

# Partisan Résumés: ESG Signaling over the Political Cycle\*

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## Abstract

We examine how political ideology shapes labor market signals. Using proprietary data on résumé edits, we identify additions and deletions of ESG-related language in descriptions of past roles. We find that these revisions are shaped by both workers' political ideology and the broader political environment. Democrat-leaning workers are more likely than Republican-leaning workers to add ESG language to their résumés, with this partisan divide widening during the Biden administration. Vague, unspecific additions appear most strategic, as they are disproportionately reversed following the start of Trump's second term. Exploiting the staggered adoption of ESG commitments by large corporations during the Biden presidency, we find that workers who view these firms as potential employers increase their use of ESG language relative to other workers. These revisions are associated with tangible career benefits, including greater job mobility and higher promotion rates. They also distort labor market matching by helping less qualified workers obtain positions, and potentially impose hiring costs on employers.

**Keywords:** ESG, Firm ESG Commitment, Labor Markets, Identity

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# 1. Introduction

Environmental, social, and governance (ESG) practices have become one of the most politically polarized issues in American life ([Gormley et al., 2024](#); [Bisetti et al., 2026](#)). Democrats and Republicans hold sharply divergent views regarding ESG initiatives and push for contrasting legislative agendas.<sup>1</sup> Attitudes toward ESG have also shifted with the political cycle, rising following President Biden’s 2020 election and receding around President Trump’s second term in 2024. Corporate behavior closely follows this pattern, as firms introduced commitments such as net-zero pledges and diversity initiatives, and later scaled them back.<sup>2</sup> These political shifts have important implications for labor markets, where workers face both changing signals regarding employers’ ESG preferences and fast-evolving social norms.

This paper examines how political ideology influences the way workers craft their résumés and how such decisions affect labor market outcomes. Illustrating the underlying behavior we study, [Figure 1](#) reveals a surge in the number of workers adding ESG-related language in job descriptions present in their online résumés around the November 2020 election of President Biden, and a spike in deletions around the November 2024 election of President Trump. Workers thus appear to revise their résumés along political cycles, adding and removing ESG signals based on what they perceive as desirable.

We construct a proprietary dataset that tracks the detailed edits individual workers make to describe their prior jobs. These revisions do not reflect contemporaneous changes in job responsibilities, and should instead reflect workers’ conscious decisions to restate past experiences, thus positioning themselves favorably in the labor market. We find that résumé revisions reflect political ideology: Democrat-leaning workers add ESG language while Republican-leaning workers refrain from doing so, and this partisan divergence widens around

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<sup>1</sup>In July 2023, the Republican-led House Financial Services Committee held seven ESG-related hearings in a single month, while Democratic members issued counter-reports defending ESG practices ([R Street Institute, 2025](#)). In 2024, Republican-controlled state legislatures passed 17 anti-ESG laws and Democratic-controlled legislatures passed eight pro-ESG laws ([Ballotpedia News, 2024](#)).

<sup>2</sup>See, for example, [Sardon \(2020\)](#), [Lublin \(2022\)](#), [Council \(2020\)](#), and [Time \(2025\)](#).

the 2020 Biden election, suggesting that political events polarize views around ESG issues. Political cycles also reach workers indirectly by reshaping corporate priorities: many firms adopted ESG commitments during the Biden administration. We show that workers who view those firms as prospective employers disproportionately add ESG language. Republican-leaning workers are especially likely to respond through vague or symbolic additions rather than specific descriptions of ESG-related job activities. Finally, ESG revisions carry real economic consequences, predicting greater job mobility and higher promotion rates. They also impose costs on firms by leading workers to obtain jobs for which they are less qualified.

Workers’ decisions to revise résumés can be understood through the lens of identity economics ([Akerlof and Kranton, 2000](#)). The intuition is straightforward: individuals derive utility not only from material payoffs but also from acting in ways consistent with the norms of their social group. Conforming to these prescriptions affirms identity and raises utility, while deviating imposes a psychological cost.<sup>3</sup> In this framework, a worker’s decision to revise a résumé reflects both the expected career return from appearing aligned with employer preferences and the utility of presenting oneself consistently with one’s own values. When a worker’s beliefs and career incentives conflict, as when a Republican-leaning worker faces career pressure to signal ESG commitment, expected material gains may compromise political identity. Strategic revisions are thus most concentrated where the career returns to signaling are high and the identity costs are low.

Our data come from Revelio, which maintains one of the most comprehensive collections of online résumés available. We obtain proprietary data that track different versions of individuals’ résumés over time and identifies all edits made to historical job descriptions over an eight-year period, from January 2018 through August 2025. These data allow us to observe not only the résumé content prospective employers see at any point in time, but also the sequence and timing of the edits workers make to earlier job entries. We focus

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<sup>3</sup>[Akerlof and Kranton \(2000\)](#) illustrate this framework with gender: social categories such as “man” and “woman” carry prescribed behaviors. Individuals who deviate from these prescriptions (e.g., a man entering a traditionally female occupation) suffer identity-related disutility, even if the material payoff is attractive.

on edits to *non-current* job descriptions, for which there is no contemporaneous change in responsibilities to report; such edits thus reflect workers’ reporting choices. Moreover, we separate *specific* and *unspecific* additions, with the latter indicating vague ESG references without concrete tasks, deliverables, or measurable outcomes. Because unspecific language is low-cost to insert and difficult for prospective employers to verify, it is the most plausibly strategic form of revision. We match workers from Revelio with U.S. voter data from L2 to identify individual-level political party affiliations. Our final sample is a panel of 2.9 million workers employed at U.S. public firms, followed annually from 2018 through 2025.

We first describe which workers are most likely to emphasize ESG language in their résumés, and find that women, underrepresented minorities, and more highly educated workers are more likely to include such language. These patterns are consistent with well-documented differences in support for ESG and DEI initiatives across demographic groups, and motivate our use of controls for gender, race, and education throughout the analyses.<sup>4</sup>

We next examine how workers’ political ideology shapes ESG disclosure. Because Democrats and Republicans hold sharply divergent views on the merits of ESG, this partisan divide extends to how workers present their own professional histories.<sup>5</sup> Our results show that Democrat-leaning workers are significantly more likely than Republican-leaning workers to add ESG language to historical job descriptions. The partisan gap amounts to 15% of the sample average and is robust to the inclusion of firm-MSA-occupation-year and gender-race-education-year fixed effects, which compare workers employed in the same establishment and occupation, and workers of the same demographic profile, in the same year. Because we restrict attention to revisions of non-current jobs, the gap cannot reflect partisan differences in current job tasks, but instead reflects deliberate disclosure choices.

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<sup>4</sup>For example, [Horowitz and Parker \(2023\)](#) finds that Black (88%), Hispanic (75%), and female (79%) workers are more likely than White (63%) and male (56%) workers to view DEI as important for businesses to promote.

<sup>5</sup>Survey evidence confirms that attitudes toward ESG and DEI are sharply divided along partisan lines. [Jones \(2023\)](#) finds that Republicans are far more likely than Democrats to view ESG negatively, and [Horowitz and Parker \(2023\)](#) reports that only 30% of Republican workers view workplace DEI efforts as a good thing, compared with 78% of Democrats.

Political ideology also shapes the way workers respond to the shifting political environment. ESG initiatives became substantially more salient under the Biden administration, and this shift in the prevailing social and corporate norm widened the divide between Democrat-leaning and Republican-leaning workers. Following the 2020 election, Democrat-leaning workers sharply increased their additions of ESG language, while Republican-leaning workers became less likely to do so. This partisan gap is around four times larger under the Biden administration than under Trump’s first term. Importantly, the divergence emerges precisely in 2020 with no pre-existing trend, supporting a political cycle interpretation. The composition of these revisions also differs by party: Democrats’ Biden-era increase is more pronounced in specific additions, while Republicans reduce specific and unspecific additions alike.

These partisan-cycle effects further differ across the components of ESG. Environmental and social initiatives differ markedly in occupational reach, with environmental language being most relevant for industries with tangible environmental footprints, and social language (e.g., DEI) being relevant across virtually all white-collar occupations. Separating the two, we find that the partisan-cycle effects are concentrated on the social dimension. The pattern is consistent with social and DEI language being more broadly valued across labor markets, and with the partisan polarization over ESG being concentrated on the social rather than the environmental margin.

We then examine whether workers reverse their earlier ESG additions once the political environment turns against ESG. If workers are simply updating their résumés to more accurately reflect prior job responsibilities, these additions should persist over time. By contrast, if ESG-related revisions are strategic responses to political incentives and norms, they should be removed once the tide shifts. The 2024 election of President Trump provides precisely such a setting, as firms began scaling back ESG and DEI initiatives and the Democratic party began shifting their policy priorities away from DEI.<sup>6</sup> We therefore examine whether workers who added ESG language during the Biden administration subsequently

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<sup>6</sup>See [Kopan \(2024\)](#), for a discussion documenting post-election backlash from Democratic moderates against the party’s progressive wing over social-issue positioning.

delete it after the political transition. Consistent with ESG descriptions being strategic responses to political environments, workers who added ESG language during the Biden years are significantly more likely to remove it following the 2024 election than workers who made comparable additions earlier in the sample period. Biden-era additions are 1.3–1.4 percentage points more likely to be removed than other additions, with the magnitudes being over twice the sample average deletion rate. Moreover, the reversals are concentrated entirely among unspecific additions: workers strip out the vague, symbolic ESG language they had inserted, while leaving more substantive additions in place.

To isolate the role of career incentives, we exploit variation in the timing of ESG commitments made by firms that are likely prospective employers for individual workers. Political cycles affect worker behavior in part because firms themselves adjust their priorities and objectives in line with the broader political environment. When major employers publicly commit to ESG, workers face stronger incentives to portray themselves as aligned with those priorities. We identify prospective employers as the top-five firms within a worker’s industry that recruit most heavily in the worker’s occupation, and we define a commitment event as the first year in which any of these firms publicly commits to ESG during an earnings conference call. Because the timing of such commitments is difficult for individual workers to anticipate, these events represent plausibly exogenous shocks to the labor market return to ESG signaling.

Using stacked difference-in-differences regressions around commitment events, we find that workers significantly increase ESG language in their résumés following these commitments, with no discernible pre-trend. The response appears across the political spectrum, but its form differs systematically by partisanship. Democrat-leaning workers add more substantive and specific ESG language, whereas Republican-leaning workers primarily add vague, symbolic references. The evidence therefore suggests that career incentives influence workers broadly, while political identity shapes the manner and intensity of their response.

We next examine whether these strategic revisions carry career benefits. If workers strategically revise their résumés to align with employer preferences, these revisions should predict favorable labor market outcomes. We first examine whether ESG revisions predict external job mobility. We document that workers who revise ESG language to historical job descriptions are significantly more likely to move to a new employer in the following year, compared with other workers who revise non-ESG content in their résumés. This contrast indicates that ESG signals are uniquely effective in conveying values and fit. Next, we show that ESG revisers are more likely to be promoted internally. This result is consistent with political ideology shaping promotion decisions (Colonnelli et al., 2025) and suggests that even though employers have detailed performance records, signaling conforming political identity helps advance workers’ careers. Notably, these gains are at least as large for unspecific additions as for substantive additions and are even larger in the case of internal promotions. If employers could reliably distinguish substantive from symbolic disclosures, more verifiable additions should command larger returns. The similar rewards we observe imply that employers pool the two, making even symbolic ESG revisions effective labor market signals.

We further examine whether these career gains reflect improved worker-job matching or whether ESG language helps workers obtain jobs for which they are less well suited. Following Coraggio et al. (2025), we construct a match quality score that measures a worker’s predicted fit with an occupation, estimated from a machine-learning model of pre-move worker characteristics trained on the hires of high-productivity firms. Among workers who move to new jobs, those who added ESG language enter positions with lower match quality, and this negative relation is concentrated among *unspecific* additions. We then ask whether ESG additions affect who obtains a job in the first place, comparing each hire with otherwise similar candidates for the same position. Match quality strongly predicts which candidate wins the job, but this relation is roughly 10% weaker for candidates who added ESG language. This substitution is concentrated in the Biden years, when employer demand for ESG was

highest. These results suggest that ESG résumé additions do not simply reveal job-relevant human capital; rather, they can substitute for measured worker-job fit.

Our study makes several contributions. First, our study relates to studies documenting the role of firms’ ESG disclosure on talent allocation and worker sorting (Colonnelli et al., 2025; Choi et al., 2023) as well as the research on how political ideology shapes labor market sorting (Ceccarelli et al., 2025; Fos et al., 2026). More broadly, we also complement prior work showing that job seekers respond to firm information, including financial performance and workplace transparency (e.g., deHaan et al., 2023; Dube and Zhu, 2021; Brown and Matsa, 2016) (see Barrios et al. (2026) for a review of this literature). We complement this literature by shifting attention to workers’ own disclosure choices, showing that individuals actively manage the presentation of their past experience to shape employers’ impressions and their career paths. By showing that ESG revisions weaken the link between worker-job suitability and hiring outcomes, we provide evidence that worker disclosure can distort, rather than merely facilitate, labor market matching.

Second, our study adds to recent work on the political cycle of ESG. Research documents that individuals’ willingness to act on climate and social issues depends on perceived social norms and public policy, and that this willingness shifts across political regimes (Andre et al., 2026; Dechezleprêtre et al., 2025; Ceccarelli et al., 2025). Consistent with this evidence, we show that workers’ willingness to disclose ESG-related experience moves systematically with the political cycle, tracking the perceived preferences of prospective employers.

Third, our study extends the literature showing that disclosure is a strategic choice by firms. Firms adjust the quality and timing of their disclosures in response to managerial incentives (Nagar et al., 2003; Rogers, 2008) and investor attention (Hirshleifer and Teoh, 2003; Segal and Segal, 2016), and strategically withhold information when disclosure invites competitive, public, or regulatory scrutiny (Botosan and Stanford, 2005; Bertomeu et al., 2020; Dyreng et al., 2020; Oh, 2026). Closest to our setting, executives use firm disclosures to manage their own media image (Blankespoor and deHaan, 2020). We extend this literature by shifting

the focus from firms to individual workers: résumé revisions are personal disclosure choices, made strategically in response to the political environment and labor market incentives.

Finally, we extend a growing literature on corporate ESG disclosure and “greenwashing” (see [Christensen et al. \(2021\)](#) for a review of this literature). Prior research shows that firms strategically relocate production, offshore pollution, choose supply chain partners, and divest assets in response to ESG-related pressures from investors, regulators, and the public ([Wu et al., 2020](#); [Ben-David et al., 2021](#); [Bartram et al., 2022](#); [Bisetti et al., 2026](#); [Giannetti et al., 2023](#); [Parise and Rubin, 2025](#); [Duchin et al., 2025](#); [Berg et al., 2026](#)). Relatedly, research in accounting finds that firms’ ESG disclosures also often diverge from their actual practices ([Basu et al., 2022](#); [Raghunandan and Rajgopal, 2022](#); [Baker et al., 2024](#)). We provide the first evidence that individual employees engage in an analogous behavior, “washing” their résumés to manage how prospective employers perceive them.

## 2. Data and Sample Construction

### 2.1. Data Sources

#### 2.1.1. Online Résumé Data

Our analysis utilizes proprietary résumé change data from Revelio Labs, which maintains one of the most comprehensive collections of online professional résumés. Unlike the standard Revelio dataset that provides only a static snapshot of a worker’s employment history at a given point in time, these data record the complete sequence of edits that individuals make to their résumés over time. This feature allows us to observe not only what prospective employers see on a worker’s résumé at any given point in time, but also when and how workers revise their professional narratives. Specifically, we observe each instance in which a worker adds to, deletes from, or otherwise modifies the text of a job description, together

with high-frequency timestamps of the edit. The sample period for observed edits spans January 2018 through August 2025.

We make two research design choices. First, we rely on job descriptions, rather than standardized employment features such as job titles or company names. We do so because job descriptions capture the subjective content of a résumé, namely how workers choose to frame their responsibilities and emphasize particular skills, making it well suited for assessing strategic behavior. Revisions to job descriptions can be made at relatively low cost and allow workers to subtly reshape how their experience is presented, whereas more extreme actions, such as deleting an entire past job or adding a fictitious position, are costly and could raise credibility concerns in the labor market.

Second, we focus on changes to *non-current*, or historical, roles, because edits to current positions may reflect genuine changes in responsibilities rather than pure disclosure choices. For example, a worker may introduce diversity language into an ongoing job in 2021 because the employer began requiring diversity-related tasks. In contrast, revisions to past job descriptions are unlikely to be driven by current job responsibilities or firm-imposed reporting requirements, but rather reflect disclosure choices. Focusing on edits to historical positions allows us to study how political ideology and labor market incentives shape workers’ professional narratives.

### **2.1.2. L2 Data**

Individuals’ political leanings are defined using data from L2, Inc., a non-partisan data provider that aggregates records from various sources, including local election boards, exit polling, and political donations. These data are commonly used in prior studies to identify individuals’ party affiliation and political ideology ([Engelberg et al., 2022](#); [Bernstein et al., 2022](#); [Spenkuch et al., 2023](#); [Fos et al., 2026](#)).

We link individuals from Revelio to those in L2 based on names and the MSA of their workplace. We use an iterative method to match the two databases, and we are able to

identify the political affiliation of approximately 37% of Revelio individuals. A detailed description of the matching procedure is provided in Appendix [IA.I](#).

### **2.1.3. Conference Call Data**

Some of our analyses rely on identifying public firms’ ESG commitments. We identify such commitments using textual analysis of quarterly earnings conference call transcripts obtained from Refinitiv Eikon. Earnings calls are well suited for this purpose for two reasons. First, they represent high-visibility settings in which senior management articulates strategic priorities, making them a natural venue for executives to signal that ESG has become part of the firm’s core narrative. Second, because earnings calls follow a standardized format and timing (e.g., after earnings announcements), they provide consistent measurement and precise timing of when firms’ ESG commitments are publicly articulated.

Earnings calls consist of a management presentation section and an unstructured Q&A session with analysts. To identify ESG commitments, we focus on the structured management presentation section of each earnings call transcript using a large language model (LLM)-based classification approach. Specifically, we prompt the model to identify whether management makes forward-looking commitments related to ESG or DEI, defined as statements signaling intent to act, improve, maintain, or prioritize ESG-related initiatives in the future. The LLM outputs indicator variables for ESG and DEI commitments at the earnings-call level. We classify a firm-year as making an ESG commitment if management makes at least one ESG- or DEI-related forward-looking commitment during any quarterly earnings call in that fiscal year. Appendix [IA.II](#) presents examples of such ESG commitments.

Figure [2](#) plots the number of firms making ESG commitments by quarter over our sample period. Two patterns stand out. First, the number of firms making first-time ESG commitments increases sharply before the Biden election in 2020, with the largest spike occurring in the third quarter of 2020 and elevated levels persisting through 2021. This surge mirrors the spike in workers highlighting ESG job histories in Figure [1](#), suggesting that both

workers and firms are motivated by political incentives to emphasize ESG during the Biden era. Second, the timing of firms’ ESG commitments does not fully coincide with the 2020 election, which allows us to use major employers’ ESG commitments as staggered shocks to workers’ career incentives across industry, occupation, and time.

## 2.2. Sample Construction

We assemble our sample in several steps. We begin with the universe of Revelio résumé edits and retain workers who revised at least one historical job description during the sample period and who were employed by a U.S. public firm, which we identify by matching the worker’s employer to a Compustat `gvkey`. For these workers, we build a worker-year panel spanning 2018 through 2025. A worker enters the panel in a given year if she holds a position at some point during that year. The active position at year-end determines the worker’s employer, occupation (ONET), industry (3-digit NAICS), state, and metropolitan area. The resulting panel contains 16,662,533 worker-year observations covering 2,943,935 workers employed at 16,753 public firms. We obtain political affiliation data from L2 for 37.4% of worker-year observations, and worker gender, race, and education from Revelio’s demographic predictions.

We identify ESG- and DEI-related language in résumé edits using a procedure that combines a keyword dictionary with large language model (LLM) classification. We first construct a dictionary of ESG- and DEI-related terms, augmenting a conventional bag-of-words list with additional keywords surfaced by an LLM and pruning terms too common to be informative. We then use an LLM to classify each edit according to whether it references environmental topics, such as sustainability and emissions, or social and diversity topics, such as diversity, equity, and inclusion. Appendix [IA.III](#) describes this procedure in detail. We restrict attention to edits of *non-current* job descriptions. Because the Revelio edit data files are sporadic, capturing a worker only when she updates her profile, we convert them into an annual panel.

Using the revision data, we construct several variables of interest. *Add ESG* equals one in a worker-year if the worker adds ESG or DEI language to a historical job description, and *Drop ESG* equals one if the worker removes such language. *Have ESG* is the corresponding stock variable and takes a value of one once a worker’s résumé contains ESG or DEI language in a historical job entry and remains one until an offsetting deletion is observed. For example, a worker whose historical job descriptions contain no ESG language in 2018 but who adds such language during an update in June 2021 has *Have ESG* equal to zero for 2018 through 2020 and one from 2021 onward, unless a later deletion is recorded. Panels A through D of Appendix [IA.IV](#) provide illustrative examples.

Some additions of ESG language reflect genuine past work rather than strategic padding. To isolate the additions that are most plausibly strategic, we classify each ESG or DEI addition as *specific* or *unspecific* using two independent methods. The first uses a large language model to score the added text on four dimensions, each on a one-to-five scale: *quantitative specificity* (whether the text contains concrete numbers, amounts, or measurable outcomes), *contextual integration* (whether the addition extends the worker’s described role or appears bolted on), *concreteness of action* (whether it describes a specific, bounded activity rather than a vague orientation), and *named-entity density* (whether it references specific programs, regulations, organizations, tools, or places). We classify an addition as unspecific if the four scores sum to less than 12 of a possible 20. Appendix [IA.V](#) presents illustrative examples of the LLM-based specific and unspecific revisions.

The second method uses spaCy’s EntityRecognizer Python package to apply named-entity recognition to the added text, counting named entities across eighteen categories, including quantities, dates, organizations, locations, laws, products, and demographic groups, and classifies an addition as unspecific if it contains no named entities of any kind. The two methods are distinct. The first relies on a holistic judgment, whereas the second utilizes a mechanical count. We aggregate each method to the worker-year level and create two variables. *Add Unspecific ESG* equals one if any ESG or DEI addition the worker makes in

the year is classified as *unspecific*, and *Add Specific ESG* equals one if the worker makes an addition that is not. Appendix [IA.VI](#) presents illustrative examples of spaCy-based specific and unspecific revisions.

Our final analyses examine whether ESG résumé revisions are associated with favorable career outcomes. We focus on two forms of career advancement observable in the Revelio position files. The first is movement to a new employer. The second is advancement within the current employer. Internal promotions reflect favorable evaluations by the firm and capture career progression that does not require changing employers. In our framework, such promotions may arise because firms value employees who publicly signal commitment to ESG, or because ESG additions attract outside offers that the current employer then matches.

To construct these measures, we order each worker’s positions chronologically and classify each job transition as *internal* if the origin and destination employers share an ultimate corporate parent, and *external* otherwise. *External Mobility* equals one if the worker makes an external transition in the following year, and *Internal Promotion* equals one if the worker advances within the same employer in the following year. Together, these measures capture two distinct channels through which workers may benefit from strategically revising their résumés: obtaining opportunities at other firms and advancing within their current organization. Both indicators are multiplied by 100, so that regression coefficients reflect percentage-point changes in the likelihood of each outcome.

Table [1](#) reports summary statistics for the main variables, for the full worker-year panel (Panel A) and for the subsample of worker-years with a résumé revision (Panel B). On average, 5.2% of worker-years display ESG language in a historical job description, 1.3% add such language during the year, and 0.6% delete it; roughly one-third of additions are unspecific under either classification. Among L2-matched worker-years, 41.8% are Democrat-leaning and 25.3% Republican-leaning. In the revising-year sample, 9% of worker-years are followed by an external move and 2.2% by an internal promotion.

### 3. Initial Descriptive Patterns

We begin by characterizing how ESG-related disclosure on résumés varies across worker types. Figure 3 presents, for groups defined by educational attainment, race and gender, and years of work experience, the unconditional likelihood (in percent) that a worker’s résumé exhibits each of two behaviors: containing any ESG description in at least one historical job entry, and adding ESG language to a historical job description in the year.

Panels A and B of Figure 3 show that ESG content rises with workers’ educational attainment, in line with experimental evidence that more-educated workers display the strongest stated preferences for employer ESG practices (Colonnelli et al., 2025). Panel A reports that workers with doctoral degrees are roughly 70% more likely than high school graduates to include ESG content on their résumés. Similarly, Panel B shows the same gradient for active additions, with doctoral-degree workers approximately 45% more likely than high school graduates to add ESG language.

Panels C and D show that ESG content also varies systematically by race and gender, with the gradient running from non-URM male workers (lowest) to URM female workers (highest) in both the stock and the flow of ESG content. The pattern is consistent with demographic alignment with ESG and DEI principles raising both the willingness and the perceived returns to ESG-related signaling (Horowitz and Parker, 2023). Demographic groups whose identities are most closely aligned with the substantive content of ESG and DEI initiatives stand to gain more from being seen as aligned, which can sustain higher disclosure rates.

Panels E and F show that ESG résumé content is concentrated among relatively early-career workers. In Panel E, the stock of ESG content is low for workers with zero to four years of experience, rises for workers with five to fourteen years of experience, and then declines steadily among more experienced workers. The low level in the first bin is partly mechanical as workers at the very beginning of their careers have fewer historical job descriptions in which ESG language could appear. Conditional on having accumulated enough prior work

experience to revise, however, the pattern is broadly declining with experience. Panel F shows this more directly. Active additions of ESG language are highest among workers with the least experience and decline almost monotonically across experience bins. Taken together, the two panels suggest that the active inclusion of ESG résumé content is concentrated among workers closer to the beginning of their careers, where career benefits associated with signaling alignment with employer preferences are likely strongest.

Overall, ESG-related résumé content is most prevalent among demographic groups and career stages that prior research associates with stronger support for ESG and DEI initiatives. Our subsequent analyses consider how political affiliation influences ESG disclosure.

## 4. Political Affiliation and ESG Descriptions in Résumés

The conceptual framework discussed earlier suggests that workers’ résumé disclosures are shaped by two forces: their personal beliefs about ESG and the career incentives created by employers’ demand for ESG-related attributes. We begin by examining the role of beliefs. Because attitudes toward ESG are sharply polarized along partisan lines, political affiliation provides a natural proxy for workers’ underlying views on ESG and DEI initiatives. Workers’ political affiliations are obtained from L2 voter records and matched to Revelio (Section 2 provides matching details). We focus on indicators for Democrat-leaning and Republican-leaning workers, with workers with other political affiliations and non-partisan workers as the omitted category.

Table 2 reports OLS regressions of ESG-disclosure outcomes on these indicators, with progressively more demanding fixed-effects structures across columns. Column (1) includes only year fixed effects; column (2) replaces them with firm-MSA-occupation-year fixed effects, comparing workers employed in the same establishment and occupation in a given year; column (3) instead uses gender-race-education-year fixed effects, comparing workers with similar demographic characteristics in the same year; and column (4) includes both sets of fixed effects.

The results show that political affiliation is a powerful determinant of ESG résumé content, with effects that survive our most demanding controls for labor market and demographic conditions. Panel A reports that, in the most saturated specification, Democrat- (Republican) leaning workers are 0.42 (0.32) percentage points more (less) likely than unaffiliated workers to display ESG content on their résumés. The implied Democrat-Republican gap of roughly 0.74 percentage points is economically meaningful given an unconditional ESG-prevalence rate of about 5%, implying that Democrat-leaning workers are roughly 15% more likely than Republican-leaning workers to display ESG content within otherwise comparable cells. The effects are highly statistically significant across all four specifications.

Panel B shows the same partisan gap in ESG addition choices. Democrat-leaning workers are roughly 0.10 percentage points more likely to add ESG language to a historical job description in a given year than other workers, while Republican-leaning workers are 0.13 percentage points less likely. Because we restrict attention to revisions of non-current job entries, this partisan gap cannot reflect concurrent changes in job responsibilities, but instead reflects deliberate disclosure choices made by workers in otherwise comparable establishment-occupation and demographic cells.

Do Democrats and Republicans differ in the types of ESG language they add? To examine this question, we classify ESG additions as either *Specific* or *Unspecific* using the two approaches described in Section 2: an LLM-based and a NER-based classification. We regress each type of addition on workers’ political affiliation. Panel A of Table IA.1 reports the results. The partisan divide is evident for both types of addition. Its composition, however, differs by party: Democrats’ higher addition rates are concentrated in specific additions, while Republicans retreat slightly more from unspecific additions. Overall, the results provide little evidence that political differences in ESG disclosure are concentrated exclusively in either substantive or symbolic revisions. Instead, workers’ political beliefs appear to influence the broader decision to emphasize ESG-related experience on their résumés.

## 5. Political Cycles and ESG Disclosure

The results above show that workers’ political affiliations are strongly associated with their ESG-related résumé disclosures. If these differences reflect underlying beliefs about ESG, they should become more pronounced when ESG and DEI issues become more politically polarized. The transition from the first Trump administration to the Biden administration provides a useful setting to examine this prediction. ESG and DEI initiatives moved to the forefront of public debate during the Biden years, increasing both their visibility and political relevance. As a result, Democrat-leaning workers may become more willing to emphasize ESG-related experience, while Republican-leaning workers may become less willing to do so. Importantly, this prediction concerns changes in the partisan gap itself. A shock that merely increased the labor market return to ESG signaling would be expected to affect workers across the political spectrum. By contrast, a widening divergence between Democrat-leaning and Republican-leaning workers is more consistent with workers’ underlying beliefs playing an important role in shaping ESG disclosure choices.

Table 3 examines this by interacting the Democratic and Republican indicators with *Biden*, an indicator equal to one for years during the Biden administration. The fixed-effects structure varies by panel by design. Panel A includes worker fixed effects because the dependent variable *Have ESG* is a stock that would otherwise be dominated by cross-sectional differences across workers. The partisan main effects are correspondingly absorbed and the table reports only the cycle interactions. Panel B omits worker fixed effects because its dependent variables are flows (additions in year  $t$ ).

The results show that political cycles strongly modulate the partisan gradient in ESG résumé content. Panel A reports that, in the most saturated specification, Democrat-leaning workers become 0.19 percentage points more likely to display ESG content under the Biden presidency, while Republican-leaning workers become 0.10 percentage points less likely to do so.

Panel B shows that political cycles amplify the partisan gap in ESG additions to a similar degree as the changes in *Have ESG*. Column (4) suggests that Democrat-leaning workers add ESG language at a baseline rate 0.026 percentage points above unaffiliated workers, but this gap rises to 0.134 percentage points under the Biden administration. Republican-leaning workers are 0.056 percentage points less likely to add at baseline. Under the Biden administration, the gap widens to 0.167 percentage points. The partisan add-rate gap is therefore roughly four times larger under a Democratic president than under a Republican one.

Panel B of Table [IA.1](#) reports the analogous cycle estimates for specific and unspecific ESG additions. The cycle-driven increase in Democrats’ addition of ESG contents in their résumés is again more pronounced for specific additions rather than unspecific additions. In contrast, Republicans are similarly less likely to add both specific and unspecific ESG descriptions. Together with Table [3](#), the results suggest that Democratic workers expand their disclosure primarily along the substantive margin while Republican workers retreat across both margins. This pattern is consistent with the identity-cost interpretation: for Republican-leaning workers, the diffuse career incentives of a pro-ESG political cycle are not sufficient to overcome identity costs, even at the low-cost unspecific margin.

Figure [4](#) reports the corresponding dynamic estimates around the 2020 election. Each panel plots year-by-year coefficients on *Democratic* and *Republican* indicators relative to 2019, holding fixed-effect-defined cells constant. The four panels reveal two patterns. First, in 2018 and 2019, Democrat-leaning and Republican-leaning workers exhibit similar disclosure behavior, lending support to a parallel-trends interpretation of the static interaction estimates in Table [3](#). Second, the partisan divergence emerges sharply in 2020 and persists through 2022, with Democrat-leaning workers’ disclosure rising by roughly 0.4 percentage points relative to 2019 and Republican-leaning workers’ disclosure declining.

## 6. Separating Environmental and Social ESG Language

The political cycle effects documented in Section 5 may differ across the environmental and social components, as they differ markedly in relevance across occupations: environmental language covers topics such as emissions and sustainability and is most directly relevant for workers in industries with tangible environmental footprints, while social and DEI language is relevant across virtually all white-collar occupations. Table 4 re-estimates the most saturated political cycle specification from Table 3 separately for Environmental (E) and Social (S) ESG language. Panel A reports *Have E* and *Have S* with worker fixed effects (the dependent variable is a stock). Panel B reports *Add E* and *Add S* without worker fixed effects (the dependent variable is a flow).

The results reveal that the partisan-cycle effects from Table 3 are concentrated on the social rather than the environmental dimension. In Panel A, the Democratic and Republican cycle interactions for *Have S* are 0.122 and -0.116, respectively, both statistically significant. For *Have E*, the Democratic interaction (0.108) remains highly significant but the Republican interaction (0.033) is statistically indistinguishable from zero. The asymmetry persists for active additions in Panel B. Democrat-leaning workers add Social ESG language at roughly twice the rate at which they add Environmental language under Democratic administrations (0.085 vs. 0.041 percentage points), and Republican workers retreat from Social additions almost twice as sharply as from Environmental ones (-0.072 vs. -0.040). The pattern is consistent with Social and DEI language being more broadly valued across employers and labor markets than Environmental language, and with the partisan polarization over ESG being concentrated on the social rather than environmental margin.

## 7. Strategic ESG Deletion

The analyses thus far show that workers add ESG language to their résumés when their beliefs and career incentives push in that direction. A direct test of whether these additions are strategic, rather than genuine updates to the record of past work, is whether they are reversed once the forces that motivated them weaken. An accurate description of a worker’s past responsibilities does not become inaccurate when the political environment shifts, so the removal of historical ESG content is most plausibly strategic. The 2024 election of President Trump provides a suitable setting to test this motive, as it sharply reduced the perceived labor market value of ESG signaling. Consistent with revisions being strategic, Figure 1 shows a sizable rise in ESG deletions. We now provide a formal test of this pattern.

Table 5 reports OLS regressions of *Drop ESG*, an indicator for whether a worker removes ESG language from a historical job description during the second Trump administration, on indicators for when the worker’s earlier ESG additions were made. The sample is restricted to workers who added ESG language during either the first Trump administration or the Biden administration. Panel A shows that deletions are concentrated among Biden-era additions. In other words, the additions made when employer demand for ESG was elevated are precisely the additions most likely to be unwound once that demand recedes. Workers who added ESG language under the Biden administration are 1.34 to 1.39 percentage points more likely to delete it than workers who added comparable language under the first Trump administration. These are large magnitudes compared to the average deletion rate of 0.58 percentage points throughout our sample or 2.9 percentage points during the second Trump term.

Panels B and C split prior additions by specificity, using the LLM-based measure and the NER-based measure, respectively; in both panels, the omitted category is workers who made specific additions during the first Trump administration. The reversal is driven entirely by *unspecific* additions made during the Biden years. Workers who added unspecific ESG language under the Biden administration are 1.48 to 1.54 percentage points more likely to

delete it under the LLM measure, and 1.24 to 1.36 percentage points more likely under the NER measure, with all estimates significant at the 1% level. Unspecific additions made during the first Trump administration, by contrast, are not reversed, and specific additions made during the Biden administration are not reversed either. In both cases the coefficients are statistically insignificant at conventional levels and, if anything, negative.

The pattern is consistent with a strategic interpretation of these revisions. Unspecific ESG additions are vague, difficult to verify, and relatively inexpensive for workers to both add and remove. As a result, they are well suited to temporary signaling and can be readily discarded when the political and labor market environment becomes less favorable to ESG. By contrast, specific additions describe concrete tasks and accomplishments and are therefore more plausibly rooted in genuine experience. Consistent with this distinction, the post-2024 reversals are concentrated among unspecific additions made during the Biden administration, precisely when incentives to signal ESG alignment were strongest.

## **8. Major Employer ESG Commitments**

The evidence thus far highlights a direct channel through which political forces shape résumé disclosures: workers' own beliefs about ESG. Political cycles may also influence workers indirectly through firms. During the Biden administration, many firms adopted ESG commitments and increased their emphasis on ESG-related initiatives. These actions can alter labor market incentives by signaling that ESG-related skills, experiences, and values are likely to be rewarded. Consequently, even workers whose personal beliefs remain unchanged may have incentives to modify their résumés to better align with the perceived preferences of prospective employers.

## 8.1. Empirical Design and Baseline Results

To explore this indirect channel, we exploit variation in the timing of ESG commitments by major prospective employers. For each industry-occupation cell (3-digit NAICS  $\times$  ONET2), we identify the top-five firms recruiting most heavily for the occupation and define a commitment event as the first year in which any of these prospective employers publicly commits to ESG in its earnings conference calls. Treated industry-occupations are those that experience such a commitment event during our sample period, while controls are matched industry-occupations whose top-five prospective employers never make an ESG commitment, selected based on pre-event prevalence of ESG language. We exclude workers employed at the firms initiating the ESG commitment, as well as workers employed at firms that had already adopted ESG commitments in the pre-period. The unit of observation in the resulting stacked sample is a match cohort-industry-occupation-worker-year. Figure 5 plots the number of industry-occupations experiencing a commitment event by year.

Table 6 reports stacked difference-in-differences estimates of workers’ ESG addition activities when prospective employers publicly commit to ESG. The coefficient on *Treated*  $\times$  *Post* captures the differential change in ESG disclosure for workers in treated industry-occupations relative to matched controls following a commitment. In the most saturated specification, which includes cohort-worker, cohort-industry-year, and cohort-gender-race-education-year fixed effects (column 4), workers exposed to a commitment are 0.51 percentage points more likely to display ESG content on their résumés. The estimate is statistically significant at the 1% level and robust across alternative specifications, suggesting that workers actively adjust their disclosures when prospective employers signal greater emphasis on ESG-related attributes.

Figures 6 and 7 plot the corresponding dynamic event-study estimates. Figure 6 reports *Have ESG*; Figure 7 reports *Add ESG* together with the LLM-based and NER-based measures of *Add Unspecific ESG* across its three panels. Workers in treated and control industry-

occupations move in parallel during the three years preceding a commitment, lending support to the parallel-trends assumption across outcomes. The treated coefficient for *Have ESG* rises sharply at the commitment year and remains elevated thereafter, indicating that workers actively reshape their résumés in response to perceived shifts in employer demand for ESG content. *Add ESG* and the two unspecific-additions measures exhibit sharp increases in the commitment year and the subsequent year, consistent with workers updating their résumés as employer demand shifts.

Taken together, the evidence suggests that workers respond not only to their own beliefs about ESG, but also to changes in the priorities of prospective employers. As firms publicly embrace ESG, workers increase the prominence of ESG-related experience on their résumés, consistent with career incentives operating as an indirect channel through which political and corporate priorities influence worker behavior.

## 8.2. Commitment Effects by Worker Political Affiliation

The estimates thus far pool workers across the political spectrum. We next examine whether workers with different political beliefs respond differently to ESG commitments by prospective employers. While such commitments alter labor market incentives for all workers, political beliefs may nonetheless shape the *form* the response takes. Table 7 therefore re-estimates the stacked difference-in-differences design of Table 6 separately for Democrat-leaning and Republican-leaning workers and separately for specific and unspecific ESG additions. Panel A uses the LLM-based specificity measure, while Panel B uses the NER-based measure.

The results show that both groups' revision behaviors respond to labor market incentives, but at different margins. Democrat-leaning workers increase *specific* ESG additions following a commitment event, by 0.144 percentage points under the LLM measure and 0.148 percentage points under the NER measure, both significant at the 10% level, with no significant change in unspecific additions. Republican-leaning workers display the mirror-image pattern: they increase *unspecific* ESG additions, by 0.123 percentage points under the LLM measure

and 0.149 percentage points under the NER measure, significant at the 10% and 1% levels respectively, while their specific additions do not change and carry a negative point estimate.

The contrast is consistent with the career-incentive force being felt broadly while a worker's beliefs govern how it is acted upon. A prospective employer's ESG commitment raises the labor market return to displaying ESG content for every worker in its hiring pool, and both Democrat-leaning and Republican-leaning workers respond. Democrat-leaning workers, for whom ESG signaling is consistent with their own beliefs, invest in substantive additions that describe concrete tasks and outcomes. Republican-leaning workers, who bear an identity cost from ESG signaling, do the minimum required to capture the career return, adding vague, low-commitment language rather than substantively rewriting their professional histories. Labor market incentives thus elicit a response regardless of political ideology, but identity determines whether that response is substantive or merely symbolic.

## 9. Career Consequences of ESG Résumé Additions

Our results so far show that workers strategically revise their résumés in response to both political ideology and changes in prospective employers' ESG priorities. A natural question is whether these revisions are consequential. If workers engage in such activity because it improves their labor market prospects, then ESG additions should be associated with favorable subsequent career outcomes. Conversely, if ESG revisions are simply made without career considerations, we should observe little to no career benefits. Moreover, we differentiate the effects of specific and unspecific ESG revisions. The differential effects between the two types of revisions indicate whether employers can readily distinguish between substantive ESG experience and symbolic ESG signaling, and whether they genuinely care about ESG-related human capital.

## 9.1. External Mobility and Internal Promotion

To examine these questions, we focus on ESG additions rather than the stock measure *Have ESG*. Our objective is to assess whether changes in résumé content are associated with subsequent changes in workers’ careers. The additions measures capture the active decision to revise a résumé in a given year and can therefore be linked directly to labor market outcomes in the following year. By contrast, *Have ESG* reflects the cumulative stock of ESG language on a worker’s résumé and may capture additions made many years earlier, making it less informative about the consequences of a particular disclosure decision in a given year.

We examine two dimensions of career advancement. The first is *External Mobility*, which captures transitions to a new employer in the following year. Because workers generally change employers to pursue improved opportunities, external mobility provides a measure of success in the outside labor market. The second is *Internal Promotion*, which captures advancement within the worker’s current employer and reflects favorable evaluations by the firm. These outcomes allow us to assess whether ESG-related résumé revisions are associated with advancement both across firms and within firms. In this analysis, we examine only worker-years where a worker is making a change in their résumé. This helps us compare among workers that are actively revising their professional narratives, likely in the hope of obtaining a new position. The comparison is thus between workers that changed ESG language and workers that changed other aspects of their résumé.

Table 8 reports the results for *External Mobility*. Columns (1) and (2) provide results for all ESG revisions, and columns (3) through (6) provide results for unspecific and specific ESG additions separately. For each type of revision we study, we first include firm-MSA-occupation-year fixed effects and then add gender-race-education-year fixed effects. Across all specifications, we find that ESG revisions are associated with significant higher external job mobility. Estimates from columns (1) and (2) suggest that workers that revise ESG in their historical profiles have around 2.6 percentage points greater likelihood of obtaining a

new job, compared to workers that revise other aspects of their résumés. This differential amounts to around 29% of the average external job mobility in our sample. When examining specific and unspecific ESG additions, we find that both types of ESG additions are associated with favorable subsequent career outcomes. Workers who add unspecific ESG language are approximately 3 percentage points more likely to move to a new employer in the following year, with estimates that are highly similar to those for specific additions and consistent across the LLM and NER classifications.

Table 9 presents results for *Internal Promotion* in a parallel format. Again, we find that ESG revisions are associated with significantly stronger career benefits. Compared to workers revising other aspects of their résumés, workers that make ESG revisions are 0.18–0.22 percentage points more likely to receive an internal promotion. Relative to the sample average of internal promotion rates observed in online profiles, this magnitude counts for around 8.2%. Again, we find both specific and unspecific ESG additions predict a greater likelihood of internal promotion, but the estimated effects of unspecific additions are consistently larger than those of specific additions. Promotions may also reflect current employers matching outside offers that ESG additions attract, linking the internal and external margins.

Taken together, these findings suggest that workers who add ESG language to their résumés subsequently experience favorable career outcomes. These findings are consistent with ESG revisions conveying information that is valued in the labor market. Moreover, the estimated associations are similar across specific and unspecific additions, suggesting that broad ESG language may be nearly as effective as more detailed ESG disclosures in shaping subsequent career outcomes. These findings provide a potential explanation for why workers strategically revise their professional narratives in response to changing employer demand for ESG-related attributes.

## 9.2. ESG Résumé Additions and Worker-Job Match Quality

The preceding results show that workers who add ESG language to their résumés experience more favorable career outcomes, including higher rates of external mobility and internal promotion. These gains are consistent with ESG-related language helping workers attract employers’ attention or satisfy perceived employer demand for ESG-aligned experience. A remaining question is whether these gains reflect better worker-job matches, or whether ESG signaling partly substitutes for underlying suitability. If employers reward ESG language without fully distinguishing whether it reflects substantive relevant experience, workers who add ESG language may be able to obtain jobs for which they appear poorly suited on observable dimensions. To examine this possibility, we measure worker-job match quality following the job assignment quality (JAQ) approach of [Coraggio et al. \(2025\)](#). We then ask whether higher match quality predicts job attainment, and how ESG signals change that relation.

For each worker-job pair, we extract workers’ characteristics and the occupation of the job. Worker characteristics include education, field of study, labor market experience, prior tenure, prior employers, prior occupations, prior industries, prior occupation, prior location, cumulative unemployment gaps, and demographic characteristics. These characteristics are measured before a job change. The above information is used to predict a worker’s suitability to an occupation. The prediction relies on a machine-learning approach, trained through high-productivity firms and their workers, based on the assumption that highly productive firms are more likely to hire well-matched workers. High-productivity firms are those in the top decile of sales per employee within fiscal year, 3-digit NAICS industry, and asset-size tercile cells, using lagged Compustat data. We exclude workers in the training sample from the regression analysis.

We begin with a simple mover-level test. The sample includes all worker-years where we observe a job change across firms. Within these movers, we regress match quality between the

worker and the destination job on an indicator for whether the worker added ESG language before the move, controlling for the same fixed effects used in Table 8. Panel A of Table 10 reports the results. Across specifications, workers with ESG additions have lower measured match quality for the destination jobs. Our estimates suggest that, conditional on detailed job and demographic cells, ESG adders have about 0.6–0.9 percentage points lower match quality than otherwise similar movers, which accounts for 2–3% of the average match quality score. The sign is consistent with the substitution hypothesis: ESG additions are associated with entering jobs for which the worker appears less suitable on pre-move observables.

Panel B separates unspecific from specific ESG additions. The negative relation is concentrated among unspecific ESG additions. Using the LLM-based specificity measure, the coefficient on *Add Unspecific ESG* is -0.016 in the most saturated specification, while the coefficient on *Add Specific ESG* is close to zero and statistically insignificant. Using the NER-based specificity measure, the coefficient on *Add Unspecific ESG* is also negative and statistically significant, whereas the coefficient on *Add Specific ESG* is smaller in magnitude. This pattern aligns with the broader interpretation of unspecific ESG language as the most strategic and least verifiable form of signaling. If ESG language were merely revealing genuine, job-relevant skills, we would not expect the negative association with match quality to be more pronounced among unspecific additions.

The mover-level test provides an ex post comparison of worker quality. We next design a test to compare the quality of hired workers among other potential candidates for the same job. We construct a pseudo-peer choice set for each filled vacancy. A focal vacancy is an observed external move into a public firm. The actual worker who fills the vacancy is coded as *Match* equal to one. We then randomly select five pseudo-peers from other workers making external moves in the same year. This criterion guarantees that we are selecting workers who are searching for jobs, rather than ones without any intention to move. When selecting peers, we draw from workers currently in the the same 3-digit NAICS industry and MSA and employed in firms within the same asset-size tercile as the focal mover. If there are insufficient

candidates, we progressively relax the criteria to broader origin-industry and location cells. This procedure creates a candidate-choice panel in which each vacancy contains the actual hire and five observationally similar alternative candidates.

For every candidate in the choice set, we compute their match quality for the focal job. Thus, for pseudo-peers, the suitability score is not their suitability for the job they actually took, but their predicted probability of fitting the focal vacancy. We then link each candidate’s decisions to revise ESG languages prior to the movement year to the likelihood of obtaining the focal job. Peers who do not appear in the worker-year revision panel are coded as having no ESG revision. This design thus asks whether actual hires are more suitable than pseudo-peers, and whether ESG additions weaken the relation between suitability and the likelihood of winning the job.

Panel C reports the estimates. The dependent variable is *Match*, equal to one for the actual hire and zero for pseudo-peers. The coefficient on *Match Quality* is positive and statistically significant across specifications, confirming that the measure captures meaningful worker-job fit: candidates with higher match quality are more likely to be the actual worker hired into the focal job. The coefficient on *Add ESG* is also positive, indicating that candidates with ESG additions are more likely to be the actual hire, holding suitability fixed. Most important, the interaction between *Match Quality* and *Add ESG* is negative in all specifications. In the specification with firm-MSA-occupation-year and gender-race-education-year fixed effects, the interaction coefficient is -0.077. The magnitudes are economically meaningful. In the full fixed-effect specification, the estimated effect of match quality on the likelihood of being hired is 0.75 for candidates without ESG additions but 0.67 ( $= 0.750 - 0.077$ ) for candidates with them. This implies that ESG additions reduce the strength of the relation between measured suitability and being hired by about 10%, suggesting that ESG signaling helps less qualified workers obtain a job.

Finally, Panel D examines whether the substitution pattern differs across political regimes. We interact match quality, ESG additions, and their interaction with an indicator for

Democratic-president years. The coefficient on *Match Quality*  $\times$  *Add ESG* captures the substitution effect during Republican-president (Trump) years, while the triple interaction captures the incremental effect during Democratic-president (Biden) years. The triple interaction is negative and statistically significant across all four specifications. In the full fixed-effect specification, the triple interaction is -0.062. This result indicates that ESG additions weaken the match quality-hiring relation more during the Biden period, when ESG and DEI issues were more salient and when employers were more likely to value ESG alignment. The result is consistent with our earlier evidence that political cycles shape both workers’ incentives to add ESG language and the labor market value of doing so.

Overall, the evidence suggests that ESG résumé additions do more than predict mobility and promotion. They appear to alter the mapping between measured worker-job fit and hiring outcomes. Workers with ESG additions are more likely to win jobs, but suitability matters less for these workers than for otherwise similar candidates. This pattern is difficult to reconcile with a pure human-capital interpretation in which ESG language simply reveals job relevant experience. Instead, it is consistent with ESG language operating as a labor market signal that can substitute, at least partly, for measured match quality.

## 10. Conclusion

This study provides evidence that workers actively manage how their professional histories are presented in response to shifting political conditions. Using proprietary data that track the complete sequence of edits individuals make to their historical job descriptions, we document widespread additions and deletions of ESG- and DEI-related language and show that these revisions respond to two forces: the worker’s own beliefs about ESG, and the career incentives that arise when firms, responding to the same political environment, embrace ESG. ESG language additions surge following the 2020 Biden election and reverse course following

Trump’s 2024 election, and the reversals are concentrated among unspecific additions, where a strategic interpretation is most plausible.

Our results underscore that ESG revisions are not merely cosmetic. Strategic revisions are associated with meaningful labor market consequences, including higher rates of employer transitions and internal promotion. Unspecific, low-cost additions are rewarded at least as much as substantive ones, which helps explain why résumé revision is a rational response to shifting employer demand. The behavior intensifies precisely when ESG alignment is most valued, surging during the Biden administration and following ESG commitments by prospective employers, consistent with workers tailoring disclosures to anticipated employer preferences. At the same time, workers’ beliefs act as a countervailing force: Republican-leaning workers are significantly less likely to add ESG language, refrain from both specific and unspecific additions when the political cycle turns pro-ESG, and respond to direct career incentives from employer commitments only through low-cost, unspecific language. Decomposing ESG language into its environmental and social components further reveals that these patterns are concentrated on the social dimension, consistent with social and DEI initiatives being more broadly valued across occupations and industries than environmental language.

By shifting the unit of analysis from firms to individuals, our findings extend a large literature on strategic disclosure and washing in corporate settings to the labor market. Prior work shows that firms selectively emphasize socially desirable activities in response to investor and regulatory pressure. We show that workers engage in similar behavior, strategically revising their professional narratives to signal alignment with prevailing employer norms. In doing so, workers respond not only to firm-level demand for ESG commitment, but to the broader political and social environment that shapes how such alignment is valued.

More broadly, our results highlight an underexplored margin of labor market behavior. Résumés are often treated as static records of past experience, yet our evidence shows that workers continuously revise these records in ways that respond to changing economic and

political conditions. As political and social attitudes toward ESG continue to evolve, and as new dimensions of employer demand emerge, so too will workers' incentives to reshape their professional narratives, with implications for the signals that employers observe and the efficiency of worker-firm matching more broadly.

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Figure 1: **Number of Workers with Résumé Revisions**

This figure plots the number of workers adding and dropping ESG language in historical job descriptions in their résumés each month in our sample period.

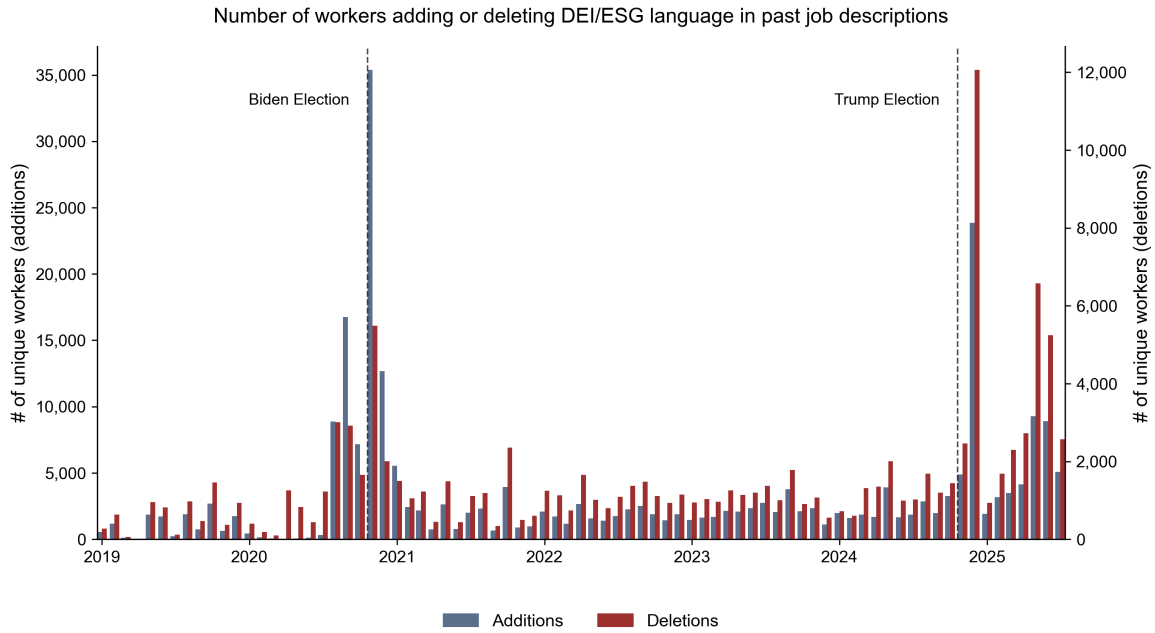
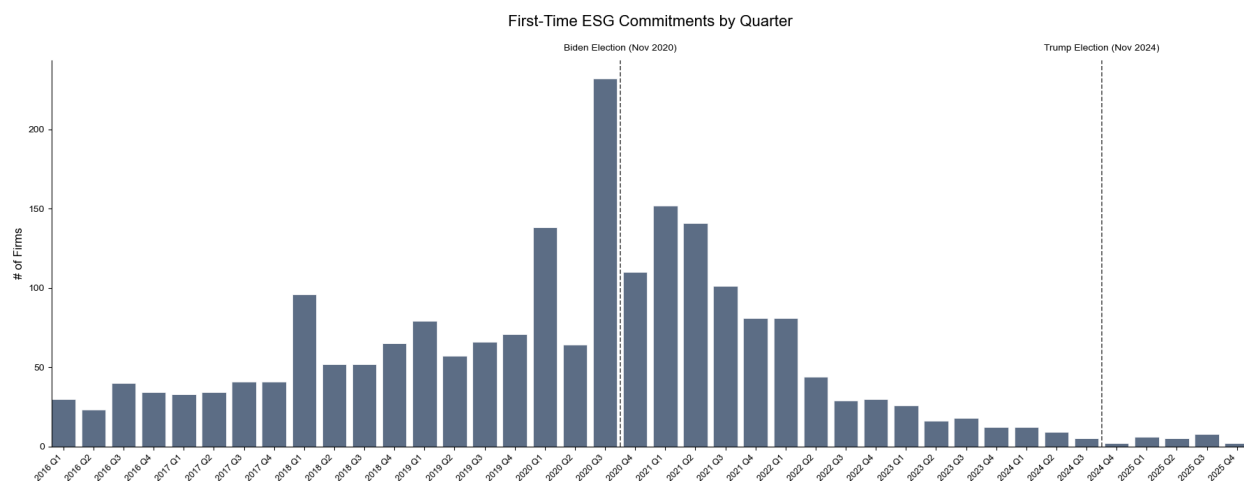


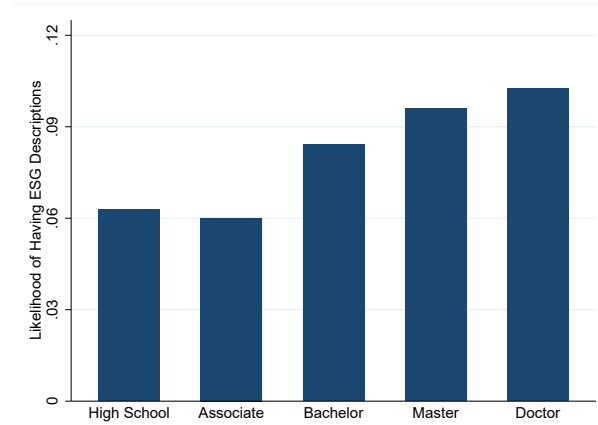
Figure 2: **Number of Firms with ESG Commitments**

This figure plots the number of firms making their first ESG commitment each quarter, identified using textual analysis of earnings conference call transcripts parsed from 2016 onward.

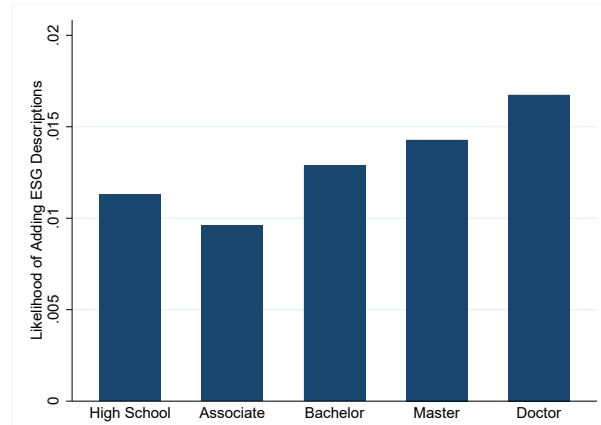


**Figure 3: ESG Disclosure by Worker Characteristics**

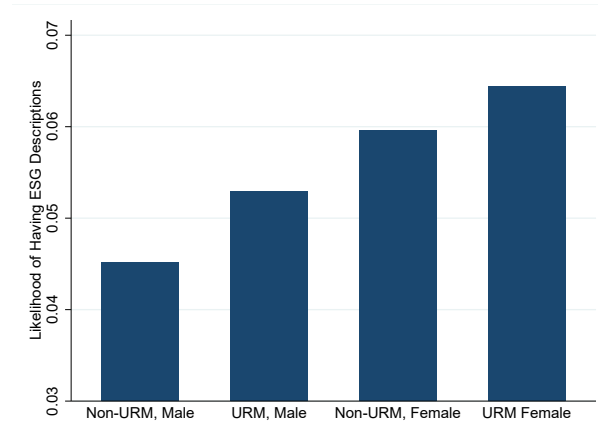
This figure plots the unconditional likelihood (in percent) that a worker's résumé contains an ESG description in a historical job entry (*Have ESG*; left column) or that a worker adds ESG language to a historical job description in the year (*Add ESG*; right column). Each row corresponds to a worker characteristic: educational attainment (Panels A and B), race and gender (Panels C and D), and years of work experience (Panels E and F).



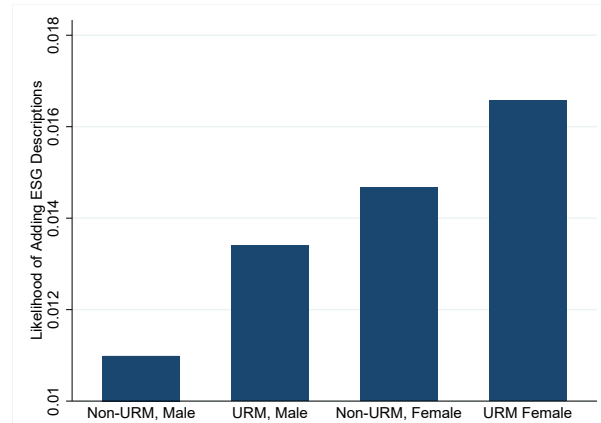
Panel A: Have ESG, by Education



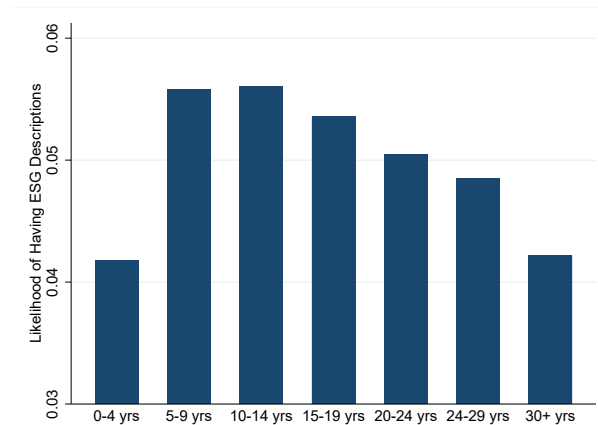
Panel B: Add ESG, by Education



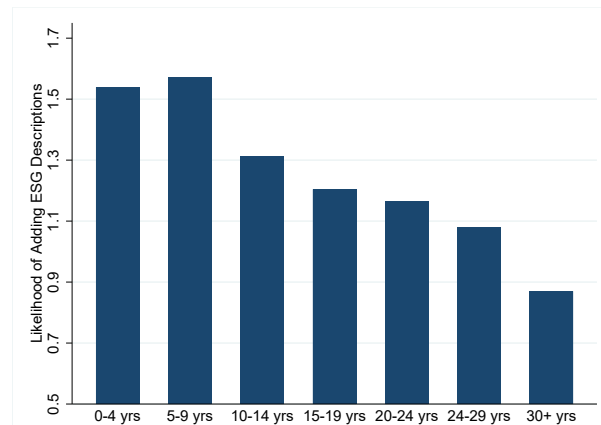
Panel C: Have ESG, by Race and Gender



Panel D: Add ESG, by Race and Gender



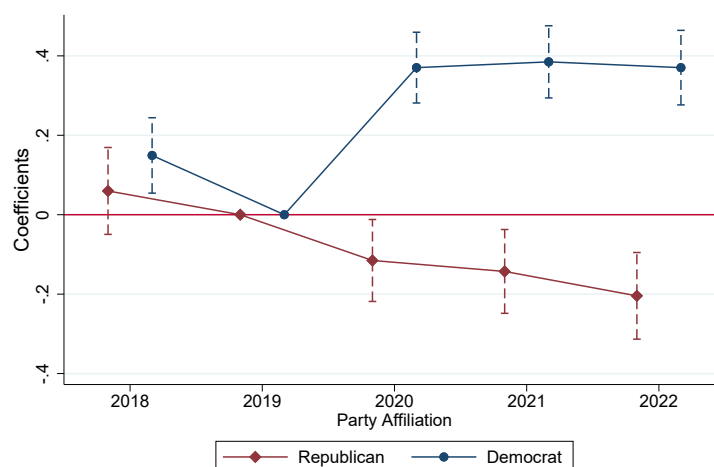
Panel E: Have ESG, by Years of Experience



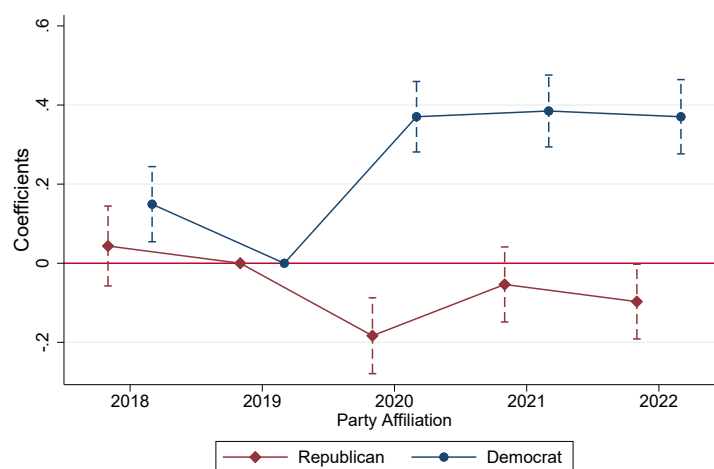
Panel F: Add ESG, by Years of Experience

Figure 4: **Political Cycles and ESG Résumé Disclosure: Dynamic Estimates**

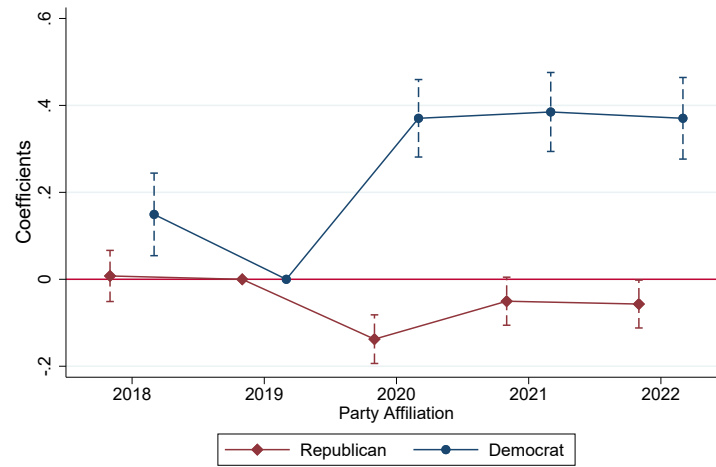
This figure plots dynamic event-study estimates of how four ESG-résumé disclosure outcomes evolve across the 2020 U.S. presidential election by workers' political affiliation. Each panel reports coefficient estimates from regressions of the indicated dependent variable on year indicators interacted with the worker's L2-identified party (*Republican* or *Democratic*), with 2019 as the omitted reference year. The dependent variables in Panels A and B correspond to those in Table 3 (*Have ESG*, *Add ESG*); Panels C and D correspond to the LLM-based and NER-based measures of *Add Unspecific ESG* reported in Table IA.1. Panel A includes worker fixed effects (the dependent variable is a stock); Panels B–D omit worker fixed effects (the dependent variables are flows). All specifications include firm-MSA-occupation-year and gender-race-education-year fixed effects. Vertical bars depict 95-percent confidence intervals. Standard errors are heteroskedasticity robust and double clustered by industry and state.



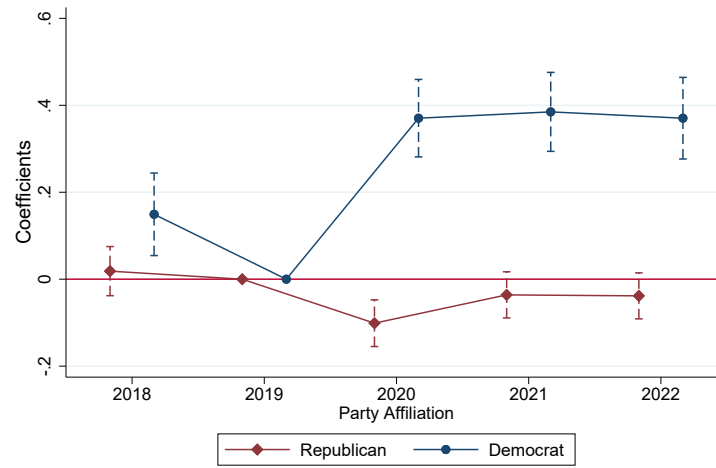
*Panel A: Has ESG Description*



*Panel B: Adds ESG to Historical Job Description*



*Panel C: Adds Unspecific ESG (LLM)*



*Panel D: Adds Unspecific ESG (NER)*

Figure 5: **Number of Industry-Occupations with ESG Commitments**

This figure plots the number of industry-occupation pairs (3-digit NAICS  $\times$  ONET2) in which at least one of the top-five prospective employers initiates an ESG commitment by year, identified using textual analysis of earnings conference call transcripts parsed from 2016 onward.

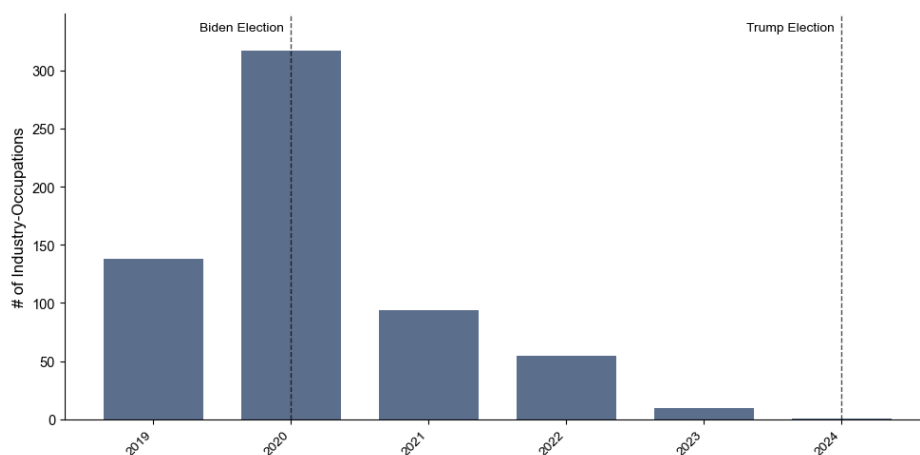
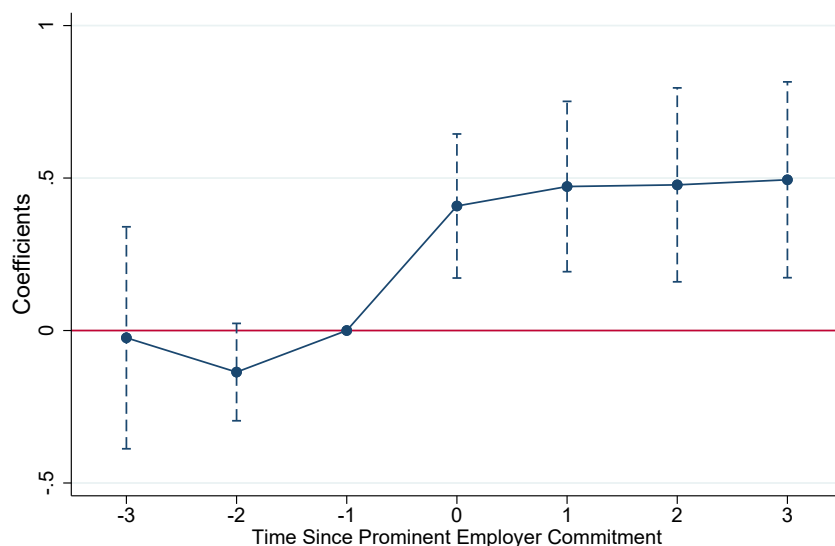


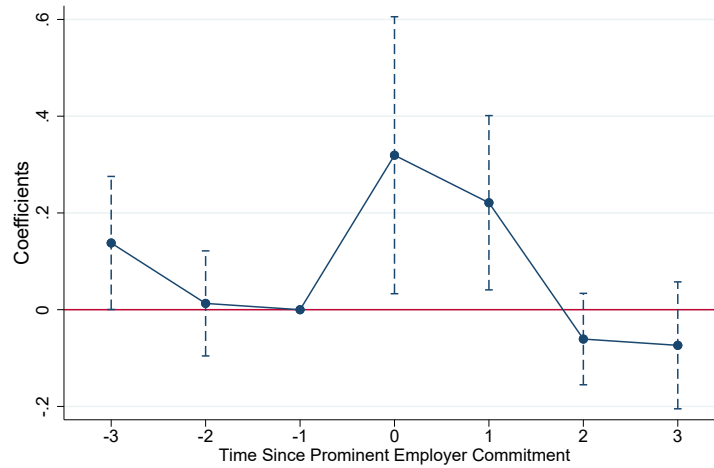
Figure 6: **Major Employer ESG Commitments: Have ESG Dynamic Estimates**

This figure plots dynamic event-study coefficients from a stacked difference-in-differences regression of *Have ESG* (an indicator for whether a worker's résumé contains any ESG description in a historical job entry, multiplied by 100) on indicators for event time relative to the year in which a top-five prospective employer in the worker's industry-occupation first commits to ESG in an earnings call. The omitted event time is  $t = -1$ . Treated industry-occupations are those whose top-five prospective employers commit at any point in the sample period; controls are matched industry-occupations whose top-five prospective employers never commit, selected based on pre-event prevalence of ESG language. The unit of observation is a match cohort-industry-occupation-worker-year. The specification includes cohort-people, cohort-industry-year, and cohort-gender-race-education-year fixed effects. Vertical bars depict 95-percent confidence intervals. Standard errors are clustered by match cohort.

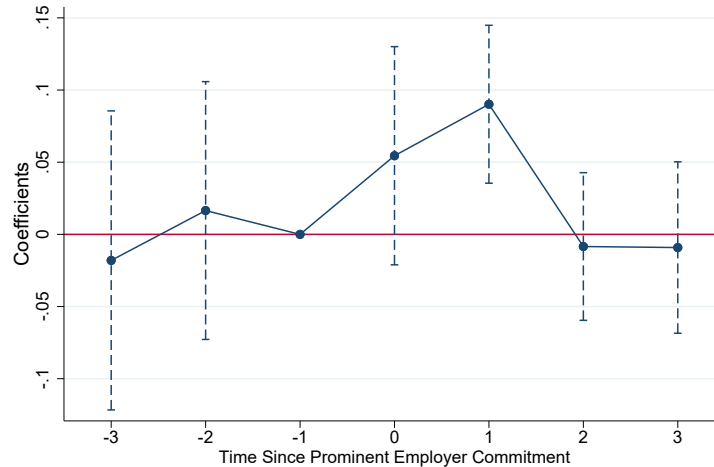


### Figure 7: Major Employer ESG Commitments: Dynamic Estimates for Résumé Additions

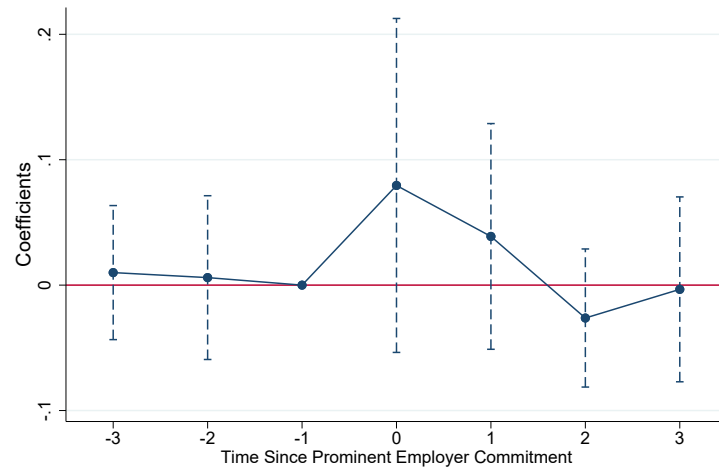
This figure plots dynamic event-study coefficients from the stacked difference-in-differences regression described in Figure 6, with résumé-addition outcomes (each multiplied by 100) as the dependent variable. Panel A reports *Add ESG*, an indicator for whether the worker added ESG language to a historical job description in the year. Panels B and C report *Add Unspecific ESG* under the LLM-based and NER-based measures, respectively. The omitted event time is  $t = -1$ . The specification includes cohort-people, cohort-industry-year, and cohort-gender-race-education-year fixed effects. Vertical bars depict 95-percent confidence intervals. Standard errors are clustered by match cohort.



Panel A: Adds ESG to Historical Job Description



Panel B: Adds Unspecific ESG (LLM)



*Panel C: Adds Unspecific ESG (NER)*

Table 1: **Descriptive Statistics**

This table presents summary statistics used in the study. Panel A reports summary statistics for the full sample and Panel B reports statistics for the revising-year only sample. The unit of observation for each sample is a worker-year. Detailed variable definitions are provided in Appendix A.

| <b>Panel A: Determinants of ESG Résumé Revisions</b> |            |        |        |
|------------------------------------------------------|------------|--------|--------|
| Variable                                             | N          | Mean   | Std    |
| <i>Have ESG (%)</i>                                  | 16,662,533 | 5.184  | 22.171 |
| <i>Add ESG (%)</i>                                   | 16,662,533 | 1.279  | 11.237 |
| <i>Add Unspecific ESG (LLM)</i>                      | 16,662,533 | 0.471  | 6.844  |
| <i>Add Unspecific ESG (NER)</i>                      | 16,662,533 | 0.470  | 6.840  |
| <i>Drop ESG (%)</i>                                  | 16,662,533 | 0.579  | 7.584  |
| <i>Experience (years)</i>                            | 16,662,533 | 16.026 | 9.075  |
| <i>Female</i>                                        | 16,662,533 | 0.386  | 0.487  |
| <i>URM</i>                                           | 16,662,533 | 0.169  | 0.375  |
| <i>Republican</i>                                    | 6,231,144  | 0.253  | 0.435  |
| <i>Democrat</i>                                      | 6,231,144  | 0.418  | 0.493  |

| <b>Panel B: Revising-Year Sample</b> |           |       |        |
|--------------------------------------|-----------|-------|--------|
| <i>Change ESG</i>                    | 4,277,982 | 0.067 | 0.251  |
| <i>External Mobility (%)</i>         | 4,277,982 | 8.960 | 28.561 |
| <i>Internal Promotion (%)</i>        | 4,277,982 | 2.196 | 14.654 |

Table 2: **Political Affiliation and ESG Résumé Disclosure**

This table reports OLS regressions of two ESG-résumé disclosure outcomes on indicators for workers' political affiliations. The dependent variable in Panel A is *Have ESG*, an indicator for whether a worker's résumé contains any ESG description in a historical job entry, and in Panel B is *Add ESG*, an indicator for whether the worker added ESG language to a historical job description in the year. Both dependent variables are multiplied by 100 to reflect percentages. *Democrats* and *Republican* are indicators for the worker's L2-identified political party. Workers that are identified as nonpartisan or affiliated with other parties are the omitted category. Estimates for unspecific ESG additions are reported in Table IA.1. See Appendix A for variable definitions. Standard errors are reported in parentheses and are heteroskedasticity robust and double clustered by industry and state. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| Panel A: Has ESG Description                    |                      |                      |                      |                      |
|-------------------------------------------------|----------------------|----------------------|----------------------|----------------------|
| Dep. Var.: <i>Have ESG</i> (%)                  | (1)                  | (2)                  | (3)                  | (4)                  |
| <i>Democrats</i>                                | 0.801***<br>(0.086)  | 0.587***<br>(0.052)  | 0.585***<br>(0.069)  | 0.419***<br>(0.047)  |
| <i>Republican</i>                               | -0.549***<br>(0.076) | -0.392***<br>(0.061) | -0.415***<br>(0.072) | -0.321***<br>(0.060) |
| Year FE                                         | Yes                  |                      |                      |                      |
| Firm×MSA×Occupation×Year FE                     |                      | Yes                  |                      | Yes                  |
| Gender×Race×Education×Year FE                   |                      |                      | Yes                  | Yes                  |
| Observations                                    | 6,231,142            | 5,046,629            | 6,231,085            | 5,046,566            |
| $R^2$                                           | 0.001                | 0.142                | 0.008                | 0.144                |
| Panel B: Adds ESG to Historical Job Description |                      |                      |                      |                      |
| Dep. Var.: <i>Add ESG</i> (%)                   | (1)                  | (2)                  | (3)                  | (4)                  |
| <i>Democrats</i>                                | 0.202***<br>(0.019)  | 0.141***<br>(0.015)  | 0.139***<br>(0.016)  | 0.098***<br>(0.014)  |
| <i>Republican</i>                               | -0.188***<br>(0.017) | -0.152***<br>(0.014) | -0.163***<br>(0.014) | -0.128***<br>(0.014) |
| Year FE                                         | Yes                  |                      |                      |                      |
| Firm×MSA×Occupation×Year FE                     |                      | Yes                  |                      | Yes                  |
| Gender×Race×Education×Year FE                   |                      |                      | Yes                  | Yes                  |
| Observations                                    | 6,231,142            | 5,046,629            | 6,231,085            | 5,046,566            |
| $R^2$                                           | 0.008                | 0.148                | 0.009                | 0.149                |

Table 3: **Political Cycles and ESG Résumé Disclosure**

This table reports OLS regressions of two ESG-résumé disclosure outcomes on workers' political affiliations and their interactions with the political regime. The dependent variable in Panel A is *Have ESG*, an indicator for whether a worker's résumé contains any ESG description in a historical job entry, and in Panel B is *Add ESG*, an indicator for whether the worker added ESG language to a historical job description in the year. Both dependent variables are multiplied by 100 to reflect percentages. *Democratic* and *Republican* are indicators for the worker's L2-identified political party. *Biden* is an indicator equal to one for years under Biden's presidency. Panel A includes worker fixed effects (the dependent variable is a stock); the Democratic and Republican main effects are absorbed and only the cycle interactions are reported. Panel B omits worker fixed effects (the dependent variable is a flow) and reports both the partisan main effects and the cycle interactions. Estimates for unspecific ESG additions are reported in Table IA.1. See Appendix A for variable definitions. Standard errors are reported in parentheses and are heteroskedasticity robust and double clustered by industry and state. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| Panel A: Has ESG Description                             |                     |                     |                     |                     |
|----------------------------------------------------------|---------------------|---------------------|---------------------|---------------------|
| Dep. Var.: <i>Have ESG</i> (%)                           | (1)                 | (2)                 | (3)                 | (4)                 |
| <i>Democratic</i> $\times$ <i>Biden</i>                  | 0.229***<br>(0.033) | 0.226***<br>(0.044) | 0.174***<br>(0.032) | 0.189***<br>(0.043) |
| <i>Republican</i> $\times$ <i>Biden</i>                  | -0.143**<br>(0.064) | -0.117<br>(0.075)   | -0.122**<br>(0.061) | -0.101<br>(0.075)   |
| Year FE                                                  | Yes                 |                     |                     |                     |
| Firm $\times$ MSA $\times$ Occupation $\times$ Year FE   |                     | Yes                 |                     | Yes                 |
| Gender $\times$ Race $\times$ Education $\times$ Year FE |                     |                     | Yes                 | Yes                 |
| People FE                                                | Yes                 | Yes                 | Yes                 | Yes                 |
| Observations                                             | 6,182,262           | 4,948,364           | 6,182,203           | 4,948,297           |
| $R^2$                                                    | 0.721               | 0.792               | 0.722               | 0.792               |

Panel B: Adds ESG to Historical Job Description

| Dep. Var.: <i>Add ESG (%)</i>                            | (1)                  | (2)                  | (3)                  | (4)                  |
|----------------------------------------------------------|----------------------|----------------------|----------------------|----------------------|
| <i>Democratic</i>                                        | 0.081***<br>(0.017)  | 0.043**<br>(0.020)   | 0.054***<br>(0.016)  | 0.026<br>(0.019)     |
| <i>Republican</i>                                        | -0.092***<br>(0.018) | -0.066***<br>(0.021) | -0.082***<br>(0.019) | -0.056**<br>(0.021)  |
| <i>Democratic</i> $\times$ <i>Biden</i>                  | 0.184***<br>(0.025)  | 0.148***<br>(0.020)  | 0.129***<br>(0.023)  | 0.108***<br>(0.018)  |
| <i>Republican</i> $\times$ <i>Biden</i>                  | -0.148***<br>(0.017) | -0.131***<br>(0.016) | -0.125***<br>(0.017) | -0.111***<br>(0.017) |
| Year FE                                                  | Yes                  |                      |                      |                      |
| Firm $\times$ MSA $\times$ Occupation $\times$ Year FE   |                      | Yes                  |                      | Yes                  |
| Gender $\times$ Race $\times$ Education $\times$ Year FE |                      |                      | Yes                  | Yes                  |
| Observations                                             | 6,231,142            | 5,046,629            | 6,231,085            | 5,046,566            |
| $R^2$                                                    | 0.008                | 0.148                | 0.009                | 0.149                |

Table 4: **Political Cycles by ESG Component: Environmental vs. Social**

This table re-estimates the most saturated political cycle specification from Table 3 separately for Environmental (E) and Social (S) ESG language. Panel A reports stock outcomes (*Have E* and *Have S*) with worker fixed effects; Panel B reports flow outcomes (*Add E* and *Add S*) without worker fixed effects, showing both the partisan main effects and the cycle interactions. All dependent variables are multiplied by 100 to reflect percentages. *Democratic* and *Republican* are indicators for the worker's L2-identified political party. *Biden* is an indicator for years under Biden's presidency. All specifications include firm-MSA-occupation-year and gender-race-education-year fixed effects. See Appendix A for variable definitions. Standard errors are reported in parentheses and are heteroskedasticity robust and double clustered by industry and state. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| Panel A: Has ESG Description                    |                      |                      |
|-------------------------------------------------|----------------------|----------------------|
| Dep. Var. (%):                                  | (1)<br><i>Have E</i> | (2)<br><i>Have S</i> |
| <i>Democratic</i> × <i>Biden</i>                | 0.108***<br>(0.026)  | 0.122**<br>(0.056)   |
| <i>Republican</i> × <i>Biden</i>                | 0.033<br>(0.025)     | -0.116*<br>(0.069)   |
| Firm×MSA×Occupation×Year FE                     | Yes                  | Yes                  |
| Gender×Race×Education×Year FE                   | Yes                  | Yes                  |
| People FE                                       | Yes                  | Yes                  |
| Observations                                    | 4,948,297            | 4,948,297            |
| $R^2$                                           | 0.792                | 0.786                |
| Panel B: Adds ESG to Historical Job Description |                      |                      |
| Dep. Var. (%):                                  | (1)<br><i>Add E</i>  | (2)<br><i>Add S</i>  |
| <i>Democratic</i>                               | -0.003<br>(0.009)    | 0.032**<br>(0.015)   |
| <i>Republican</i>                               | -0.018<br>(0.016)    | -0.054***<br>(0.016) |
| <i>Democratic</i> × <i>Biden</i>                | 0.041***<br>(0.011)  | 0.085***<br>(0.018)  |
| <i>Republican</i> × <i>Biden</i>                | -0.040**<br>(0.015)  | -0.072***<br>(0.014) |
| Firm×MSA×Occupation×Year FE                     | Yes                  | Yes                  |
| Gender×Race×Education×Year FE                   | Yes                  | Yes                  |
| Observations                                    | 5,046,566            | 5,046,566            |
| $R^2$                                           | 0.149                | 0.144                |

Table 5: **Strategic Deletion of ESG Language**

This table reports OLS regressions of *Drop ESG*, an indicator (multiplied by 100) for whether a worker removed ESG or DEI language from a historical job description during the second Trump administration (2024–2025), on indicators for the worker’s earlier ESG additions. The sample comprises workers who added ESG language during either the first Trump administration or the Biden administration. In Panel A, *Added ESG during Biden* is measured relative to the omitted category of additions made during the first Trump administration. Panels B and C split prior additions into unspecific and specific components, using the LLM-based measure (Panel B) and the NER-based measure (Panel C); specific additions made during the first Trump administration are the omitted category. Column (1) includes year fixed effects; column (2) firm-MSA-occupation-year fixed effects; column (3) gender-race-education-year fixed effects; and column (4) both. See Appendix A for variable definitions. Standard errors are reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| <b>Panel A: Prior ESG Additions, by Timing</b>             |                     |                     |                     |                     |
|------------------------------------------------------------|---------------------|---------------------|---------------------|---------------------|
| Dep. Var.: <i>Drop ESG</i> (%)                             | (1)                 | (2)                 | (3)                 | (4)                 |
| <i>Added ESG during Biden</i>                              | 1.389***<br>(0.074) | 1.340***<br>(0.105) | 1.385***<br>(0.074) | 1.342***<br>(0.106) |
| Year FE                                                    | Yes                 |                     |                     |                     |
| Firm×MSA×Occupation×Year FE                                |                     | Yes                 |                     | Yes                 |
| Gender×Race×Education×Year FE                              |                     |                     | Yes                 | Yes                 |
| Observations                                               | 177,608             | 102,899             | 177,581             | 102,859             |
| $R^2$                                                      | 0.003               | 0.226               | 0.004               | 0.228               |
| <b>Panel B: Prior Additions Split by Specificity (LLM)</b> |                     |                     |                     |                     |
| Dep. Var.: <i>Drop ESG</i> (%)                             | (1)                 | (2)                 | (3)                 | (4)                 |
| <i>Added Unspecific ESG during Biden</i>                   | 1.541***<br>(0.359) | 1.496***<br>(0.393) | 1.510***<br>(0.355) | 1.484***<br>(0.370) |
| <i>Added Unspecific ESG during Trump I</i>                 | 0.006<br>(0.348)    | -0.129<br>(0.354)   | -0.044<br>(0.342)   | -0.152<br>(0.326)   |
| <i>Added Specific ESG during Biden</i>                     | -0.233<br>(0.181)   | -0.433*<br>(0.233)  | -0.266<br>(0.181)   | -0.446*<br>(0.236)  |
| Year FE                                                    | Yes                 |                     |                     |                     |
| Firm×MSA×Occupation×Year FE                                |                     | Yes                 |                     | Yes                 |
| Gender×Race×Education×Year FE                              |                     |                     | Yes                 | Yes                 |
| Observations                                               | 177,608             | 102,899             | 177,581             | 102,859             |
| $R^2$                                                      | 0.003               | 0.226               | 0.004               | 0.228               |

**Panel C: Prior Additions Split by Specificity (NER)**

| Dep. Var.: <i>Drop ESG (%)</i>             | (1)                 | (2)                 | (3)                 | (4)                 |
|--------------------------------------------|---------------------|---------------------|---------------------|---------------------|
| <i>Added Unspecific ESG during Biden</i>   | 1.355***<br>(0.351) | 1.263***<br>(0.406) | 1.310***<br>(0.345) | 1.243***<br>(0.381) |
| <i>Added Unspecific ESG during Trump I</i> | 0.005<br>(0.348)    | -0.127<br>(0.351)   | -0.046<br>(0.343)   | -0.150<br>(0.324)   |
| <i>Added Specific ESG during Biden</i>     | 0.062<br>(0.197)    | -0.068<br>(0.346)   | 0.050<br>(0.198)    | -0.068<br>(0.348)   |
| Year FE                                    | Yes                 |                     |                     |                     |
| Firm×MSA×Occupation×Year FE                |                     | Yes                 |                     | Yes                 |
| Gender×Race×Education×Year FE              |                     |                     | Yes                 | Yes                 |
| Observations                               | 177,608             | 102,899             | 177,581             | 102,859             |
| $R^2$                                      | 0.003               | 0.226               | 0.004               | 0.228               |

Table 6: **Major Employer ESG Commitments and ESG Résumé Disclosure**

This table reports stacked difference-in-differences estimates of how the likelihood of displaying ESG content on worker résumés changes after a major prospective employer in the worker’s industry-occupation publicly commits to ESG. For each industry-occupation cell (3-digit NAICS  $\times$  ONET2), we identify the top-five firms recruiting most heavily for the occupation. A commitment event is the first year in which any of these prospective employers publicly commits to ESG in an earnings call. *Treated* indicates industry-occupations that experience such an event; controls are matched industry-occupations whose top-five prospective employers never commit, selected based on pre-event prevalence of ESG language. *Post* equals one in years on or after the commitment year. The dependent variable is *Have ESG*, an indicator for whether a worker’s résumé contains any ESG description in a historical job entry, multiplied by 100. The unit of observation is a match cohort-industry-occupation-worker-year. See Appendix A for variable definitions. Standard errors are reported in parentheses and are clustered by match cohort. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| Dep. Var.: <i>Have ESG</i> (%)                                           | (1)                 | (2)               | (3)                 | (4)                 |
|--------------------------------------------------------------------------|---------------------|-------------------|---------------------|---------------------|
| <i>Treated</i> $\times$ <i>Post</i>                                      | 0.377***<br>(0.130) | 0.217*<br>(0.129) | 0.490***<br>(0.172) | 0.510***<br>(0.162) |
| Cohort $\times$ Sector $\times$ Occupation FE                            | Yes                 |                   |                     |                     |
| Cohort $\times$ Year FE                                                  | Yes                 | Yes               |                     |                     |
| Cohort $\times$ People FE                                                |                     | Yes               | Yes                 | Yes                 |
| Cohort $\times$ Industry $\times$ Year FE                                |                     |                   | Yes                 | Yes                 |
| Cohort $\times$ Gender $\times$ Race $\times$ Education $\times$ Year FE |                     |                   |                     | Yes                 |
| Observations                                                             | 9,780,707           | 9,751,667         | 9,718,445           | 9,684,112           |
| $R^2$                                                                    | 0.025               | 0.746             | 0.751               | 0.754               |

**Table 7: Major Employer ESG Commitments and ESG Additions by Political Affiliation**

This table re-estimates the stacked difference-in-differences design of Table 6 separately for Republican-leaning and Democrat-leaning workers, with specific and unspecific ESG additions as the dependent variables. Panel A uses the LLM-based specificity measure and Panel B the NER-based measure.  $Treated \times Post$  is the difference-in-differences coefficient defined as in Table 6. All specifications include cohort-sector-occupation, cohort-gender-race-education-year, and cohort-industry-year fixed effects. See Appendix A for variable definitions. Standard errors are reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| <b>Panel A: LLM-Based Specificity</b> |                             |                   |                               |                  |
|---------------------------------------|-----------------------------|-------------------|-------------------------------|------------------|
|                                       | <i>Add Specific ESG (%)</i> |                   | <i>Add Unspecific ESG (%)</i> |                  |
| Worker affiliation:                   | Republican                  | Democrat          | Republican                    | Democrat         |
| $Treated \times Post$                 | -0.049<br>(0.117)           | 0.144*<br>(0.083) | 0.123*<br>(0.071)             | 0.067<br>(0.051) |
| Cohort×Sector×Occupation FE           | Yes                         | Yes               | Yes                           | Yes              |
| Cohort×Gender×Race×Education×YearFE   | Yes                         | Yes               | Yes                           | Yes              |
| Cohort×Industry×Year FE               | Yes                         | Yes               | Yes                           | Yes              |
| Observations                          | 793,784                     | 1,322,662         | 793,784                       | 1,322,662        |
| $R^2$                                 | 0.103                       | 0.086             | 0.103                         | 0.082            |
| <b>Panel B: NER-Based Specificity</b> |                             |                   |                               |                  |
|                                       | <i>Add Specific ESG (%)</i> |                   | <i>Add Unspecific ESG (%)</i> |                  |
| Worker affiliation:                   | Republican                  | Democrat          | Republican                    | Democrat         |
| $Treated \times Post$                 | -0.080<br>(0.130)           | 0.148*<br>(0.088) | 0.149***<br>(0.057)           | 0.073<br>(0.048) |
| Cohort×Sector×Occupation FE           | Yes                         | Yes               | Yes                           | Yes              |
| Cohort×Gender×Race×Education×YearFE   | Yes                         | Yes               | Yes                           | Yes              |
| Cohort×Industry×Year FE               | Yes                         | Yes               | Yes                           | Yes              |
| Observations                          | 793,784                     | 1,322,662         | 793,784                       | 1,322,662        |
| $R^2$                                 | 0.102                       | 0.087             | 0.105                         | 0.082            |

Table 8: **ESG Signals and External Mobility**

This table reports OLS regressions of *External Mobility*, an indicator (multiplied by 100) for whether a worker moves to a different employer in the following year, on indicators for ESG revisions in the current year. The sample includes all workers that are making any edits in the current year. Columns (1) and (2) report results for all revisions. Columns (3) through (6) report results for adding unspecific (*Add Unspecific ESG*) and specific (*Add Specific ESG*) ESG language to a historical job entry in the prior year. Columns (3) and (4) use an LLM-based detection of ESG-language revisions; columns (5) and (6) use a named-entity-recognition (NER) based detection. Within each definition, the first column includes firm-MSA-occupation-year fixed effects, and the second column adds gender-race-education-year fixed effects. See Appendix A for variable definitions. Standard errors are reported in parentheses and are heteroskedasticity robust and double clustered by industry and state. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| Dep. Var.: <i>External Mobility</i> (%) | (1)                 | (2)                 | (3)                 | (4)                 | (5)                 | (6)                 |
|-----------------------------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Specificity detection:                  |                     |                     | LLM                 | LLM                 | NER                 | NER                 |
| <i>ESG Revisions</i>                    | 2.716***<br>(0.129) | 2.590***<br>(0.123) |                     |                     |                     |                     |
| <i>Add Unspecific ESG</i>               |                     |                     | 3.185***<br>(0.165) | 3.053***<br>(0.155) | 3.169***<br>(0.177) | 3.029***<br>(0.167) |
| <i>Add Specific ESG</i>                 |                     |                     | 2.898***<br>(0.145) | 2.767***<br>(0.140) | 2.928***<br>(0.145) | 2.802***<br>(0.141) |
| Firm×MSA×Occupation×Year FE             | Yes                 | Yes                 | Yes                 | Yes                 | Yes                 | Yes                 |
| Gender×Race×Education×Year FE           |                     | Yes                 |                     | Yes                 |                     | Yes                 |
| Observations                            | 3,413,964           | 3,413,886           | 3,413,964           | 3,413,886           | 3,413,964           | 3,413,886           |
| $R^2$                                   | 0.176               | 0.178               | 0.176               | 0.178               | 0.176               | 0.178               |

Table 9: **ESG Signals and Internal Promotion**

This table reports OLS regressions of *Internal Promotion*, an indicator (multiplied by 100) for whether a worker moved up the seniority ladder within the same employer in the following year, on indicators for ESG revisions in the current year. The sample includes all workers making revisions to their résumés in the current year. Columns (1) and (2) report results for all revisions. Columns (3) through (6) report results for adding unspecific (*Add Unspecific ESG*) and specific (*Add Specific ESG*) ESG language to a historical job entry in the prior year. Columns (3) and (4) use an LLM-based detection of ESG-language revisions; columns (5) and (6) use a named-entity-recognition (NER) based detection. Within each definition, the first column includes firm-MSA-occupation-year fixed effects, and the second column adds gender-race-education-year fixed effects. See Appendix A for variable definitions. Standard errors are reported in parentheses and are heteroskedasticity robust and double clustered by industry and state. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| Dep. Var.: <i>Internal Promotion</i> (%) | (1)                 | (2)                 | (3)                 | (4)                | (5)                 | (6)                 |
|------------------------------------------|---------------------|---------------------|---------------------|--------------------|---------------------|---------------------|
| Specificity detection:                   |                     |                     | LLM                 | LLM                | NER                 | NER                 |
| <i>ESG Revisions</i>                     | 0.223***<br>(0.065) | 0.181***<br>(0.064) |                     |                    |                     |                     |
| <i>Add Unspecific ESG</i>                |                     |                     | 0.257***<br>(0.086) | 0.213**<br>(0.085) | 0.293***<br>(0.086) | 0.252***<br>(0.085) |
| <i>Add Specific ESG</i>                  |                     |                     | 0.168***<br>(0.057) | 0.127**<br>(0.057) | 0.150***<br>(0.054) | 0.108**<br>(0.053)  |
| Firm×MSA×Occupation×Year FE              | Yes                 | Yes                 | Yes                 | Yes                | Yes                 | Yes                 |
| Gender×Race×Education×Year FE            |                     | Yes                 |                     | Yes                |                     | Yes                 |
| Observations                             | 3,078,587           | 3,078,515           | 3,078,587           | 3,078,515          | 3,078,587           | 3,078,515           |
| $R^2$                                    | 0.131               | 0.132               | 0.131               | 0.132              | 0.131               | 0.132               |

Table 10: **ESG Résumé Additions and Worker-Job Match Quality**

This table reports tests of whether ESG résumé additions are associated with lower worker-job match quality and whether ESG signaling weakens the relation between suitability and being hired. Panel A reports mover-level regressions of *Match Quality* on *Add ESG* among actual external movers, excluding workers used in the JAQ training sample. Panel B separates *Add ESG* into *Add Unspecific ESG* and *Add Specific ESG*; columns (1) and (2) report the most saturated fixed-effect specification using the LLM-based and NER-based specificity measures, respectively. Panel C reports pseudo-peer regressions in which the dependent variable is *Match*, an indicator equal to one for the actual worker hired into the focal vacancy and zero for pseudo-peers. Panel D reports the corresponding pseudo-peer regressions with interactions for Democratic-president years. *Match Quality* is the predicted match quality between a candidate and the focal destination ONET occupation based on pre-move characteristics. For pseudo-peers, match quality is computed relative to the focal job, not the job the pseudo-peer actually took. *Add ESG* is measured using the candidate’s own résumé revision activity in the year before the focal move. Pseudo-peer panels include five pseudo-peers per actual hire. See Appendix A for variable definitions. Standard errors are reported in parentheses and are heteroskedasticity robust and double clustered by industry and state. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| <b>Panel A: ESG Additions and Ex Post Match Quality Among Movers</b> |                       |                       |                       |                       |
|----------------------------------------------------------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| Dep. Var.: <i>Match Quality</i>                                      | (1)                   | (2)                   | (3)                   | (4)                   |
| <i>Add ESG</i>                                                       | -0.0089***<br>(0.003) | -0.0070***<br>(0.002) | -0.0088***<br>(0.003) | -0.0061***<br>(0.002) |
| Firm×MSA×Occupation×Year FE                                          |                       | Yes                   |                       | Yes                   |
| Gender×Race×Education×Year FE                                        |                       |                       | Yes                   | Yes                   |
| Observations                                                         | 597,763               | 361,127               | 597,553               | 360,936               |
| $R^2$                                                                | 0.000                 | 0.290                 | 0.018                 | 0.295                 |

**Panel B: Specific and Unspecific ESG Additions Among Actual Movers**

|                                 | (1)                   | (2)                  |
|---------------------------------|-----------------------|----------------------|
| Specificity detection:          | LLM                   | NER                  |
| Dep. Var.: <i>Match Quality</i> |                       |                      |
| <i>Add Unspecific ESG</i>       | -0.0157***<br>(0.005) | -0.0084**<br>(0.004) |
| <i>Add Specific ESG</i>         | -0.0015<br>(0.003)    | -0.0056*<br>(0.003)  |
| Firm×MSA×Occupation×Year FE     | Yes                   | Yes                  |
| Gender×Race×Education×Year FE   | Yes                   | Yes                  |
| Observations                    | 360,936               | 360,936              |
| $R^2$                           | 0.295                 | 0.295                |

**Panel C: Predicted Match Quality and ESG Revisions, A Pseudo-Peer Test**

| Dep. Var.: <i>Match</i>                                  | (1)                  | (2)                 | (3)                 | (4)                 |
|----------------------------------------------------------|----------------------|---------------------|---------------------|---------------------|
| <i>Match Quality</i>                                     | 0.712***<br>(0.027)  | 0.757***<br>(0.034) | 0.702***<br>(0.026) | 0.750***<br>(0.033) |
| <i>Add ESG</i>                                           | 0.442***<br>(0.025)  | 0.444***<br>(0.027) | 0.434***<br>(0.024) | 0.436***<br>(0.027) |
| <i>Match Quality</i> $\times$ <i>Add ESG</i>             | -0.105***<br>(0.038) | -0.088**<br>(0.042) | -0.094**<br>(0.037) | -0.077*<br>(0.041)  |
| Firm $\times$ MSA $\times$ Occupation $\times$ Year FE   |                      | Yes                 |                     | Yes                 |
| Gender $\times$ Race $\times$ Education $\times$ Year FE |                      |                     | Yes                 | Yes                 |
| Observations                                             | 3,403,032            | 2,758,759           | 3,399,651           | 2,755,549           |
| $R^2$                                                    | 0.089                | 0.250               | 0.097               | 0.256               |

**Panel D: Predicted Match Quality and ESG Revisions by Political Regime**

| Dep. Var.: <i>Match</i>                                            | (1)                 | (2)                 | (3)                 | (4)                 |
|--------------------------------------------------------------------|---------------------|---------------------|---------------------|---------------------|
| <i>Match Quality</i>                                               | 0.691***<br>(0.024) | 0.744***<br>(0.030) | 0.679***<br>(0.024) | 0.736***<br>(0.030) |
| <i>Add ESG</i>                                                     | 0.397***<br>(0.029) | 0.413***<br>(0.035) | 0.393***<br>(0.028) | 0.407***<br>(0.035) |
| <i>Match Quality</i> $\times$ <i>Add ESG</i>                       | -0.060<br>(0.047)   | -0.031<br>(0.051)   | -0.047<br>(0.048)   | -0.023<br>(0.053)   |
| <i>Match Quality</i> $\times$ <i>Biden</i>                         | 0.027***<br>(0.009) | 0.017<br>(0.011)    | 0.028***<br>(0.009) | 0.017<br>(0.011)    |
| <i>Add ESG</i> $\times$ <i>Biden</i>                               | 0.052***<br>(0.008) | 0.034*<br>(0.018)   | 0.046***<br>(0.009) | 0.032*<br>(0.018)   |
| <i>Match Quality</i> $\times$ <i>Add ESG</i> $\times$ <i>Biden</i> | -0.053**<br>(0.021) | -0.065**<br>(0.032) | -0.056**<br>(0.022) | -0.062**<br>(0.031) |
| Firm $\times$ MSA $\times$ Occupation $\times$ Year FE             |                     | Yes                 |                     | Yes                 |
| Gender $\times$ Race $\times$ Education $\times$ Year FE           |                     |                     | Yes                 | Yes                 |
| Observations                                                       | 3,403,032           | 2,758,759           | 3,399,651           | 2,755,549           |
| $R^2$                                                              | 0.089               | 0.250               | 0.097               | 0.256               |

## A. Variable Definitions

- *Have ESG*: An indicator that equals one if a worker’s résumé contains any ESG- or DEI-related language in a historical job description as of the end of the year, and zero otherwise. Data are obtained from the Revelio Labs changes file.
- *Add ESG*: An indicator that equals one if a worker adds ESG- or DEI-related language to a historical job description in a given year, and zero otherwise. Data are obtained from the Revelio Labs changes file.
- *Add Unspecific ESG*: An indicator that equals one if a worker adds an ESG or DEI description classified as *unspecific* to a historical job description in a given year, and zero otherwise. An unspecific addition is a vague reference to ESG themes that lacks concrete tasks, deliverables, or measurable outcomes. We use two measures. The LLM-based measure classifies an addition as unspecific if a large language model’s four specificity scores (quantitative specificity, contextual integration, concreteness of action, and named-entity density, each on a one-to-five scale) sum to less than 12. The NER-based measure classifies an addition as unspecific if named-entity recognition detects no named entities in the added text. See Section 2.2 for details. Data are obtained from the Revelio Labs changes file.
- *Add Specific ESG*: An indicator that equals one if a worker adds an ESG or DEI description that is not classified as unspecific (under the measure used in the corresponding column) to a historical job description in a given year, and zero otherwise. Data are obtained from the Revelio Labs changes file.
- *Have E (Have S)*: An indicator that equals one if a worker’s résumé contains any environmental-related (respectively, social- or DEI-related) language in a historical job description as of the end of the year, and zero otherwise. Data are obtained from the Revelio Labs changes file.
- *Add E (Add S)*: An indicator that equals one if a worker adds environmental-related (respectively, social- or DEI-related) language to a historical job description in a given year, and zero otherwise. Data are obtained from the Revelio Labs changes file.
- *External Mobility*: An indicator that equals one if a worker transitions to a position at an employer with a different ultimate corporate parent in the following year, and zero otherwise. The indicator is multiplied by 100 in the regressions. Data are obtained from the Revelio Labs positions file.
- *Internal Promotion*: An indicator that equals one if a worker transitions to a new position within the same ultimate corporate parent in the following year, and zero otherwise. The indicator is multiplied by 100 in the regressions. Data are obtained from the Revelio Labs positions file.
- *Democrat (Republican)*: An indicator that equals one if the worker is affiliated with the Democratic (respectively, Republican) party, and zero otherwise. Party affiliation is obtained from voter registration records provided by L2, Inc. Appendix IA.I describes the matching procedure.
- *Biden*: An indicator equal to one for years under Biden’s presidency, and zero otherwise.

- *Treated*: An indicator that equals one for industry-occupation pairs (3-digit NAICS  $\times$  ONET2) in which at least one of the top-five prospective employers initiates an ESG commitment during the sample period, detected using textual analysis of quarterly earnings call transcripts. Prospective employers are the five firms hiring the most workers within the industry-occupation pair. Control units are industry-occupation pairs in which none of the top-five prospective employers makes an ESG commitment, matched to treated units on pre-event ESG language prevalence. Data on ESG commitments are obtained from quarterly earnings call transcripts in Refinitiv Eikon.
- *Post*: An indicator that equals one in years on or after the first ESG commitment by a top-five prospective employer in the worker’s industry-occupation pair, and zero otherwise.
- *Female*: An indicator that equals one if the worker is female, and zero otherwise. Data are obtained from the Revelio Labs positions file.
- *URM*: An indicator that equals one if the worker belongs to an underrepresented minority group (Black or Hispanic), and zero otherwise. Data are obtained from the Revelio Labs positions file.
- *Experience*: The worker’s total years of labor market experience. Data are obtained from the Revelio Labs positions file.
- *Match Quality*: The predicted probability that a worker’s pre-move characteristics fit the destination ONET occupation. The measure follows the logic of job assignment quality (JAQ) in [Coraggio et al. \(2025\)](#). We define jobs using ONET occupation codes and train prediction models on workers hired by high-productivity firms, defined as firms in the top decile of sales per employee within fiscal year, 3-digit NAICS industry, and asset-size tercile cells using lagged Compustat data. The prediction model uses pre-move worker characteristics, including education, field of study, labor market experience, prior tenure, prior employers, prior occupations, prior industries, prior location, cumulative nonemployment gaps, gender, and ethnicity. The prediction model is implemented using scikit-learn’s regularized log-loss classifier with feature hashing.
- *Match*: An indicator that equals one for the actual worker hired into the focal vacancy and zero for pseudo-peers.

## INTERNET APPENDIX

### Partisan Résumés: ESG Signaling over the Political Cycle

Janet Gao, Jun Oh, Joseph Pacelli

## IA.I. Matching of Revelio Users to Partisan Affiliation in L2

This appendix describes the procedure used to match individuals in the Revelio résumé database to political affiliation information from the L2 voter database. The goal of this matching exercise is to assign a political leaning to individuals identified in Revelio based on their voter registration and voting history records in L2. L2 is organized by state, so the matching proceeds by state. Due to the size of the data files, each state file is partitioned into 27 subfiles based on the first letter of the individual’s last name, corresponding to the letters *a* through *z* and a residual category for all other characters. This partitioning is performed to enable computationally feasible merging of the large L2 and Revelio datasets in subsequent steps.

In Revelio, we infer age for each user based on education records in Revelio’s user file wherever available. Individuals are assumed to begin college at age 18 and graduate at age 22, and age is inferred from reported graduation dates accordingly. Age is recorded only for users for whom education information is available.

For both Revelio and L2 files, last names are cleaned to remove special characters, hyphens, and other non-standard formatting prior to matching.

Similar to the L2 structure, we partition the Revelio file into subfiles defined by the individual’s state of employment and the first letter of their cleaned last name. The **Endyear** variable is preserved in these subfiles for use in the subsequent matching step.

We merge Revelio and L2 subfiles within cells defined by state and first letter of last name. For example, Revelio records for individuals who worked in Washington D.C. with last names beginning with “a” are merged against L2 records from Washington D.C. whose last names also begin with “a.” To improve temporal alignment, each Revelio record is matched against the L2 snapshot whose timestamp corresponds to the **Endyear** of the Revelio record.

Matching is performed on cleaned first and last names using exact string matching; fuzzy matching is not employed. For individuals with hyphenated last names, matching is attempted both on the full hyphenated string and on the final component of the hyphenated name. All possible L2 matches for each Revelio user are retained at this stage, along with the **user\_id** and **LALVOTERID** identifiers.

Because name-based matching often yields multiple candidate L2 records for a single Revelio user, a sequential deduplication procedure is applied. Party affiliation is drawn from L2 through the following iterative process:

1. If all candidate matches for a given Revelio user share the same party affiliation, that affiliation is assigned and the process concludes for that individual.
2. If over 90% of candidate matches share the same party affiliation (either Democrat or Republican), that majority affiliation is assigned and the process concludes.
3. If ambiguity remains, age information from both sources is compared. Candidate matches are excluded if the reported age differs by more than two years in either direction. If, after this age-based filtering, over 90% of remaining candidates share the same party affiliation, that affiliation is assigned.
4. If ambiguity remains, candidate matches are further filtered by excluding records where the gender recorded in L2 clearly differs from the gender recorded in Revelio.
5. If after applying all of the above criteria a clear match cannot be established, the individual is classified as having no identified party affiliation and is excluded from analyses that rely on this variable.

## IA.II. Examples of ESG Commitments in Earnings Calls

This appendix provides illustrative examples of ESG commitments identified in earnings call transcripts. These excerpts correspond to cases used to construct the *Treated* indicator, which equals one for industry-occupation pairs (3-digit NAICS  $\times$  ONET2) in which at least one of the top-five largest prospective employers initiates an ESG commitment by the end of the sample period. Each example reports the firm name, occupational category (ONET), industry classification (NAICS), and the year of the statement.

### Classification Prompt

To identify firm ESG commitments in earnings call transcripts (Section 2), we apply the following classification prompt to each call. The classification logic is summarized below; category-specific examples used in the prompt are omitted for space.

You analyze corporate earnings call excerpts to identify whether management is making  
→ forward-looking commitments to ESG or DEI. A commitment is management signaling  
→ intent to act, improve, or maintain a focus on these values in the future.

WHAT COUNTS (Indicator = 1): forward-looking phrasing ("We will," "We plan to," "We are  
→ committed to"); strategic-intent statements (e.g., "ESG remains a top priority");  
→ generic but forward-looking statements; promises to continue existing programs.

WHAT DOES NOT COUNT (Indicator = 0): purely past actions; false positives (financial  
→ "equity," technical "inclusion of data," "sustainable" business growth, "diverse"  
→ portfolios); neutral descriptions of current state.

RULES: 'dei\_commitment' and 'esg\_commitment' must be 0 or 1. If any part of the  
→ transcript contains a future commitment, the corresponding score is 1.

OUTPUT (JSON): {"row\_id": N, "dei\_commitment": 0/1, "esg\_commitment": 0/1}

### Panel A: Diversity and Inclusion Commitments

- **3M Co (ONET: 11, NAICS: 339, Year: 2019):**  
“In 2018, we expanded development opportunities for 3Mers while launching initiatives to deepen our commitment to sustainability, diversity and inclusion.”
- **Matrix Service Co (ONET: 25, NAICS: 493, Year: 2019):**  
“In the past week, I was honored to join the CEO Action for Diversity & Inclusion initiative, the largest CEO-driven business commitment to advancing inclusion and diversity in the workplace.”
- **Cerner Corp (ONET: 31, NAICS: 513, Year: 2020):**  
“And as I mentioned in a recent all-associate town hall, the Cerner leadership team is committed to making even more progress in our diversity and inclusion programs and policies.”
- **Central Garden & Pet Co (ONET: 37, NAICS: 459, Year: 2020):**  
“As part of our Vision2025 strategy, we are committed to continuing to build a great place to work and a winning growth culture that embraces diversity and inclusion as a fundamental area of focus.”
- **Boston Scientific Corp (ONET: 29, NAICS: 339, Year: 2020):**  
“So as we continue our commitment to anti-racism in both actions and resources, including our important Close the Gap initiative to close the health equity gap in underserved communities through provider education and collaboration, advocacy and society partnerships and patient disease state awareness.”

- **Avis Budget Group Inc (ONET: 29, NAICS: 532, Year: 2020):**  
“We are committed to equality and inclusion, and we’re taking action within our company to meet our commitment.”

## Panel B: Environmental and Sustainability Commitments

- **Salesforce.com Inc (ONET: 17, NAICS: 513, Year: 2020):**  
“We’ve delivered a carbon-neutral cloud to our customers, and we’re committing to reach 100% renewable energy for our global operations by 2022 because the planet is a stakeholder.”
- **Interface Inc (ONET: 25, NAICS: 314, Year: 2021):**  
“These now validated science-based targets commit Interface to further reduce our Scope 1, 2 and 3 emissions in alignment with our goal of becoming a carbon-negative company by 2040. Interface continues to lead the pack when it comes to our commitment to sustainability.”
- **Annaly Capital Management (ONET: 11, NAICS: 525, Year: 2021):**  
“With this year’s report, we included additional SASB disclosures under the mortgage finance standards for our residential credit business and made a new commitment to further assess climate change risks and opportunities through the consideration of the Task Force on Climate-related Financial Disclosures.”
- **Walmart Inc (ONET: 11, NAICS: 455, Year: 2021):**  
“Over the next 10 years, we’ve set a goal to purchase an additional \$350 billion on items made, grown or assembled in the U.S. We estimate this commitment will create more than 750,000 new American jobs and avoid 100 million metric tons of CO<sub>2</sub> emissions.”

## IA.III. Identifying ESG and DEI Language in Résumé Edits

This appendix describes the procedure used to identify environmental, social, and governance (ESG) and diversity, equity, and inclusion (DEI) language in résumé edits. The procedure combines a keyword dictionary with large language model (LLM) classification, and proceeds in three phases: constructing a comprehensive keyword list, pruning terms that are too common to be informative, and classifying the resulting set of edits.

### Phase 1: Constructing the Keyword List

We begin with a bag-of-words (BOW) dictionary of ESG- and DEI-related terms. To assess its coverage, we draw a random sample of 1,000 résumé edits from the raw edit data and flag ESG and DEI content using the BOW dictionary. In parallel, we develop an LLM prompt that independently classifies whether each edit references ESG or DEI topics. We compare the two approaches edit by edit, examine the cases in which they disagree, and iteratively refine the prompt to reduce both false positives and false negatives. We repeat this exercise on several additional independent random samples of 1,000 edits until the prompt’s classifications stabilize. The final prompt also returns, for each edit it flags, the specific ESG- and DEI-related keywords and phrases that drive the classification.

We then apply the final prompt to a random sample of 100,000 edits using the Claude Sonnet 4.6 model, recovering ESG- and DEI-related terms that the original BOW dictionary does not contain. This step yields 2,326 unique keywords and phrases. Augmenting the original BOW dictionary with these terms produces a combined list, which we refer to as the BOW+LLM list.

### Phase 2: Pruning Common Terms

Applying the BOW+LLM list to the full raw edit data, and retaining any job description that contains at least one listed term, flags an implausibly large share of edits. The reason is that the list includes terms that are very common in general résumé text (for example, “include”) and therefore appear frequently outside any ESG or DEI context. To address this, we draw a random sample of 100,000 edits and use the Claude Sonnet 4.6 model to classify, for each occurrence of a listed term, whether the term is used in a genuine ESG or DEI context (a true positive) or not (noise). This produces, for every keyword, the share of its occurrences in the 100,000-edit sample that reflect genuine ESG or DEI content.

Two of the authors independently review every keyword whose true-positive rate falls below 5%, and we remove the 64 terms that both authors flag for deletion. The result is a refined BOW+LLM list.

### Phase 3: Sample Construction and Classification

We apply the refined BOW+LLM list to the full raw edit data and retain each edit in which at least one listed term appears in either the old or the new job description. This step yields 21,605,995 job edits, roughly 55% of the raw data. We then restrict the sample to edits made by workers employed at U.S. public firms, identified using a crosswalk that links Revelio company identifiers to Compustat `gvkey` identifiers, which reduces the sample to 4,989,316 edits. Finally, we apply a cleaning step that removes edits whose only matched terms are clearly noisy, such as an edit matched solely because the word “social” appears within the phrase “social media,” when no other listed term is present. This step reduces the sample to approximately 4.7 million job edits.

To classify these edits, we draw a random sample of 1,000 edits and iteratively refine a classification prompt that characterizes each edit along four dimensions: an indicator for whether the edit contains DEI content, an indicator for whether it contains ESG content, a DEI intensity score on a zero-to-five scale, and an ESG intensity score on a zero-to-five scale. Given the cost of classifying roughly 4.7 million edits, we evaluate alternative models and ultimately classify all edits using the Claude Haiku 4.5 model with a concise prompt, which provides a cost-effective balance between scalability and classification accuracy.

The scoring rubric and output schema used by the LLM classifier are summarized below; the keyword lists from Phases 1 and 2 are omitted for space.

You are quantifying the presence of ESG and DEI values in job descriptions. For each row,  
→ evaluate the OLD and NEW descriptions; the standard is whether a reasonable employer  
→ would perceive ESG or DEI alignment. DEI/ESG keywords are taken from the BOW+LLM list  
→ constructed in Phases 1-2.

SCORING RUBRIC (0-5 signal intensity):

0: No signal.

1: Trace signal -- single keyword or boilerplate (e.g., "inclusive culture").

2: Identified signal -- specific program, task, or metric (e.g., "led DEI committee").

3: Sustained signal -- multiple sentences treating ESG/DEI as a core job function.

4: High-density signal -- specialized frameworks (GRI, SASB, Scope 1-3) or technical  
→ outcomes.

5: Maximum signal -- ESG/DEI is the dominant lens of the role.

RULES: 'dei' and 'esg' are 0 or 1; 'int\_dei' and 'int\_esg' are integers 0-5; if 'dei' is  
→ 0 then 'int\_dei' must be 0 (same for ESG).

OUTPUT (JSON, one object per row): {"row\_index": N, "old\_metrics": {"dei": 0/1, "esg":  
→ 0/1, "int\_dei": 0-5, "int\_esg": 0-5}, "new\_metrics": {...}}

## Specificity Scoring of ESG Additions

Section 2 describes the LLM specificity measure used to classify each ESG or DEI addition as *Unspecific* or *Specific*. The scoring rubric and output schema are reproduced below; the prompt's few-shot examples are omitted for space.

You evaluate whether additions to job descriptions reflect genuine work experience or  
→ vague resume padding. Given OLD\_DESCRIPTION, NEW\_DESCRIPTION, and ADDED\_TEXT, score  
→ the ADDED\_TEXT on four dimensions (each 1-5):

QUANTITATIVE SPECIFICITY (quant\_specificity): concrete numbers, amounts, percentages,  
→ timeframes, or measurable outcomes. 5 = multiple specific quantities with context; 1  
→ = no quantities of any kind.

CONTEXTUAL INTEGRATION (context\_integration): does the addition fit the existing role or  
→ appear bolted on? 5 = fully embedded in job-specific language; 1 = entirely  
→ disconnected.

CONCRETENESS OF ACTION (action\_concreteness): does the text describe a specific bounded  
→ activity (what, to whom, how, with what result), or a vague orientation? 5 = what +  
→ to whom + how + result; 1 = bare adjective or buzzword.

NAMED ENTITY DENSITY (named\_entity\_density): does the text reference specific programs,  
→ regulations, organizations, tools, or places? 5 = multiple externally identifiable  
→ entities; 1 = no named entities.

OUTPUT (JSON): {"row\_index": N, "quant\_specificity": 1-5, "context\_integration": 1-5,  
→ "action\_concreteness": 1-5, "named\_entity\_density": 1-5, "reasoning": "<brief>"}

## IA.IV. Examples of Retrospective Résumé Edits

This appendix provides illustrative examples of retrospective résumé edits. Panels A and C (B and D) present examples in which DEI/ESG language is added (deleted) to a previous job description. The added or deleted language is highlighted in blue. In Panel A, the individual was employed at Bank of America from 1995 to 1996 but edited the job description in 2022 (during the Biden administration). In Panel B, the individual was employed at Zillow Group, Inc. from 2021 to 2022 but edited the job description in 2025 (during the Trump administration). In Panel C, the individual was employed at Amazon from 2014 to 2015 but edited the job description in 2021 (during the Biden administration). In Panel D, the individual was employed at Dow Inc. in 2022 but edited the job description in 2025 (during the Trump administration).

### Panel A: Adding DEI Language

#### Previous job description (Bank of America):

- Selected to evaluate an individual's potential to perform in a managerial capacity and measure job-related behaviors in a practice opportunity/role-play environment.
- Worked directly with senior executives to develop strategies and align the selection and placement process as a fair promotional approach.

#### After editing job description (Bank of America):

- Selected to evaluate an individual's potential to perform in a managerial capacity and measure job-related behaviors in a practice opportunity/role-play environment.
- **Used HR metrics to improve workforce diversity.**
- Worked directly with senior executives to develop strategies and align the selection and placement process as a fair promotional approach.

### Panel B: Deleting DEI Language

#### Previous job description (Zillow Group, Inc.):

- Traveled with a small team to assist the Denver market with inspections of over 300 vacant homes on inventory, to ensure quality control and renovations timelines were being met.
- Continuing education in leadership and **diversity**, change management, real estate, project management, digital transformation and customer experience.

#### After editing job description (Zillow Group, Inc.):

- Traveled with a small team to assist the Denver market with inspections of over 300 vacant homes on inventory, to ensure quality control and renovations timelines were being met.
- Continuing education in leadership, change management, real estate, project management, digital transformation and customer experience.

### Panel C: Adding ESG Language

#### Previous job description (Amazon):

- Led implementation and management of Amazon global EH&S programs and metrics for a new facility with 80% new hires. Held full accountability for maintaining regulatory compliance.
- Served as site representative during regulatory audits and inspections.

#### After editing job description (Amazon):

- Led implementation and management of Amazon global EH&S programs and metrics for a new facility with 80% new hires. Held full accountability for maintaining regulatory compliance.
- Implemented a sustainability program that minimized energy consumption, waste, and chemical use.
- Served as site representative during regulatory audits and inspections.

## Panel D: Deleting ESG Language

### Previous job description (Dow Inc.):

- Won Dow's annual intern Create-a-thon competition with a machine learning camera solution [to bolster sustainability](#).
- Identified \$2M in annual logistics cost savings opportunities for Dow's bulk hopper truck and rail supply chain networks.

### After editing job description (Dow Inc.):

- Won Dow's annual intern Create-a-thon competition with a machine learning camera solution.
- Identified \$2M in annual logistics cost savings opportunities for Dow's bulk hopper truck and rail supply chain networks.

## IA.V. Examples Using LLM-Based Specificity

This appendix provides illustrative examples of retrospective résumé edits that add ESG or DEI language to previous job descriptions. Panels A and B present ESG additions, while Panels C and D present DEI additions. For each example, we report the period of employment, the date on which the edit was observed, and the four LLM-based specificity components: quantitative specificity, contextual integration, action concreteness, and named entity density. The added language is highlighted in blue.

### Panel A: Unspecific ESG Addition

*The individual was employed at Versar from November 2007 to August 2011 and edited the job description on December 30, 2019. The four component scores are: quantitative specificity = 1, contextual integration = 1, action concreteness = 1, and named entity density = 1.*

#### Previous job description (Versar):

- Responsible for financial and supervisory project management and execution for technical programs at various government agencies.
- Activities included programming project funds, tracking timelines, reviewing deliverables, tailoring project teams to ensure success, supervising project teams, facilitating client and stakeholder meetings, and ensuring client and employee satisfaction.

#### After editing job description (Versar):

- Responsible for financial and supervisory project management and execution for **sustainability** programs at various government agencies.
- Activities included programming project funds, tracking timelines, reviewing deliverables, tailoring project teams to ensure success, supervising project teams, facilitating client and stakeholder meetings, and ensuring client and employee satisfaction.

### Panel B: Specific ESG Addition

*The individual was employed at Advanced Cooling Technologies, Inc. from May 2019 to August 2020 and edited the job description on March 20, 2021. The four component scores are: quantitative specificity = 5, contextual integration = 5, action concreteness = 5, and named entity density = 5.*

#### Previous job description (Advanced Cooling Technologies, Inc.):

- Developed novel technology combining flat plate heat exchanger and evaporative condenser to function with chiller.
- Designed a 3D model of a closed-loop thermosyphon in SolidWorks and performed structural FEA and thermal analysis.

#### After editing job description (Advanced Cooling Technologies, Inc.):

- **Project: design and analysis of novel loop thermosyphon integrated with building HVAC system.**
- Developed novel technology combining flat plate heat exchanger and evaporative condenser to function with chiller.
- **Improved system efficiency by removing cooling tower unit in order to reduce energy consumption by 28%.**
- Designed a 3D model of a closed-loop thermosyphon in SolidWorks and performed structural FEA and thermal analysis.

## Panel C: Unspecific DEI Addition

*The individual was employed at JPMorgan Chase & Co. from January 2016 to January 2022 and edited the job description on March 2, 2023. The four component scores are: quantitative specificity = 1, contextual integration = 1, action concreteness = 1, and named entity density = 1.*

### Previous job description (JPMorgan Chase & Co.):

- Recruiting lead for the Chief Technology Office and client relationship manager.
- Hands-on executive talent acquisition and talent advisory.
- Building high-caliber teams aligned to global enterprise technology, including AI/ML, cloud, data, quantum computing, and blockchain.

### After editing job description (JPMorgan Chase & Co.):

- Recruiting lead for the Chief Technology Office and client relationship manager.
- Hands-on executive talent acquisition and talent advisory.
- Building high-caliber **diverse and inclusive** teams aligned to global enterprise technology, including AI/ML, cloud, data, quantum computing, and blockchain.

## Panel D: Specific DEI Addition

*The individual was employed at Biogen from January 2017 to April 2019 and edited the job description on November 15, 2019. The four component scores are: quantitative specificity = 5, contextual integration = 5, action concreteness = 5, and named entity density = 5.*

### Previous job description (Biogen):

- Reporting to the Chief Procurement Officer, leading three distinct shared centers of excellence with budget > \$3 million.
- Leading a strategic and technology-focused organization enabling procurement to hit world-class benchmarks, such as a 13x multiplier on savings for every head in procurement.

### After editing job description (Biogen):

- Reporting to the Chief Procurement Officer, leading three distinct shared centers of excellence **and supplier diversity** with a total budget of approximately **\$5 million**, including approximately **\$3 million in operating expenses and \$2 million in personnel**.
- **Led a team of 30 individuals on three continents supporting 32 countries, including offshore BPO service centers.**
- Leading a strategic and technology-focused organization enabling procurement to hit world-class benchmarks, such as a 13x multiplier on savings for every head in procurement.

## IA.VI. Examples Using spaCy-Based Specificity

This appendix provides illustrative examples of retrospective résumé edits classified using the spaCy-based specificity measure. An addition is classified as unspecific if spaCy detects no named entities in the added text; an addition is classified as specific if spaCy detects at least one named entity. Panels A and C present unspecific ESG and DEI additions, respectively. Panels B and D present specific ESG and DEI additions, respectively. The added language is highlighted in blue.

### Panel A: Unspecific ESG Addition

*The individual was employed at Boston Consulting Group from January 2019 to January 2021 and edited the job description on March 24, 2025. No named entities were detected in the added text.*

#### Previous job description (Boston Consulting Group):

- Key industries: technology, media and telecom, financial institutions, consumer packaged goods, and retail.

#### After editing job description (Boston Consulting Group):

- Solved complex business challenges and drove strategic transformation for C-suite executives across industries.
- Collaborated with diverse teams to develop actionable insights and implement high-impact solutions.
- Delivered tangible value and drove sustainable growth for clients worldwide.
- Key industries: technology, media and telecom, financial institutions, consumer packaged goods, and retail.

### Panel B: Specific ESG Addition

*The individual was employed at Amazon from June 2021 to August 2022 and edited the job description on December 30, 2024. spaCy detected three named entities in the added text, including CARDINAL entities (over 40, 38.4) and DATE (annual).*

#### Previous job description (Amazon):

- Led industrial engineering team for Amazon robotics fulfillment centers, responsible for integrating the equipment and dictating the material flow within Amazon's largest and most complex capital projects.

#### After editing job description (Amazon):

- Led industrial engineering team for Amazon robotics fulfillment centers, responsible for integrating the equipment and dictating the material flow within Amazon's largest and most complex capital projects.
- Rapidly deployed prototype of high-efficiency motor technology, reducing fulfillment-center energy consumption by over 40% with resultant \$38.4m annual savings.
- Identified and performed due diligence on emerging technology companies for investment or potential purchase in support of Amazon's Climate Pledge and new technology funds.

## Panel C: Unspecific DEI Addition

*The individual was employed at Autodesk from January 2016 to January 2018 and edited the job description on May 12, 2025. No named entities were detected in the added text.*

### Previous job description (Autodesk):

- Closely partnered with global client group leadership to align the team vision with business and corporate strategy.
- Recommended and implemented improvements to organizational structure, compensation philosophy, and performance standards within teams.
- Facilitated change using collaboration and diagnostic tools to drive growth and development.

### After editing job description (Autodesk):

- [Increased inclusion and collaboration](#) by aligning client group vision with business and corporate strategy.
- Took full-cycle ownership over global client group HR initiatives, including performance calibration, talent reviews, focal compensation review, [equity programs](#), and engagement strategy.
- Optimized change management processes and performance transparency by collaborating with leaders to identify and remove obstacles and measure impact.

## Panel D: Specific DEI Addition

*The individual was employed at Cisco from May 2015 to July 2018 and edited the job description on January 28, 2020. spaCy detected eight named entities in the added text, including **GPE** (San Jose), **DATE** entities (2017, annual), and **CARDINAL** entities (400, 2).*

### Previous job description (Cisco):

- Provided customers with technical support for ACI, including diagnosing, troubleshooting, analyzing, recreating, and resolving software and hardware problems.
- Collaborated with other team members, cross-technology teams, and engineering team to resolve complex problems more efficiently and effectively.
- Created internal and external configuration, troubleshooting, and process guides.
- Mentored and trained new team members.

### After editing job description (Cisco):

- Provided customers with technical support for ACI, including diagnosing, troubleshooting, analyzing, recreating, and resolving software and hardware problems.
- Collaborated with other team members, cross-technology teams, and engineering team to resolve complex problems more efficiently and effectively.
- Created internal and external configuration, troubleshooting, and process guides.
- Mentored and trained new team members.
- [Served as Women of Impact San Jose site co-lead from November 2016 to March 2017.](#)
- [Coordinated and executed Cisco's annual global Women of Impact event for over 400 guests, including catering, decorations, management, registration, agenda, and networking activities.](#)

## IA.VII. Specific and Unspecific ESG Additions by Political Affiliation and Political Cycles

Table IA.1: **Political Affiliation, Political Cycles, and Specific/Unspecific ESG Additions**

This table reports how workers' political ideology affects their addition of specific and unspecific ESG descriptions on workers' résumés under different political regimes. Panel A reports results regarding specific and unspecific additions by workers' political leaning, while Panel B reports how such additions vary across political regimes. *Add Unspecific ESG* is an indicator (multiplied by 100) for whether the worker added an ESG description to a historical job entry that lacks concrete tasks, deliverables, or measurable outcomes; *Add Specific ESG* indicates additions that have such contents. Columns (1) and (2) define specificity based on a large language model (LLM) and Columns (3) and (4) define specificity based on named-entity recognition (NER). *Democratic* and *Republican* are indicators for the worker's L2-identified political party. Workers that are identified as nonpartisan or affiliated with other parties are the omitted category. *Biden* is an indicator for years under Biden's presidency. All specifications include firm-MSA-occupation-year and gender-race-education-year fixed effects. See Appendix A for variable definitions. Standard errors are reported in parentheses and are heteroskedasticity robust and double clustered by industry and state. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

**Panel A: Political Affiliation**

| Dep. Var.:<br>Definition of Specific: | (1)<br><i>Add Unspecific ESG</i> (%)<br>LLM | (2)<br><i>Add Specific ESG</i> (%)<br>LLM | (3)<br><i>Add Unspecific ESG</i> (%)<br>NER | (4)<br><i>Add Specific ESG</i> (%)<br>NER |
|---------------------------------------|---------------------------------------------|-------------------------------------------|---------------------------------------------|-------------------------------------------|
| <i>Democratic</i>                     | 0.026***<br>(0.009)                         | 0.076***<br>(0.012)                       | 0.033***<br>(0.010)                         | 0.069***<br>(0.012)                       |
| <i>Republican</i>                     | -0.074***<br>(0.009)                        | -0.058***<br>(0.010)                      | -0.075***<br>(0.009)                        | -0.060***<br>(0.013)                      |
| Firm-MSA-Occupation-Year FE           | Yes                                         | Yes                                       | Yes                                         | Yes                                       |
| Gender-Race-Education-Year FE         | Yes                                         | Yes                                       | Yes                                         | Yes                                       |
| Observations                          | 5,046,566                                   | 5,046,566                                 | 5,046,566                                   | 5,046,566                                 |
| $R^2$                                 | 0.145                                       | 0.143                                     | 0.145                                       | 0.146                                     |

Panel B: Political Cycle

| Dep. Var.:<br>Definition of Specific: | (1)<br><i>Add Unspecific ESG (%)</i><br>LLM | (2)<br><i>Add Specific ESG (%)</i><br>LLM | (3)<br><i>Add Unspecific ESG (%)</i><br>NER | (4)<br><i>Add Specific ESG (%)</i><br>NER |
|---------------------------------------|---------------------------------------------|-------------------------------------------|---------------------------------------------|-------------------------------------------|
| <i>Democratic</i>                     | 0.012<br>(0.009)                            | 0.018<br>(0.019)                          | 0.011<br>(0.011)                            | 0.019<br>(0.014)                          |
| <i>Republican</i>                     | -0.029***<br>(0.010)                        | -0.026*<br>(0.016)                        | -0.037***<br>(0.011)                        | -0.022<br>(0.019)                         |
| <i>Democratic</i> × <i>Biden</i>      | 0.021**<br>(0.010)                          | 0.087***<br>(0.016)                       | 0.033***<br>(0.012)                         | 0.075***<br>(0.015)                       |
| <i>Republican</i> × <i>Biden</i>      | -0.069***<br>(0.011)                        | -0.049***<br>(0.013)                      | -0.058***<br>(0.011)                        | -0.059***<br>(0.022)                      |
| Firm-MSA-Occupation-Year FE           | Yes                                         | Yes                                       | Yes                                         | Yes                                       |
| Gender-Race-Education-Year FE         | Yes                                         | Yes                                       | Yes                                         | Yes                                       |
| Observations                          | 5,046,566                                   | 5,046,566                                 | 5,046,566                                   | 5,046,566                                 |
| $R^2$                                 | 0.145                                       | 0.145                                     | 0.143                                       | 0.146                                     |