When Values Align: Corporate Philanthropy and Employee Turnover*

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Abstract

We study how corporate philanthropy affects employee retention and productivity, using comprehensive resume data from a popular professional networking website. Using large natural disasters as shocks to the demand for disaster relief to identify exogenous variation in corporate charitable giving, we show that corporate philanthropy significantly reduces employee turnover by 5.9% to 7.8%. The effect is distinct from other CSR activities, and more pronounced for employees with volunteering experience and for female and younger employees, even within the same firm and year. Our findings indicate that an alignment in values between workers and firms can increase employee commitment.

Key Words: CSR, Philanthropy, Employee Retention, Labor Supply, Human Capital
JEL Codes: J22, J24, J28

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1 Introduction

In today's knowledge economy, human capital is among the most important factors for the production of goods and services (Kahle and Stulz, 2017), and the ability to attract and retain talented employees is a key driver of firm value (Belo, Li, Lin, and Zhao, 2017). Both anecdotal evidence and economic theory (Besley and Ghatak, 2005; Bénabou and Tirole, 2006) suggest that shared social values between employers and employees are important for attracting and motivating talent. For example, a recent PWC survey found that 59% of CEOs believe that "top talent prefers to work for organizations with social values which are aligned to their own."[1] Nonetheless, empirical evidence on the role of social values for employee retention and motivation is scant.[2]

Our paper addresses this question by examining the role of *value alignment* – i.e., the overlap in values between employees and their employers – for the career decisions of individual employees. We study this question in the context of corporate charitable donations using comprehensive resume data for 1.6 million unique U.S. employees from LinkedIn. The high granularity of this data allows us to track the careers of individual employees and observe experiences and revealed preferences at the person-level. Our main contribution is to show that corporate pro-social activities – i.e., corporate donations to charitable causes – *reduce* the likelihood of employee turnover, particularly for individuals with higher pro-social preferences, even within the same firm and year.

Charitable giving represents a substantial part of firms' total CSR activities and provides an ideal laboratory for our research question.[3] In contrast to other CSR activities such as workplace safety, childcare, or emissions reductions programs, contributions to charitable organizations do not have tangible pecuniary or non-pecuniary benefits to employees, but can

[1] https://www.pwc.com/gr/en/publications/19th-annual-global-ceo-survey-main-report.pdf

[2] Existing research focuses mostly on the effects of CSR-related benefits, such as family friendliness and employee well-being, on firm performance (Edmans, 2011; Bloom, Kretschmer, and Van Reenen, 2011; Edmans, Li, and Zhang, 2014; Huang, Li, Meschke, and Guthrie, 2015; Chen, Chen, Hsu, and Podolski, 2016).

[3] Charitable giving by corporations totaled $21.09 billion in 2019 in the U.S.: https://bit.ly/3uvgbIS.

be directly observed and quantified. Intuitively, every dollar spent on philanthropy reduces a firm's available resources that could otherwise be used to benefit employees or shareholders directly. If employees primarily care about their compensation and non-pecuniary benefits, firms' contributions to charitable causes might hence lead to higher employee turnover. Consistent with this *agency conflict perspective*, Masulis and Reza (2015), Krüger (2015), and Cai, Xu, and Yang (2021) document negative stock price reactions to the announcement of corporate charitable grants.

In contrast, economic theory argues that an organizational mission that is aligned with employee values can help attract and motivate employees (Besley and Ghatak, 2005). For example, Prendergast (2007) and Jones, Willness, and Madey (2014) present models in which corporate philanthropy allows employees to associate themselves with a "good" organization, hence fostering a greater sense of purpose, commitment, and pride. In a recent survey, 83% of respondents stated that they would be "more loyal to a company that helps them contribute to social and environmental issues."[4] This notion, which we dub the *value alignment perspective*, is supported by laboratory experiments in psychology and organizational behavior.[5]

Disentangling the effect of charitable donations from other CSR activities is empirically challenging, as both activities are endogenously determined and likely correlated. For example, a CEO who establishes a corporate charitable foundation might be more likely to also invest in corporate childcare programs. Further, high-growth firms who hire and retain more employees might have better financial resources to donate to charity and also improve working conditions. Consequently, prior research on the effect of corporate philanthropy on employee behavior has been limited to surveys (Carnahan, Kryscynski, and Olson, 2017), laboratory experiments (Tonin and Vlassopoulos, 2015; Burbano, 2016; Jones et al., 2014; Cassar, 2019), and small sample correlational studies (Turban and Greening, 1997; Albinger and Freeman, 2000).

[4] See `https://bit.ly/3Cxnxif` and `https://bit.ly/3wOHgbE`. Similarly, in a review on Glassdoor.com, an employee of the Hertz Corporation writes "I am very pleased that we are taking a more active role in our communities and in the world, for example 2 for 1 matching of money donated to Haiti."

[5] See for example Meglino and Ravlin (1998), Podsakoff, MacKenzie, Paine, and Bachrach (2000) and Edwards and Cable (2009) for a summary of the literature.

We overcome these challenges by using large-scale natural disasters abroad as exogenous shocks to the demand for disaster relief and corporate philanthropy, that is plausibly unrelated to other CSR activities and firm choices. The literature has documented that natural disasters – which by their nature cannot be anticipated – induce large increases in corporate charitable contributions (Muller and Kräussl, 2011; Tilcsik and Marquis, 2013; Ballesteros, Useem, and Wry, 2017; Choi, Park, and Xu, 2023; Liang and Vansteenkiste, 2023).[6] At the same time, there are strong internal frictions, such as the approval of large non-operational expenditures, and administrative frictions, e.g. IRS tax-exemption waiting periods, that can prevent firms from contributing to disaster relief efforts (Ballesteros, Useem, and Wry, 2020). Consequently, firms without corporate charitable foundations are constrained in their ability to give to philanthropic causes in the wake of a disaster. We use the random timing of disaster events in combination with the pre-existence of corporate foundations as a Difference-in-Differences (DiD) instrument for corporate charitable contributions in a two-stage least-squares (2SLS) "DiD shock-IV" design following Atanasov and Black (2016, 2021).

Intuitively, this empirical design uses a DiD specification to instrument for corporate charitable donations, and regresses employee career outcomes on instrumented corporate donations to estimate a local average treatment effect of charitable grants. Importantly, this identification strategy does *not* rely on the assumption that firms with- and without foundations are identical across other dimensions, or the exclusion restriction that foreign disasters do not affect firms in other ways, but rather on the parallel trends assumption: In the absence of a foreign disaster, the trends in charitable donations of treated and control firms would have remained on the same trajectory, and changes in employee turnover are affected by corporate charitable giving only through the $\mathbb{1}(Treated) \times \mathbb{1}(Post)$ *interaction* term.

Our sample combines data on corporate foundations from the Foundation Directory

[6]We confirm that this is also the case in our sample of firms and disaster events. We explicitly focus on disasters that occurred in remote areas without direct economic links to the sample firms or a direct impact on our sample of U.S.-based employees.

Online (FDO) and charitable donations from the National Center for Charitable Statistics (NCCS) with employee career transitions, education history, personal activities and preferences such as volunteering experiences, and job qualifications from LinkedIn.com for the period from 2000 to 2014. We focus on the three most deadly natural disasters in our sample period – the 2004 Indian Ocean earthquake and tsunami, the 2008 earthquake in Sichuan Province (China), and the 2010 Haiti earthquake.

We estimate a significant, negative effect of charitable donations on the likelihood of employee turnover. Our results indicate a decrease in turnover probability of 0.77 to 1.04 percentage points, which is equivalent to 5.9% to 7.8% relative to the sample mean, after the occurrence of natural disasters for treated compared to control firms in our DiD specifications. Using the "shock-IV" design, we confirm that changes in charitable contributions are a direct channel for reducing turnover: we estimate a turnover-to-contributions sensitivity of -0.23. For comparison, the labor economics literature documents a turnover-to-wage sensitivity of -2 to -5 (e.g. Bassier, Dube, and Naidu, 2020). This finding is consistent with the value alignment perspective, i.e., the notion that employees consider firms' pro-social activities when making career decisions. Our results remain robust using logit and probit estimators, and after controlling for employee-level (age, gender, education) and firm-level (e.g., financial constraints, size, age, profitability) characteristics, and firm-by-event, year-by-industry, and employee-by-event fixed effects.[7]

The value alignment hypothesis implies that employees with higher pro-social values will align more closely with firms that engage in corporate pro-social activities (Gneezy, Meier, and Rey-Biel, 2011; Prendergast, 2007). Our next set of tests directly examines this idea by focusing on differences in personal attributes and characteristics across individual employees. We begin by collecting person-level information on the volunteering experiences of the 1.6 million unique employees in our sample from LinkedIn. We consider personal volunteering

[7]Our stacked-regression design also ensures that our results are robust to issues with two-way fixed effects (TWFE) specifications in staggered DiD designs as highlighted by Baker, Larcker, and Wang (2022).

experience as a proxy for revealed preferences towards pro-social activities: all else equal, an employee who chooses to donate their time and volunteer for a social cause is expected to have a closer alignment with corporate pro-social activities. In line with this conjecture, we find a significantly stronger effect of corporate charitable donations in the subsample of employees with volunteering experience. The sensitivity of turnover to corporate donations is approximately 1.1 to 1.5 times larger in this subsample of employees with a revealed 'pro-social' preference. This difference is present in both DiD and Shock-IV estimations, and holds when including our most stringent set of fixed effects.

Next, we consider employee gender. Existing research has documented that women on average have stronger preferences for equality, fairness, and corporate social responsibility (e.g., Rand, Brescoll, Everett, Capraro, and Barcelo, 2016). Consistent with this notion, our main effect is 4.9 to 6.6% larger among female relative to male employees, which is a smaller difference compared to the revealed pro-social preferences inferred from volunteering experiences. Further, anecdotes and surveys suggest that an employer's social values are particularly important for the career decisions of young workers.[8] Indeed, we find a substantially larger effect among employees of the 'millennial' generation compared to 'Gen X' employees. In addition, we use firm-level employee review data from Glassdoor.com and measures of labor productivity to document that CEO approval, employee satisfaction, and operating profits per employee increase in response to higher charitable contributions.

Importantly, our findings are inconsistent with alternative explanations related to firm performance or other types of CSR activities. For example, one might be concerned that firms use charitable donations as a signal of financial strength, and that employees primarily react to this signal. However, this interpretation is inconsistent with our cross-sectional evidence at the person-level comparing employees *within the same firm*. If our results were driven by such a signal, we would instead expect employees at the same firm to respond similarly on

[8] E.g., https://www.conecomm.com/research-blog/2016-millennial-employee-engagement-study.

average.[9] To further support this interpretation, we implement triple-difference estimations with firm-by-year fixed effects, ruling out any alternative explanations related to time-varying firm characteristics. Similarly, our tests do *not* reveal a bump in firm sales, employment, sales, investment, or R&D expenses in response to increases in donations. Further, we find no evidence of positive short-term abnormal returns around the announcement of charitable contributions for both charitable donations in general (negative CARs) and disaster-related contributions specifically (zero CARs).

Last, to address potential concerns about self-reported data on LinkedIn.com and external validity, we validate our findings with employee turnover data from an alternative data source. We match corporate inventors to their employers using the patent database of Kogan, Papanikolaou, Seru, and Stoffman (2017), allowing us to track the careers of 400,000 inventors based on their patenting activity. We estimate similar results on both turnover sensitivity, cross-sectional patterns, and labor productivity using individual patent filings compared to our main results.

Our main contribution is to provide empirical evidence that an alignment in social values between employees and their employers can improve the retention and productivity of individual employees, particularly for workers with pro-social preferences and high human capital. Previous research, e.g., Prendergast (2007), has proposed theoretical models in which an overlap in values held by employees and their employers is important for motivating public officials and employees at non-profit enterprises.[10] Our paper provides empirical evidence in line with this value alignment hypothesis using large and highly granular data of U.S. employees at the person-level. This complements the evidence from laboratory experiments presented by Imas (2014) and DellaVigna and Pope (2018), who document that a "warm glow" feeling can increase worker motivation.

Prior research in finance has primarily focused on employee satisfaction and firm-level

[9] We also find significantly stronger effects within the same firm-year among employees with better labor market opportunities and higher human capital, i.e., advanced and graduate degrees.

[10] See Gneezy et al. (2011) and Cassar and Meier (2018) for a summary of the literature.

outcomes. For example, Edmans (2011) finds that a portfolio of the "100 best companies to work for" generates an annual alpha of 3.5%, and Chen et al. (2016) and Fauver, McDonald, and Taboada (2018) document a positive effect of employee friendliness on innovation and Tobin's Q, respectively. While these papers focus on how firms "treat their workers" and examine firm-level outcomes, we explicitly focus on firm activities *without* pecuniary or non-pecuniary employee benefits and study person-level career outcomes.

Our paper is also related to Bode, Singh, and Rogan (2015), who find lower wage demands and higher employee retention in a field experiment with management consultants who participated in projects with non-profit organizations. Laboratory experiments (Tonin and Vlassopoulos, 2015; Gosnell, List, and Metcalfe, 2016; Cassar, 2019) indicate that charitable donations made on a worker's behalf can increase productivity, job satisfaction, and retention. Further, Krüger, Metzger, and Wu (2022) find that employees accept lower wages and are less likely to leave firms in more sustainable *industries* using administrative data from Scandinavia. In contrast to this existing literature, our paper uses a unique quasi-natural experiment in a large-scale sample of U.S. employees with person-level heterogeneity.

2 Data and Summary Statistics

In this section we describe our data sources, explain how we link the individual datasets, and provide summary statistics for our main sample. The summary statistics presented in Table 1 represent the full sample of firms over the period from 2000 to 2014. Throughout the paper, we provide relevant summary statistics and details in the context of the respective tests.

2.1 Corporate Philanthropy

We obtain data on philanthropic giving from the Urban Institute's National Center for Charitable Statistics (NCCS), and use the Foundation Directory Online (FDO) database to link foundations recorded by the NCCS to public corporations. The NCCS provides annual

IRS Return Transaction Files (RTFs) that contain financial data for all private foundations (PFs) and public charities (PCs) that file IRS Forms 990, 990-EZ, or 990-PF.

Identifying corporations and their respective philanthropies is challenging. For example, Abbott Laboratories (ABT) has two philanthropic organizations, 'Abbott Laboratories Corporate Giving' and 'Abbott Fund'. However, text-matching based on firm and foundation names would incorrectly also associate other foundations such as the 'Abbott Foundation' and the 'Abbott Family Foundation' – which are unrelated – with the company. To ensure an accurate link of philanthropic organizations with publicly traded firms, we rely on the Foundation Directory Online (FDO). FDO, an online database of over 235,000 U.S. grantmakers, carefully researches philanthropic organizations associated with corporations, solicits direct giving dollar amounts, and provides their individual Employer Identification Numbers (EINs). We hand-collect the identity of each grantmaking organization associated with the public firms in our sample from FDO, and match them to their annual charitable donations from the NCCS database via EINs.

Firms often operate several types of grant-making organizations, such as corporate direct giving programs, private foundations (PF), and public charities (PC). Corporate direct giving programs and company-sponsored PFs are funded by firms directly, whereas PCs receive a majority of their funds from public contributions. To avoid selection issues associated with firms' abilities to solicit donations from the public, we exclude PCs from our analysis and obtain the total amount of charitable giving (in $M.) for each PF from NCCS. Since the NCCS data does not include donations from corporate direct giving programs as they are exempt from IRS filing requirements, we supplement NCCS donations data with direct corporate giving amounts from FDO, following Akey, Lewellen, Liskovich, and Schiller (2021).

2.2 Employee Job Movement and Resumes

To track the job movement of employees we rely on resume data from LinkedIn.com, the largest online job networking website in the world. LinkedIn has approximately 199 million users in the United States. These users have an incentive to keep their profiles up to date as the site is a valuable tool for professional networking.[11] We start with a sample of 34 million LinkedIn profiles that were collected during 2021 and 2022 and merge the names of employers provided in LinkedIn profiles to the firms in our sample. This procedure yields a total of 3,213,401 unique individuals who are associated with publicly listed firms between 2000 and 2014, comprising a sample of 37,796,747 employee-year observations. In some of our tests in Section 4, we require employees to be present in both the pre- and post-sample periods around a given event. This reduces the sample size to 1,581,606 unique individuals representing 20,361,040 employee-year observations.

Our main variable of interest, '$\mathbb{1}$(Employee Exit)', is an indicator variable set to one in employee's last year at their current employer, and zero otherwise. For employees who list starting and ending months, we follow the literature and differentiate between voluntary and involuntary turnover by using the time between an employee's previous and new employment. We also use profile data to obtain the following individual characteristics: gender, educational attainment (i.e., degree type and graduation year), job title, and volunteering experience. To determine an employee's gender, we use the Damegender database, which provides name classifications based on data from the statistical offices of twenty-four countries that have a combined population of 666 million individuals. We classify an employee as female (male) if the probability of the individual being female (male) for a given name is greater than or equal to 95% (less than or equal to 5%).

[11] Analysis from LinkedIn shows that 40 million people search for jobs every week on the platform. In addition, comprehensive profiles have a 71% higher chance of getting an interview.

2.3 Corporate Social Responsibility

We obtain corporate social responsibility (CSR) scores from the widely-used MSCI ESG KLD Stats (KLD) database. To calculate a firm's CSR score, MSCI determines the presence or absence of "strengths" or "concerns" within a firm across several dimensions of CSR: community relations, product characteristics, environmental impact, employee relations, diversity, and governance. The overall score as well as each category score is an index that equals the number of strengths minus the number of concerns. Since KLD changed the methodology and data items used to construct the KLD CSR score several times throughout our sample period, we follow Akey et al. (2021) and identify data items that covered the same issues but changed names over time, and retain only data items that were covered throughout our full sample period.

2.4 Employee Reviews

We obtain data on employee reviews from Glassdoor.com, the most widely-used employee review website. Glassdoor's "give to get policy" requires users to provide employer reviews, salary information, and/or interview details before gaining access to the same information provided by other users. Individuals can rate their overall satisfaction with their employer, compensation & benefits, work-life balance, firm culture & values, career opportunities, and senior management on a five-point scale as well as express their opinion on the firm's business outlook and CEO approval.

Due to a lack of company identifiers, we rely on name matching to identify reviews associated with firms in our sample. We are able to obtain 592,384 employee reviews for 592 firms from 2008 to 2017. Our main variables of interest are the average overall employee satisfaction and CEO approval ratings for each firm-year.[12] To avoid ambiguity regarding which CEO is being reviewed we exclude reviews from employees working for subsidiaries.

[12] Data availability issues prevent us from using reviews on firm culture & values and business outlook, as Glassdoor did not ask these questions until 2012, two years after our latest disaster event.

2.5 Financial and Accounting Data

Financial and accounting data are from CRSP and Compustat, including total employment, the natural log of market capitalization, operating profitability, sales, R&D, SG&A, Capx, market leverage, M/B, ROA, cash flow, and the Whited and Wu (2006) (WW) index of financial constraints. To control for outliers, we winsorize all firm financial variables at the 5% level within the full Compustat universe.

2.6 Summary Statistics

Panel 1a of Table 1 provides summary statistics for our full sample of firms over the sample period from 1992 to 2016. The average sample firm in a given year has approximately 22,000 employees, $6 billion in assets, and an overall CSR score of 0.57. Sample firms on average contribute approximately $0.59 million dollars to philanthropic causes when including years without donations and $3.86 million conditional on making a charitable donation. As shown in Figure 1, the distribution of annual charitable donations is highly skewed, with many firms donating between $50 and $150 million dollars in some sample years.

[Insert Table 1 and Figure 1 here.]

Table 1b provides summary statistics for our full sample of employee-year observations. The unconditional likelihood of employee turnover in the sample is 13%, which is similar to the turnover rate in studies that use LinkedIn data (Jeffers, 2019; Gortmaker, Jeffers, and Lee, 2022). Approximately 37% of the sample-employees are female, about 11% list volunteering experience on their profile, 78% have an undergraduate degree, and 22% have a graduate degree. The mean age in our sample is 33 years, the mean tenure – i.e., the number of years in the current job – is 4.5 years.

Panel 1c of Table 1 presents the industry breakdown of philanthropic firms within our sample. Of the 2,209 unique firms in our study, approximately 25% initiate some form of charitable giving during the sample period. The industries with the highest concentration of philanthropic firms includes automobile & automobile component manufacturers, utilities, and food retailers. Industries with the lowest concentration include real estate, software & services, and energy firms.

3 Empirical Approach

3.1 Identification Strategy

Our empirical setting uses the differential effect of large-scale natural disasters abroad on firms with and without pre-existing corporate foundations as a source of exogenous variation in corporate charitable donations. This setting has several advantages. First, donating to charitable causes in the wake of a deadly disaster is highly salient and closely aligned with the concept of pro-social firm actions that contribute to an organizational mission, in line with economic theory (Besley and Ghatak, 2005; Prendergast, 2007). At the same time, charitable donations earmarked for foreign disaster relief do not have pecuniary or non-pecuniary benefits for employees, in contrast to other CSR activities. Further, in contrast to policy or regulation changes studied in the literature, natural disasters are exogenous and cannot be anticipated by firms or employees.

We implement a "difference-in-difference (DiD) shock IV" design as proposed by Atanasov and Black (2016, 2021). Intuitively, this identification strategy uses a DiD design in the first stage as an instrument for corporate charitable donations, and estimates the effect of *instrumented* charitable giving on employee turnover in the second stage. Importantly, this design does not require that firms with- and without corporate foundations are similar along all other dimensions (i.e., random assignment), or that natural disasters abroad affect firms through no channels other than charitable donations. Instead, we are relying on the parallel trends assumption that absent the occurrence of foreign disasters the charitable giving of treated and control firms would have remained on the pre-treatment trajectory, and the exclusion restriction that outside of charitable donations, foreign disasters have no *differential* effect on treated and control firms. Our *instrument* for charitable giving in this setting is hence the *interaction term* of $\mathbb{1}(Post\ Disaster)$ and $\mathbb{1}(Treated\ Firm)$.

These assumptions are supported by the previous literature and our data. Among others, Muller and Kräussl (2011), Tilcsik and Marquis (2013), Ballesteros et al. (2017), Choi et al. (2023), and Liang and Vansteenkiste (2023) show that natural disasters are a key driver of corporate charitable donations and represent a growing share of all disaster aid. Figures 2a and 2b plot the annual number of deaths due to natural disasters and the median annual corporate donations and disaster-related donations in our sample period. In support of the relevance criterion, both figures show that the three events accounted for the majority of total disaster casualties in our sample period, and were each followed by a visible spike in median charitable grants and disaster-related grants by our sample firms. We provide direct evidence for the relevance of foreign disasters for corporate charitable giving by U.S. firms in our sample in Section 4.1.

To address concerns that disasters may directly affect individual employees or firms' economic activities and resources, we focus on events that occurred in regions without direct economic links to our sample firms.[13] Specifically, we study the three natural disasters with the highest number of casualties in our sample period, i.e., the 2004 Indian Ocean earthquake and tsunami (166k casualties), the 2008 earthquake in Sichuan Province (China) (87k casualties), and the 2010 earthquake in Haiti (223k casualties)[14]. In robustness tests, we explicitly rule out that our sample firms are directly exposed to these events for example through their foreign operations or international supply-chains.

Further, Ballesteros et al. (2020), among others, document that efficient corporate contributions to disaster relief require a grantmaking infrastructure within a company, such

[13] Choi et al. (2023) find that banks strategically direct disaster relief aid to counties with existing bank branches. In contrast, we focus on U.S.-based employees and international disasters to avoid any direct links.

[14] Event dates, casualties, and damages are obtained from the EM-DAT (2020) Emergency Events Database.

as a corporate charitable foundation or giving program, with expertise and well-established relationships to disaster relief organizations. In addition to such internal frictions, firms face external frictions, for example when setting up a corporate foundation. The average waiting period to receive tax-exempt status for a private foundation for firms in our sample is 9.6 months from a foundation's inception to the receipt of the IRS determination letter.[15]

In support of this idea, Figure 3 plots the number of newly established private foundations by our sample firms against the number of disaster casualties over the sample period. We find no evidence that firms respond to natural disasters by starting new corporate foundations, consistent with the presence of significant frictions in setting up a corporate charitable organization. In fact, we observe lower rates of new private foundation starts in the years 2009 to 2012, i.e., after two of our main disasters, compared to the earlier sample period.

3.2 Matching

To further address concerns that firms with corporate foundations may be affected by foreign disasters differentially from control firms in ways that are correlated with charitable giving and employee turnover over time, we construct a sample of treated and matched control firms for each disaster event using propensity score matching (PSM) based on pre-event characteristics.

Firms are considered to be treated if they made at least one charitable contribution through an associated private foundation in the four years before the occurrence of a major natural disaster, and untreated otherwise. Specifically, within each natural disaster event, we implement $k = 10$ nearest neighbor matching with replacement, by matching on the following firm-level covariates observed during the four years before the disaster occurrence: number

[15]IRS rules require that foundations file returns once they are established, even if they do not make donations or are not tax-exempt. This allows us to manually inspect all initial returns submitted by the foundations in our sample to determine the waiting time until receiving tax-exempt status. During this waiting period firms can make contributions through their foundations and retroactively claim deductions once their tax exempt status is granted, but risk losing these deductions if their application is denied.

of employees, number of patents, CSR (standardized KLD score), market capitalization, book value of assets, market leverage, cash flows, profitability (ROA), growth opportunities (i.e., log(1+M/B)), and financial constraints (WW Index). We ensure common support and pre-treatment balance by removing observations outside of a caliper of 0.05 of the propensity score (Atanasov and Black, 2021).

Figure 4 and Appendix Table A.1 document the covariates balance pre- and post matching. As shown in Figure 4, while firms with corporate foundations are generally larger, employ more workers, and have higher profitability and CSR scores than the universe of Compustat firms, there are no significant differences in observable firm characteristics between treated and control firms in the matched sample. As shown in Panels A.1a and A.1b in the Appendix, both mean and variance as well as the overall distribution (i.e., empirical CDF) of the covariates are statistically indistinguishable across the two groups.

We retain four years of observations for treated and control firms before and after each event to create a balanced sample of pre- and post-event observations. To ensure that employee-level job transitions are captured accurately, we only retain individuals who were present in the pre- and the post-period of each event.

3.3 Main Specification

We estimate DiD and "shock-IV" regressions to identify the effects of corporate philanthropy on firm and employee outcomes. The data is organized at the firm- and employee-year level for firm and turnover regressions, respectively, by stacking four pre- and post-observations around each event. Our DiD tests take the following form:

$$\begin{aligned} y_{ifet} = {} & \beta \times Post\ \text{1-4}_{et} \times \mathbb{1}(Treated)_{fe} \\ & + \Gamma \cdot X_{iet} + \Psi \cdot X_{fet} + \delta_{ie} + \gamma_{fe} + \theta_{te} + \omega_{j(f)et} + \epsilon_{ifet} \end{aligned} \tag{1}$$

where y_{ifet} measures employee-level outcomes such as turnover of employee i or firm-level outcomes such as donations and CSR performance of firm f in event-year t of event e. X_{fet} is a vector of time-varying firm characteristics, including firm size, leverage, cash flows, ROA, market-to-book ratio, and the Whited and Wu (2006) index of financial constraints. We include industry (4-digit GICS)-by-year ($\omega_{j(f)et}$) and event-time fixed effects (θ_{te}), which indicate the year relative to event e. We also include firm-by-event fixed effects (γ_{fe}) and firm-by-event-by-CEO fixed effects in our most stringent specifications, which eliminates any time-invariant firm or CEO characteristics. This further helps us address concerns that our results are driven by unobserved factors.[16] Employee-level regressions further include additional controls for individual characteristics (X_{iet}), such as age, education level, gender, and tenure, and employee-by-event fixed effects (δ_{ie}). Our estimates therefore stem from within-employee variation across time.

The indicator variable $Post$ 1-4_{et} takes the value of one in the four years after each respective event, and zero otherwise, and $\mathbb{1}(Treated)_{fe}$ indicates treated firms, i.e., firms that made a charitable donation through an associated private foundation in the four years before event e. Hence, our main coefficient of interest, β, captures the difference-in-difference effect on treated relative to control firms around natural disasters. The coefficient for $\mathbb{1}(Treated)_{fe}$ is subsumed by the inclusion of firm-by-event fixed effects (γ_{fe}), and the coefficient for $Post$ 1-4_{et} is subsumed by the inclusion of relative event-time fixed effects (θ_{et}). Robust standard errors are clustered at the level of treatment variation, i.e., the firm level.

To identify how shocks affect employee turnover *through* corporate charitable donations, we implement a shock-IV design (Atanasov and Black, 2016, 2021). This design uses the DiD specification in Equation (1) to instrument for corporate donations in the first stage, and regresses employee turnover on the instrumented value in the second stage to estimate the local average treatment effect (LATE) of charitable donations. The second stage takes the

[16]We interact time, firm, and employee fixed effects with event (i.e., disaster) fixed effects, since firms can switch from control to treated group across disaster events.

following form:

$$\mathbb{1}(Employee\ Exit)_{ifet} = \beta \times \widehat{Charitable\ Grants}_{fet} + \Gamma \cdot X_{iet} + \Psi \cdot X_{fet} + \delta_{ie} + \gamma_{fe} + \theta_{et} + \omega_{j(f)et} + \epsilon_{ifet} \tag{2}$$

where $\mathbb{1}(Employee\ Exit)_{ifet}$ is an indicator variable that takes the value of one if employee i exits firm f after year t around event e, and zero otherwise, $\widehat{Charitable\ Grants}_{ifet}$ is the instrumented value of charitable donations from the first stage regression, and all other variables and fixed effects are defined as in Equation (1). While the standard DiD approach as specified in Equation (1) is an "intent-to-treat" design, estimating the average effect on all firms exposed to the shock, the shock-IV design specified in Equation (2) requires a specific channel – i.e., charitable donations – and provides an estimate only for compliers, i.e., treated firms whose behavior changed after the shock.

4 Corporate Philanthropy and Employee Turnover

4.1 Natural Disasters and Charitable Contributions

Before turning to employee turnover in our main tests, we begin by examining the relevance of the large-scale foreign disasters for the charitable giving behavior of U.S. firms. To this end, we estimate Equation (1) at the firm-year level, using charitable donations ($M) as the dependent variable y_{ifet} in Table 2.

[Insert Table 2 here.]

We find that the occurrence of a natural disaster has a significant, positive effect on the charitable donations of firms with pre-existing philanthropic organizations. The documented effect is economically large. The estimates for $Post\ 1\text{-}4_{et} \times \mathbb{1}(Treated)_{fet}$ in columns (1) and (2) indicate that philanthropic grants of treated firms with foundations increase by $548k to

$672K per year after a natural disaster relative to the control sample. This is equivalent to an increase by about 17% relative to the sample average of $3.89M (conditional on making philanthropic grants). The results are similar using log-transformed charitable grants in columns (3) and (4), corresponding to an increase in grants between 13.95% and 11.19%. This finding is consistent with the literature (Muller and Kräussl, 2011; Tilcsik and Marquis, 2013; Ballesteros et al., 2017) and Figure 2, and indicates that natural disasters are a key driver of corporate charitable donations.[17]

4.2 Employee-level Job Turnover

Next, we present our main results on the effect of natural disasters abroad and charitable donations on employee turnover. For this purpose, we estimate the models in Equations (1) and (2) at the employee-year level, using $\mathbb{1}(\text{Employee Exit})_{ifet}$ as the main dependent variable.

[Insert Table 3 here.]

Panel 3a presents the results for the DiD specification in Equation (1) at the employee-year level. Across all specifications, we find a negative treatment effect of natural disaster occurrence on the likelihood of employee exit for treated firms with pre-existing charitable organizations. The effect is both statistically and economically significant. The likelihood of employee turnover decreases between 0.77 and 1.04 percentage points across specifications, which is equivalent to 5.9% to 8.0% relative to the sample mean of 13%.[18] This result holds after including employee-by-event and firm-by-CEO-by-event fixed effects controlling for any time-invariant employee and firm characteristics, along with employee-level controls for education, career length, and gender. By including firm-by-CEO-by-event fixed effects, we

[17] With the exception of firm size we do not find any significant patterns with respect to our control variables, supporting the idea that our sample is well-balanced along observable covariates.

[18] We find similar results using logit and probit models (Appendix Table A.4), as explained in Section 4.4.3.

ensure that our results are not driven by time-invariant firm characteristics, CEO preferences, or their interactions.

Figure 5 shows the corresponding dynamic effect, plotting the coefficient estimates of $\mathbb{1}(\text{Employee Exit})_{ifet}$ on event-time dummy variables interacted with an indicator for treated firms, controlling for fixed effects and covariates. We find no discernible pre-trend in employee turnover likelihood. The plotted coefficient is flat and indistinguishable from zero, with narrow confidence intervals in periods $t = -4$ to $t = -1$, drops significantly below zero for treated firms in period $t = 1$ as treated firms increase their philanthropic contributions after natural disasters, and remains below pre-event levels in the following years.

Next, we estimate 'shock-IV' tests to pin down charitable donations as the channel for our results. Panel 3b documents the results of estimating Equation (2), summarizing the first (columns 1 and 3) and second stage regressions (columns 2 and 4), respectively. Similar to Table 2, we first document a significant, positive first-stage effect of disaster occurrence on treated firms' charitable donations in column (1).[19] The effect is virtually unchanged when including employee-by-event fixed effects in column (3). Consistent with the evidence presented in Table 2, the DiD parameter 'Post 1-4 $\times$ $\mathbb{1}$(Had Foundation)' is a strong instrument for charitable donations: the Kleibergen–Paap Wald F statistic is well above standard critical values (Stock, Wright, and Yogo, 2002).

Our main result (columns 2 and 4) shows that instrumented charitable contributions have a negative effect on the likelihood of employee turnover. The effect is both statistically and economically significant, and holds after including high-dimensional fixed effects and controls for employee education and gender. The coefficient estimate for $log(\widehat{1 + Grants})$ of -0.0437 in column (2) indicates that an increase in charitable donations of 10% is associated with a 0.42 $(= 0.0437 * log(1.10))$ percentage point decrease in the likelihood of employee turnover in the current year. This is equivalent to a 3.2% reduction relative to the sample

[19]The coefficient estimates differ from Table 2 because Panel 3b is estimated at the employee-year level and Table 2 is estimated at the firm-year level.

mean. Equivalently, we find a turnover-to-donations sensitivity of approximately -0.23: when charitable donations double, the likelihood of turnover decreases by 23% relative to the sample mean ($= -0.0437 \times log(1+100\%)/0.13$). This is meaningful compared to the turnover-to-wages sensitivity of -2 to -5 documented in the labor economics literature (e.g., Bassier et al., 2020).

4.3 Voluntary and Involuntary Turnover

The value alignment hypothesis predicts that employees who hold strong pro-social values will align more closely with employers who display pro-social corporate values, increasing identification and loyalty to the company, and hence reducing employee turnover. Naturally, this prediction applies to voluntary but not involuntary employee turnover, i.e., when employees are terminated by their employers for business or personal performance reasons.

To test this conjecture, we follow the literature and differentiate between voluntary and involuntary employee by considering the time between two consecutive employments. Typically, an employee who chooses to voluntarily leave their current employer has already secured a new job to transition to, resulting in a short gap between the two consecutive employments. In contrast, an employee who is involuntarily terminated on average has a longer gap between jobs as they search for a new employment opportunity. We exploit the highly granular information provided by most LinkedIn profiles to measure the time between jobs in months, whenever available.

[Insert Table 4 here.]

The results, summarized in Table 4 show that our main result is driven by voluntary rather than involuntary employment turnover, in line with the value alignment hypothesis. Compared to the baseline estimates in column (1), the estimated coefficients are virtually identical in both magnitude and statistical significance when we restrict the sample to employment transitions with a maximum gap of 1, 2, or 3 months between consecutive jobs, as shown in columns (2), (3), and (4). In contrast, we find a smaller and statistically insignificant estimate when considering only involuntary turnover in column (5).[20]

4.4 Robustness and Alternative Explanations

4.4.1 CSR Performance

To address concerns that our result may be driven by simultaneous changes in CSR activities with direct benefits for employees, we add CSR performance scores across several categories (environment, community, human rights, employee relations, product, diversity, and governance from KLD) as additional controls in Appendix Table A.2. Each CSR score is measured with a lag of one year. Across all specifications we find similar coefficient estimates of our main explanatory variables as in our baseline results, both for the DiD design in Panel A.2a and the shock-IV design in Panel A.2b.[21]

4.4.2 Firms with Foreign Operations

Next, one might be concerned that U.S. firms with international operations may be directly affected by the natural disasters in our sample. In this case, our results may be driven by an omitted variable bias. To address this, we exclude firms which report earnings from operations based outside of the U.S. in Appendix Table A.3. Despite a significant reduction in sample size, the results are quantitatively and qualitatively similar to our main results.

4.4.3 Alternative Estimation Methods

Further, we implement our main test in Equation (1) as binary response models to test the robustness of our linear probability model to alternative estimation methods. The results are

[20] Note that our definition of involuntary turnover is conservative in column (5), considering every turnover with more than a 1 month gap between jobs as 'involuntary'.

[21] Further, contrary to the concern that simultaneous changes in employee treatment could be the main determinant of turnover, we find no relation between employee treatment and turnover in Panel A.2a, supporting the idea that our changes in charitable donations following natural disasters are not systematically correlated with other CSR activities.

presented in Appendix Table A.4. We continue to find similar results both when implementing Equation (1) as logit models (columns 1 and 2) and probit models (columns 3 and 4). The economic magnitude of our estimates is similar to the effect size estimated in Table 3. The likelihood of employee exit decreases by 5 to 9% across specifications for treated firms in the post-period, controlling for firm and employee characteristics and time-, year-by-industry-, and firm-CEO-by-event fixed effects.

4.4.4 Corporate Donations and Other Firm Outcomes

A potential threat to our identification is the possibility that corporate charitable contributions might increase firm performance, for example due to marketing and reputation benefits. Under this scenario, employees may interpret charitable donation announcements of their employers as a signal of better future employment conditions, which in turn may be driving employee turnover. We address this concern in three ways.

First, we hand-collect data on individual announcements of corporate charitable contributions related to natural disasters and other causes from RavenPack to study the market reaction to these announcements. In Appendix Table A.5, we estimate Cumulative Abnormal Returns (CARs) for the [-1;1] (Panel A.5a) and [-1;30] (Panel A.5b) day event window around these charitable contribution announcements. We find a small, negative CAR of -0.26% to -0.27% (significant at the 5% level) over the [-1;1] window for the full sample of charitable donations, and an insignificant CAR of -0.11% for charitable donations related specifically to natural disasters. These results are consistent with Masulis and Reza (2015) and indicate that markets, if anything, on average react *negatively* to firms' charitable contribution announcements, inconsistent with the concern that firms signal better future performance. The estimates do not show any significant CARs in the [-1;30] event window, further supporting this interpretation.

Second, we document that natural disasters abroad do not lead to changes in other firm policies and characteristics, by estimating Equation (2) using employee treatment scores (from KLD), employment, investment, R&D, SG&A, sales, and profitability as alternative outcome variables. The results, summarized in Appendix Table A.6, show no significant effect on the employee treatment dimension of CSR performance (column 1). Further, we find no significant effect on employment growth, tangible investment, intangible (intellectual and human capital) investment (i.e., R&D and SG&A) or financial performance (sales and profitability) in columns (2)–(7), indicating that our results on employee turnover are unlikely to be due to contemporaneous firm growth or investment.

Third, in the following Section 5 we estimate differential effects of instrumented charitable donations on employees with high and low revealed pro-social preferences. If the employees in our sample were primarily reacting to effects of charitable donations on future firm performance, such as an expected bump in sales or investments, we should not find differences across employees related to person-level characteristics. Using heterogeneity at the employee-level allows us to further include firm-by-year fixed effects, effectively ruling out explanations related to time-varying firm characteristics.

5 Value Alignment and Employee Turnover

Our results up to this point document that exogenous increases in corporate charitable donations promote employee retention, in line with the idea that some employees prefer to work at firms that engage in social activities without pecuniary or non-pecuniary employee benefits. While this interpretation rests on a revealed preferences argument, we explicitly explore the role of value alignment – i.e., an overlap in social preferences between employees and employers – in the following sections by considering individual employee characteristics. If our results are at least partially due to value alignment, we would expect to find stronger results for employees who have plausibly stronger preferences for pro-social activities.

5.1 Personal Volunteer Experiences

We begin by studying individuals' personal volunteering experiences as a salient proxy of revealed pro-social preferences. Everything else equal, we would expect employees who choose to donate their time and volunteer for a social cause to have a stronger preference for corporate pro-social activities.

To test this conjecture, we use information on volunteering experiences from individual profiles on LinkedIn.com. While LinkedIn profile data is self-reported and may be incomplete, an individual who chooses to write about their volunteering experience likely places a higher value on it, allowing us to identify employees with stronger pro-social preferences. We split our sample into employees with and without individual volunteering experience and re-estimate our main tests on the two subsamples separately. The results are presented in Panel 5a.

[Insert Table 5 here.]

Consistent with the value alignment hypothesis, we find a stronger negative effect of our main interaction term of interest, i.e., Post 1-4 $\times$ $\mathbb{1}$(Had Foundation), on the likelihood of employee turnover in the sample *with* volunteering experience (column 1) compared to the subsample without volunteering experience (column 2). The difference between coefficient estimates across the two subsamples is statistically significant at the 1% level and indicates that the effect is about 1.5x larger for employees with volunteering experience. We find similar economic magnitudes and differences between the two subsamples using the Shock-IV specification in columns (3) and (4), with the effect being 1.1x larger in the volunteer group.

Importantly, since our regressions include firm-by-disaster-event fixed effects, these results come from across-individuals within-firm variation. This further helps alleviate concerns that our results are due to employees anticipating stronger firm performance as a result of corporate donations, as employees within the same firm should react similarly in that case. In Appendix Table A.7, we alternatively implement our tests as triple-difference estimations across different proxies for pro-social preferences, which allows us to further include firm-by-year fixed effects. We continue to find similar results.[22]

5.2 Age

According to a recent survey, 75% of 'millennials' (vs. 55% average) – i.e., individuals born between 1981 and 1996 – would "take a smaller salary to work at a company more in alignment with their values" and 83% (vs. 70% U.S. average) would be "more loyal to a company that helps them contribute to social and environmental issues."[23] Other surveys find similar results, indicating that younger workers have a stronger preference for employers who reflect their personal values. If our results are driven by value alignment, we would therefore expect to see a stronger effect of corporate philanthropic contributions on the retention of younger relative to older workers.

Since we cannot directly observe an employee's age using LinkedIn profile data, we use the year they obtained their undergraduate degree while assuming an average graduation age of 22, as a proxy for their age. To control for biases resulting from the retirement of workers from the Baby Boomer generation, we compare the Millennial generation (born 1981-1996) to 'Gen X' generation (born 1965-1980), and estimate similar sample splits as in the previous panel.

Panel 5b summarizes the results. Consistent with the idea that younger individuals care more about social purpose, we estimate a stronger effect of instrumented charitable donations on employee turnover for younger workers. The effect is about 29% stronger in the younger compared to the older age subsample in the DiD setting, as shown in columns (1) and (2). We find a similar result using the shock-IV setting in columns (3) and (4): the point estimate for instrumented charitable contributions, $log(\widehat{1 + Grants})$, is about 57% higher in

[22]The triple-difference regressions do not allow us to use *instrumented* charitable donations. Hence, we rely on sample splits for our main person-level heterogeneity tests.

[23]See https://www.conecomm.com/research-blog/2016-millennial-employee-engagement-study.

the subsample of young employees. The difference is significant at the 1% level for both tests. In an unreported test we find that the difference between the Millennial and Baby Boomer cohorts is even larger than the difference between the Millennial and Gen X cohorts.[24]

5.3 Gender

Last, we consider the mediating role of employee gender for our finding. The literature in finance and management has documented that women on average have a higher sensitivity to CSR than men. For example, Nath, Holder-Webb, and Cohen (2013) show that female retail investors have a greater interest in using CSR information when making investment choices relative to male retail investors. Similarly, Droms-Hatch and Stephen (2015) document that women have higher levels of 'Internalized Moral Identity' and on average believe that organizations should be more beneficial to society than men. Finally, Mesch, Osili, Ackerman, and Dale (2015) find that single women have a higher likelihood of philanthropic giving and give a higher average dollar amount than single men. Hence, if our results are driven by an alignment of pro-social preferences between employers and employees, we would expect to find a stronger effect of corporate philanthropy on the retention of female employees compared to their male colleagues.

The results of sample splits based on employee gender are shown in Panel 5c. In this analysis we drop all employees with surnames that have a probability of being considered "female" or "male" that is less than 95%. In line with the idea that female employees have a relatively higher preference for pro-social corporate activities, we find a stronger negative treatment effect of natural disasters at firms with pre-existing foundations on employee turnover in the female relative to the male employee subsample. The coefficient estimate of *Post* 1-4 $\times$ $\mathbb{1}$(Had Foundation) is about 6.7% larger in the female subsample using the DiD specification as reported in columns (1) and (2) of Panel 5c. Similarly, the point estimate

[24] We find the effect is 77% (DiD) and 95% (shock-IV) stronger in the Millennial cohort when compared to the Baby Boomer cohort.

for our instrumented charitable contributions variable, $log(\widehat{1 + Grants})$, is about 4.9% larger for the group of female employees in column (3) than the corresponding point estimate for male employees in column (4). While the difference in the effect size across the male and female subsample is statistically highly significant at the 1% level, the magnitude of these difference is small compared to our proxies of pro-social preferences, especially with respect to volunteering experience. This is consistent with the notion that revealed pro-social preferences captured by volunteering experience is a sharper proxy for value alignment than gender.

5.4 Effects on Employee Satisfaction and Productivity

5.4.1 Employee Satisfaction

It is plausible that corporate philanthropic activity affects employee commitment in important ways that ultimately do not lead to employee turnover. To study this question, we combine our sample with scores of employee satisfaction at the firm-level from employee-reviews posted to Glassdoor.com. We obtain two Glassdoor metrics of employee satisfaction: 'Overall Rating' of the employer and 'CEO Approval', and estimate Equations (1) and (2) at the firm-level. Since Glassdoor data is only available starting in 2008, we are limited to the earthquake in Haiti in 2010 as our only natural disaster in these tests.[25]

[Insert Table 6 here.]

The results, presented in Table 6, show a significant positive effect of corporate charitable contributions following the 2010 Haiti earthquake on both employees' overall assessment of their employers and their approval of the CEO in the following years. As documented in columns (1) and (2), in the years following the disaster, the 'Overall Rating' and the 'CEO Approval' score of treated firms with existing corporate foundations increases by 3.27%

[25] Our specifications therefore do not include relative event-time fixed effects, as they would be collinear with our industry-by-year fixed effects.

and 6.54% relative to the sample mean (= 0.021/0.643 and = 0.0409/0.625), respectively, compared to the control firms. Estimates are statistically significant at the 10% and 5% levels.

To determine if this finding is driven by corporate philanthropic activity, we use our shock-IV specification as specified in Equation (2) at the firm-year level. The 2nd stage IV results are summarized in columns (3) and (4) of Table 6. We find a positive effect of instrumented charitable donations on both 'Overall Rating' and 'CEO Approval' scores. The results are weakly insignificant, which can be attributed to small sample sizes in these tests. Our estimates indicate that for a 10% increase in $log(1 + \widehat{Grants})$, overall satisfaction increases by 2.06% and CEO approval increases by 4.09% relative to the sample mean.

5.4.2 Employee Productivity

If corporate philanthropy can lead to more satisfied employees who are more likely to be retained by their firm, it is plausible that value alignment may also lead to higher levels of labor productivity. Since LinkedIn profile data does not allow us to measure labor productivity at the person-level, we construct contemporaneous and forward-looking measures of labor productivity at the firm-level, i.e., the log of operating income before depreciation and amortization per employee, and estimate Equations (1) and (2).[26] In Section 6.2 below, we additionally study labor productivity at the individual person-level for a sample of corporate inventors, using patent filing data.

[Insert Table 7 here.]

The results, presented in Table 7, show a significant positive effect of corporate charitable contributions on both the contemporaneous and forward-looking labor productivity measures. As documented in our DiD specification in columns (1) and (3), in the years following the

[26]We use operating income before depreciation and amortization (OIBDA) to exclude the effect of extraordinary items, capital structure, and other non-operating firm decisions.

disaster, treated firms with existing corporate foundations experience an increase in labor productivity of 3.1% and 3.5%, respectively. These estimates are statistically significant at the 5% level. We confirm that this finding is driven by corporate philanthropic activity using our shock-IV specification as specified in Equation (2) at the firm-year level. The 2nd stage IV results are summarized in columns (2) and (4) of Table 7. We find a significant positive effect of instrument charitable donations on labor productivity. Our estimates indicate that for a 10% increase in $log(1+\widehat{Grants})$, labor productivity increases by 2.9% and 3.5%. The results are significant at the 5% and 10% levels, respectively. Taken together our findings point to a positive effect of corporate charitable activity on an employee's view of their firm, and its CEO, and their level of productivity.

5.5 Employee Education and Outside Job Options

A natural question given our results up to this point is how our findings on value alignment and employee turnover vary across employees with different levels of educational attainment and human capital. Employees with critical human capital are highly coveted in the labor market (Hirshleifer, Hsu, and Li, 2018; Ouimet and Zarutskie, 2020) and costly to hire and replace (Belo et al., 2017). Hence, it is important to understand how alignment in social values affects the retention of such high-skilled employees.

We use an employee's academic qualifications – i.e., the presence of an advanced degree – from LinkedIn profiles as a proxy for their level of human capital.[27] This test also provides a natural validation exercise for our main result: all else equal, employees with a higher educational pedigree have more labor market mobility and better outside job options, and should hence be more sensitive to changes in workplace satisfaction and alignment with their employers' actions. Similar to our previous tests shown in Table 5, we split the sample by employees with and without advanced degrees, i.e., outside career options, and estimate

[27] Advanced degrees include the following: Doctorates, M.D., J.D., and Master's degrees.

Equations (1) and (2). These results are presented in Table 8.

[Insert Table 8 here.]

We estimate a higher sensitivity in the subsample of employees with advanced degrees. The effect is approximately 1.9x stronger in the 'Yes' compared to the 'No' advanced degree subsample in both our DiD (columns 1 and 2) and Shock-IV (columns 3 and 4) settings. The difference in coefficient estimates in both settings is significant at the 1% level.[28]

6 Inventor Turnover and Productivity

A potential concern with our results using resume data from LinkedIn.com is that profile information is self-reported by users, and may therefore be subject to self-selection or reporting biases. For example, employees who are looking for a new job may be more likely to create a LinkedIn profile and provide detailed resume information, potentially amplifying our findings on employee turnover. In the following, we therefore study employee turnover using corporate inventors with patenting activity as an alternative data source to address this concern.

Focusing on inventors has at least four key advantages. First, our results in Section 5.5 show the effect of value alignment on employee retention is stronger among employees with high educational attainment. Inventors are similarly high-skilled employees, which closely aligns with our previous results. Further, employees who file patents provide critical human capital for corporate innovation, which is an important driver of firm performance (Hirshleifer, Hsu, and Li, 2013), economic growth, and productivity (Kogan et al., 2017). Second, by matching inventors to their employers using the patent database of Kogan et al. (2017), we are able to track the careers of over one million individuals over a 15-year period and measure their labor productivity and other employee characteristics such as race, gender, and location. Third, similar to the employees identified via LinkedIn, inventors are not involved in choosing

[28] In Appendix Table A.7 we find similar results when looking at within firm-year differences in employee turnover as well.

corporate donations at the firm level, in contrast to CEOs or other executives. Fourth, patent data allows us to determine the productivity of individual workers, rather than relying on firm-level aggregates as in Section 5.4.2.

6.1 Employee Turnover among Corporate Inventors

Following the related literature, we merge patent filing data from the United States Patent and Trademark Office, which identifies the filer's name, identity, and employer, with public firm IDs using the patent data of Kogan et al. (2017). This allows us to infer if an inventor changed employers based on the company listed on a given patent filing. This procedure yields a total of 4,354,385 inventor-year observations between 1985 and 2015. Section A.II.1 in the Appendix describes the sample and variable construction in detail and provides summary statistics.

Similar to Table 3, we estimate the models in Equations (1) and (2) at the inventor-year level, using $\mathbb{1}(\text{Inventor Exit})_{ifet}$ — a dummy variable indicating the turnover of an inventor in the given year — as the main dependent variable. Panel 9a presents the results.

[Insert Table 9 here.]

Consistent with our results using LinkedIn.com data, we find a robust negative effect of natural disasters on the likelihood of inventor turnover for treated firms with pre-existing charitable foundations using the DiD specification, as shown in Panel 9a columns (1) and (2). Our estimates indicate that inventor turnover decreases between 0.52 and 1.11 percentage points across specifications, which is equivalent to 17% to 26% relative to the sample mean. This result holds after including inventor-by-event and firm-by-CEO-by-event fixed effects controlling for any time-invariant inventor, firm, and CEO characteristics, along with inventor-level controls for cumulative number of patents, career length, and gender. Figure 6 displays the corresponding dynamic effect. Similar to Figure 5, the coefficient estimates are indistinguishable from zero in periods $t = -4$ through $t = -1$, drop significantly below zero for treated firms in period $t = 1$, and remains below zero in the following periods.

Next, we examine charitable donations as the channel for this results by using natural disaster occurrence as an instrument for charitable donations (Equation 2). In the unreported 1st stage we confirm that the occurrence of natural disasters is a strong instrument for treated firms' charitable donations. Columns (3) and (4) show the second stage of the 2SLS estimation results. We find that instrumented charitable contributions have a significant negative effect on the likelihood of inventor turnover. This effect holds after including high-dimensional fixed effects and controls for inventor productivity, career length, and gender. The coefficient estimate for $log(\widehat{1 + Grants})$ of -0.046 in column (4) indicates that an increase in charitable donations of 10% is associated with a 0.19 percentage point decrease in the likelihood that an inventor exits after the current year.

We perform a number of robustness tests for this result in the Appendix. As described in detailed in Section A.II.2, we continue to find similar results when we exclude firms with foreign operations and inventors based outside of the U.S. (Table A.9), and when we retain only inventors who patent every year to more precisely measure turnover (Table A.10).

6.2 Labor Productivity of Inventors

A major benefit of using patent data is that it allows us to track the productivity of individual employees over their careers using patent output. This allows us to include individual-level controls for time-varying and time-invariant inventor characteristics. In Panel 9b we use the number of patents filed by an inventor in a given year as our measure of labor productivity. Following Cohn, Liu, and Wardlaw (2022), we use Poisson regressions for patent counts rather than OLS regressions with log-transformed patents as the dependent variable, since Poisson regressions produce more consistent and efficient estimates for count data. It is important to note that because Poisson regressions are non-linear, we can only use our DiD specification in this context.

Similar to columns (1) and (3) in Table 7, we estimate the model in Equation (1) at the inventor-year level, using $N.\ Patents_{ifet}$ — i.e., the number of patents filed by inventor i in year t — as the main dependent variable. Panel 9b presents the results.

Consistent with our firm-level results in Table 7, we find a significant positive effect of corporate charitable contributions on inventor productivity. In the years following a disaster, inventors at treated firms with existing corporate foundations exhibit an increase in patenting output of 10% and 14%, respectively. These estimates are statistically significant at the 5% and 10% levels, and are robust to in inclusion of inventor-by-event fixed effects. Taken together, our findings point to a positive effect of corporate charitable activity on employee productivity, both measured at the firm and individual level, and employee retention with both high- and low-skilled workers.

7 Conclusion

Given the increasing importance of human capital for firm performance, we examine whether an alignment in social values between firms and their employees can reduce turnover, increase satisfaction, and lead to higher levels of productivity. In contrast to the prior literature, which typically either studies broad definitions of CSR or focuses on aspects of CSR that *directly* affect employees, we focus on corporate philanthropic giving which provides no direct benefits to a firm's employees.

We use large natural disasters abroad as an exogenous shock to the demand for philanthropic giving. Using multiple sources of employee turnover data, we find robust evidence that changes in philanthropic giving can affect employee turnover by an economically sizable magnitude.

In this setting we employ propensity-score matching on pre-disaster firm characteristics, to compare the post-disaster effects on employee turnover between firms with (treated) and without (control) philanthropic foundations. Using employee career data from LinkedIn.com, we find that natural disasters drive large increases in philanthropic giving, and that these increases in giving are associated with a 5.9-7.8% decrease in employee turnover. Importantly, this effect is much more pronounced among employees with characteristics associated with higher pro-social preferences, i.e., volunteering experience listed on LinkedIn, younger (Millenials vs. Gen X), and female employees. We also find a subsequent increase in CEO approval, employee satisfaction, and worker productivity at the firm-level.

Using data on inventors from patent filings, which is free from biases which may result from self-reporting, we find similar effects of disaster giving on employee turnover. We also find that changes in philanthropic giving can affect inventor productivity by an economically sizable magnitude.

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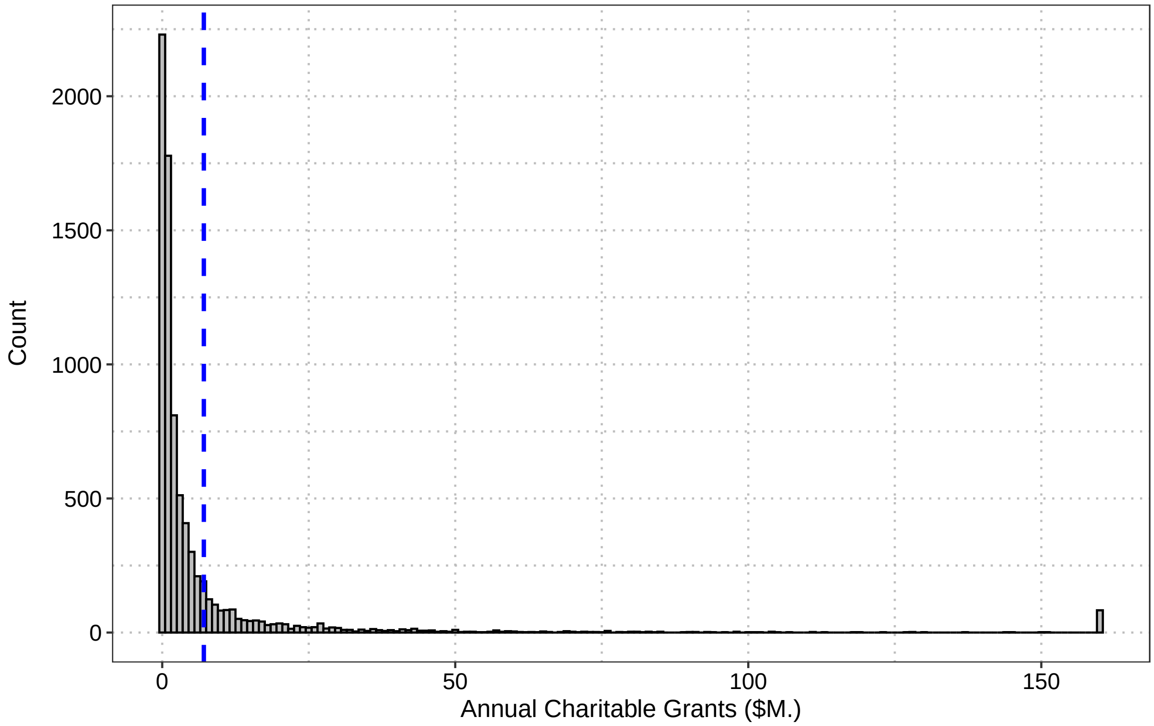
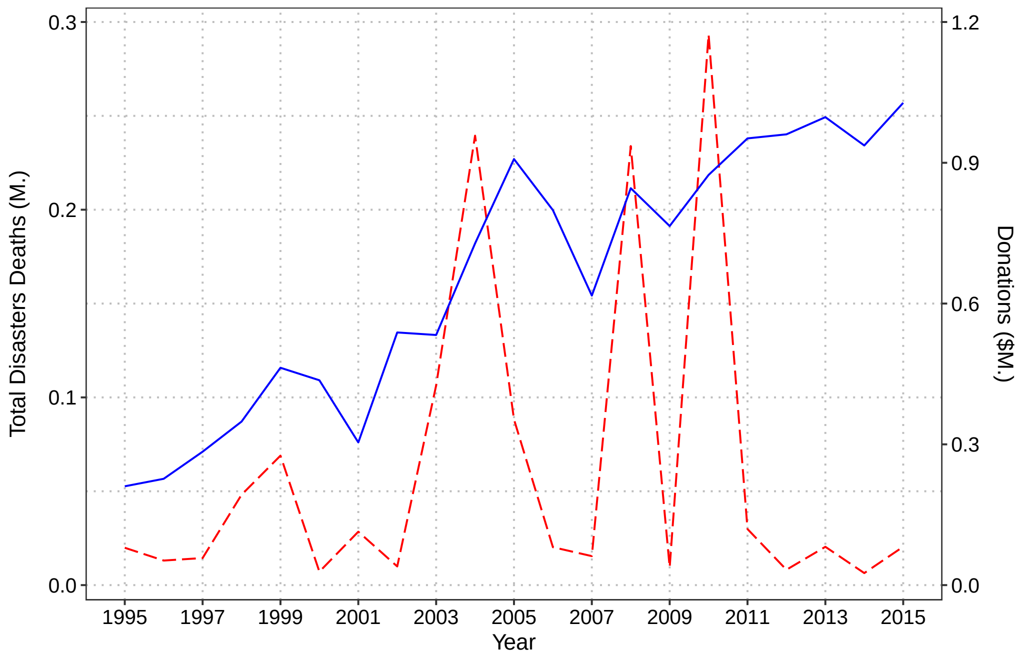
Figure 1: Histogram of Corporate Donations



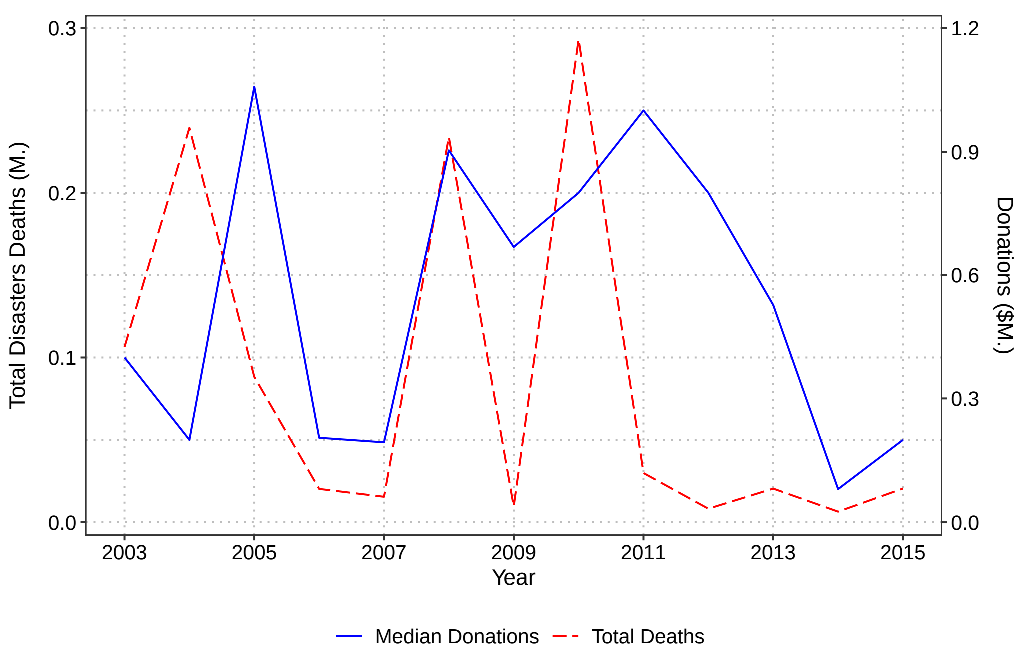
Notes: This figure shows the distribution of the annual amounts of corporate charitable donations, for firms with an existing charitable foundation or corporate giving program. The blue dashed line indicates the sample mean. Donations data is obtained from Foundation Directory Online (FDO) and the National Center for Charitable Statistics (NCCS), as outlined in Section 2.

Figure 2: Disasters and Corporate Donations

(a) All Charitable Donations

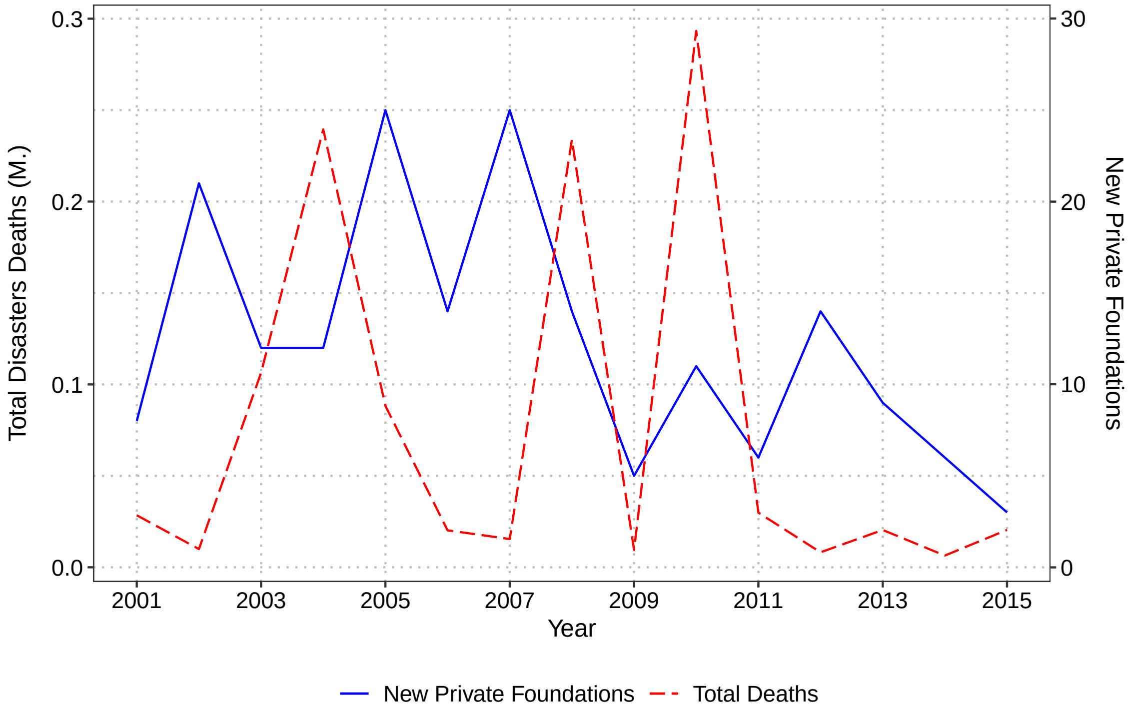


(b) Charitable Donations Earmarked for Disaster Relief



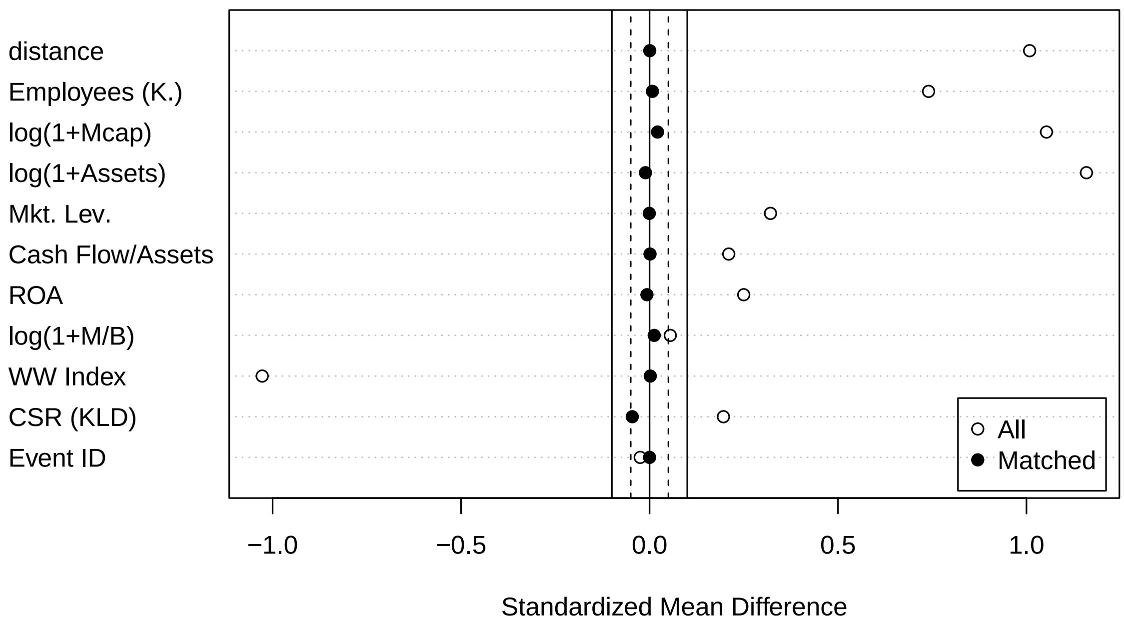
Notes: This figure shows the median amount of charitable donations ($M.) per firm per year (blue solid line) for all firms which have a foundation in the given year (right axis), and the total number of deaths globally (M.) (red dashed line) caused by major natural disasters (left axis) over the sample period from 1995 to 2015 for in Panel 2a. Panel 2b shows the median amount of charitable donations specifically earmarked for disaster relief. Disaster dates and casualties are from the EMDAT database, donations data for Panel 2a is from Foundation Directory Online (FDO) and the National Center for Charitable Statistics (NCCS), and donations data and purposes for Panel 2b is from the FDO, as outlined in Section 2.

Figure 3: Disasters and Corporate Private Foundation Starts



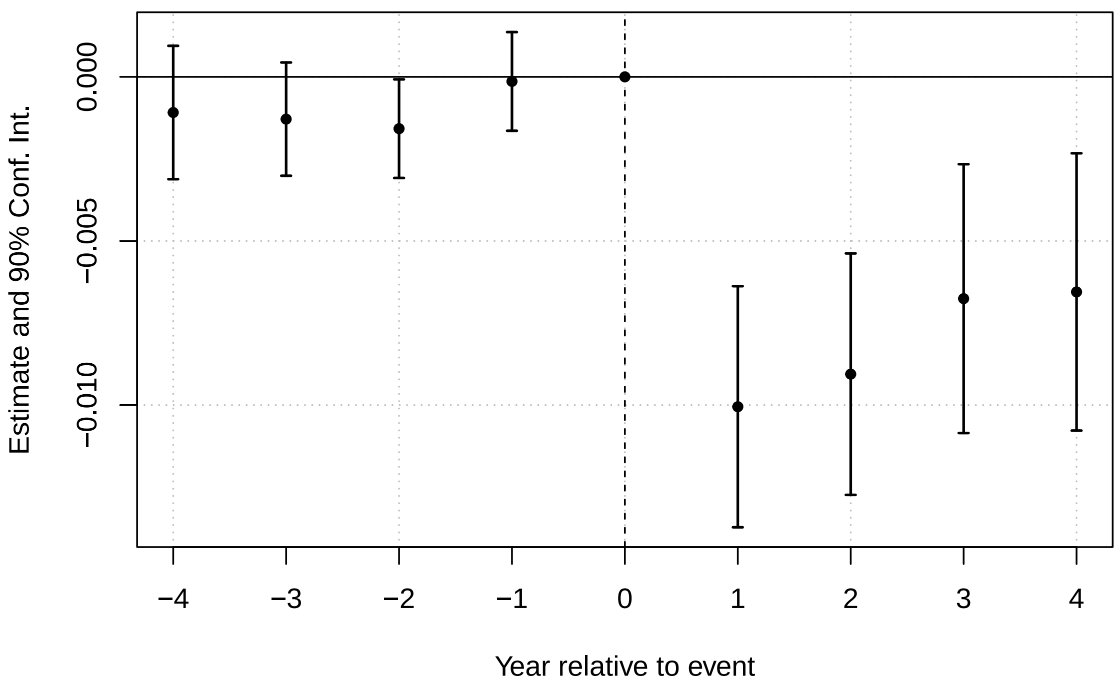
Notes: This figure shows the annual number of newly established corporate private foundations (PF) associated with firms in our sample (blue solid line, right axis), and the total number of deaths globally (M.) caused by major natural disasters (red dashed line, left axis) over the sample period from 2001 to 2015. Disaster information is from the EMDAT database and private foundation start dates are determined using 990-PF filings provided by the FDO, as outlined in Section 2.

Figure 4: Firm-Level PSM Matching Covariates Balance



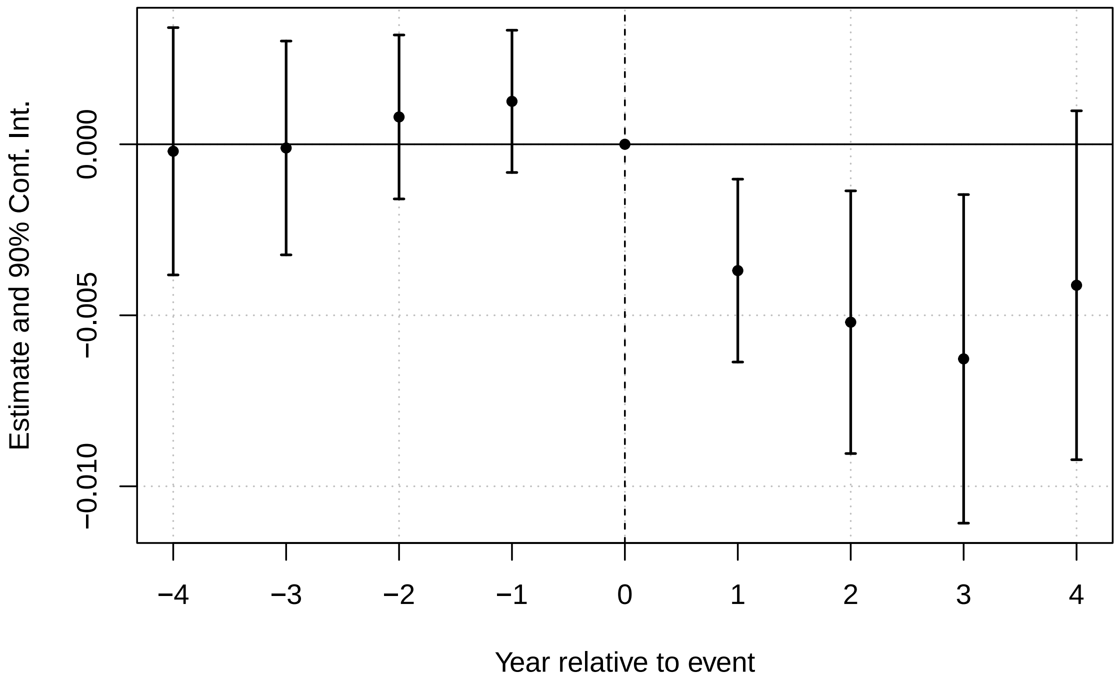
Notes: This figure summarizes the covariate balance of the propensity score matching (PSM) procedure detailed in Section 3, comparing treated and matched firms (solid points) as well as treated firms and the full sample (hollow points). Firms are considered to be treated if they had a corporate charitable foundation in the four years before the occurrence of a major natural disaster, and untreated otherwise. Within each natural disaster event, we implement $k = 10$ nearest neighbor matching with replacement, by matching on the following covariates observed during the four years before the disaster occurrence: Employees (K), log(1+Mcap), log(1+Assets), Mkt. Lev., Cash Flow/Assets, ROA, log(1+M/B), WW Index, and CSR (KLD). Each point represents the standardized mean difference of the corresponding covariate in the matched or unmatched sample. 'distance' corresponds to the Propensity Score from a logistic regression. The solid and dashed vertical lines indicate the 10% and 5% threshold, respectively.

Figure 5: Disasters and Employee Turnover



Notes: This figure plots the dynamic effect of major natural disasters abroad on the turnover of U.S. employees from LinkedIn.com in the four years before and after the occurrence of the disaster at treated compared to control firms, as constructed in Section 2. Specifically, the figure plots the coefficient estimates and corresponding 90% confidence intervals from a stacked linear probability regression of a dummy variable indicating the turnover of an employee (i.e., "$\mathbb{1}$(Employee Exit)") on interaction terms of dummy variables indicating the distance (in years) relative to the major disaster event (i.e., relative time dummies) with an indicator for treated firms, i.e., firms that had a charitable foundation prior to the occurrence of the disaster event. The estimation is at the employee-year level, standard errors are clustered at the firm-event level. Control firms are matched to treated firms based on pre-event characteristics as described in Section 3 and Figure 4. The estimation includes year-by-industry ('Year $\times$ GICS4 FE'), relative event-time, and firm-by-CEO-by-event fixed effects, as well as firm-level controls for size, leverage, cash flows, profitability, growth opportunities, and financial constraints, and employee-level controls for education history, career length, and gender.

Figure 6: Disasters and Inventor Turnover



Notes: This figure plots the evolution of inventor turnover in the four years before and after a major natural disaster event, as constructed in Section 2. Specifically, the figure plots the coefficient estimates and corresponding 90% confidence intervals from a stacked linear probability regression of a dummy variable indicating the exit of an inventor (i.e., "$\mathbb{1}$(Inventor Exit)") on interaction terms of dummy variables indicating the distance (in years) relative to the major disaster event (i.e., relative time dummies) with an indicator for treated firms, i.e., firms that had a charitable foundation prior to the occurrence of the disaster event. The estimation is at the inventor-year level, standard errors are clustered at the firm-event level. Control firms are matched to treated firms based on pre-event characteristics as described in Section 3 and Figure 4. The estimation includes year-by-industry ('Year × GICS4 FE'), relative event-time, and firm-by-CEO-by-event fixed effects, as well as firm-level controls for "log(1+Mkt. Capitalization)", "Mkt. Leverage", "Cash Flow/Assets", "ROA", "log(1+Market-to-Book)" and the "Whited-Wu Index" and inventor-level controls for "Cumulative Patents", "Career Length (Years)", and "Gender (Male=1)".

Table 1: Summary Statistics

Notes: This table reports summary statistics for the firms (Panel 1a) and employees (Panel 1b) and the industry breakdown (Panel 1c) of firms with charitable foundations in our sample. Panel 1a reports summary statistics for unique firm-year observations over the sample period from 1992 to 2016. 'Donations ($M.)' is the annual amount of charitable donations (in $Millions) given by all private foundations associated with a firm, from the Foundation Directory Online (FDO) and the National Center for Charitable Statistics (NCCS). 'Overall Rating' and 'CEO Approval' are firm-level averages of overall employee satisfaction and CEO approval. 'CSR (KLD)' and 'EMP (KLD)' are the time-consistent CSR and Employment scores from KLD, respectively. 'Number of Employees' (Employment, K.), 'Market Capitalization' (MCap, $B.), 'Total Book Assets' (Assets, $B.), 'Market Leverage', 'Cash Flow / Assets', 'ROA', 'Market-to-Book Ratio', and 'WW Index' are winsorized at the 5% level within the full Compustat universe. Panel 1b reports summary statistics for unique employee-year observations from LinkedIn.com resume data, including the gender 'Female (0/1)', age, volunteering experience, educational attainment (secondary and graduate degree), tenure (years in the current job), and career length. 'Employee Exit' takes the value of one if an employee left their employer after the current year. Panel 1c reports the number of firms with and without charitable organizations by (GICS 4-digit) industry. Details on data sources and variable construction are summarized in Section 2 and variable descriptions can be found in the Appendix.

(a) Firm-year Summary Statistics

	N	Mean	SD	P05	P25	P50	P75	P95
Grants ($M.)	33157	0.59	3.91	0.00	0.00	0.00	0.00	2.00
log(1+Grants)	33157	0.15	0.51	0.00	0.00	0.00	0.00	1.10
Overall Rating	4215	0.64	0.12	0.43	0.58	0.65	0.72	0.80
CEO Approval	4175	0.63	0.20	0.25	0.50	0.64	0.76	0.96
CSR (KLD)	21078	0.57	2.00	-2.00	0.00	0.00	1.00	4.00
EMP (KLD)	21078	0.02	0.84	-1.00	0.00	0.00	0.00	1.00
Employment (K.)	32207	12.13	13.25	0.35	1.94	6.10	18.01	38.60
MCap ($B.)	32514	4.38	4.52	0.22	0.84	2.34	6.84	13.07
Assets ($B.)	32520	5.94	6.79	0.20	0.83	2.65	8.94	19.62
Mkt. Leverage	32384	0.24	0.21	0.00	0.06	0.19	0.37	0.67
Cash Flow / AT	31187	0.08	0.09	-0.04	0.04	0.08	0.13	0.20
ROA	32519	0.04	0.09	-0.09	0.01	0.04	0.08	0.15
Market-to-Book	31839	2.71	2.08	0.71	1.30	2.02	3.33	8.20
WW Index	30786	-0.35	0.11	-0.49	-0.44	-0.37	-0.29	-0.16
OIBDA / EMP	30865	0.07	0.08	0.00	0.02	0.04	0.10	0.26

(b) Employee-year Summary Statistics

	N	Mean	SD	P05	P25	P50	P75	P95
Employee Exit	37796747	0.13	0.33	0.00	0.00	0.00	0.00	1.00
Female	33526350	0.37	0.48	0.00	0.00	0.00	1.00	1.00
Age	17941444	33.27	11.34	18.00	25.00	32.00	41.00	53.00
Volunteer Experience	36873297	0.11	0.31	0.00	0.00	0.00	0.00	1.00
Secondary Degree	37796747	0.78	0.42	0.00	1.00	1.00	1.00	1.00
Graduate Degree	37796747	0.22	0.42	0.00	0.00	0.00	0.00	1.00
Tenure	37796747	4.47	3.49	1.00	2.00	3.00	6.00	12.00
Career Length	37796747	10.49	8.52	0.00	4.00	9.00	15.00	27.00

... continued

(c) Philanthropic Firms by Industry

GICS	Industry Description	Total Firms	Charitable Firms	% of Total
1010	Energy	132	39	30%
1510	Materials	130	53	41%
2010	Capital Goods	163	71	44%
2020	Commercial & Professional Services	66	23	35%
2030	Transportation	43	19	44%
2510	Automobiles & Components	26	14	54%
2520	Consumer Durables & Apparel	80	35	44%
2530	Consumer Services	85	44	52%
2540	Media & Entertainment	32	10	31%
2550	Retailing	110	48	44%
3010	Food & Staples Retail	22	13	59%
3020	Food, Beverage, Tobacco	67	36	54%
3030	Household and Personal Products	22	9	41%
3510	Health Care Equipment & Services	165	57	35%
3520	Pharma, Biotech & Life Sciences	107	31	29%
4010	Banks	159	60	38%
4020	Diversified Financials	74	35	47%
4030	Insurance	76	34	45%
4510	Software & Services	174	40	23%
4520	Technology Hardware & Equipment	128	31	24%
4530	Semiconductors & Equipment	75	16	21%
5010	Telecommunication Services	39	15	38%
5020	Media & Entertainment	38	25	66%
5510	Utilities	97	57	59%
6010	Real Estate	99	17	17%
Full Sample		2,209	832	38%

Table 2: Natural Disasters and Charitable Grants

Notes: This table presents OLS regression results for the effect of major natural disasters abroad on firm-level charitable grants by U.S. firms. The dependent variables are the amount of charitable grants ($M.) in columns (1) and (2) and the corresponding log-transformation in columns (3) and (4). 'Post 1-4' is a dummy variable that takes the value of one if a major natural disaster occurred in the past four years, and zero otherwise. '$\mathbb{1}$(Had Foundation)' takes the value of one if the firm had a corporate charitable organization before the occurrence of the natural disaster, and zero otherwise. The data is organized at the firm-year level and stacked around each event. Control variables include size ('log(1+Mkt. Cap.)'), market leverage ('Mkt. Lev.'), cash flow scaled by assets ('CF/Assets'), 'ROA', Market-to-Book ratio ('log(1+M/B)'), and the Whited-Wu Index ('WW Index'), all lagged by one period. Year-by-industry ('Year × GICS4 FE'), relative event-time, firm-by-event, and firm-by-CEO-by-event fixed effects are included as indicated. Kleibergen-Paap Wald F (clustered at the firm-event level) report the test statistics of F-tests for weak identification with respect to 'Post 1-4 × $\mathbb{1}$(Had Foundation)'. Standard errors are clustered at the firm-event level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Dep. Variable	Grants		Log(1+Grants)	
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	0.6716***	0.5476***	0.1306***	0.1061***
	(0.1216)	(0.1477)	(0.0166)	(0.0202)
log(1+Mkt. Cap.) (t-1)	-0.0216	-0.0275	0.0133	0.0051
	(0.0478)	(0.0603)	(0.0082)	(0.0101)
Mkt. Lev. (t-1)	-0.0958	0.0038	0.0080	0.0150
	(0.2007)	(0.2166)	(0.0322)	(0.0391)
CF/Assets (t-1)	1.024	0.8207	0.1538	0.0407
	(0.7350)	(0.8106)	(0.1208)	(0.1426)
ROA (t-1)	-0.7704	-0.7425	-0.1270	-0.0507
	(0.7306)	(0.8241)	(0.1183)	(0.1394)
log(1+M/B) (t-1)	-0.1517*	-0.1040	-0.0404***	-0.0280
	(0.0803)	(0.1015)	(0.0145)	(0.0174)
WW Index (t-1)	0.5880*	0.3551	0.0554	0.0137
	(0.3107)	(0.3583)	(0.0445)	(0.0489)
Observations	21,937	21,937	21,937	21,937
R^2	0.74501	0.79920	0.82027	0.85806
Kleibergen-Paap Wald F-Stat	30.516	13.743	62.087	27.569
Year × GIC4 FE	✓	✓	✓	✓
Relative Time FE	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓
Firm × CEO × Event FE		✓		✓

Table 3: Natural Disasters, Charitable Grants, and Employee Turnover

Notes: This table presents stacked OLS- and 2SLS-IV regression results for the effect of major natural disasters abroad on employee turnover. The dependent variable in Panel 3a is an indicator that takes the value of one if an employee leaves their employer in year t. In Panel 3b, the dependent variable in the first IV-stage is the logarithmic transformation of charitable donations, i.e., log(1+Grants ($M.)). The second IV-stage regresses an indicator for employee exit on the instrumented value of charitable donations. In both panels, the data is organized at the employee-year level and stacked around each event. We include only employees who are present in the sample in both the pre- and post-period for each individual disaster event. In both panels, 'Post 1-4' is an indicator variable that takes the value of one if a major natural disaster occurred in the past four years. '$\mathbb{1}$(Had Foundation)' takes the value of one if the firm made at least one donation in the years before the occurrence of the natural disaster, and zero otherwise. We use the same firm-level control variables as in Table 2 and include additional firm-level controls for 'Employment' and 'Employment^2', and employee-level controls for their tenure a their firm ('Tenure'), qualifications ('Advanced Degree', 'Secondary Degree'), and gender ('Female'). Year-by-industry ('Year × GICS4 FE'), relative event-time, firm-by-event, employee-by-event, and firm-by-CEO-by-event fixed effects are included as indicated. In Panel 3b, Kleibergen-Paap (K-P) Wald F (clustered at the firm-event level) reports the test statistics of F-tests for weak identification with respect to 'Post 1-4 × $\mathbb{1}$(Had Foundation)'. Standard errors are clustered at the firm-event level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Difference-in-Difference Setting

	Dep. Variable: $\mathbb{1}$(Employee Exit)			
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	-0.0077***	-0.0084***	-0.0090***	-0.0104***
	(0.0019)	(0.0019)	(0.0029)	(0.0028)
Employment (t-1)	0.0007*	0.0017***	-0.0004	0.0009
	(0.0004)	(0.0004)	(0.0006)	(0.0006)
Sq. Employment (t-1)	-9.867	-24.10***	-1.764	-15.31
	(8.069)	(8.266)	(11.63)	(12.44)
Tenure (t)	-0.0057***	-0.0057***	0.0302***	0.0306***
	(0.00009)	(0.00009)	(0.0004)	(0.0004)
Graduate Degree	0.0110***	0.0110***		
	(0.0005)	(0.0005)		
Secondary Degree	0.0170***	0.0170***		
	(0.0004)	(0.0004)		
Female	-0.0032***	-0.0032***		
	(0.0003)	(0.0003)		
Observations	17,499,046	17,499,046	19,670,572	19,670,572
R^2	0.0415	0.0433	0.2640	0.2669
Relative Time FE	✓	✓	✓	✓
Year × GIC4 FE	✓	✓	✓	✓
Firm × Event FE	✓		✓	
Firm × CEO × Event FE		✓		✓
Employee × Event FE			✓	✓
Other Firm Controls	✓	✓	✓	✓

... continued

(b) Shock-IV Setting

Dep. Variable	Log(1+Grants)	$\mathbb{1}$(Emp. Exit)	Log(1+Grants)	$\mathbb{1}$(Emp. Exit)
IV Stages	1st	2nd	1st	2nd
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	0.1754***		0.1687***	
	(0.0417)		(0.0447)	
$log(1+\widehat{Grants})(t)$		-0.0437***		-0.0534**
		(0.0153)		(0.0223)
Employment (t-1)	0.0025	0.0008	0.0028	-0.0003
	(0.0105)	(0.0006)	(0.0109)	(0.0008)
Sq. Employment (t-1)	-9.912	-10.30	-11.11	-2.357
	(179.5)	(11.04)	(185.7)	(14.74)
Tenure (t)	-0.0005***	-0.0057***	-0.0004	0.0302***
	(0.0002)	(0.00009)	(0.0016)	(0.0004)
Graduate Degree	-0.0002	0.0110***		
	(0.0003)	(0.0005)		
Secondary Degree	0.00010	0.0170***		
	(0.0002)	(0.0004)		
Female	-0.000006	-0.0032***		
	(0.0003)	(0.0003)		
Observations	17,499,046	17,499,046	19,670,572	19,670,572
R^2	0.8377	0.0355	0.8462	0.2556
Kleibergen-Paap Wald F-Stat	17.680		14.276	
Year × GIC4 FE	✓	✓	✓	✓
Relative Time FE	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓
Employee × Event FE			✓	✓
Other Firm Controls	✓	✓	✓	✓

Table 4: Voluntary and Involuntary Employee Turnover

Notes: This table presents 2SLS-IV regression results for the effect of major natural disasters abroad on employee turnover analogous to Panel 3b, including subsample analyses. In columns (2) through (4), we exclude all employee-position observations where the employee takes more than 1 month, 2 months, and 3 months to find new employment, respectively. In column (5) we only include employee-position observations where an employee takes more than 1 month to find new employment. The main dependent variable is an indicator variable that takes the value of one if an employee leaves their employer during year t. The dependent variable in the first IV-stage is the logarithmic transformation of charitable donations, i.e., log(1+Grants ($M.)). The second IV-stage regresses an indicator for employee exit on the instrumented value of charitable donations. We report only the second stage regression results in this table. The data is organized at the employee-year level and stacked around each event. All data filters, controls, and fixed effects are similar to Table 3. Kleibergen-Paap (K-P) Wald F (clustered at the firm-event level) reports the test statistic of F-tests for weak identification with respect to 'Post 1-4 × $\mathbb{1}$(Had Foundation)'. Standard errors are clustered at the firm-event level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dep. Variable: $\mathbb{1}$(Employee Exit)				
Time Until Reemployment	Baseline (1)	<1 mth (2)	<2 mths (3)	<3 mths (4)	>1 mth (5)
$log(1+\widehat{Grants})(t)$	-0.0534**	-0.0467**	-0.0479**	-0.0486**	-0.0402
	(0.0223)	(0.0209)	(0.0212)	(0.0214)	(0.0303)
Employment (t-1)	-0.0003	-0.0002	-0.0002	-0.0002	-0.0024
	(0.0008)	(0.0007)	(0.0008)	(0.0008)	(0.0017)
Sq. Employment (t-1)	-2.357	-2.209	-2.487	-2.757	37.55
	(14.74)	(13.30)	(13.59)	(13.79)	(31.35)
Observations	19,670,572	18,257,539	18,523,778	18,733,543	1,413,033
R^2	0.2556	0.2576	0.2570	0.2566	0.4242
K-P Wald F-Stat	14.276	13.575	13.709	13.811	18.542
Year × GIC4 FE	✓	✓	✓	✓	✓
Relative Time FE	✓	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓	✓
Employee × Event FE	✓	✓	✓	✓	✓
Other Firm Controls	✓	✓	✓	✓	✓
Employee Controls	✓	✓	✓	✓	✓

Table 5: Turnover and Employee Preferences

Notes: This table presents OLS- and 2SLS-IV regression results for the cross-sectional differences with respect to past volunteering experience (Panel 5a), age (Panel 5b), and gender (Panel 5c) in the effect of major natural disasters abroad on employee turnover. In each panel, the dependent variable is an indicator that takes the value of one if an employee leaves their employer during year t, columns (1) and (2) report the DiD estimations, and columns (3) and (4) report the second stage of the corresponding shock-IV regression. 'Post 1-4' is an indicator variable that takes the value of one if a major natural disaster occurred in the past four years, '$\mathbb{1}$(Had Foundation)' takes the value of one if the firm made at least one donation in the years before the occurrence of the natural disaster, and zero otherwise, and '$log(1+\widehat{Grants})$' is the instrumented value of charitable donations from a first IV-stage estimation. The data is organized at the employee-year level and stacked around each event. All data filters, controls, and fixed effects are similar to Table 3. Kleibergen-Paap (K-P) Wald F (clustered at the firm-event level) reports the test statistics of F-tests for weak identification with respect to 'Post 1-4 × $\mathbb{1}$(Had Foundation)'. Standard errors are clustered at the firm-event level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Past Volunteer Experience

	Dep. Variable: $\mathbb{1}$(Employee Exit)			
Model	OLS		IV 2nd	
Volunteer Experience	No	Yes	No	Yes
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	-0.0082***	-0.0207***		
	(0.0028)	(0.0037)		
$log(1+\widehat{Grants})(t)$			-0.0496**	-0.1063***
			(0.0218)	(0.0337)
Observations	17,236,775	1,973,039	17,236,775	1,973,039
R^2	0.2623	0.2763	0.2549	0.2484
K-P Wald F-Stat			14.459	13.599
Coef. Diff: χ^2 (p-Value)	31.017***	(0.000)	10.050***	(0.002)
Relative Time FE	✓	✓	✓	✓
Year × GIC4 FE	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓
Employee × Event FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Employee Controls	✓	✓	✓	✓

... continued

(b) Age

	Dep. Variable: $\mathbb{1}$(Employee Exit)			
Model	OLS		IV 2nd	
Generation	Millennial	Gen X	Millennial	Gen X
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	-0.0181***	-0.0140***		
	(0.0057)	(0.0028)		
$log(1+\widehat{Grants})(t)$			-0.1190**	-0.0759***
			(0.0488)	(0.0249)
Observations	2,338,423	4,446,853	2,338,423	4,446,853
R^2	0.2936	0.2632	0.2729	0.2468
K-P Wald F-Stat			8.029	13.503
Coef. Diff: χ^2 (p-Value)	24.227***	(0.000)	9.213***	(0.002)
Relative Time FE	✓	✓	✓	✓
Year × GIC4 FE	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓
Employee × Event FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Employee Controls	✓	✓	✓	✓

... continued

(c) Gender

	Dep. Variable: $\mathbb{1}$(Employee Exit)			
Model	OLS		IV 2nd	
Gender	Male	Female	Male	Female
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	-0.0090***	-0.0096***		
	(0.0031)	(0.0030)		
$log(1+\widehat{Grants})(t)$			-0.0542**	-0.0569**
			(0.0233)	(0.0243)
Observations	11,166,395	6,332,651	11,166,395	6,332,651
R^2	0.2645	0.2631	0.2564	0.2527
K-P Wald F-Stat			13.383	14.669
Coef. Diff: χ^2 (p-Value)	10.125***	(0.001)	5.475**	(0.019)
Relative Time FE	✓	✓	✓	✓
Year × GIC4 FE	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓
Employee × Event FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Employee Controls	✓	✓	✓	✓

Table 6: Charitable Donations, Employee Satisfaction, and CEO Approval

Notes: This table presents OLS- and 2SLS-IV regression results for the effect of charitable donations on employee satisfaction outcomes. The dependent variables, '*Overall Rating*' and '*CEO Approval*', are the firm's user-provided scores from Glassdoor.com, respectively. Columns (1) and (2) report the DiD estimations, columns (3) and (4) report the second stage of the corresponding shock-IV regression. 'Post 1-4' is an indicator variable that takes the value of one if a major natural disaster occurred in the past four years, '$\mathbb{1}$(Had Foundation)' takes the value of one if the firm made at least one donation in the years before the occurrence of the natural disaster, and zero otherwise, and '$log(\widehat{1+Grants})$' is the instrumented value of charitable donations from a first IV-stage estimation. The data is organized at the firm-year level. We include similar firm-level control variables as in Table 3. Year-by-industry ('Year × GICS4 FE') and firm-by-CEO fixed effects are included as indicated. Kleibergen-Paap Wald F (clustered at the firm-event level) report the test statistics of F-tests for weak identification with respect to 'Post 1-4 × $\mathbb{1}$(Had Foundation)'. Standard errors are clustered at the firm-event level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Model	OLS		IV 2nd	
Dep. Variable	Overall Rating (1)	CEO Approval (2)	Overall Rating (3)	CEO Approval (4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	0.0210*	0.0409**		
	(0.0116)	(0.0207)		
$log(\widehat{1+Grants})(t)$			0.1390	0.2686
			(0.0925)	(0.1650)
Observations	2,668	2,631	2,668	2,631
R^2	0.57157	0.58050	0.45423	0.44434
K-P Wald F-Stat			8.374	8.532
Year × GIC4 FE	✓	✓	✓	✓
Firm × CEO × Event FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Table 7: Charitable Donations and Employee Productivity

Notes: This table presents stacked OLS and 2SLS-IV regression results for the effect of major natural disasters abroad on employee productivity. The dependent variables are the log of operating profits before depreciation and amortization (scaled by the number of employees), $Log(OIBDA/EMP)$, for years t and t+1. Columns (1) and (3) report the DiD estimations, and columns (2) and (4) report the second stage of the corresponding shock-IV regression. 'Post 1-4' is an indicator variable that takes the value of one if a major natural disaster occurred in the past four years, '$\mathbb{1}$(Had Foundation)' takes the value of one if the firm made at least one donation in the years before the occurrence of the natural disaster, and zero otherwise, and '$log(\widehat{1+Grants})$' is the predicted value of charitable donations from a first IV-stage estimation. The data is organized at the firm-year level and stacked around each event. All data filters, controls, and fixed effects are similar to Table 3. Kleibergen-Paap (K-P) Wald F (clustered at the firm-event level) reports the test statistics of F-tests for weak identification with respect to 'Post 1-4 × $\mathbb{1}$(Had Foundation)'. Standard errors are clustered at the firm-event level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Dep. Variable	Log(OIBDA/EMP) (t)		Log(OIBDA/EMP) (t+1)	
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	0.0309**		0.0346**	
	(0.0157)		(0.0160)	
$log(\widehat{1+Grants})(t)$		0.2991*		0.3489**
		(0.1599)		(0.1749)
Observations	21,242	21,242	18,566	18,566
R^2	0.9377	0.9332	0.9384	0.9325
K-P Wald F-Stat		33.924		30.590
Year × GIC4 FE	✓	✓	✓	✓
Relative Time FE	✓	✓	✓	✓
Firm × CEO × Event FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Table 8: Turnover and Outside Employment Options

Notes: This table presents OLS- and 2SLS-IV regression results for the cross-sectional differences with respect to employees' outside job options in the effect of major natural disasters abroad on employee turnover. This table splits the sample based on the presence of an advanced degree (i.e. graduate degree). The dependent variable is an indicator that takes the value of one if an employee leaves their employer after year t, columns (1) and (2) report the DiD estimations, and columns (3) and (4) report the second stage of the corresponding shock-IV regression. 'Post 1-4' is an indicator variable that takes the value of one if a major natural disaster occurred in the past four years, '$\mathbb{1}$(Had Foundation)' takes the value of one if the firm made at least one donation in the years before the occurrence of the natural disaster, and zero otherwise, and '$log(1+\widehat{Grants})$' is the instrumented value of charitable donations from a first IV-stage estimation. The data is organized at the employee-year level and stacked around each event. All data filters, controls, and fixed effects are similar to Table 3. Kleibergen-Paap (K-P) Wald F (clustered at the firm-event level) reports the test statistics of F-tests for weak identification with respect to 'Post 1-4 $\times$ $\mathbb{1}$(Had Foundation)'. Standard errors are clustered at the firm-event level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dep. Variable: $\mathbb{1}$(Employee Exit)			
Model	OLS		IV 2nd	
Human Capital	Low	High	Low	High
	(1)	(2)	(3)	(4)
Post 1–4 $\times$ $\mathbb{1}$(Had Foundation)	-0.0071**	-0.0205***		
	(0.0029)	(0.0033)		
$log(1+\widehat{Grants})(t)$			-0.0425**	-0.1224***
			(0.0206)	(0.0420)
Observations	15,310,336	4,360,236	15,310,336	4,360,236
R^2	0.2614	0.2734	0.2559	0.2335
K-P Wald F-Stat			14.977	10.488
Coef. Diff: χ^2 (p-Value)	38.578***	(0.000)	8.570***	(0.003)
Relative Time FE	✓	✓	✓	✓
Year $\times$ GIC4 FE	✓	✓	✓	✓
Firm $\times$ Event FE	✓	✓	✓	✓
Employee $\times$ Event FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Employee Controls	✓	✓	✓	✓

Table 9: Alternative Sample — Inventors

Notes: This table presents stacked OLS- and 2SLS-IV regression results for the effect of major natural disasters abroad on inventor turnover, and stacked Poisson regression results for their effect on inventor productivity. In Panel 9a the dependent variable is an indicator that takes the value of one if an employee leaves their employer after year t, columns (1) and (2) report the DiD estimations, and columns (3) and (4) report the second stage of the corresponding shock-IV regression. In Panel 9b, the dependent variable is the number of patents filed by inventor i in year t. In both panels, 'Post 1-4' is an indicator variable that takes the value of one if a major natural disaster occurred in the past four years, and '$\mathbb{1}$(Had Foundation)' takes the value of one if the firm made at least one donation in the years before the occurrence of the natural disaster, and zero otherwise. The data is organized at the inventor-year level and stacked around each event. We include only inventors who are present in the sample in both the pre- and post-period for each individual disaster event. We use the same firm-level control variables as in Table 2 and include additional firm-level controls for 'Employment' and 'Employment^2', and inventor-level controls for 'Cumulative Patents', 'Years since career start', and 'inventor gender'. Year-by-industry ('Year × GICS4 FE'), relative event-time, firm-by-event, inventor-by-event, and firm-by-CEO-by-event fixed effects are included as indicated. In Panel 9a, Kleibergen-Paap Wald (K-P) F reports the test statistics of F-tests for weak identification with respect to 'Post 1-4 × $\mathbb{1}$(Had Foundation)'. Standard errors are clustered at the firm-event level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Turnover

	Dep. Variable: $\mathbb{1}$(Inventor Exit)			
Model	OLS		IV 2nd	
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	-0.0052***	-0.0078***		
	(0.0018)	(0.0025)		
log(1+Grants) (t)			-0.0306**	-0.0460**
			(0.0140)	(0.0199)
Employment (t-1)	0.0001**	0.0002*	0.00010	0.0001
	(0.00007)	(0.0001)	(0.00008)	(0.0001)
Sq. Employment (t-1)	-0.2738*	-0.4250*	-0.1530	-0.2494
	(0.1635)	(0.2354)	(0.1930)	(0.2702)
Cumul. Patents (t)	-0.0003***	-0.0016***	-0.0003***	-0.0016***
	(0.00005)	(0.0002)	(0.00005)	(0.0002)
Career Length (t)	0.0008***	-0.0310	0.0008***	-0.0293
	(0.00006)	(0.1779)	(0.00006)	(0.1796)
Male (0/1)	0.0014**	-10.52	0.0014**	-9.885
	(0.0006)	(46.62)	(0.0006)	(47.07)
Observations	1,164,009	1,164,009	1,164,009	1,164,009
R^2	0.0410	0.2461	0.0369	0.2370
K-P Wald F-Stat			9.436	8.210
Relative Time FE	✓	✓	✓	✓
Year × GIC4 FE	✓	✓	✓	✓
Firm × CEO × Event FE	✓	✓	✓	✓
Inventor × Event FE		✓		✓
Other Firm Controls	✓	✓	✓	✓

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(b) Productivity

Model	Dep. Variable: N. Patents		
	Poisson		
	(1)	(2)	(3)
Post 1–4 × 𝟙(Had Foundation)	0.1320**	0.0957*	0.0912*
	(0.0529)	(0.0525)	(0.0517)
Observations	1,263,466	1,263,251	1,169,269
Pseudo R^2	0.1147	0.1193	0.3526
Year × GIC4 FE	✓	✓	✓
Relative Time FE	✓	✓	✓
Firm × Event FE	✓	✓	✓
Firm × CEO FE		✓	
Inventor × Event FE			✓
Firm and Inventor Controls	✓	✓	✓

Internet Appendix

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A.I Variable Descriptions

$\mathbb{1}$***(Inventor Exit)*****:** An indicator variable that takes the value of one if an inventor applies for a patent in year t+1 that is assigned to a different firm than their current employer.

Log(1 + Grants)**:** Amount of charitable grants ($M.) donated in year t by all private foundations (PFs) associated with firm f.

$\mathbb{1}$***(Had Foundation)*****:** An indicator variable that takes the value of one if a firm has a corporate charitable foundation.

Post 1-4**:** An indicator variable that takes the value of one if a major international natural disaster occurred within the past four years.

CSR (KLD)**:** Composite score consisting of the following dimensions: community relations, product characteristics, environmental impact, employee relations, diversity, and governance. The overall score, and each category score, is the number of strengths minus the number of concerns.

EMP (KLD)**:** Employee relations score determined by the number of strengths minus the number of concerns.

Employment**:** Number of employees (Compustat item *emp*) in thousands.

Market Capitalization**:** Market capitalization calculated as common shares outstanding (Compustat item *csho*) multiplied by fiscal year end stock price (Compustat item *prcc_f*).

Market Leverage Total debt (Compustat items *dltt* + *dlc*) scaled by total debt plus the market value of equity.

CF/Assets: Income before extraordinary items and depreciation (Compustat items *ib*+*dp*) scaled by the book value of assets (Compustat item *at*).

OIBDA Operating income before amortization and depreciation (Compustat item *oibdp*) scaled by the book value of assets (Compustat item *at*).

M/B**:** Market capitalization scaled by the firm's book value (Compustat items *at-lt-pstkrv+txditc+dcvt*). If preferred stock redemption value is missing (Compustat item *pstkrv*) then preferred stock liquidating value (Compustat item *pstkl* or preferred stock (capital) - Total (Compustat item *pstk*) will be used in that order, respectively.

WW Index The Whited and Wu index of financial constraints calculated using the following formula. WW Index = (-0.091)*(CF/AT) - 0.062*(Issues Dividends) + 0.021*(dltt/at) - 0.044*(Log(1+AT)) + 0.102*(Industry (sic2) Sales Growth) - 0.035*(Sales Growth).

Log(OIBDA/EMP) The natural log of operating income before depreciation and amortization (Compustat item *oibdp*, in millions) scaled by the number of employees (Compustat item *emp*, in millions).

N Patents**:** Total number of patent applications, for each inventor, filed in year t.

Cumulative Patents**:** Cumulative number of granted patents applications, for each inventor, filed up to year t.

N Citations**:** Total number of citations for each inventor's patents in t.

Cumulative External Citations**:** Cumulative number of citations by patents belonging firms other than the inventor's current employer up to year t.

Career Length**:** The number of years since an inventor applied for their first granted patent.

Male**:** Takes the value of one if an inventor is a male, as determined by the USTPO, using the Global Name Recognition (IBM-GNR) and the Worldwide Gender-Name Dictionary (WGND) databases.

Female**:** Takes the value of one if an employee is female, as determined by the Damegender database. We classify an adviser as female if the probability of the individual being female for a given name is greater than or equal to 99%, and male if the probability is less than or equal to 1%.

Tenure**:** The number of years an employee works for their employer.

Past Volunteer Experience**:** Takes the value of one for individuals who list any volunteering experience on their profile.

Age**:** Calculated as year minus undergraduate graduation year plus 22 (average of U.S. graduates).

Graduate Degree**:** Takes the value of one for individuals who have obtained an post-graduate degree.

Secondary Degree**:** Takes the value of one for individuals who have obtained an undergraduate degree.

Overall Rating**:** The overall employer rating from the Glassdoor database, measured annually using the average of all reviews submitted that year for each firm. Takes a value between zero and one.

CEO Approval**:** The overall CEO approval rating (where 0 equals disapprove, 0.5 equals no opinion, and 1 equals approve) from the Glassdoor database, measured annually using the average of all reviews submitted that year for each firm.

Table A.1: Propensity Score Matching

Notes: This table presents summary statistics for the Propensity Score Matching (PSM) procedure detailed in Section 3 around major natural disasters. Within each natural disaster event, we implement $k = 10$ nearest neighbor matching with replacement, by matching on the following covariates observed during the four years before the disaster occurrence: 'Employees (K)', 'log(1+Mcap)', 'log(1+Assets)', 'Mkt. Lev.', 'Cash Flow/Assets', 'ROA', 'log(1+M/B)', 'WW Index', and 'CSR (KLD)'. 'PSM Distance' corresponds to the Propensity Score from a logistic regression. Panels A.1a and A.1b present summary statistics for average firm-level observations across the four years before the occurrence of a natural disaster for the sample before and after matching, respectively. The standardized mean differences are computed as the difference in treatment group means divided by the standard deviation in the treated group. The variance ratio is computed as the ratio of the treatment group variances. The eCDF difference statistics are computed by creating a (weighted) eCDF for each group and taking the difference between them for each covariate's value. Panel A.1c presents summary statistics at the individual employee level across control (i.e., 'No') and treated (i.e., 'Yes') firms for the averages across the four years before the occurrence of a major natural disaster.

(a) Pre-event covariates balance pre-matching

Variable	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio	eCDF Mean	eCDF Max
PSM Distance	0.416	0.210	1.008	1.431	0.285	0.421
Employees (K.)	19.727	9.080	0.740	1.542	0.264	0.369
log(1+Mcap)	8.462	7.379	1.053	0.736	0.272	0.378
log(1+Assets)	8.682	7.361	1.159	0.656	0.283	0.397
Mkt. Lev.	0.254	0.191	0.321	1.107	0.113	0.170
Cash Flow/Assets	0.084	0.072	0.210	0.502	0.025	0.066
ROA	0.048	0.034	0.250	0.438	0.025	0.082
log(1+M/B)	1.227	1.203	0.055	1.063	0.020	0.050
WW Index	-0.406	-0.325	-1.028	0.682	0.269	0.403
CSR (KLD)	0.520	0.027	0.196	2.501	0.051	0.166

(b) Pre-event covariates balance post-matching

Variable	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio	eCDF Mean	eCDF Max
PSM Distance	0.405	0.405	0.001	1.000	0.001	0.008
Employees (K.)	19.211	19.101	0.008	0.931	0.024	0.061
log(1+Mcap)	8.434	8.412	0.021	0.991	0.008	0.033
log(1+Assets)	8.648	8.661	-0.011	0.958	0.007	0.030
Mkt. Lev.	0.249	0.249	-0.001	0.920	0.011	0.038
Cash Flow/Assets	0.085	0.085	0.001	0.997	0.007	0.031
ROA	0.048	0.049	-0.007	1.009	0.008	0.028
log(1+M/B)	1.224	1.218	0.012	1.012	0.012	0.034
WW Index	-0.404	-0.404	0.002	1.190	0.014	0.060
CSR (KLD)	0.364	0.480	-0.046	1.019	0.013	0.080

(c) Pre-event employee-year summary statistics

	No (N=3616526)		Yes (N=4906445)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
Employee Exit (0/1)	0.032	0.175	0.027	0.163	-0.004	0.000
Female (0/1)	0.343	0.475	0.373	0.484	0.030	0.000
Age	32.767	11.808	32.648	10.775	-0.119	0.012
Volunteer Experience	0.100	0.300	0.105	0.307	0.005	0.000
Secondary Degree	0.744	0.437	0.766	0.423	0.022	0.000
Graduate Degree	0.206	0.405	0.233	0.422	0.026	0.000
Tenure	3.982	2.609	4.099	2.639	0.117	0.002
Career Length	9.711	8.078	9.962	8.214	0.251	0.006

Table A.2: Robustness — CSR Controls

Notes: This table presents robustness tests for the effect of major natural disasters abroad on employee turnover analogous to Table 3, including additional CSR controls. The dependent variable in Panel A.2a takes the value of one if an employee leaves their employer after year t, and zero otherwise. In Panel A.2b, the dependent variable in the first IV-stage is the logarithmic transformation of charitable donations, i.e., log(1+Grants ($M.)). The second IV-stage regresses an indicator for employee exit on the instrumented value of charitable donations. 'Post 1-4' is an indicator variable that takes the value of one if a major natural disaster occurred in the past four years. '$\mathbb{1}$(Had Foundation)' takes the value of one if the firm made at least one donation in the four years before the occurrence of the natural disaster. In all panels data is organized at the employee-year level, stacked around each event. All data filters, controls, and fixed effects are similar to Table 3. Standard errors are clustered at the firm-event level and reported in parentheses. In Panel A.2b, Kleibergen-Paap (K-P) Wald F reports the test statistics of F-tests for weak identification with respect to 'Post 1-4 × $\mathbb{1}$(Had Foundation)'. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Include CSR controls – DiD Setting

	Dep. Variable: $\mathbb{1}$(Employee Exit)			
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	-0.0074***	-0.0092***	-0.0084***	-0.0105***
	(0.0018)	(0.0028)	(0.0019)	(0.0028)
CSR Env. (t-1)	0.0009	0.0005	0.0014*	0.0008
	(0.0008)	(0.0012)	(0.0008)	(0.0011)
CSR Comm. (t-1)	-0.0017*	-0.0021	-0.0005	-0.0013
	(0.0010)	(0.0014)	(0.0009)	(0.0012)
CSR Hum. (t-1)	-0.0030**	-0.0015	-0.0032**	-0.0023
	(0.0015)	(0.0020)	(0.0016)	(0.0020)
CSR Emp. (t-1)	0.0002	-0.0004	0.0008	-0.0001
	(0.0006)	(0.0009)	(0.0007)	(0.0009)
CSR Prod. (t-1)	-0.000009	0.0003	-0.0002	0.0004
	(0.0007)	(0.0010)	(0.0006)	(0.0009)
CSR Div. (t-1)	-0.0006	-0.0004	-0.0004	0.0001
	(0.0006)	(0.0009)	(0.0006)	(0.0009)
CSR Gov. (t-1)	0.0015	0.0035	0.0006	0.0015
	(0.0016)	(0.0022)	(0.0015)	(0.0019)
Observations	17,019,511	19,132,982	17,019,511	19,132,982
R^2	0.0416	0.2693	0.0433	0.2722
Relative Time FE	✓	✓	✓	✓
Year × GIC4 FE	✓	✓	✓	✓
Firm × Event FE	✓	✓		
Employee × Event FE		✓		✓
Firm × CEO × Event FE			✓	✓
Firm Controls	✓	✓	✓	✓
Employee Controls	✓	✓	✓	✓

... continued

(b) Include CSR controls – Shock-IV Setting

Dep. Variable	Log(1+Grants)	$\mathbb{1}$(Emp. Exit)	Log(1+Grants)	$\mathbb{1}$(Emp. Exit)
IV Stages	1st	2nd	1st	2nd
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	0.1395***		0.1351***	
	(0.0416)		(0.0446)	
$log(1+\widehat{Grants})(t)$		-0.0531**		-0.0684**
		(0.0209)		(0.0306)
CSR Env. (t-1)	0.0376**	0.0029**	0.0349*	0.0029
	(0.0178)	(0.0015)	(0.0193)	(0.0021)
CSR Comm. (t-1)	-0.0781***	-0.0059***	-0.0758***	-0.0073**
	(0.0226)	(0.0021)	(0.0240)	(0.0029)
CSR Hum. (t-1)	0.1505*	0.0050	0.1488*	0.0086
	(0.0789)	(0.0049)	(0.0842)	(0.0074)
CSR Emp. (t-1)	-0.0120	-0.0004	-0.0122	-0.0012
	(0.0126)	(0.0009)	(0.0132)	(0.0012)
CSR Prod. (t-1)	0.0171	0.0009	0.0179	0.0015
	(0.0196)	(0.0014)	(0.0206)	(0.0019)
CSR Div. (t-1)	-0.0130	-0.0013	-0.0131	-0.0013
	(0.0128)	(0.0009)	(0.0137)	(0.0013)
CSR Gov. (t-1)	0.0891**	0.0062*	0.0867*	0.0094**
	(0.0447)	(0.0033)	(0.0482)	(0.0045)
Observations	17,019,511	17,019,511	19,132,982	19,132,982
R^2	0.8477	0.0333	0.8556	0.2565
Kleibergen-Paap Wald F-Stat	11.252		9.191	
Year × GIC4 FE	✓	✓	✓	✓
Relative Time FE	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓
Employee × Event FE			✓	✓
Firm Controls	✓	✓	✓	✓
Employee Controls	✓	✓	✓	✓

Table A.3: Robustness — Excluding Firms with Foreign Operations

Notes: This table presents OLS- and 2SLS-IV regression results for the effect of major natural disasters abroad on employee turnover analogous to Table 3, excluding firms who report any earnings from overseas operations. The dependent variable is an indicator that takes the value of one if an employee leaves their employer in year *t*. Columns (1) and (2) report the DiD estimates, and columns (3) and (4) report the second stage of the corresponding shock-IV regression. 'Post 1-4' is an indicator variable that takes the value of one if a major natural disaster occurred in the past four years, '$\mathbb{1}$(Had Foundation)' takes the value of one if the firm made at least one donation in the years before the occurrence of the natural disaster, and zero otherwise, and '$log(\widehat{1+Grants})$' is the instrumented value of charitable donations from a first IV-stage estimation. The data is organized at the employee-year level and stacked around each event. All data filters, controls, and fixed effects are similar to Table 3. Kleibergen-Paap (K-P) Wald F reports the test statistics of F-tests for weak identification with respect to 'Post 1-4 $\times$ $\mathbb{1}$(Had Foundation)'. Standard errors are clustered at the firm-event level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dep. Variable: $\mathbb{1}$(Employee Exit)			
Model	OLS		IV 2nd	
	(1)	(2)	(3)	(4)
Post 1–4 $\times$ $\mathbb{1}$(Had Foundation)	-0.0111***	-0.0134***		
	(0.0021)	(0.0032)		
$log(\widehat{1+Grants})(t)$			-0.1220***	-0.1543**
			(0.0419)	(0.0632)
Observations	7,451,331	8,337,700	7,451,331	8,337,700
R^2	0.0462	0.3033	0.0315	0.2809
K-P Wald F-Stat	10.163	8.259	10.163	8.259
Relative Time FE	✓	✓	✓	✓
Year $\times$ GIC4 FE	✓	✓	✓	✓
Firm $\times$ Event FE	✓	✓	✓	✓
Employee $\times$ Event FE		✓		✓
Firm Controls	✓	✓	✓	✓
Employee Controls	✓		✓	

Table A.4: Robustness — Logistic and Probit Regression

Notes: This table presents robustness tests for the effect of major natural disasters abroad on employee turnover analogous to Table 3, using logit and probit models in place of a linear probability model. The dependent variable is an indicator that takes the value of one if an employee leaves their employer after year *t*. 'Post 1-4' is an indicator variable that takes the value of one if a major natural disaster occurred in the past four years. '$\mathbb{1}$(Had Foundation)' takes the value of one if the firm made at least one donation in the years before the occurrence of the natural disaster. In all panels data is organized at the employee-year level, stacked around each event. All data filters, controls, and fixed effects are similar to Table 3. Standard errors are clustered at the firm-event level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dep. Variable: $\mathbb{1}$(Employee Exit)			
Model	Logit		Probit	
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	-0.0988***	-0.0879***	-0.0517***	-0.0484***
	(0.0248)	(0.0278)	(0.0114)	(0.0126)
Employment (t-1)	0.0310***	0.0464***	0.0135***	0.0210***
	(0.0075)	(0.0074)	(0.0035)	(0.0034)
Sq. Employment (t-1)	-350.4**	-667.7***	-156.5**	-300.0***
	(142.2)	(127.7)	(65.65)	(59.36)
Tenure (t)	-0.0860***	-0.0864***	-0.0441***	-0.0444***
	(0.0018)	(0.0018)	(0.0008)	(0.0008)
Graduate Degree	0.1848***	0.1849***	0.0950***	0.0950***
	(0.0071)	(0.0071)	(0.0036)	(0.0036)
Secondary Degree	0.3753***	0.3755***	0.1822***	0.1825***
	(0.0071)	(0.0071)	(0.0033)	(0.0033)
Female	-0.0574***	-0.0573***	-0.0299***	-0.0299***
	(0.0055)	(0.0055)	(0.0027)	(0.0027)
Observations	17,497,319	17,490,443	17,497,319	17,490,443
Pseudo R^2	0.0885	0.0903	0.0890	0.0908
Relative Time FE	✓	✓	✓	✓
Year × GIC4 FE	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓
Firm × CEO × Event FE		✓		✓
Other Firm Controls	✓	✓	✓	✓

Table A.5: Corporate Charitable Donation Announcement CARs

Notes: This table presents Cumulative Abnormal Returns (CARs) for firms in our sample around the announcement of corporate charitable donations. Panels A.5a and A.5b use event windows of [-1;1] and [-1;30] respectively. Abnormal returns are computed using the Fama and French (1993) three-factor (FF3) and Carhart (1997) four-factor (FF3+C) model as indicated. Columns (1)–(2), (3)–(4), and (5)–(6) summarize the CARs for the full sample of charitable donation announcements, donations unrelated to natural disasters, and donations explicitly related to natural disaster relief, respectively. Charitable donation announcement dates are obtained from RavenPack. Standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) [-1;1] Event window

	CAR [-1;1]					
Split Sample	Full Sample		Non-Disaster		Disaster	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.0027**	-0.0026**	-0.0026**	-0.0030**	-0.0032	-0.0011
	(0.0012)	(0.0012)	(0.0013)	(0.0012)	(0.0034)	(0.0036)
Abn. Returns	FF3	FF3+C	FF3	FF3+C	FF3	FF3+C
Observations	514	514	407	407	107	107

(b) [-1;30] Event window

	CAR [-1;30]					
Split Sample	Full Sample		Non-Disaster		Disaster	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0014	0.0008	0.0062	0.0039	-0.0168	-0.0107
	(0.0046)	(0.0045)	(0.0047)	(0.0046)	(0.0129)	(0.0130)
Abn. Returns	FF3	FF3+C	FF3	FF3+C	FF3	FF3+C
Observations	514	514	407	407	107	107

Table A.6: Natural Disasters, Charitable Contributions, and Firm-Level Outcomes

Notes: This table presents 2SLS-IV regression results for the effect of major natural disasters abroad on firm-level outcomes of U.S. firms. The dependent variables are the overall CSR score from KLD (column 1), the number of employees (2), capital expenditures (3), R&D expenses (4), SG&A expenses (5), sales (6), and net income (7), respectively, all scaled by book assets (except CSR (KLD)). The dependent variable in the first IV-stage is the logarithmic transformation of charitable donations, i.e., log(1+Grants ($M.)). The second IV-stage regresses firm-level outcomes on the instrumented value of charitable donations. We report only the second stage regression results in this table. The data is organized at the firm-year level and stacked around each event. We include similar firm-level control variables as in Table 3. Year-by-industry- ('Year × GICS4 FE'), relative event-time, firm-by-event, and firm-by-CEO-by-event fixed effects are included as indicated. Standard errors are clustered at the firm-event level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Dep. Variable	EMP (KLD)	Empl. Growth	Capx/Assets	R&D/Assets	SG&A/Assets	Sales/Assets	OIBDA/Assets
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$log(1+\widehat{Grants})(t)$	-0.3073	0.1839	-0.0007	-0.0067	-0.0471	-0.1120	0.0062
	(0.3613)	(0.2238)	(0.0086)	(0.0055)	(0.0307)	(0.0912)	(0.0176)
Observations	20,758	19,253	21,721	21,936	18,237	21,936	21,901
R^2	0.7062	0.2078	0.8794	0.9504	0.9591	0.9660	0.8280
Year × GIC4 FE	✓	✓	✓	✓	✓	✓	✓
Relative Time FE	✓	✓	✓	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓	✓	✓	✓
Firm × CEO × Event FE	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓

Table A.7: Turnover and Employee Preferences — Within Firm-Year

Notes: This table presents OLS-regression results for cross-sectional differences at the person-level with respect to past volunteering experience, age, gender, and human capital in the effect of major natural disasters abroad on employee turnover. The dependent variable is an indicator that takes the value of one if an employee leaves their employer during year *t*, all columns report the DiD estimations. ‘Post 1-4’ is an indicator variable that takes the value of one if a major natural disaster occurred in the past four years and ‘$\mathbb{1}$(Had Foundation)’ takes the value of one if the firm made at least one donation in the years before the occurrence of the natural disaster, and zero otherwise. The data is organized at the employee-year level and stacked around each event. All data filters and controls are similar to Table 3. Standard errors are clustered at the firm-event level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dep. Variable: $\mathbb{1}$(Employee Exit)			
	(1)	(2)	(3)	(4)
$\mathbb{1}$(Had Foundation) × Volunteer Exp.	-0.0009			
	(0.0023)			
Post 1–4 × Volunteer Exp.	0.0311***			
	(0.0013)			
Post 1–4 × $\mathbb{1}$(Had Foundation) × Volunteer Exp.	-0.0093***			
	(0.0022)			
$\mathbb{1}$(Had Foundation) × Female		-0.0047**		
		(0.0018)		
Post 1–4 × Female		-0.0029***		
		(0.0010)		
Post 1–4 × $\mathbb{1}$(Had Foundation) × Female		-0.0026*		
		(0.0014)		
$\mathbb{1}$(Had Foundation) × Gen X			0.0005	
			(0.0042)	
Post 1–4 × Gen X			-0.0437***	
			(0.0024)	
Post 1–4 × $\mathbb{1}$(Had Foundation) × Gen X			0.0041	
			(0.0041)	
$\mathbb{1}$(Had Foundation) × Graduate Degree				-0.0051**
				(0.0022)
Post 1–4 × Graduate Degree				0.0302***
				(0.0013)
Post 1–4 × $\mathbb{1}$(Had Foundation) × Graduate Degree				-0.0051***
				(0.0020)
Observations	19,884,522	18,114,505	7,008,388	20,361,040
R^2	0.2682	0.2679	0.2823	0.2687
Firm × Event × GIC4 × Relative Time FE	✓	✓	✓	✓
Employee × Event FE	✓	✓	✓	✓
Employee Controls	✓	✓	✓	✓

A.II Inventor Movement

A.II.1 Data – Patenting Activity and Inventor Turnover

To track the job movement of inventors we rely on the fact that U.S. employment contracts generally require that the rights to any patents developed during an individual's course of employment be assigned to their employer. This allows us to track individuals who patent regularly over time and across firms. We use disambiguated inventor data from the United States Patent and Trademark Office (USTPO). The USTPO uses the 'Discriminative Hierarchical Coreference' method to infer inventors' identities using their names, employers, patented technology classes, and co-authorship networks and assigns them an unique time-invariant ID.[1] With this identifier, we can observe an individual's employment history at the time when they apply for a patent which is eventually granted. By combining this data with the patent-permno links provided by Kogan et al. (2017), we are able to trace the work histories of inventors who work for publicly traded firms.[2]

Our main variable of interest is an indicator variable equal to one in year t if inventor i applies for a patent in year $t+1$ that is assigned to a firm different from their previous employer on record f, and 0 otherwise. This approach to identifying inventor turnover has a few limitations. First, for inventors who do not file a patent every year, the actual turnover event might have occurred at any time between $t+1$ and the previous time inventor i filed for a patent. Second, as we cannot identify the reason why an individual stops patenting, we drop inventors from the sample after their last patent application. This likely underestimates the number of turnover events if inventors change jobs but do not patent again, for example by moving to a managerial role. To mitigate this, we only include inventors who were present

[1] Disambiguated patent data can be found at https://patentsview.org and a description of the Discriminative Hierarchical Coreference used for inventor disambiguation can be found at https://s3.amazonaws.com/data.patentsview.org/documents/UMassInventorDisambiguation.pdf.

[2] To address potential inaccuracies in the disambiguation process, we exclude all inventors who simultaneously patent for more than one firm for two or more consecutive years.

in both the pre- and post-sample periods in our tests.[3]

This procedure yields a total of 1,074,271 unique inventors associated with publicly listed firms, who filed patents between 1985 and 2015. To identify employment changes, we retain only inventors who filed patents in at least 2 years throughout our sample period. After applying these data filters, the sample reduces to 549,179 unique inventors and 4,354,385 inventor-year observations.

We also use the USTPO patent data to obtain the following individual-level characteristics: the cumulative number of patents an inventor has filed up to the current year (as a proxy for employee productivity), the number of years since first occurring in the database (as a proxy for career length and age), gender, geographic location, and the cumulative number of citations an inventor's patents have received from other firms.

Table A.8 reports summary statistics at the inventor-year level. The unconditional inventor turnover rate in our sample is 3%, which is slightly lower than the overall seasonally-adjusted turnover rate of 3.4% reported by the Bureau of Labor Statistics (BLS) based on data from 2004 to 2019. Inventors have an average of 0.87 new patents and 6.53 cumulative patents (i.e., patents since career start) per year. The average career length in our sample, i.e., the time since the year of an inventor's first patent, is 6.6 years. Finally, 9% of the inventors in our sample are female, which is in line with the growing number of female inventors who represented between 7% and 12% of all U.S. inventors from 1992 to 2016 (Toole et al., 2020).

A.II.2 Robustness Tests – Employee Turnover among Inventors

We perform two additional robustness tests with respect to our main result on inventor turnover shown in Table 9. First, a potential concern is that inventors who live outside the U.S., and firms that operate internationally, can be directly affected by natural disasters. If true, our results may be driven by some omitted variable bias, e.g. direct contributions to

[3]Table A.10 shows that our results are robust to only including inventors who filed patents in all sample years.

employees or business units affected by natural disasters. To address this, we exclude firms who report earnings overseas and inventors who live outside of the U.S. The results from this analysis, found in Table A.9, are quantitatively and qualitatively similar to our main results.

Second, we cannot precisely identify when an inventor leaves their current employer as we can only identify turnover when an inventors applies for a patent. While this would bias us against finding a significant treatment effect, we address this issue by including only inventors who filed patents in at least 25%, 50%, 75% and 100% of years in the sample, respectively. By excluding less active inventors we improve our ability to accurately capture employee turnover timing. Appendix Table A.10 shows that despite a large reduction in sample size our results remain qualitatively similar across all specifications.

Table A.8: Summary Statistics – Inventors

Notes: This table reports summary statistics for the inventors in our sample. The data represents unique inventor-year observations from 1984 to 2015. The variables include the number of new and cumulative patents ('N Patents' and 'Cumul. Patents'), new and cumulative outside citations ('N Citations' and 'Cumul. Citations'), number of years since first appearing in the dataset ('Career Length'), and gender 'Male (0/1)'. 'Investor Exit (0/1)' takes the value of one if an inventor left their current employer after the current year. Details on data sources and variable construction are summarized in Section A.II.1 and variable descriptions can be found in the Appendix.

	N	Mean	SD	P05	P25	P50	P75	P95
Inventor Exit (0/1)	4354385	0.03	0.18	0.00	0.00	0.00	0.00	0.00
N Patents	4354385	0.76	0.93	0.00	0.00	1.00	1.00	3.00
Cumul. Patents	4354385	6.53	13.14	1.00	1.00	3.00	7.00	23.00
N Citations	4354385	4.98	11.06	0.00	0.00	1.00	4.00	24.00
Cumul. Citations	4354385	31.11	79.28	0.00	0.00	4.00	21.00	162.00
Career Length	4354385	6.55	6.43	0.00	2.00	5.00	10.00	20.00
Male (0/1)	4004942	0.91	0.28	0.00	1.00	1.00	1.00	1.00

Table A.9: Robustness — Excluding Foreign Inventors and Firms With Foreign Operations

Notes: This table presents OLS- and 2SLS-IV regression results for the effect of major natural disasters abroad on inventor turnover analogous to Panel 9a, including a subsample analysis. In columns (1) and (3), we exclude firms who report earnings from overseas operations, and in columns (2) and (4) we exclude inventors who patent overseas. The dependent variable is an indicator that takes the value of one if an inventor leaves their employer after year t, columns (1) and (3) report the DiD estimates, and columns (2) and (4) report the second stage of the corresponding shock-IV regression. 'Post 1-4' is an indicator variable that takes the value of one if a major natural disaster occurred in the past four years, '$\mathbb{1}$(Had Foundation)' takes the value of one if the firm made at least one donation in the years before the occurrence of the natural disaster, and zero otherwise, and '$log(\widehat{1+Grants})$' is the instrumented value of charitable donations from a first IV-stage estimation. The data is organized at the inventor-year level and stacked around each event. All data filters, controls, and fixed effects are similar to Table 9. Kleibergen-Paap (K-P) Wald F reports the test statistics of F-tests for weak identification with respect to 'Post 1-4 $\times$ $\mathbb{1}$(Had Foundation)'. Standard errors are clustered at the firm-event level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dep. Variable: $\mathbb{1}$(Inventor Exit)			
Model	OLS		IV 2nd	
Domestic	Firm	Inventor	Firm	Inventor
	(1)	(2)	(3)	(4)
Post 1–4 $\times$ $\mathbb{1}$(Had Foundation)	-0.0071***	-0.0072***		
	(0.0026)	(0.0017)		
$log(\widehat{1+Grants})(t)$			-0.0228***	-0.0352***
			(0.0085)	(0.0115)
Observations	348,819	1,111,009	348,819	1,111,009
R^2	0.0480	0.0362	0.0464	0.0298
C-D F-Stat	17596.617	15891.337	17596.617	15891.337
K-P Wald F-Stat	18.575	15.481	18.575	15.481
Relative Time FE	✓	✓	✓	✓
Year $\times$ GIC4 FE	✓	✓	✓	✓
Firm $\times$ Event FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Inventor Controls	✓	✓	✓	✓

Table A.10: Robustness — Accuracy of Inventor Turnover

Notes: This table presents 2SLS-IV regression results for the effect of major natural disasters abroad on inventor turnover analogous to Panel 9a, including subsample analyses. In columns (1) through (4), we exclude all inventors who appear in less than 25%, 50%, 75% and 100% of all available sample years. The main dependent variable is an indicator variable that takes the value of one if an inventor leaves their employer after *t*. The dependent variable in the first IV-stage is the logarithmic transformation of charitable donations, i.e., log(1+Grants ($M.)). The second IV-stage regresses an indicator for inventor exit on the instrumented value of charitable donations. We report only the second stage regression results in this table. The data is organized at the inventor-year level and stacked around each event. All data filters, controls, and fixed effects are similar to Table 9. Kleibergen-Paap Wald F (clustered at the firm-event level) report the test statistics of F-tests for weak identification with respect to 'Post 1-4 × $\mathbb{1}$(Had Foundation)'. Standard errors are clustered at the firm-event level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Dep. Variable	$\mathbb{1}$(Inventor Exit)			
Min. % of Sample Years	25%	50%	75%	100%
	(1)	(2)	(3)	(4)
$log(1+\widehat{Grants})(t)$	-0.0514***	-0.0463***	-0.0354*	-0.0474**
	(0.0166)	(0.0171)	(0.0184)	(0.0226)
Observations	912,381	448,470	197,418	80,462
R^2	0.2380	0.2747	0.3301	0.3812
C-D F-Stat	11372.052	5484.297	2340.475	979.554
K-P Wald F-Stat	13.626	11.032	9.139	8.193
Year × GICS4 FE	✓	✓	✓	✓
Relative Time FE	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓
Inventor × Event FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Inventor Controls	✓	✓	✓	✓