above based on respondent demographics (age, sex, education level, income, state of residence, political party).

B. Hiring Discrimination Measurement

My primary goal is to identify hiring discrimination against transgender women and consider the extent to which this is driven by (1) indirect identity disclosure and (2) whether the transgender woman "passes" as cisgender. To do this, I will run the following linear probability model:

$$y_{itocj} = \delta DT_i + \gamma NP_i + \lambda[DT_i \cdot NP_i] + X_i'\beta_1 + Z_j'\beta_2 + \theta_t + \phi_o + \xi_c + \varepsilon_{itocj}$$

where: y_{itocj} equals 1 if applicant i in twin t, occupation o, and city c receives a callback from job posting j; DT_i equals 1 if applicant i indirectly discloses their transgender identity through a MtF name change; NP_i equals 1 if applicant i does not pass; X_i' is a vector of applicant control variables that may influence baseline callback rates; Z_j' is a vector of job posting control variables that may influence baseline callback rates; and $\theta_t,\ \phi_o,\ \xi_c$ are twin, occupation, and city fixed effects.[1]

To consider heterogeneity in discrimination, I can add interaction terms to the above. Due to limited power, I may replace DT_i and NP_i with $T_i = \min(DT_i, NP_i)$. I plan to consider heterogeneity in terms of:

- Passing Level—based on Survey Experiment One image-specific ratings
    - Rationale: the less one passes, the more discrimination one may face
- Geographic Politics—based on state and/or city "Rank" or the sum of Union and AfD vote share (see Tables 3, 4)

[1] Note: I do not expect that disclosing a female-to-female (FtF) name change to meaningfully affect employer response rates. Splitting DT_i into two separate indicators—(1) whether any name change is disclosed, and (2) whether a male-to-female (MtF) name change specifically is disclosed—would substantially reduce statistical power. Therefore, I will first check if revealing a FtF name change has a notable impact on response rates. If not, I will include a separate indicator for a FtF name change in the control vector X_i', and DT_i will continue to equal 1 only when a male-to-female name change is disclosed.

    - Rationale: transgender people may experience heightened discrimination in more politically conservative areas (Eames, 2024)
- Occupation Sex Composition—based on % male, female (see Table 5)
    - Rationale: transgender people may experience heightened discrimination in male- or female-dominated occupations (Granberg et al., 2020)
- Occupation Customer-Facing Interaction—based on O*Net Scores
    - Rationale: employers may be discriminating on behalf of their customers (they expect their customers to be discriminatory)
- Occupation Coworker Interaction—based on O*Net Scores
    - Rationale: employers may be discriminating on behalf of their employees (they expect their employees to be discriminatory)
- Hiring Manager Sex—based on name and title (e.g., Frau Leonie is a female)
    - Rationale: there is some evidence that females are less discriminatory
- Job Posting Wage
    - Rationale: higher-paying employers may attract a more competitive group of applicants, which increases their ability to discriminate. On the other hand, these employers may be fundamentally different than lower-paying employers, and may value diversity and equity.
- Job Posting Wage Range
    - Rationale: employers with wide wage ranges may be able to defer discrimination to the wage-setting stage and thus exhibit less discrimination in hiring (Eames, 2024)
- Years of Experience
    - Rationale: this can provide insight into statistical discrimination
- Disclosure Timing
    - Rationale: employers may not even open an applicant's documents if they disclose a name change in their introductory email

To consider mechanisms, I can leverage image-specific ratings from Survey Experiment Two. For example, I can:

1. Identify the impact of per-image attributes on employer response for cisgender applicants (i.e., for cisgender people, how much does being "approachable/warm" influence employer response rates)
2. Extrapolate this to transgender people—for example:
    a. Suppose a 10-point increase in "approachable/warm" improves employer response by 1 p.p.
    b. Suppose the transgender gap (difference in average "approachable/warm" rating per image) is 40 points
    c. Then, this mechanism is responsible for 1 p.p. X 4 = 4 p.p. of discrimination

Sample Size and Power Analysis

I plan to collect the following field experiment sample size. In total, I plan to send application pairs to 9,000 job postings (18,000 total applications distributed):

Table 7: Sample Size

Group	Headshot	Name Change	Disclosure Timing	Sample Size
Treatment 1	Pass Poorly	Disclosed (MtF)	Email	1,500
			Cover Letter	1,500
Treatment 2	Pass Well	Disclosed (MtF)	Email	1,500
			Cover Letter	1,500
Treatment 3	Pass Poorly	Not Disclosed	n/a	3,000
Control 1	Pass Well	Not Disclosed	n/a	3,000
Control 2	Pass Well	Disclosed (FtF)	Email	1,500
			Cover Letter	1,500

Consider proportion test $H_0: p_1 - p_2 = 0$, $H_1: p_1 - p_2 < 0$, where p_1 is positive employer response for the group 1, and p_2 is positive employer response for the group 2. Power to detect difference in group proportions are as follows:

Table 8: Power Calculations

Group 1	Group 2	P.P. Differences (G1 – G2)			
		3.5%	**3.0%**	**2.5%**	**2.0%**
Panel A: Group 1 has a positive employer response rate of 30%					
Pass: well (N=12,000)	Pass: poorly (N=6,000)	99.8%	98.7%	93.5%	79.0%
Mtf: disclosed (N=6,000)	MtF: not disclosed (N=12,000)	99.8%	98.7%	93.6%	79.2%
well / not disclosed (N=9,000)	poorly / not disclosed (N=3,000)	95.6%	87.8%	73.5%	53.9%
well / disclosed (N=3,000)	poorly / disclosed (N=3,000)	83.7%	72.1%	56.0%	38.9%
Panel B: Group 1 has a positive employer response rate of 20%					
Pass: well (N=12,000)	Pass: poorly (N=6,000)	100.0%	99.8%	98.0%	89.3%
Mtf: disclosed (N=6,000)	MtF: not disclosed (N=12,000)	100.0%	99.8%	98.1%	89.4%
well / not disclosed (N=9,000)	poorly / not disclosed (N=3,000)	99.0%	95.3%	85.1%	66.1%
well / disclosed (N=3,000)	poorly / disclosed (N=3,000)	93.6%	84.2%	68.8%	49.3%

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