When Values Align: Corporate Philanthropy and Employee Turnover*

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Abstract

This paper studies how corporate philanthropy affects employee retention among high-skilled employees, focusing on the turnover of inventors. In a difference-in-differences-IV setting, we use large-scale natural disasters as shocks to demand for disaster relief to identify exogenous variation in corporate charitable giving. We show that corporate philanthropy significantly reduces inventor turnover with a contributions-to-turnover sensitivity of -0.5. The effect is distinct from other CSR activities and more pronounced for firms with ex-ante weaker employee relations and inventors with greater outside options and stronger pro-social preferences. Our findings indicate that an alignment in values between employees 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

The ability to attract, motivate, and retain talented employees is an essential driver of firm performance (Zingales, 2000; Ian Carlin and Gervais, 2009; Eisfeldt and Papanikolaou, 2013).[1] Practitioners increasingly recognize the importance of social values for attracting and managing talent. For example, in a recent PricewaterhouseCoopers survey, 59% of CEOs expressed that "top talent prefers to work for organizations with social values which are aligned to their own."[2] Despite the growing attention from firms and managers, academic research has primarily focused on the non-pecuniary benefits of CSR to employees, such as family friendliness and employee well-being.[3] Much less is known about the role of social values for employee motivation and retention.

Our paper addresses this question by examining the role of value congruence – i.e. the overlap in values held by employees and their employers – for the career decisions of high-skilled employees. We study this question in the context of corporate charitable donations and examine the turnover of an important group of employees: inventors. Our main contribution is to show that corporate pro-social activities – i.e. contributions to charitable causes – reduce the likelihood of employee turnover among inventors, particularly for individuals with higher pro-social preferences and stronger outside options in the labor market.

Charitable giving represents a substantial part of firms' total CSR activities and provides an ideal testbed for our research question.[4] In contrast to other CSR activities such as workplace safety, childcare, or emissions reductions programs, contributions to charitable organizations do not have tangible non-pecuniary benefits to employees, but can 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 lead to higher employee

[1]While the direct costs of replacing an employee are substantial – estimates range from 150% to 175% of a worker's annual pay (Hansen, 2007) – the indirect costs can be many times higher, particularly for employees with high human capital and organizational externalities (Groysberg, Lee, and Nanda, 2008; David and Brachet, 2011).

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

[3]See for example 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.

[4]Charitable giving by corporations totaled $21.09 billion in 2019 in the US: `https://bit.ly/3uvgbIS`. For example, Alphabet's corporate giving program has donated over $1.5 billion in the past 5 years to charitable causes, equal to approximately 1% of their net income on average.

turnover. Consistent with this *agency conflict perspective*, Masulis and Reza (2015) and Krüger (2015) document negative stock price reactions to the announcement of corporate charitable awards.

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) suggest that corporate philanthropy allows employees to associate themselves with a "good" organization, hence fostering a greater sense of purpose, commitment, and pride. Indeed, in a recent LinkedIn survey, 71% of professionals stated that "they would be willing to take a pay cut to work for a company that has a mission they believe in and shared values". In another survey, 83% of respondents said that they would be "more loyal to a company that helps them contribute to social and environmental issues".[5] This notion, which we dub the *value congruence perspective*, is further supported by an extensive literature in psychology and organizational behavior documenting the importance of commonly held values for employee motivation.[6]

We focus on inventors for several reasons. First, highly innovative inventors are an important driver of firm performance (Hirshleifer, Hsu, and Li, 2013) and economic growth and productivity (Kogan, Papanikolaou, Seru, and Stoffman, 2017). Second, inventors are key employees with critical human capital, who are likely to be highly coveted in the labor market (Hirshleifer, Hsu, and Li, 2018; Ouimet and Zarutskie, 2020) and costly to hire and replace (Belo, Li, Lin, and Zhao, 2017). Third, 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 as well as a host of employee characteristics such as race, gender, and location. Fourth, unlike CEOs and other executives, inventors are not involved in choosing corporate donations at the firm level.

Disentangling the effect of charitable donations from other CSR activities is empirically challenging, as both activities are endogenously determined and likely correlated. For example,

[5] 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."

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

a CEO who establishes a corporate charitable foundation might be more likely to also invest in corporate childcare and health & safety 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).

We overcome these challenges by using large-scale natural disasters abroad as an exogenous shock to the demand for disaster relief and corporate philanthropy, that is plausibly unrelated to other CSR activities and firm characteristics. 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).[7] However, 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. The random timing of disaster events therefore allows us to use the Difference-in-Differences (DiD) effect of firms with and without charitable foundations around a disaster as an instrument for corporate charitable contributions.[8]

Our sample combines data on corporate foundations from the Foundation Directory Online (FDO), charitable donations from the National Center for Charitable Statistics (NCCS), and inventor career transitions, innovation output, and personal characteristics by matching the patent database of Kogan et al. (2017) with CRSP/Compustat firms. We focus on the three most deadly natural disasters in our sample period – the 2004 Indian Ocean earthquake and tsunami, the 2008 earthquake

[7]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 and without any direct impact on the individual inventors in our sample who are based almost entirely in the US.

[8]To ensure that firms with and without charitable foundations are similar along fundamental characteristics, we match each treated firm (i.e. firm with a charitable foundation) to a sample of controls firms based on their pre-event firm characteristics. We conduct extensive tests to verify pre-treatment balance (Atanasov and Black, 2021).

in Sichuan Province (China), and the 2010 Haiti earthquake. Our tests implement a Difference-in-Differences (DiD) and a 2SLS "DiD shock-IV" design (Atanasov and Black, 2016, 2021). Intuitively, our "shock-IV" uses a DiD specification to instrument for corporate charitable donations in the first stage, and regresses inventor-level and firm-level outcomes on the instrumented value in the second stage to estimate a local average treatment effect of charitable grants.

We document a significant, negative effect of charitable donations on the likelihood of inventor turnover. Our results indicate a decrease in turnover probability of 0.52 to 1.11 percentage points 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 and estimate a turnover-to-disaster sensitivity of -0.5. For comparison, the labor economics literature documents a turnover-to-wage sensitivity of -2 to -5 (Bassier, Dube, and Naidu, 2020). Our finding is consistent with the value congruence perspective, i.e. the notion that high-value employees consider firms' pro-social activities when making career decisions. Our results remain robust after controlling for inventor-level (productivity, career length, gender, location) and firm-level (CSR, number of employees, financial constraints, cash flow, size, age, profitability) characteristics, and firm-by-CEO, year-by-industry, and inventor fixed effects.[9]

Importantly, our findings are not consistent with alternative explanations related to other CSR activities *with* non-pecuniary benefits for employees, or with firm-level growth, investment or performance. For example, one might be concerned that firms who donate to charity experience a bump in sales or R&D expenses, which may be driving inventor retention. We find no evidence for this notion. Our results show either no effect or a moderately negative effect on overall CSR scores, employment, sales, investment, and R&D expenses. Similarly, we find no evidence of positive abnormal returns around corporate charitable contribution announcements.

We next explore the role of value congruence – the alignment of pro-social values between employees and employers – as the proposed economic mechanism for our findings. Under this perspective, we would expect to find a stronger effect for firms with relatively poor employee relations, as workers at firms with high employee satisfaction have a lower propensity to switch jobs

[9]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 recently highlighted by Baker, Larcker, and Wang (2022).

in the first place. We conduct sample splits based on 'employee relations' scores from KLD and find that the effect of charitable donations on inventor turnover is mainly concentrated in firms with poor employee relations. Consistent with this idea, we also find an increase in firm-level measures of CEO approval and employee satisfaction in response to higher charitable contributions, using employee review data from Glassdoor.com. Further, we find a stronger effect for employees with higher outside job options, as measured by the number of cumulative external citations an inventor has received for their patents from other firms.

To explore this mechanism further, we consider the social preferences of the inventors in our sample. A key advantage of our highly granular data is that it allows us to consider heterogeneity at different (i.e. state and county) inventor-levels. First, we use state-level charity scores from wallethub.com, and county-level household charitable giving from IRS tax returns, to document a larger effect for inventors located in counties or states with high levels of charitableness. Second, we use county-level Republican vote shares as a proxy for preferences towards more decentralized charitable giving, and less towards corporate charitable giving, and find a larger effect for inventors located in more Democratic-leaning counties.

Last, to address potential concerns about external validity, we study an alternative empirical setting by focusing on the 2003 dividend tax cut. The tax cut was part of the 2003 Jobs and Growth Tax Relief Reconciliation Act (JGTRRA) and reduced the qualified dividends tax rate by 61%. As a result, it lead to significantly higher dividend payouts and increased the opportunity cost of philanthropic contributions, particularly for firms with high levels of CEO share ownership (Chetty and Saez, 2005, 2010; Masulis and Reza, 2015). We again estimate 2SLS shock-IV regressions, using the DiD estimator comparing firms with high and low CEO ownership before and after 2003 as our instrument for corporate charitable grants.

Consistent with our previous results, we find a significant negative effect of (instrumented) corporate philanthropy on inventor turnover. In DiD estimations, we document an increase in turnover probability after the tax cut for high CEO ownership of 0.82 to 1.03pp compared to control firms. Our shock-IV regressions indicate that this result is at least partially driven by a negative effect of the dividend tax cut on the charitable contributions of the treated 'compliers' in our sample.

The magnitude of the Shock-IV results is economically meaningful and comparable to our results using large natural disasters.

The main contribution of our paper is to provide causal evidence that value congruence between employees and their employing organizations can improve the retention individuals with high human capital. Previous research proposes that an overlap in values held by employees and their employers is important for motivating public officials and employees at non-profit enterprises.[10] For example, Prendergast (2007) theoretically argues that 'purpose' and 'mission' drive public officials' behavior, and Imas (2014) and DellaVigna and Pope (2018) provide evidence from laboratory experiments that a "warm glow" feeling can increase worker motivation. Our paper provides novel empirical evidence consistent with the idea that similar considerations also affect the career choices of high-skilled employees at for-profit firms.

Prior research on CSR and labor in finance has focused almost exclusively on the effect of employee *treatment* on firm performance. For example, Edmans (2011) finds that a value-weighted portfolio of the "100 best companies to work for" outperformed industry benchmarks by 2.1%. Chen et al. (2016) find that employee treatment scores are associated with increases in innovation output, and Fauver, McDonald, and Taboada (2018) find that an employee-friendly culture is associated with a higher Tobin's Q. While these papers study how firms "treat their workers", we explicitly focus on pro-social firm activities without non-pecuniary employee benefits.

Our paper is also related to Bode, Singh, and Rogan (2015), who conduct a field experiment and find that management consultants who participated in projects with non-profit organizations accepted lower wages and were 30% less likely to leave their firm. 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, Flammer and Kacperczyk (2019) document that firms increase their combined environmental performance and community relations when labor mobility increases, and Krueger, Metzger, and Wu (2022) use survey data to show that employees accept lower wages and are less likely to leave firms in more sustainable industries. Our study extends this literature by using quasi-natural experiments

[10] See Gneezy, Meier, and Rey-Biel (2011) and Cassar and Meier (2018) for a summary of the literature.

to examine high-skilled employee turnover at the individual person-level.

Finally, while Masulis and Reza (2015) and Cai, Xu, and Yang (2021) document agency conflicts of corporate charities, other papers document positive effects of corporate philanthropy on firm performance (Wang, Choi, and Li, 2008), revenue growth (Lev, Petrovits, and Radhakrishnan, 2010), and competitive differentiation (Gong and Grundy, 2019). Our paper remains agnostic as to the motives and overall value implications of corporate philanthropy. Instead, we focus on the effect of charitable giving for attracting and retaining talented employees, who are unlikely to investigate the motives behind charitable giving.

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 1992 to 2016. 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 (RTF) 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' 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 Inventor Movement

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 disambugated 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.[11] 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.[12]

[11]Disambugated patent data can be found at https://www.patentsview.org and a description of the Discriminative Hierarchical Coreference used for inventor disambugation can be found at https://www.patentsview.org/data/presentations/UMassInventorDisambiguation.pdf.

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

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, since we cannot identify the reason why an individual stops patenting, we drop inventors from the sample after their last patent application. This will likely underestimate the number of turnover events if inventors change jobs but do not patent again, for example by moving to a managerial role. To mitigate under-counting, we only include inventors who were present in both the pre- and post-sample periods in our tests.[13]

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, as shown in Table 1b.

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.

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

[13] In Online Appendix Table IA.5 we show that our results are robust to only including inventors who filed patents in all sample years.

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 make several modifications. 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 and were non-missing after the major index redefinition in 2009. This approach yields time-consistent scores for each firm's overall CSR performance (across all dimensions of CSR) and for each CSR dimension.

2.4 Employee Reviews

We obtain data on employee reviews from Glassdoor.com, the most widely-used employee review website. Glassdoor requires individuals to provide employer reviews before gaining access to its content on employer reviews, salary, and interview details. 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 and 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.[14] To avoid ambiguity regarding which CEO is being reviewed we exclude reviews from employees working for subsidiaries.

2.5 Financial and Other Variables

Financial and accounting data are from CRSP and Compustat, including total employment, the natural log of market capitalization, market leverage, M/B, ROA, cash flow, and the Whited and Wu (2006) (WW) index of financial constraints. We obtain managerial compensation data from Execucomp to determine CEO ownership levels. Finally, we collect county presidential election returns from the MIT Election data and Science Lab, philanthropic rankings of states by WalletHub,

[14] 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.

and county-level donations per household by the IRS. To control for outliers, we Winsorize all firm financial variables at the 1% 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, $17 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.]

Panel 1b of Table 1 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 2004-2019. 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 between 1992-2016 (Toole et al., 2020).

Panel 1c of Table 1 presents the industry breakdown of philanthropic firms within our sample. Of the 2,200 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 main empirical setting uses the differential effect of foreign large-scale natural disasters on firms with and without 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, as proposed by economic theory (Besley and Ghatak, 2005; Prendergast, 2007). At the same time, charitable donations earmarked for foreign disaster relief do not have direct 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 clearly exogenous and cannot be anticipated by firms or employees.

We make two main identifying assumptions: First, conditional on observables, philanthropic giving due to foreign disasters is unrelated to other CSR activities *with* non-pecuniary employee benefits and other firm choices. Second, firms without existing corporate foundations or corporate giving program are constrained in their ability to quickly make charitable contributions following a natural disaster. Together, the random timing of large-scale natural disasters combined with the pre-existing establishment of corporate foundations allows us to use the occurrence of a disaster combined with the existence of a foundation as an instrument for corporate charitable giving.

These assumptions are supported by previous literature and our data. Among others, Muller and Kräussl (2011) and Tilcsik and Marquis (2013), and Ballesteros et al. (2017) show that large-scale natural disasters are a key driver of corporate charitable donations and represent a growing share of all disaster aid. 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. 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).[15] Figure 2a plots the annual number of deaths due

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

to natural disasters and the median annual corporate donations from 1995 to 2015. Additionally, we identify the purpose of individual charitable grants from FDO and plot the donations earmarked for disaster relief along with natural disaster casualties in Figure 2b. 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 significant increase in median charitable grants and disaster-related grants by our sample firms.

However, Ballesteros et al. (2020), among others, document that efficient corporate contributions to disaster relief require a grantmaking infrastructure within a company, such as a corporate charitable foundation or giving program, with expertise and well-established relationships to disaster relief organizations. Firms without such an infrastructure face frictions in their ability to react to unanticipated natural disasters with charitable contributions. In addition to such internal frictions, firms face significant administrative frictions, for example when setting up a corporate foundation. Due to the size and complexity of the firms in our sample, the average waiting period to receive tax-exempt status for a private foundation is 9.6 months from the start of a foundation's inception to the receipt of the IRS determination letter.[16] 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.

Figure 3 provides evidence for this idea by plotting the number of newly established private foundations of our sample firms against the number of disaster casualties through the sample period. As shown, we find no evidence that firms respond to natural disasters by starting new private 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. the years after two of our main disasters, compared to the earlier sample period.

Our second empirical setting follows Masulis and Reza (2015) and uses the 2003 Jobs and Growth Tax Relief Reconciliation Act (JGTRRA) as a shock to dividend payouts and corporate philanthropic giving. We explain our empirical setting and identification strategy using the 2003

[16] 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.

tax cut in detail in Section 5.

3.2 Matching

A potential concern is that firms with corporate foundations may differ from other firms in ways that also correlate with our main outcome variables in the time series. For example, firms that are large and profitable may have more resources to establish a corporate foundation relative to industry peers, and these resources may also allow them to improve employee retention through better compensation and other direct employee benefits.

To address this concern and ensure pre-treatment balance, 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 had a corporate charitable foundation within 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 of employees, number of inventors, number of patents, CSR performance (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).[17]

[Insert Table 2 here.]

Fig. 4 and Table 2 document the covariates balance pre- and post matching. As shown in Fig. 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 2a and 2b, 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

[17]We ensure common support and pre-treatment balance by removing observations outside of a caliper of 0.05 of the propensity score, following Atanasov and Black (2021).

create a balanced sample of pre- and post observations. To ensure that inventor-level job transitions are captured accurately, we only retain individual inventors who were present (i.e. filed patents) at least once in the pre- and the post period of each event.

3.3 Main Specification

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

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

where y_{ifet} measures inventor-level outcomes such as turnover of inventor 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 characteristics that could affect the propensity of a firm or CEO to establish a foundation. This further helps us address concerns that our results are driven by unobserved factors.[18] Inventor-level regressions further include additional controls for individual inventor characteristics (X_{iet}), such as cumulative patents, career length, and gender, and inventor-by-event fixed effects (δ_{ie}). Our estimates therefore stem from within-inventor variation across time.

The indicator variable $Post\ 1\text{-}4_{et}$ 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 with a foundation or corporate giving program before event e. Hence, our main coefficient of interest, β, captures

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

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 firm level, i.e. the level of treatment variation.

To identify how our shocks affect inventor turnover *through* corporate charitable donations, we implement a 'shock-IV' design (Atanasov and Black, 2016, 2021). Intuitively, this empirical design uses the difference-in-difference specification in Equation (1) to instrument for corporate charitable donations in the first stage, and regresses inventor 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 following form:

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

where $\mathbb{1}(Inventor\ Exit)_{ifet}$ is an indicator variable that takes the value of one if inventor i exits firm f after year t around event e, and zero otherwise, $\widehat{Charitable\ Grants}_{ifet}$ is the predicted 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 Results — Natural Disasters

4.1 Philanthropic Contributions and Other Firm Outcomes

Before examining inventor turnover we first provide evidence for our main identifying assumptions, by examining the effect of natural disaster occurrence on charitable donations, CSR performance, and other firm-level outcomes in Table 3. We begin by focusing on the relevance of natural disasters abroad for firms' philanthropic giving by estimating Equation (1) at the firm-year level, using the (log-transformed) amount of charitable donations ($M.) as the dependent variable y_{ifet}.

[Insert Table 3 here.]

As shown in Table 3, 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 sizable. 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 $787k to $800K in the four years after a natural disaster relative to the control sample. This is equivalent to an increase by about 20% 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). The estimates correspond to an increase in grants between 14.80% and 16.95%. 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.

The test statistics for the Cragg-Donald and Kleibergen-Paap Walk F-tests for weak identification reported in Table 3 further confirm this result. In all specifications, the F-Statistics are well-above conventional critical values (Stock, Wright, and Yogo, 2002) for both tests, alleviating concerns about weak instrumental variable problems. Particularly the Kleibergen-Paap Walk F-test is informative as it accounts for clustered standard errors at the firm-event level, whereas the Cragg-Donald F-test assumes homoscedastic and serially uncorrelated standard errors.[19]

Figure 5 presents the corresponding dynamic effect of natural disasters on donations, plotting the coefficient estimates of a stacked regression of *Grants* on interaction terms of event-time dummy variables with an indicator for treated firms, including firm controls and industry-by-year-, event-time-, and firm-by-CEO-by-event fixed effects. As shown, there are no discernible pre-trends in charitable donations prior to disaster occurrence. In line with Table 3, firms with foundations respond to disasters by significantly increasing contributions in the year after a disaster, and subsequently maintain this higher level throughout the following four years.

A potential threat to our identification is the possibility that corporate charitable contributions might increase firm performance and value, for example, due to marketing and reputation benefits.

[19]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.

Under this scenario, inventors may interpret charitable donation announcements of their employers as a signal of better future employment conditions, which in turn may be driving inventor turnover.

We address this concern in two 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 the announcement of corporate philanthropic donations. In Appendix Table IA.1, we estimate Cumulative Abnormal Returns (CARs) for the [-1;1] (Panel IA.1a) and [-1;30] (Panel IA.1a) day event window around charitable contribution announcements. We estimate 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 donation announcements, and an insignificant CAR of -0.11% for charitable donations related to natural disasters. These results are consistent with Masulis and Reza (2015) and Krüger (2015) and indicate that markets, if anything, on average react negatively to firms' charitable contribution announcements. The estimates for the [-1;30] do not show any significant CARs in the event window, further supporting this interpretation.

Second, we provide evidence that natural disasters abroad do not lead to changes in other firm policies and characteristics, by estimating Equation (2) using CSR, employment, investment, R&D, SG&A, sales, and ROA as outcome variables. The results (Appendix Table IA.2) show no significant effect on overall CSR performance (column 1). Similarly, we do not find a significant effect on tangible investment, intangible (intellectual and human capital) investment (i.e. R&D and SG&A) or financial performance (Sales and ROA) in columns (2)–(7), indicating that our main results on inventor turnover are unlikely to be driven by contemporaneous firm growth or investment effects. [20]

4.2 Inventor Turnover

After establishing that natural disasters are relevant exogenous shocks to corporate philanthropy, we next present our main tests and explore the effect of charitable donations on inventor turnover. For this purpose, we estimate the models in Equations (1) and (2) at the inventor-year level, using

[20] As shown in column (2), we find a weakly significant negative effect on overall employment. However, the effect is not robust across specifications and cannot explain our main findings, as a firm with decreasing employment should exhibit higher, not lower inventor turnover.

$\mathbb{1}(\text{Inventor Exit})_{ifet}$ as our main dependent variable.

[Insert Table 4 here.]

Panel 4a presents the results for the DiD specification in Equation (1) at the inventor-year level. Across all specifications, we find a negative treatment effect of natural disaster occurrence on the likelihood of inventor exit for treated firms with pre-existing charitable organizations. The effect is both statistically and economically significant. We find that inventor turnover decreases between 0.52 and 1.11 percentage points across specifications, which is equivalent to 12% 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. Consistent with the idea that employees with high human capital can extract a higher value from their employers, we also find a significant negative effect of cumulative patents on the likelihood of inventor turnover.[21] By including firm-by-CEO-by-event fixed effects, we ensure that our results are not driven by time-invariant firm characteristics, CEO preferences, or their interactions.

Figure 6 displays the corresponding dynamic effect, plotting the coefficient estimates of $\mathbb{1}(\text{Inventor Exit})_{ifet}$ on event-time dummy variables interacted with an indicator for treated firms, controlling for fixed effects and covariates. Similar to Figure 5, we find no discernible pre-trend in inventor turnover likelihood. The plotted coefficient is flat and indistinguishable from zero in periods $t = -4$ to $t = -1$, drops significantly for treated firms in period $t = 1$ after natural disasters as firms with charitable foundations increase their philanthropic contributions, and remains below zero in the following periods.

In our main tests, we examine charitable donations as the channel for our results by using natural disaster occurrence as an instrument for charitable donations. Panel 4b documents the results of the 'shock-IV' specification detailed in Equation (2), summarizing the first (columns 1 and 3) and second stage regressions (columns 2 and 4) with and without inventor-by-event fixed effects, respectively. Similar to Table 3, we first document a significant, positive first-stage effect of disaster

[21] This finding is consistent with the management literature (e.g. Campbell, Ganco, Franco, and Agarwal, 2012) showing that while employees with higher human capital have higher bargaining power, they are less likely to exit.

occurrence on treated firms' charitable donations in column (1).[22] The effect is virtually unchanged when including inventor-by-event fixed effects in column (3). Consistent with the evidence presented in Table 3, the DiD parameter 'Post 1-4 $\times$ $\mathbb{1}$(Had Foundation)' is a strong instrument for charitable donations: both the Cragg–Donald F and Kleibergen–Paap Wald F statistic (clustered at the firm-event level) are well above standard critical values (Stock et al., 2002).[23]

Our core finding (columns 2 and 4) is that instrumented charitable contributions have a large negative effect on the likelihood of inventor turnover. The effect is both statistically and economically significant, and 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 -0.0346 in column (2) indicates that an increase in charitable donations of 10% is associated with a 0.14 percentage point decrease in the likelihood that the inventor leaves his employer after the current year. This is equivalent to a 4.6% reduction relative to the sample mean. In other words, we find a turnover-to-donations sensitivity of approximately -0.46, which 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 Robustness

We perform a number of additional tests to ensure that our main result is robust to changes in other corporate policies, CSR performance, and alternative measures of inventor turnover. First, a potential concern is that our result may be driven by simultaneous changes in CSR activities with direct benefits for employees. We therefore include CSR performance scores across several categories (environment, community, human rights, employee relations, product, diversity, and governance) as additional controls in our tests. Each CSR score is measured with a lag of one year. We include the same firm and individual-inventor controls and fixed effects used in Table 4.

[Insert Table 5 here.]

[22] The coefficient estimates differ from Table 3 because 4b is estimated at the inventor-year level and Table 3 is estimated at the firm-year level.

[23] The very large F-Statistics for Cragg–Donald F-tests are likely due to clusters in the standard errors at the firm-event level.

Panels 5a and 5b report the results for Equations (1) and (2), respectively. In both panels and across all fixed effects specifications we find similar coefficient estimates of our main explanatory variables as in our baseline results.[24] Similarly, in the 'shock-IV' specification in Panel 5b, we find no significant relationships between turnover and CSR performance, supporting the idea that our results are not driven by concurrent changes in employee relations or other CSR activities.

Next, we address potential concerns about our stacked DiD design. The first concern is that the timing of one of the disaster events might coincide with other significant but unrelated events, which could affect treated and control firms differently. The second concern involves the validity of two-way fixed effects (TWFE) specifications for DiD estimations with staggered treatment. Recent work (e.g. Baker et al., 2022) shows that such estimators are biased due to a "bad comparisons" problem, and can result in both Type-I and Type-II errors. While our stacked-regression design has been shown to be less susceptible to these biases (Baker et al., 2022), we replicate column (2) of Panel 5a and columns (3)–(4) of Panel 5b but consider each disaster event individually to address these concerns. Panels 5c and 5d report the results and show that our results are not driven by one specific disaster event or the validity of TWFE.

Further, firms in reality can operate either corporate direct giving programs or private foundations (PFs), or both. While PFs are subject to both the administrative and internal frictions discussed earlier, direct corporate giving programs are only subject to internal frictions and may therefore be able to quickly react to natural disasters. To address this concern, we exclude all firms in the sample who have had registered direct corporate giving programs, irrespective of whether they contributed to charitable causes at any point during the sample period. The results from this analysis, found in Appendix Table IA.6, are qualitatively similar to our main results.

A drawback of our setting is that it does not allow us to differentiate directly between voluntary and forced turnover of inventors, which may introduce noise into our estimates. Although this noise in the dependent variable would bias us against finding a significant treatment effect, we further address this concern by examining subsamples of firms with strong economic fundamentals which

[24]Further, contrary to the concern that simultaneous changes in employee treatment could be the main determinant of turnover, we find a weak positive relation between employee treatment and turnover in Panel 5a. In the same regression, we also find that turnover is weakly negatively related to corporate governance and positively related to human rights performance.

are less likely to be actively reducing their workforce. Specifically, we exclude firms in the bottom quartile of the Compustat universe with respect to ROA, scaled cash holdings, sales growth, and Tobin's Q, respectively in columns (1) through (4) of Appendix Table IA.4. The results from this table are qualitatively and quantitatively similar to our main results.

Finally, 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 isssue 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 inventor turnover timing. Appendix Table IA.5 shows that despite a large reduction in sample size our results remain qualitatively similar across all specifications.

4.4 Cross-Sectional Heterogeneity

To further strengthen our results and shed additional light on the economic mechanism underlying our main finding, we next examine cross-sectional differences at the firm- and inventor-level. As a plausibility test, we first examine the moderating effects of employee relations and inventor outside job options on the turnover-to-donations sensitivity. Second, we examine the role of inventors' pro-social preferences to study the role of value congruence between employers and employees or our main finding.

4.4.1 Employee Satisfaction

We begin by examining cross-sectional differences in the documented effect across firms with strong and weak employee relations. As shown in the literature, workers with high employee satisfaction are less likely to leave their jobs (e.g. Bode et al., 2015; Chen et al., 2016), and we would hence expect them to be less sensitive to changes in pro-social activities of their employers. If our main finding is indeed driven by a higher commitment of inventors to their employers, one would expect the relation to be stronger in firms with weaker employee relations.

To test this idea, we begin by splitting the sample into firms with above- and below-median 'employee relations' scores from KLD within each industry and year, and estimate Equations (1) and (2) for each subsample. The employee relations score is determined by a firm's performance in regards to issues such as union relations, employee involvement, health and safety, and human capital development. All of these metrics are directly related to how well a firm treats its employees.

[Insert Table 6 here.]

Panel 6a summarizes the results. Consistent with our conjecture, we find that the relation between philanthropic contributions and turnover is more pronounced in the subsample of firms with poor employee relations. In the DiD setting presented in columns (1) and (2), treated firms in the 'low' employee relations group experience a statistically robust decrease of 36% in the likelihood of turnover after natural disasters compared to a decrease of 12% in the likelihood of turnover for treated firms in the 'high' employee relations group. The difference in coefficient estimates is significant at the 1% level.

Columns (3) and (4) of Panel 6a report the 2nd stage of the corresponding "shock-IV" results. Again, we find that the relation between charitable donations and employee turnover is stronger for firms with low employee relations (KLD) scores. The point estimate for our instrumented charitable contributions variable, $log(\widehat{1+Grants})$, for the 'low' employee relations group in column (4) is about 3 times larger than the corresponding point estimate for the 'high' employee relations group in columns (3). The difference in coefficient estimates is significant at the 5% level.

4.4.2 External Patent Citations

We next consider the role of employee outside options as an additional validity test. All else equal, employees with pro-social preferences should be more sensitive to firms' charitable activities if they have higher labor mobility. We use inventor i's cumulative number of external citations – i.e. from firms other than i's current employer – for i's patents up to year t, as a proxy for inventor i's outside job opportunities. Intuitively, the number of citations from other firms will be higher if other firms are aware of the inventor's work and quality, and if the patents are relevant for applications outside of the inventor's current employer. Similar to prior panels in Table 6, we split the sample by inventors with above- and below-median cumulative external citations, i.e. outside career options, within a given firm-year and estimate Equations (1) and (2).

These results are presented in Panel 6b. We estimate a higher sensitivity in the subsample of inventors with a higher number of external citations. The effect is approximately 35% stronger in the 'high' compared to the 'low' outside options subsample in the DiD setting, as shown in columns (1) and (2). The difference in coefficient estimates is significant at the 5% level. We find a similar result using the shock-IV setting in columns (3) and (4): the point estimate for predicted charitable contributions, $log(\widehat{1 + Grants})$, is about 28% higher in the subsample of inventors with a high outside job options.

4.4.3 Local Preferences for Charity

Next, we provide more direct evidence for the proposed economic mechanism underlying our main result – i.e. the value congruence between employers and employees – by studying cross-sectional differences with respect to inventors' personal preferences. If corporate philanthropic contributions reduce turnover because shared pro-social preferences increase the sense of purpose and mission of employees (Besley and Ghatak, 2005), we would expect individuals in regions with higher preferences for charity to be more sensitive to firms' charitable activities in response to a disaster event.

We first explore differences in the documented effect across regional levels of charitableness, using state-level charitable giving scores as a proxy for regional preferences. Our conjecture, is that inventors who reside in areas with a higher propensity to contribute to charitable causes, either with their time or money, are either more likely to be directly involved in charitable activities or highly exposed to individuals who are, and hence will be more sensitive to corporate philanthropic giving.

To test this idea we use WalletHub's 2020 state-level charitable giving scores, which ranks each state based on nine metrics spanning different metrics of charitable giving, to split the sample by inventors who reside in states whose charity score is above and below the median and estimate Equations (1) and (2).

[Insert Table 7 here.]

The results are presented in Panel 7a. In line with the idea that inventors exposed to higher levels of charitableness have a greater sensitivity to corporate philanthropic activity, we find a stronger effect of (instrumented) corporate donations on inventor turnover in the subsample of inventors who reside in more charitable states. The effect is 66% stronger in the above- compared to the below-median charitable state 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 predicted charitable contributions, $log(\widehat{1 + Grants})$, is about 1.1 times higher in the subsample of inventors who reside in highly charitable states. The difference in coefficient estimates is significant at the 5% level for both the DiD and shock-IV settings.

4.4.4 Republican Vote Share

Next, we explore differences in the documented effect across different partisan preferences. Surveys on philanthropy find that while Republicans have a stronger preference for charitable giving, their donating behavior primarily focuses on religious organizations.[25] When looking at the primary reason for donating, Republicans are less like to donate to help the "greater good", and instead prefer to contribute directly to specific charities and issues that they care about.[26] These facts, coupled with Republicans' strong stance against institutional wealth redistribution, leads us to conjecture that these individuals would rather donate to causes themselves, than for their employer to do so on their behalf.

To test this idea, we obtain data on presidential election returns for each U.S. county from the MIT Election Data and Sciences Lab. While we cannot accurately observe inventors' party affiliation, we use the partisan leaning of an inventor's county of residence during the last preceding presidential election as a proxy. Similar to the prior panels in Table 7, we split the sample by inventors who reside in counties whose support for Republican candidates, estimated on year t for each disaster event, is above and below the sample median and estimate Equations (1) and (2).

As shown in Panel 7b, we estimate a lower sensitivity of inventor turnover to (instrumented) corporate charitable donations in the subsample of inventors who reside in more Republican leaning counties. The effect is 30% stronger in the 'low' compared to the 'high' Republican county subsample in the DiD setting, as shown in columns (1) and (2). We find a similar result using the

[25] Source: https://www.philanthropyroundtable.org/almanac/statistics/u.s.-generosity

[26] https://apply.surveymonkey.com/resources/partisanship-influence-charitable-giving/

shock-IV setting in columns (3) and (4): the point estimate for predicted charitable contributions, $log(\widehat{1+Grants})$, is 1.1 times higher in the subsample of inventors who reside in mostly Democrat counties. The difference in coefficient estimates is marginally insignificant.

4.5 Employee Satisfaction Outcomes

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 commitment and satisfaction at the firm-level from employee-reviews posted to Glassdoor.com. Specifically, 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. Our specifications therefore do not include relative event-time fixed effects, as they would be collinear with our industry-by-year fixed effects.

The results, presented in Table 8, show a significant positive effect of corporate charitable contributions following large foreign natural disasters on both employees' overall assessment of their employers and their approval of the CEO. As documented in columns (1) and (2), in the years following a major foreign disaster, the 'Overall Rating' and the 'CEO Approval' score of treated firms with existing corporate foundations increases by 3.37% and 6.93% relative to the sample mean (= 0.0217/0.643 and = 0.0433/0.625), respectively, compared to the control firms. Estimates are statistically significant at the 10% and 5% levels.

We confirm that this finding is indeed driven by corporate philanthropic activity using shock-IV specifications as specified in Equation (2) at the firm-year level as before. The 2nd stage IV results are summarized in columns (3) and (4) of Table 8. We find a positive effect of (instrumented) charitable donations on both 'Overall Rating' and 'CEO Approval' scores. The results are weakly significant at the 10% level, which is unsurprising given the small sample size in these tests. Our estimates indicate that for a 10% increase in $log(1+\widehat{Grants})$, overall satisfaction increases by 1.96% and CEO approval increases by 2.02% relative to the sample mean. Taken together our findings point to a positive effect of corporate charitable activity on an employee's view of their firm and its

CEO.

5 Results — Dividend Tax Cut

The previous section established that charitable donations reduce the likelihood of inventor turnover, using natural disasters as an instrument for corporate charitable donations. However, since natural disasters are a 'positive' shock to corporate philanthropic giving, it is unclear if reductions in charitable donations have a similar effect. To study this question, we consider the 2003 Jobs and Growth Tax Relief Reconciliation Act (JGTRRA) as a 'negative' shock to corporate philanthropic giving in an alternative empirical setting.

5.1 Philanthropic Contributions and other Firm Outcomes

The 2003 tax cut reduced the qualified dividends tax rate by 61%, leading to significantly higher dividend payouts (Chetty and Saez, 2005, 2010), and hence increased the opportunity cost of philanthropic contributions. This is particularly true for firms with high levels of CEO share ownership (Masulis and Reza, 2015), as the tax cut increased the CEOs' marginal benefits of dividends payouts relative to other uses of corporate cash. Since CEO share ownership was established well in advance of the 2003 tax change for most firms, we can use the differential effect of the 2003 dividend tax on firms with high and low CEO ownership to identify exogenous variation in corporate charitable contributions, following Masulis and Reza (2015). An advantage of this setting is that it allows us to limit our sample to firms with existing corporate foundations and study plausibly exogenous changes in charitable donations within this group of firms.

We first provide evidence supporting our identifying assumptions by estimating Equation (1) at the firm-year level, using dividend payouts, charitable donations, CSR performance, and other firm outcomes (employment, CapX, R&D) as dependent variables, respectively. We use the variable '$\geq$ 2003' to indicate the post-period starting in 2003, and 'CEO Own (%)' (the proportion of shares owned by the CEO in 2002) and '$\mathbb{1}$(CEO Own. High)' (a dummy indicating 2002 CEO share ownership in the top quartile), respectively, to indicate treated firms in Equation (1).

[Insert Table 9 here.]

Table 9 summarizes the results. Panel 9a focuses on dividend payouts and confirms the main result of Chetty and Saez (2005): the 2003 dividend tax cut had a large, positive effect on the dividend payouts of firms with high CEO share ownership. This result is similar using both dummy (columns 1—3) and continuous variables (columns 4—6) for CEO ownership, and holds after including industry-by-year-, firm-, and firm-by-CEO fixed effects.

Panel 9b presents the corresponding result for corporate charitable donations. Similar to Masulis and Reza (2015), we find a significant negative treatment effect of the 2003 dividend tax cut on firms with high CEO ownership across all specifications. The magnitude of this effect is sizable. As firms increase their dividend payouts in response to the tax cuts, corporate donations decrease between 9.24% ($= exp(0.0884) - 1$) to 12.06% ($= exp(0.1139) - 1$) in the post-period for treated relative to control firms. The effect is similar using dummy or continuous CEO ownership variables.

The dynamic effect of the 2003 tax cut on dividend payouts and charitable grants, plotted in Appendix Figures IA.1a and IA.1b, is consistent with this finding. The difference between dividends and donations of treated relative to control firms is flat and indistinguishable from zero leading up to 2003. In 2004, dividends of treated firms increase sharply. Correspondingly, charitable donations of high-CEO ownership firms decline significantly in the post period and remain at a lower level in the following years.

In Appendix Table IA.7, we further provide evidence that the effect on donations and dividends was not associated with other observable firm reactions. Using both dummy and continuous CEO ownership measures, we neither find a significant positive treatment effect on overall CSR performance (KLD) nor on employment, capital expenditures, R&D expenses, and sales.

5.2 Inventor Turnover

We next study the effect of charitable contributions on inventor turnover, using the 2003 dividend tax cut to isolate exogenous variation in charitable contributions. Similar to Section 4, we first present the DiD setting at the inventor-year level, as specified in Equation (1). The results are summarized in Table 10.

[Insert Table 10 here.]

Consistent with our previous results, we find a significant, positive effect of the 2003 dividend tax cut on the likelihood of employee turnover for treated relative to control firms in the post period in Panel 10a. The effect is statistically significant at the 1% level across all specifications and economically sizable. In our tightest specification with industry-by-year fixed effects and firm-by-CEO fixed effects (column 3), the coefficient estimate for "$\geq 2003 \times \mathbb{1}$(CEO Own. High)" indicates an increase in the likelihood of inventor turnover of 0.82 to 1.03 percentage points. The corresponding dynamics plot in Appendix Figure IA.2 reveals no evidence of a pre-trend prior to 2003, and indicates a growing increase in inventor turnover likelihood in each of the four years after the dividend tax cut.

In Panel 10b we implement the model in Equation (2) to estimate the role of charitable donations as the channel for our documented effect. The first-stage regressions (columns 1, 3, and 5) indicate that the difference-in-difference parameter is a valid instrument for charitable donations. Our main result, documented in the second-stage regressions in columns (2), (4), and (6), shows that an increase in corporate charitable donations reduces the likelihood of an inventor leaving his current employer. The economic magnitude of the effect is similar to the results presented in Section 4, and indicates a 0.15 percentage point decrease in turnover likelihood for a 10% increase in corporate charitable donations (significant at the 1% level, respectively). The economic magnitude of this result is strikingly similar to our findings in the natural disaster settings, which alleviate potential concerns about external validity and our identifying assumptions.

Similar to Section 4, we additionally include CSR controls across various categories to address concerns that our results are driven by changes in firm activities with *direct* personal benefits for employees. The results remain robust as shown in Appendix Table IA.8.

6 Conclusion

Given the increasing importance of human capital for firm performance, we examine whether an alignment in social values between firms and their employees, also known as value congruence, can reduce inventor turnover. In contrast to the prior literature, which typically either studies broad definitions of CSR or focuses on aspects of CSR that *directly* affect employees, such as employee treatment and worker benefits, we focus on corporate philanthropic giving which provides no direct benefits to a firm's employees.

We use large international disasters as an exogenous shock to the demand for philanthropic giving and the 2003 Jobs and Growth Tax Relief Reconciliation Act (JGTRRA) as a shock to the opportunity cost of philanthropic giving for CEOs with high levels of share ownership. In both settings, we find robust evidence that changes in philanthropic giving can affect employee turnover by an economically sizable magnitude.

In our first 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. We find that natural disasters are associated with a large increase in philanthropic giving and 21% decrease in employee turnover. In our second setting, we isolate firms with foundations and rely on the differential treatment of JGTRRA conditional on CEO share ownership. In this setting, we find that CEOs with high share ownership drastically reduce their firms' corporate philanthropic giving, due to the opportunity cost of not issuing dividends, and subsequently experience significant increases in employee turnover.

Further, we show that our results are robust to the inclusion of controls for different categories of CSR, inventor- and firm characteristics, and the use of various high-dimensional fixed-effects specifications. Finally, we find that the effects of corporate philanthropy are concentrated in firms with low levels of employee relations as employees in these firms have an ex-ante higher probability of leaving.

References

Akey, P., S. Lewellen, I. Liskovich, and C. Schiller (2021). Hacking corporate reputations. Rotman School of Management Working Paper, Number 3143740.

Albinger, H. S. and S. J. Freeman (2000). Corporate social performance and attractiveness as an employer to different job seeking populations. *Journal of Business Ethics 28*(3), 243–253.

Atanasov, V. A. and B. S. Black (2016). Shock-based causal inference in corporate finance and accounting research. *Critical Finance Review 5*, 207–304.

Atanasov, V. A. and B. S. Black (2021). The trouble with instruments: The need for pretreatment balance in shock-based instrumental variable designs. *Management Science 67*(2), 1270–1302.

Baker, A. C., D. F. Larcker, and C. C. Wang (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics 144*(2), 370–395.

Ballesteros, L., M. Useem, and T. Wry (2017). Masters of disasters? An empirical analysis of how societies benefit from corporate disaster aid. *Academy of Management Journal 60*(5), 1682–1708.

Ballesteros, L., M. Useem, and T. Wry (2020). Halos or horns? Reputation and the contingent financial returns to non-market behavior. George Washington University, Working Paper.

Bassier, I., A. Dube, and S. Naidu (2020). Monopsony in movers: The elasticity of labor supply to firm wage policies. Technical report, National Bureau of Economic Research.

Belo, F., J. Li, X. Lin, and X. Zhao (2017). Labor-force heterogeneity and asset prices: The importance of skilled labor. *The Review of Financial Studies 30*(10), 3669–3709.

Besley, T. and M. Ghatak (2005). Competition and incentives with motivated agents. *American Economic Review 95*(3), 616–636.

Bloom, N., T. Kretschmer, and J. Van Reenen (2011). Are family-friendly workplace practices a valuable firm resource? *Strategic Management Journal 32*(4), 343–367.

Bode, C., J. Singh, and M. Rogan (2015). Corporate social initiatives and employee retention. *Organization Science 26*(6), 1702–1720.

Burbano, V. C. (2016). Social responsibility messages and worker wage requirements: Field experimental evidence from online labor marketplaces. *Organization Science 27*(4), 1010–1028.

Cai, Y., J. Xu, and J. Yang (2021). Paying by donating: Corporate donations affiliated with independent directors. *The Review of Financial Studies 34*(2), 618–660.

Campbell, B. A., M. Ganco, A. M. Franco, and R. Agarwal (2012). Who leaves, where to, and why worry? Employee mobility, entrepreneurship and effects on source firm performance. *Strategic Management Journal 33*(1), 65–87.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *Journal of Finance 52*, 57–82.

Carnahan, S., D. Kryscynski, and D. Olson (2017). When does corporate social responsibility reduce employee turnover? Evidence from attorneys before and after 9/11. *Academy of Management Journal 60*(5), 1932–1962.

Cassar, L. (2019). Job mission as a substitute for monetary incentives: Benefits and limits. *Management Science 65*(2), 896–912.

Cassar, L. and S. Meier (2018). Nonmonetary incentives and the implications of work as a source of meaning. *Journal of Economic Perspectives 32*(3), 215–38.

Chen, C., Y. Chen, P.-H. Hsu, and E. J. Podolski (2016). Be nice to your innovators: Employee treatment and corporate innovation performance. *Journal of Corporate Finance 39*, 78–98.

Chetty, R. and E. Saez (2005). Dividend taxes and corporate behavior: Evidence from the 2003 dividend tax cut. *The Quarterly Journal of Economics 120*(3), 791–833.

Chetty, R. and E. Saez (2010). Dividend and corporate taxation in an agency model of the firm. *American Economic Journal: Economic Policy 2*(3), 1–31.

David, G. and T. Brachet (2011). On the determinants of organizational forgetting. *American Economic Journal: Microeconomics 3*(3), 100–123.

DellaVigna, S. and D. Pope (2018). What motivates effort? evidence and expert forecasts. *The Review of Economic Studies 85*(2), 1029–1069.

Edmans, A. (2011). Does the stock market fully value intangibles? Employee satisfaction and equity prices. *The Journal of Financial Economics 101*, 621–640.

Edmans, A., L. Li, and C. Zhang (2014). Employee satisfaction, labor market flexibility, and stock returns around the world. National Bureau of Economic Research.

Edwards, J. R. and D. M. Cable (2009). The value of value congruence. *Journal of Applied Psychology 94*(3), 654.

Eisfeldt, A. L. and D. Papanikolaou (2013). Organization capital and the cross-section of expected returns. *The Journal of Finance 68*(4), 1365–1406.

EM-DAT (2020). EM-DAT: The emergency events database. Universite Catholique de Louvain (UCL), CRED, available at http://www.emdat.be, Brussels, Belgium.

Fama, E. F. and K. R. French (1993). Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics 33*, 3–56.

Fauver, L., M. B. McDonald, and A. G. Taboada (2018). Does it pay to treat employees well? International evidence on the value of employee-friendly culture. *Journal of Corporate Finance 50*, 84–108.

Flammer, C. and A. Kacperczyk (2019). Corporate social responsibility as a defense against knowledge spillovers: Evidence from the inevitable disclosure doctrine. *Strategic Management Journal 40*(8), 1243–1267.

Gneezy, U., S. Meier, and P. Rey-Biel (2011). When and why incentives (don't) work to modify behavior. *Journal of Pconomic Perspectives 25*(4), 191–210.

Gong, N. and B. D. Grundy (2019). Can socially responsible firms survive competition? An analysis of corporate employee matching grant schemes. *Review of Finance 23*(1), 199–243.

Gosnell, G. K., J. A. List, and R. Metcalfe (2016). A new approach to an age-old problem: Solving externalities by incenting workers directly. Working Paper 22316, National Bureau of Economic Research.

Groysberg, B., L.-E. Lee, and A. Nanda (2008). Can they take it with them? The portability of star knowledge workers' performance. *Management Science 54*(7), 1213–1230.

Hansen, F. (2007). Currents in compensation and benefits. *Compensation & Benefits Review 39*(3), 5–27.

Hirshleifer, D., P.-H. Hsu, and D. Li (2013). Innovative efficiency and stock returns. *Journal of Financial Economics 107*(3), 632–654.

Hirshleifer, D., P.-H. Hsu, and D. Li (2018). Innovative originality, profitability, and stock returns. *The Review of Financial Studies 31*(7), 2553–2605.

Huang, M., P. Li, F. Meschke, and J. P. Guthrie (2015). Family firms, employee satisfaction, and corporate performance. *Journal of Corporate Finance 34*, 108–127.

Ian Carlin, B. and S. Gervais (2009). Work ethic, employment contracts, and firm value. *The Journal of Finance 64*(2), 785–821.

Imas, A. (2014). Working for the "warm glow": On the benefits and limits of prosocial incentives. *Journal of Public Economics 114*, 14–18.

Jones, D. A., C. R. Willness, and S. Madey (2014). Why are job seekers attracted by corporate social performance? Experimental and field tests of three signal-based mechanisms. *Academy of Management Journal 57*(2), 383–404.

Kogan, L., D. Papanikolaou, A. Seru, and N. Stoffman (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics 132*(2), 665–712.

Krueger, P., D. Metzger, and J. Wu (2022). The sustainability wage gap. *Swedish House of Finance Research Paper* (20-14), 21–17.

Krüger, P. (2015). Corporate goodness and shareholder wealth. *Journal of Financial Economics 115*(2), 304–329.

Lev, B., C. Petrovits, and S. Radhakrishnan (2010). Is doing good good for you? How corporate charitable contributions enhance revenue growth. *Strategic Management Journal 31*(2), 182–200.

Masulis, R. W. and S. W. Reza (2015). Agency problems of corporate philanthropy. *The Review of Financial Studies 28*(2), 592–636.

Meglino, B. M. and E. C. Ravlin (1998). Individual values in organizations: Concepts, controversies, and research. *Journal of Management 24*(3), 351–389.

Muller, A. and R. Kräussl (2011). Doing good deeds in times of need: A strategic perspective on corporate disaster donations. *Strategic Management Journal 32*(9), 911–929.

Ouimet, P. and R. Zarutskie (2020). Acquiring labor. *Quarterly Journal of Finance 10*(03), 2050011.

Podsakoff, P. M., S. B. MacKenzie, J. B. Paine, and D. G. Bachrach (2000). Organizational citizenship behaviors: A critical review of the theoretical and empirical literature and suggestions for future research. *Journal of Management 26*(3), 513–563.

Prendergast, C. (2007). The motivation and bias of bureaucrats. *American Economic Review 97*(1), 180–196.

Stock, J. H., J. H. Wright, and M. Yogo (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics 20*(4), 518–529.

Tilcsik, A. and C. Marquis (2013). Punctuated generosity: How mega-events and natural disasters affect corporate philanthropy in us communities. *Administrative Science Quarterly 58*(1), 111–148.

Tonin, M. and M. Vlassopoulos (2015). Corporate philanthropy and productivity: Evidence from an online real effort experiment. *Management Science 61*(8), 1795–1811.

Toole, A. A., M. J. Saksena, C. A. Degrazia, K. P. Black, F. Lissoni, E. Miguelez, and G. Tarasconi (2020). Progress and potential: 2020 update on us women inventor-patentees. US Patent and Trademark Office (USPTO).

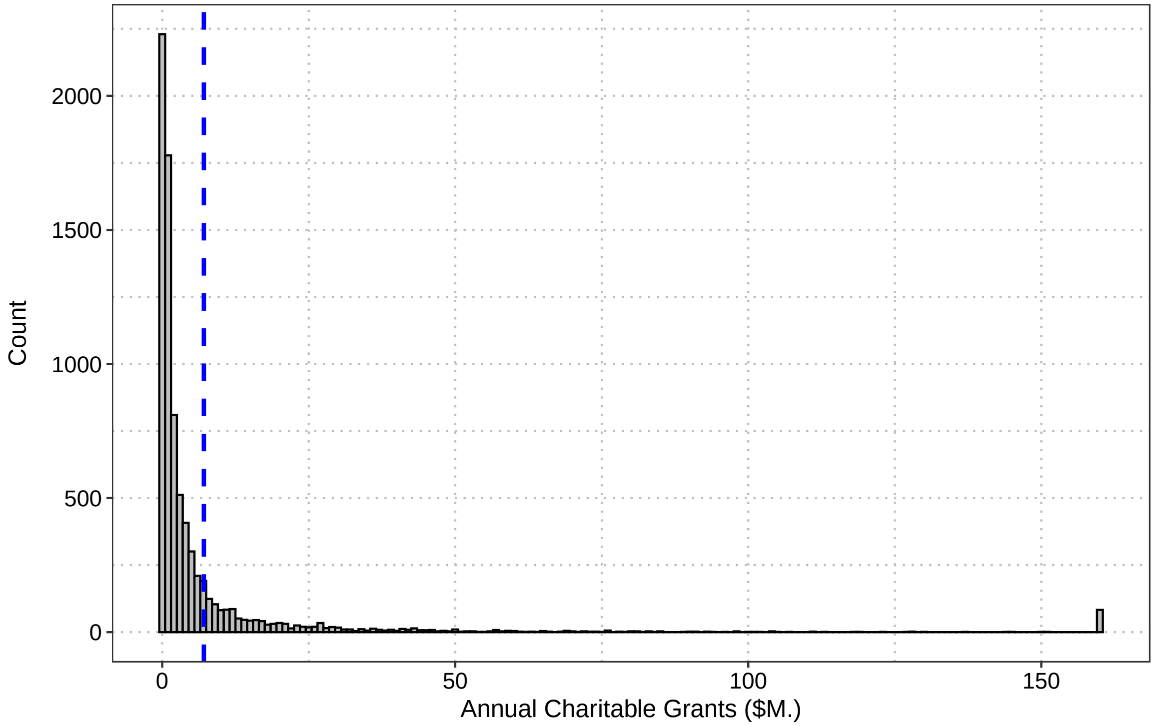
Turban, D. B. and D. W. Greening (1997). Corporate social performance and organizational attractiveness to prospective employees. *Academy of Management Journal 40*(3), 658–672.

Wang, H., J. Choi, and J. Li (2008). Too little or too much? Untangling the relationship between corporate philanthropy and firm financial performance. *Organization Science 19*(1), 143–159.

Whited, T. M. and G. Wu (2006). Financial Constraints Risk. *Review of Financial Studies 19*(2), 531–559.

Zingales, L. (2000). In search of new foundations. *The Journal of Finance 55*(4), 1623–1653.

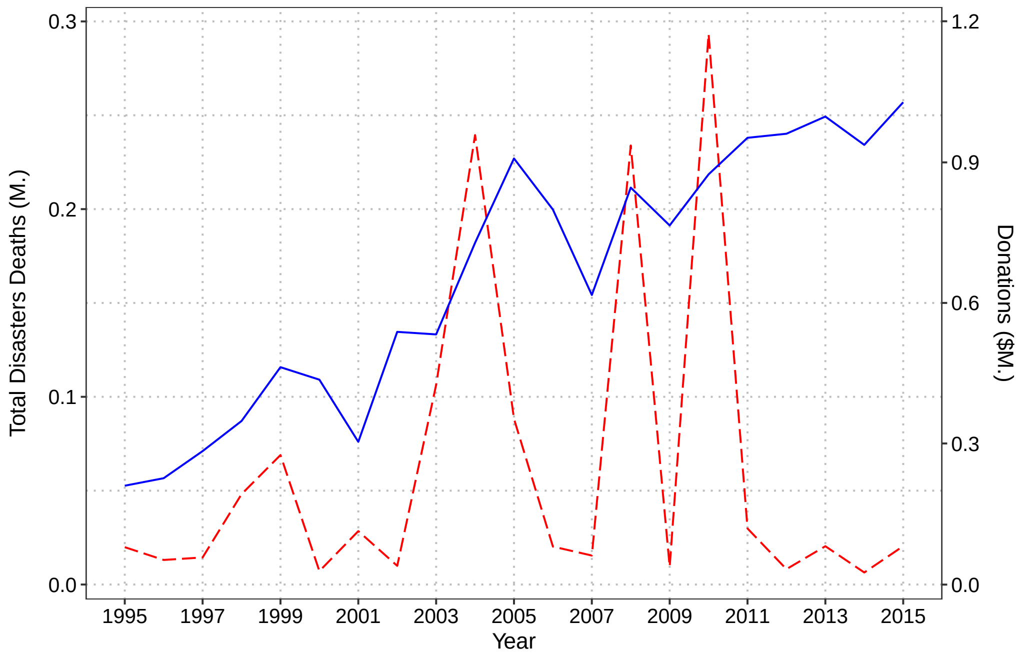
Figure 1: Histogram of Corporate Donations



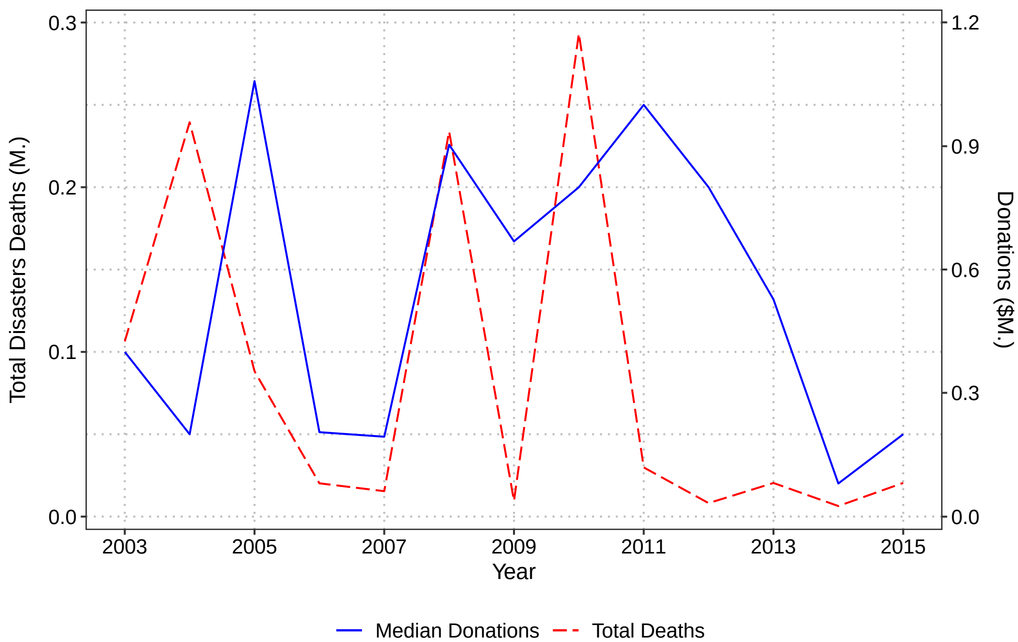
Notes: This figure shows the distribution of the annual amounts of corporate charitable donations, for firms with an existing charitable foundation or corporate giving program. The blue dashed line indicates the sample mean. Donations data is obtained from Foundation Directory Online (FDO) and the National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

Figure 2: Disasters and Corporate Donations

(a) All Charitable Donations

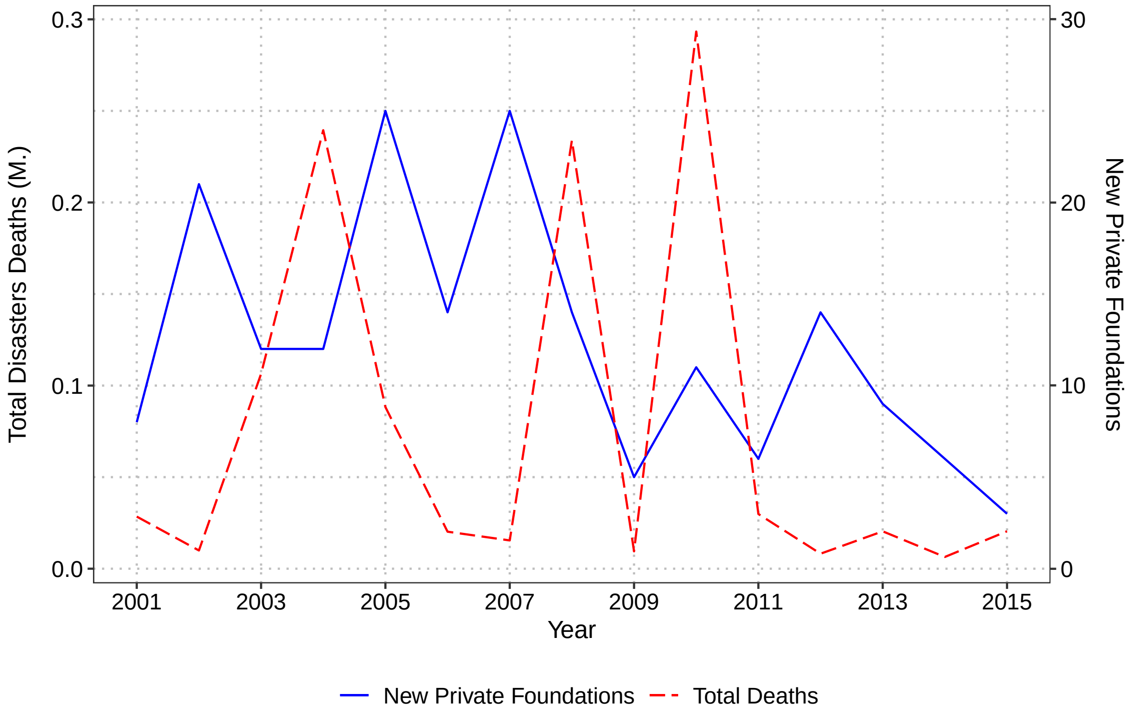


(b) Charitable Donations Earmarked for Disaster Relief



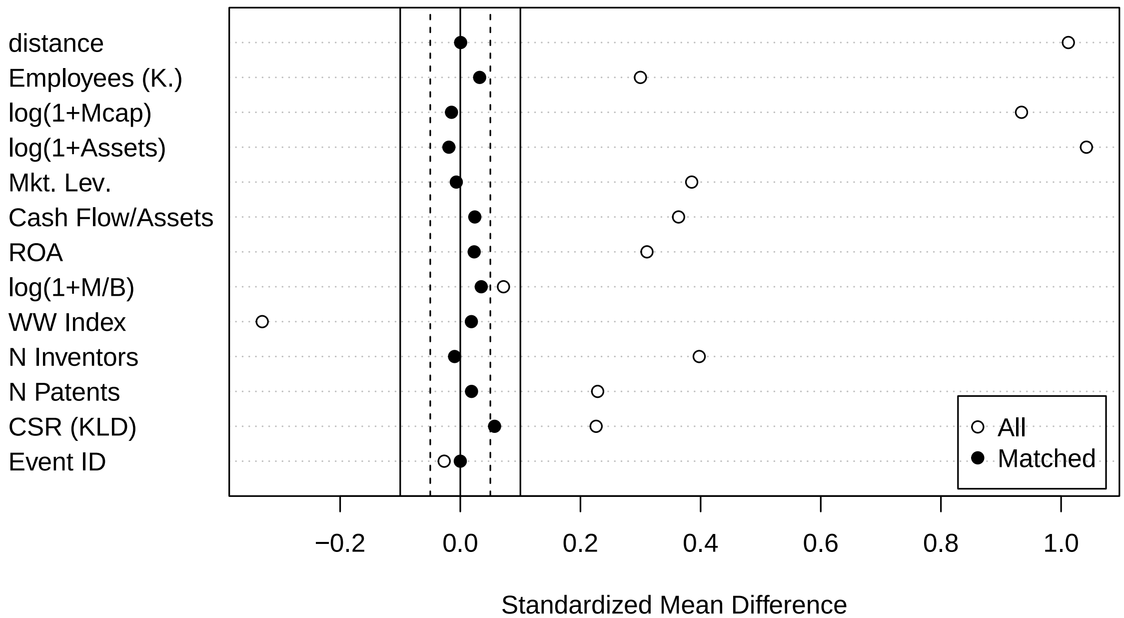
Notes: This figure shows the median amount of charitable donations ($M.) per firm per year (blue solid line) for all firms which have a foundation in the given year (right axis), and the total number of deaths globally (M.) (red dashed line) caused by major natural disasters (left axis) over the sample 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



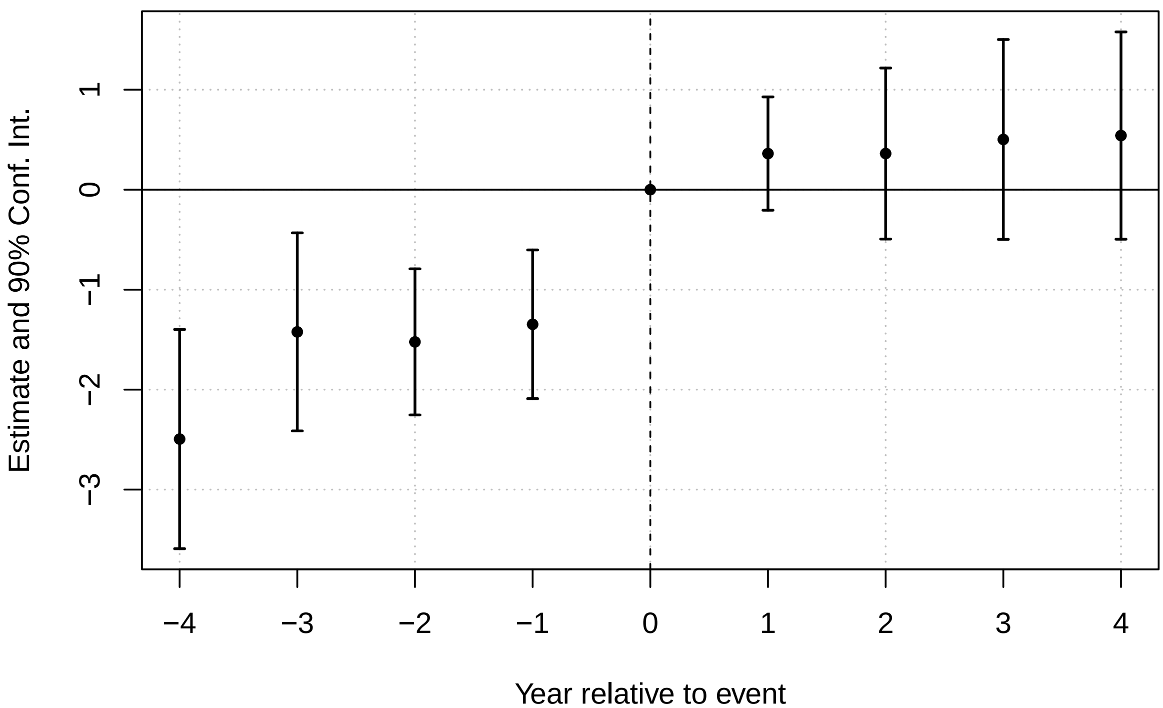
Notes: This figure shows the annual number of newly established corporate private foundations (PF) associated with firms in our sample (blue solid line, right axis), and the total number of deaths globally (M.) caused by major natural disasters (red dashed line, left axis) over the sample period from 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



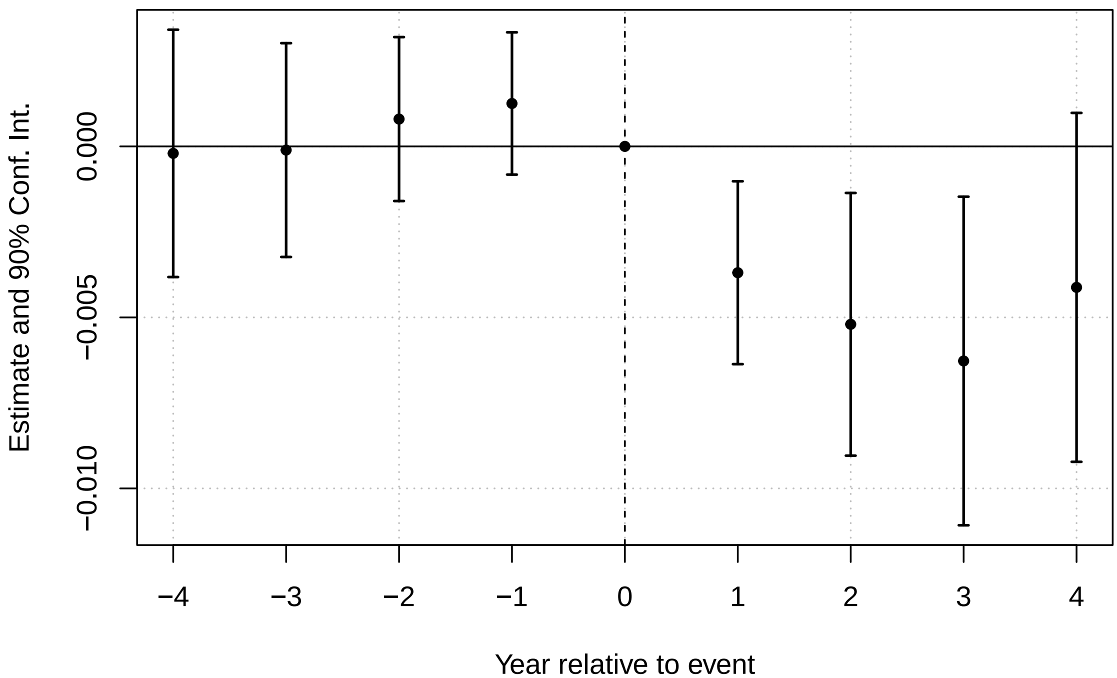
Notes: This figure summarizes the covariate balance of the propensity score matching (PSM) procedure detailed in Section 3, comparing treated and matched firms (solid points) as well as treated firms and the full sample (hollow points). Firms are considered to be treated if they had a corporate charitable 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, N Inventors, N Patents, 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 Charitable Grants



Notes: This figure plots the evolution of firms' corporate charitable grants 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 for a stacked regression of "Grants ($M.)" 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 firm-year level. Control firms are matched to treated firms based on pre-event characteristics as described in Section 3.2 and Figure 4. The estimation includes year-by-industry- ('Year × GIC4 FE'), relative time-, and firm-by-CEO-by-event fixed effects, as well as controls for "log(1+Mkt. Capitalization)", "Mkt. Leverage", "Cash Flow/Assets", "ROA", "log(1+Market-to-Book)" and the "Whited-Wu Index".

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. "Inventor Exit (0/1)") 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. 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 × GIC4 FE'), relative 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 inventors (Panel 1b) as well as 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 1c reports summary statistics for unique inventor-year observations, including 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. Panel 1c reports the number of firms with and without charitable organizations by (GIC 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 ($M.)	33157	0.59	3.91	0.00	0.00	0.00	0.00	2.00
log(1+Grants)	33157	0.15	0.51	0.00	0.00	0.00	0.00	1.10
Overall Rating	4215	0.64	0.12	0.43	0.58	0.65	0.72	0.80
CEO Approval	4175	0.63	0.20	0.25	0.50	0.64	0.76	0.96
CSR (KLD)	21078	0.57	2.00	-2.00	0.00	0.00	1.00	4.00
EMP (KLD)	21078	0.02	0.84	-1.00	0.00	0.00	0.00	1.00
Employment (K.)	32207	22.23	66.35	0.35	1.94	6.10	18.01	90.00
MCap ($B.)	32514	9.44	27.59	0.22	0.84	2.34	6.84	37.13
Assets ($B.)	32520	17.71	91.96	0.20	0.83	2.65	8.94	53.87
Mkt. Leverage	32384	0.24	0.22	0.00	0.06	0.19	0.37	0.67
Cash Flow / AT	31187	0.08	0.13	-0.04	0.04	0.08	0.13	0.21
ROA	32519	0.04	0.14	-0.09	0.01	0.04	0.08	0.16
Market-to-Book	31839	3.63	38.59	0.71	1.30	2.02	3.33	8.20
WW Index	30786	-0.33	0.40	-0.53	-0.44	-0.37	-0.29	-0.16

(b) Inventor-year Summary Statistics

	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

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(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: Propensity Score Matching – Natural Disasters

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', 'N Inventors', 'N Patents', and 'CSR (KLD)'. 'PSM Distance' corresponds to the Propensity Score from a logistic regression. Panels 2a and 2b 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 2c presents summary statistics at the individual inventor 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	0.460	0.238	1.012	1.457	0.292	0.421
Employees (K.)	48.662	16.113	0.300	2.244	0.284	0.441
log(1+Mcap)	9.041	7.567	0.934	1.162	0.254	0.367
log(1+Assets)	9.037	7.277	1.042	1.098	0.279	0.420
Mkt. Lev.	0.223	0.149	0.385	1.512	0.140	0.218
Cash Flow/Assets	0.096	0.063	0.363	0.512	0.076	0.123
ROA	0.056	0.024	0.311	0.522	0.067	0.135
log(1+M/B)	1.348	1.308	0.072	1.111	0.030	0.072
WW Index	-0.330	-0.208	-0.330	0.644	0.247	0.458
N Inventors	221.239	80.020	0.398	3.526	0.157	0.213
N Patents	252.671	63.469	0.229	16.502	0.142	0.209
CSR (KLD)	0.883	0.238	0.226	2.768	0.066	0.191

(b) Pre-event covariates balance post-matching

Variable	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio	eCDF Mean	eCDF Max
PSM Distance	0.435	0.435	0.001	1.000	0.002	0.017
Employees (K.)	43.161	39.663	0.032	1.153	0.034	0.073
log(1+Mcap)	8.897	8.920	-0.015	1.046	0.016	0.050
log(1+Assets)	8.843	8.875	-0.019	0.883	0.011	0.053
Mkt. Lev.	0.212	0.213	-0.007	0.923	0.016	0.053
Cash Flow/Assets	0.099	0.097	0.024	0.866	0.024	0.062
ROA	0.059	0.057	0.023	0.861	0.021	0.065
log(1+M/B)	1.347	1.328	0.035	1.000	0.024	0.066
WW Index	-0.319	-0.326	0.018	1.043	0.033	0.118
N Inventors	198.609	201.974	-0.009	0.876	0.017	0.044
N Patents	186.264	170.785	0.019	2.045	0.017	0.066
CSR (KLD)	0.738	0.575	0.057	1.446	0.022	0.068

... continued

(c) Pre-event inventor-year summary statistics

	No (N=230445)		Yes (N=332113)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
Inventor Exit (0/1)	0.024	0.154	0.015	0.122	-0.009	0.000
N Patents	0.715	0.998	0.724	0.993	0.008	0.003
Cumul. Patents	7.520	17.042	7.194	12.133	-0.326	0.041
N Citations	6.981	13.594	6.558	13.311	-0.423	0.037
Cumul. Citations	44.035	94.565	41.151	91.855	-2.884	0.253
Career Length	6.880	6.403	6.857	6.433	-0.023	0.017
Male (0/1)	0.920	0.272	0.905	0.294	-0.015	0.001

Table 3: 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 × GIC4 FE'), relative event-time-, firm-by-event-, and firm-by-CEO-by-event fixed effects are included as indicated. Cragg-Donald F and 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)	0.7996***	0.7874***	0.1566***	0.1380***
	(0.1505)	(0.1842)	(0.0227)	(0.0289)
log(1+Mkt. Cap.) (t-1)	0.2278***	0.1236	0.0457***	0.0301*
	(0.0869)	(0.1034)	(0.0142)	(0.0180)
Mkt. Lev. (t-1)	0.0217	0.0197	-0.0200	-0.0143
	(0.2886)	(0.3024)	(0.0467)	(0.0579)
CF/Assets (t-1)	2.316	2.889	0.3554*	0.3513
	(1.462)	(1.980)	(0.2075)	(0.2692)
ROA (t-1)	-2.379	-2.887	-0.3747*	-0.3794
	(1.462)	(1.970)	(0.2052)	(0.2658)
log(1+M/B) (t-1)	-0.1778	-0.1642	-0.0433**	-0.0411*
	(0.1299)	(0.1525)	(0.0205)	(0.0249)
WW Index (t-1)	-0.0008	-0.0008	-7.61×10^{-6}	-0.0006
	(0.0042)	(0.0032)	(0.0005)	(0.0006)
Observations	10,823	10,823	10,823	10,823
R^2	0.77910	0.83017	0.82198	0.85445
Cragg-Donald F-Stat	63.106	39.633	128.061	60.529
Kleibergen-Paap Wald F-Stat	28.225	18.278	47.707	22.740
Year × GIC4 FE	✓	✓	✓	✓
Relative Time FE	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓
Firm × CEO × Event FE		✓		✓

Table 4: Natural Disasters, Charitable Grants, and Inventor Turnover

Notes: This table presents stacked OLS- and 2SLS-IV regression results for the effect of major natural disasters abroad on inventor turnover. The dependent variable in Panel 4a is an indicator that takes the value of one if an inventor leaves their employer after year t. In Panel 4b, the dependent variable in the first IV-stage is the logarithmic transformation of charitable donations, i.e. log(1+Grants ($M.)). The second IV-stage regresses an indicator for inventor exit on the instrumented value of charitable donations. In both panels, the data is organized at the inventor-year level and stacked around each event. We include only inventors who are present in the sample in both the pre- and post-period for each individual disaster event. In both panels, 'Post 1-4' is an indicator variable that takes the value of one if a major natural disaster occurred in the past four years. '$\mathbb{1}$(Had Foundation)' takes the value of one if the firm had a corporate charitable foundation in the years before the occurrence of the natural disaster, and zero otherwise. We use the same firm-level control variables as in Table 3 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 × GIC4 FE'), relative event time-, firm-by-event-, inventor-by-event-, and firm-by-CEO-by-event fixed effects are included as indicated. In Panel 4b, Cragg-Donald F and 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.

(a) Difference-in-Difference Setting

	Dep. Variable: $\mathbb{1}$(Inventor Exit)			
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	-0.0070***	-0.0111***	-0.0052***	-0.0078***
	(0.0017)	(0.0024)	(0.0018)	(0.0025)
Employment (t-1)	0.00003	0.00006	0.0001**	0.0002*
	(0.00007)	(0.0001)	(0.00007)	(0.0001)
Sq. Employment (t-1)	-0.0461	-0.0961	-0.2738*	-0.4250*
	(0.1578)	(0.2413)	(0.1635)	(0.2354)
Cumul. Patents (t)	-0.0003***	-0.0017***	-0.0003***	-0.0016***
	(0.00005)	(0.0002)	(0.00005)	(0.0002)
Career Length (t)	0.0008***	-0.0260	0.0008***	-0.0310
	(0.00006)	(0.1911)	(0.00006)	(0.1779)
Male (0/1)	0.0014**	-8.685	0.0014**	-10.52
	(0.0006)	(50.65)	(0.0006)	(46.62)
Observations	1,164,009	1,164,009	1,164,009	1,164,009
R^2	0.0357	0.2372	0.0410	0.2461
Relative Time FE	✓	✓	✓	✓
Year × GIC4 FE	✓	✓	✓	✓
Firm × Event FE	✓	✓		
Inventor × Event FE		✓		✓
Firm × CEO × Event FE			✓	✓
Other Firm Controls	✓	✓	✓	✓

... continued

(b) Shock-IV Setting

Dep. Variable	Log(1+Grants)	$\mathbb{1}$(Inv. Exit)	Log(1+Grants)	$\mathbb{1}$(Inv. Exit)
IV Stages	1st	2nd	1st	2nd
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	0.2031***		0.2013***	
	(0.0489)		(0.0516)	
$log(1+\widehat{Grants})(t)$		-0.0346***		-0.0552***
		(0.0111)		(0.0170)
Employment (t-1)	0.0005	0.00005	0.0005	0.00009
	(0.0014)	(0.00008)	(0.0015)	(0.0001)
Sq. Employment (t-1)	1.521	0.0065	1.513	-0.0125
	(2.471)	(0.1654)	(2.662)	(0.2458)
Cumul. Patents (t)	0.00004	-0.0003***	0.0007	-0.0017***
	(0.00005)	(0.00005)	(0.0008)	(0.0003)
Career Length (t)	-0.000007	0.0008***	0.0053	-0.0257
	(0.00006)	(0.00006)	(0.4723)	(0.1953)
Male (0/1)	0.0003	0.0014**	14.21	-7.900
	(0.0005)	(0.0006)	(128.6)	(51.56)
Observations	1,164,009	1,164,009	1,164,009	1,164,009
R^2	0.9010	0.0292	0.9045	0.2209
Cragg-Donald F-Stat	17233.149		14438.960	
Kleibergen-Paap Wald F-Stat	17.248		15.196	
Year × GIC4 FE	✓	✓	✓	✓
Relative Time FE	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓
Inventor × Event FE			✓	✓
Other Firm Controls	✓	✓	✓	✓

Table 5: Natural Disasters and Inventor Turnover — Robustness

Notes: This table presents robustness tests for the effect of major natural disasters abroad on inventor turnover analogous to Table 4, including additional CSR controls and subsample analyses. The dependent variable in Panels 5a and 5c is an indicator that takes the value of one if an inventor leaves their employer after year *t*. In Panels 5b and 5d, the dependent variable in the first IV-stage is the logarithmic transformation of charitable donations, i.e. log(1+Grants ($M.)). The second IV-stage regresses an indicator for inventor exit on the instrumented value of charitable donations. 'Post 1-4' is an indicator variable that takes the value of one if a major natural disaster occurred in the past four years. '$\mathbb{1}$(Had Foundation)' takes the value of one if the firm had a corporate charitable foundation in the years before the occurrence of the natural disaster. In all panels data is organized at the inventor-year level, in Panels5a and 5b the data is stacked around each event. All data filters, controls, and fixed effects are similar to Table 4. Standard errors are clustered at the firm-event level and reported in parentheses. In Panels 5b and 5d, Cragg-Donald *F* and 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)'. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Include CSR controls – DiD Setting

	Dep. Variable: $\mathbb{1}$(Inventor Exit)			
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	-0.0082***	-0.0124***	-0.0060***	-0.0091***
	(0.0017)	(0.0025)	(0.0019)	(0.0025)
CSR Env. (t-1)	0.0006	0.0012	-0.000007	0.0005
	(0.0012)	(0.0016)	(0.0008)	(0.0011)
CSR Comm. (t-1)	0.0018**	0.0015	0.0021**	0.0022**
	(0.0007)	(0.0010)	(0.0008)	(0.0011)
CSR Hum. (t-1)	0.0073**	0.0113***	0.0068**	0.0100**
	(0.0030)	(0.0040)	(0.0031)	(0.0040)
CSR Emp. (t-1)	0.0010*	0.0013*	0.0015**	0.0020**
	(0.0006)	(0.0008)	(0.0007)	(0.0009)
CSR Prod. (t-1)	0.0007	0.0007	0.0017**	0.0018**
	(0.0010)	(0.0013)	(0.0007)	(0.0008)
CSR Div. (t-1)	-0.0012**	-0.0015**	-0.0012**	-0.0015*
	(0.0005)	(0.0008)	(0.0006)	(0.0008)
CSR Gov. (t-1)	-0.0035**	-0.0037	-0.0020	-0.0023
	(0.0018)	(0.0024)	(0.0016)	(0.0020)
Observations	1,139,463	1,139,463	1,139,463	1,139,463
R^2	0.0334	0.2396	0.0384	0.2476
Relative Time FE	✓	✓	✓	✓
Year × GIC4 FE	✓	✓	✓	✓
Firm × Event FE	✓	✓		
Inventor × Event FE		✓		✓
Firm × CEO × Event FE			✓	✓
Firm Controls	✓	✓	✓	✓
Inventor Controls	✓	✓	✓	✓

... continued

(b) Include CSR controls – Shock-IV Setting

Dep. Variable	Log(1+Grants)	$\mathbb{1}$(Inv. Exit)	Log(1+Grants)	$\mathbb{1}$(Inv. Exit)
IV Stages	1st	2nd	1st	2nd
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	0.2098***		0.2082***	
	(0.0468)		(0.0497)	
$log(1+\widehat{Grants})(t)$		-0.0391***		-0.0598***
		(0.0112)		(0.0168)
CSR Env. (t-1)	0.0074	0.0009	0.0093	0.0017
	(0.0153)	(0.0014)	(0.0164)	(0.0020)
CSR Comm. (t-1)	-0.0358*	0.0004	-0.0379*	-0.0008
	(0.0210)	(0.0011)	(0.0221)	(0.0016)
CSR Hum. (t-1)	-0.1079**	0.0030	-0.1093**	0.0048
	(0.0450)	(0.0038)	(0.0491)	(0.0054)
CSR Emp. (t-1)	-0.0045	0.0009	-0.0054	0.0010
	(0.0153)	(0.0008)	(0.0164)	(0.0012)
CSR Prod. (t-1)	0.0310	0.0019	0.0318	0.0026
	(0.0214)	(0.0012)	(0.0227)	(0.0018)
CSR Div. (t-1)	-0.0084	-0.0015*	-0.0087	-0.0021
	(0.0160)	(0.0009)	(0.0170)	(0.0013)
CSR Gov. (t-1)	0.1382**	0.0019	0.1347**	0.0043
	(0.0599)	(0.0034)	(0.0630)	(0.0050)
Observations	1,139,463	1,139,463	1,139,463	1,139,463
R^2	0.9030	0.0246	0.9065	0.2198
Cragg-Donald F-Stat	17689.908		14827.643	
Kleibergen-Paap Wald F-Stat	20.078		17.566	
Year × GIC4 FE	✓	✓	✓	✓
Relative Time FE	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓
Inventor × Event FE			✓	✓
Firm Controls	✓	✓	✓	✓
Inventor Controls	✓	✓	✓	✓

... continued

(c) Each disaster individually – DiD Setting

Dep. Variable	$\mathbb{1}$(Inventor Exit)		
Keep Only Event	IDN 2004	CHN 2008	HTI 2010
	(1)	(2)	(3)
Post 1–4 × $\mathbb{1}$(Had Foundation)	-0.0168***	-0.0095**	-0.0120***
	(0.0052)	(0.0040)	(0.0044)
Observations	319,220	440,920	380,781
R^2	0.2532	0.2331	0.2374
Inventor Controls	✓	✓	✓
CSR Controls	✓	✓	✓
Firm Controls	✓	✓	✓
Year × GIC4 FE	✓	✓	✓
Relative Time FE	✓	✓	✓
Firm × Event FE	✓	✓	✓
Inventor × Event FE	✓	✓	✓

(d) Each disaster individually – Shock-IV Setting

Keep Only Event	IDN 2004		CHN 2008		HTI 2010	
Dep. Variable	Log Grts	$\mathbb{1}$(Exit)	Log Grts	$\mathbb{1}$(Exit)	Log Grts	$\mathbb{1}$(Exit)
IV Stages	1st	2nd	1st	2nd	1st	2nd
	(1)	(2)	(3)	(4)	(5)	(6)
Post 1–4 × $\mathbb{1}$(Had Foundation)	0.3347***		0.1846***		0.1340	
	(0.0897)		(0.0578)		(0.1344)	
$log(1+\widehat{Grants})(t)$		-0.0486***		-0.0553**		-0.0502
		(0.0185)		(0.0250)		(0.0571)
Observations	335,104	335,104	445,952	445,952	382,953	382,953
R^2	0.7722	0.2286	0.9443	0.2203	0.8779	0.2255
C-D F-Stat	9789.835		5046.533		1939.318	
K-P Wald F-Stat	13.935		10.193		0.993	
Year × GIC4 FE	✓	✓	✓	✓	✓	✓
Relative Time FE	✓	✓	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓	✓	✓
Inventor × Event FE	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓
Inventor Controls	✓	✓	✓	✓	✓	✓

Table 6: Inventor Turnover, Employee Relations, and Outside Options

Notes: This table presents OLS- and 2SLS-IV regression results for the cross-sectional differences with respect to employee relations (Panel 6a) and inventors' outside job options (Panels **??** and 6b) in the effect of major natural disasters abroad on inventor turnover. In Panel 6a, we split the sample into firms with high and low employee-relations scores from KLD (relative to the sample median within a given industry-year). Panel 6b splits the sample based on the cumulative number of citations of an inventor's patents by other firms. In each panel, the dependent variable is an indicator that takes the value of one if an inventor 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 had a corporate charitable foundation 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 inventor-year level and stacked around each event. All data filters, controls, and fixed effects are similar to Table 4. Cragg-Donald F and 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.

(a) Employee Relations

	Dep. Variable: $\mathbb{1}$(Inventor Exit)			
Model	OLS		IV 2nd	
Employee (KLD) Score	High	Low	High	Low
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	-0.0036**	-0.0107***		
	(0.0016)	(0.0023)		
$log(\widehat{1+Grants})(t)$			-0.0158*	-0.0668***
			(0.0081)	(0.0213)
Observations	522,677	624,638	522,677	624,638
R^2	0.0348	0.0393	0.0335	0.0187
C-D F-Stat			7455.263	5293.804
K-P Wald F-Stat			8.644	16.470
Coef. Diff: χ^2 (p-Value)	7.390***	(0.007)	5.685**	(0.017)
Relative Time FE	✓	✓	✓	✓
Year × GIC4 FE	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Inventor Controls	✓	✓	✓	✓

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(b) Cumulative External Citations

	Dep. Variable: $\mathbb{1}$(Inventor Exit)			
Model	OLS		IV 2nd	
Cumul. External Citations	High	Low	High	Low
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	-0.0115***	-0.0085***		
	(0.0022)	(0.0019)		
$log(1+\widehat{Grants})(t)$			-0.0549***	-0.0428***
			(0.0159)	(0.0129)
Observations	577,997	530,700	577,997	530,700
R^2	0.04184	0.03728	0.02268	0.02131
C-D F-Stat			9710.421	7066.596
K-P Wald F-Stat			17.479	17.391
Coef. Diff: χ^2 (p-Value)	3.998**	(0.046)	1.846	(0.174)
Relative Time FE	✓	✓	✓	✓
Year × GIC4 FE	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Inventor Controls	✓	✓	✓	✓

Table 7: Inventor Turnover and Pro-Social Preferences

Notes: This table presents OLS- and 2SLS-IV regression results for the cross-sectional differences with charitableness (Panel 7a) and political party affiliation (Panel 7b), in the effect of major natural disasters in foreign countries on inventor turnover. In Panel 7a, we split the sample into inventors who reside in states with above- and below-median charity scores (from Wallethub). Panel 7b splits the sample into inventors who reside counties with high and low republican vote share, measured on the year of each disaster event, as determined by presidential general elections. In each panel, the dependent variable is an indicator that takes the value of one if an inventor 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 had a corporate charitable foundation in the years before the occurrence of the natural disaster, and zero otherwise, and '$log(1+\widehat{Grants})$' is the predicted 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 4. Cragg-Donald F and 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.

(a) Charity Score

	Dep. Variable: $\mathbb{1}$(Inventor Exit)			
Model	OLS		IV 2nd	
Charity Score	High	Low	High	Low
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	-0.0171***	-0.0103***		
	(0.0036)	(0.0027)		
$log(1+\widehat{Grants})(t)$			-0.0923***	-0.0450***
			(0.0329)	(0.0143)
Observations	456,720	455,055	456,720	455,055
R^2	0.2739	0.2736	0.2399	0.2607
C-D F-Stat			5157.207	5920.857
K-P Wald F-Stat			8.575	22.639
Coef. Diff: χ^2 (p-Value)	2.858*	(0.091)	2.412	(0.120)
Relative Time FE	✓	✓	✓	✓
Year × GIC4 FE	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓
Inventor × Event FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Inventor Controls	✓	✓	✓	✓
Inventor County Controls	✓	✓	✓	✓

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(b) Republican Vote Share

	Dep. Variable: $\mathbb{1}$(Inventor Exit)			
Model	OLS		IV 2nd	
Political Tilt	Dem.	Rep.	Dem.	Rep.
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	-0.0152***	-0.0117***		
	(0.0031)	(0.0027)		
$log(1+\widehat{Grants})(t)$			-0.0954***	-0.0462***
			(0.0317)	(0.0146)
Observations	429,409	451,135	429,409	451,135
R^2	0.2092	0.2066	0.1670	0.1895
C-D F-Stat			3802.540	7868.563
K-P Wald F-Stat			13.678	15.341
Coef. Diff: χ^2 (p-Value)	1.284	(0.257)	3.132*	(0.077)
Relative Time FE	✓	✓	✓	✓
Year × GIC4 FE	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓
Inventor × Event FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Inventor Controls	✓	✓	✓	✓
Inventor County Controls	✓	✓	✓	✓

Table 8: 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 had a corporate charitable foundation in the years before the occurrence of the natural disaster, and zero otherwise, and '$log(1+\widehat{Grants})$' is the predicted 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 4. Year-by-industry ('Year × GIC4 FE'), relative-time, and firm-by-event fixed effects are included as indicated. Standard errors are clustered at the firm-event level and reported in parentheses. Cragg-Donald F and 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 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)	0.0217*	0.0433**		
	(0.0112)	(0.0204)		
$log(1+\widehat{Grants})(t)$			0.1261*	0.2482*
			(0.0753)	(0.1358)
Observations	2,433	2,411	2,433	2,411
R^2	0.61385	0.60853	0.50768	0.48452
C-D F-Stat			26.999	27.217
K-P Wald F-Stat			10.549	10.661
Year × GIC4 FE	✓	✓	✓	✓
Firm × CEO FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Table 9: The 2003 Dividend Tax Cut, Dividends, and Charitable Grants

Notes: This table presents OLS regression results for the effect of the 2003 dividend tax cut on dividends and charitable grants. The dependent variables in Panels 9a and 9b are the logarithmic transformations of dividends (log(1+Dividends ($M.))) and charitable donations (log(1+Grants ($M.))), respectively. '𝟙(CEO Own. High)' is an indicator variable that takes the value of one if the CEO's share ownership (i.e. 'CEO Own (%)') is in the top quartile of the sample, and "𝟙(≥ 2003)' takes the value of one if the year observation is in or after 2003. The data is organized at the firm-year level. We include similar firm-level control variables as in Table 4. Year-by-industry ('Year × GIC4 FE'), firm-, and firm-by-CEO fixed effects are included as indicated. Standard errors are clustered at the firm level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Effect on Dividends

	Dep. Variable: Log (1+Dividends)					
	(1)	(2)	(3)	(4)	(5)	(6)
𝟙(≥ 2003) × 𝟙(CEO Own. High)	0.0328*	0.0200	0.0288**			
	(0.0172)	(0.0158)	(0.0122)			
𝟙(≥ 2003) × CEO Own. (%)				0.0044***	0.0032**	0.0023**
				(0.0014)	(0.0013)	(0.0011)
𝟙(≥ 2003)	0.0155*			0.0147*		
	(0.0091)			(0.0087)		
𝟙(CEO Own. High)	-0.1047***	-0.0656***				
	(0.0190)	(0.0172)				
CEO Own. (%)				-0.0112***	-0.0070***	
				(0.0029)	(0.0025)	
CEO Own. (%) Sq.				0.0003**	0.0001	-0.00002
				(0.0001)	(0.0001)	(0.00005)
Observations	8,039	8,039	8,039	7,903	7,903	7,903
R^2	0.2226	0.4765	0.8785	0.2160	0.4724	0.8776
Year × GIC4 FE		✓	✓		✓	✓
Firm × CEO FE			✓			✓
Firm Controls	✓	✓	✓	✓	✓	✓

(b) Effect on Donations

	Dep. Variable: Log (1+Grants)					
	(1)	(2)	(3)	(4)	(5)	(6)
𝟙(≥ 2003) × 𝟙(CEO Own. High)	-0.1086***	-0.1139***	-0.0884***			
	(0.0239)	(0.0249)	(0.0223)			
𝟙(≥ 2003) × CEO Own. (%)				-0.0060***	-0.0054***	-0.0045***
				(0.0014)	(0.0014)	(0.0012)
𝟙(≥ 2003)	0.1098***			0.1016***		
	(0.0176)			(0.0159)		
𝟙(CEO Own. High)	0.0112	0.0127				
	(0.0159)	(0.0158)				
CEO Own. (%)				-0.0033*	-0.0032	
				(0.0019)	(0.0021)	
CEO Own. (%) Sq.				0.0001*	0.0001	-0.00006
				(0.00007)	(0.00008)	(0.00004)
Observations	8,347	8,347	8,347	8,200	8,200	8,200
R^2	0.0926	0.1488	0.7553	0.0926	0.1486	0.7528
Year × GIC4 FE		✓	✓		✓	✓
Firm × CEO FE			✓			✓
Firm Controls	✓	✓	✓	✓	✓	✓

Table 10: The 2003 Dividend Tax Cut and Inventor Turnover

Notes: This table presents OLS regression results for the effect of the 2003 dividend tax cut on inventor turnover. The main dependent variable in both panels is an indicator that takes the value of one if an inventor leaves their employer after year t. In the first IV-stage estimation in Panel 10b, the dependent variable is the log-transformation of charitable grants, i.e. log(1+Grants ($M.)), and '$\widehat{logGrants}(t)$' is the instrumented value of charitable donations in the second IV-stage. As in Table 9, '$\mathbb{1}$(CEO Own. High)' and '$\mathbb{1}(\geq 2003)$' are indicators for high CEO ownership and years in or after 2003, respectively. The data is organized at the inventor-year level. We include similar firm-level and inventor-level control variables as in Table 3. Year × GIC4-, firm-, and firm-by-CEO fixed effects are included as indicated. Standard errors are clustered at the firm level and reported in parentheses. In Panel 10b, Cragg-Donald F and Kleibergen-Paap Wald F Statistic (clustered at the firm-event level) report the test statistics of F-tests for weak identification for the first stage (columns 1, 3, 5). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) DiD Setting

	Dep. Variable: $\mathbb{1}$(Inventor Exit)		
	(1)	(2)	(3)
$\mathbb{1}(\geq 2003)$	-0.0109***		
	(0.0020)		
$\mathbb{1}$(CEO Own. High)	-0.0014	-0.0018	
	(0.0038)	(0.0028)	
$\mathbb{1}(\geq 2003) \times \mathbb{1}$(CEO Own. High)	0.0096***	0.0103***	0.0082***
	(0.0026)	(0.0033)	(0.0030)
Observations	923,064	923,064	923,064
R^2	0.0037	0.0078	0.0167
Year × GIC4 FE		✓	✓
Firm × CEO FE			✓
Firm Controls	✓	✓	✓
Inventor Controls	✓	✓	✓

... continued

(b) Shock-IV Setting

Dep. Variable	Log Grants	$\mathbb{1}$(Exit)	Log Grants	$\mathbb{1}$(Exit)	Log Grants	$\mathbb{1}$(Exit)
IV Stages	1st	2nd	1st	2nd	1st	2nd
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}(\geq 2003) \times \mathbb{1}$(CEO Own. High)	-0.4488***		-0.3260***		-0.2130***	
	(0.1174)		(0.0997)		(0.0622)	
$\mathbb{1}(\geq 2003)$	0.4396***		0.3233***			
	(0.0966)		(0.0774)			
$\mathbb{1}$(CEO Own. High)	-0.2138					
	(0.1564)					
$log(1 + \widehat{Grants})(t)$		-0.0171***		-0.0217***		-0.0395**
		(0.0057)		(0.0063)		(0.0192)
Observations	934,463	934,463	934,463	934,463	934,463	934,463
R^2	0.5294	-0.0039	0.8635	0.0108	0.8998	0.0046
K-P Wald F-Stat	7.504		10.248		11.740	
Firm × CEO FE			✓	✓	✓	✓
Year × GIC4 FE					✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓
Inventor Controls	✓	✓	✓	✓	✓	✓

Internet Appendix

Intended for online publication only

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.

Donations ($M.) $\mathbb{1}$***(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.

$\mathbb{1}$***(CEO Own. High)*:** An indicator variable that takes the value of one if a CEO is in the top quartile of share ownership in year t.

***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.

***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*).

ROA Net income (Compustat item *ni*) 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 (item *pstkrv*) then preferred stock liquidating value (item *pstkl* or preferred stock (capital) - Total (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).

***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.

***Republican Vote Share*:** Percent of a county's votes for the Republican candidate in the current or most recent presidential general election.

***Charity Score*:** WalletHub's 2020 state-level composite score based on nineteen metrics spanning different volunteering and charitable giving activities.

***Local Donations Per Household*:** County-level annual charitable contributions per household obtained from IRS tax return data.

***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 IA.1: 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 IA.1a and IA.1b 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 IA.2: Natural Disasters 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 4. Year-by-industry- ('Year × GIC4 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	CSR (KLD)	Empl./Assets	Capx/Assets	R&D/Assets	SG&A/Assets	Sales/Assets	NI/Assets
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$log(1 + \widehat{Grants})(t)$	0.1930	-0.9038*	0.0087	-0.0169	-0.0317	-0.1361	0.0020
	(1.014)	(0.5023)	(0.0114)	(0.0104)	(0.0282)	(0.1060)	(0.0299)
Observations	10,345	10,794	10,797	10,823	10,051	10,823	10,823
R^2	0.8395	0.9736	0.8154	0.8823	0.9559	0.9454	0.6346
Year × GIC4 FE	✓	✓	✓	✓	✓	✓	✓
Relative Time FE	✓	✓	✓	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓	✓	✓	✓
Firm × CEO × Event FE	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓

Table IA.3: Robustness — Excluding Direct Corporate Giving Programs

Notes: This table presents 2SLS-IV regression results for the effect of major natural disasters abroad on inventor turnover analogous to Panel 4b, including a subsample analysis. All firms that participate in direct corporate giving are excluded from the analysis. The dependent variable is an indicator variable for inventor turnover. Similar to Panel 4b, the dependent variable in the first IV-stage is the logarithmic transformation of charitable donations, i.e. log(1+Grants). The second IV-stage regresses an indicator for inventor exit on the instrumented value of charitable donations. 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 4. Cragg-Donald F and 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	Log Grants	$\mathbb{1}$(Inv. Exit)	Log Grants	$\mathbb{1}$(Inv. Exit)
IV Stages	1st	2nd	1st	2nd
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	0.3005***		0.2978***	
	(0.0844)		(0.0903)	
$log(1+\widehat{Grants})(t)$		-0.0413***		-0.0770***
		(0.0123)		(0.0226)
Observations	387,276	387,276	387,276	387,276
R^2	0.8689	0.0471	0.8749	0.2980
Cragg-Donald F-Stat	17873.755		14813.184	
Kleibergen-Paap Wald F-Stat	12.683		10.881	
Year × GIC4 FE	✓	✓	✓	✓
Relative Time FE	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓
Inventor × Event FE			✓	✓
Firm Controls	✓	✓	✓	✓
Inventor Controls	✓	✓	✓	✓

Table IA.4: Robustness — Excluding Constrained Firms

Notes: This table presents 2SLS-IV regression results for the effect of major natural disasters abroad on inventor turnover analogous to Panel 4b, including subsample analyses. In Columns (1) through (4), we exclude firm-year observations in the bottom quartile of the Compustat universe with respect ROA, cash scaled by assets, sales growth, and Tobin's Q, respectively. The main dependent variable is an indicator variable that takes the value of one if an inventor leaves their employer after 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 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 4. Cragg-Donald F and 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)			
Drop Bottom Quartile	ROA	Cash/AT	Sales Gr.	Tobin's Q
	(1)	(2)	(3)	(4)
$log(1+\widehat{Grants})(t)$	-0.0492***	-0.0586***	-0.0468***	-0.0610***
	(0.0182)	(0.0221)	(0.0172)	(0.0207)
Observations	1,101,734	1,049,749	984,473	1,120,409
R^2	0.2365	0.2380	0.2596	0.2272
C-D F-Stat	10221.882	10457.742	10452.829	10705.243
K-P Wald F-Stat	10.768	9.412	10.100	12.390
Year × GIC4 FE	✓	✓	✓	✓
Relative Time FE	✓	✓	✓	✓
Firm × Event FE	✓	✓	✓	✓
Inventor × Event FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Inventor Controls	✓	✓	✓	✓

Table IA.5: Robustness — Accuracy of Movement

Notes: This table presents 2SLS-IV regression results for the effect of major natural disasters abroad on inventor turnover analogous to Panel 4b, 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 4. Cragg-Donald F and 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 $\times$ $\mathbb{1}$(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)			
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 $\times$ GIC4 FE	✓	✓	✓	✓
Relative Time FE	✓	✓	✓	✓
Firm $\times$ Event FE	✓	✓	✓	✓
Inventor $\times$ Event FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Inventor Controls	✓	✓	✓	✓

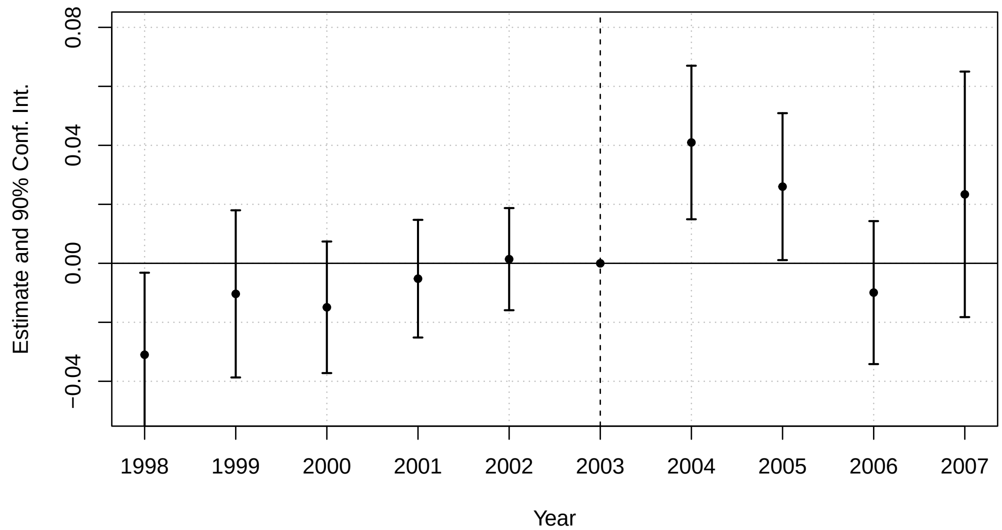
Table IA.6: Natural Disasters and Employee Attraction

Notes: This table presents the OLS regression results for the effect of major natural disasters abroad on inventor attraction. The dependent variable is an indicator for whether an inventor moved to a firm that had a corporate charitable foundation, in the years before the occurrence of the natural disaster, and zero otherwise. In both panels, the data is organized at the inventor-year level and stacked around each event. We include only observations where inventors make career transitions. '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 had a corporate charitable foundation in the years before the occurrence of the natural disaster, and zero otherwise. We use the same firm-level control variables as in Table 4. Year-by-industry- ('Year × GIC4 FE'), relative event time-, industry-, industry-by-event-, and firm-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.

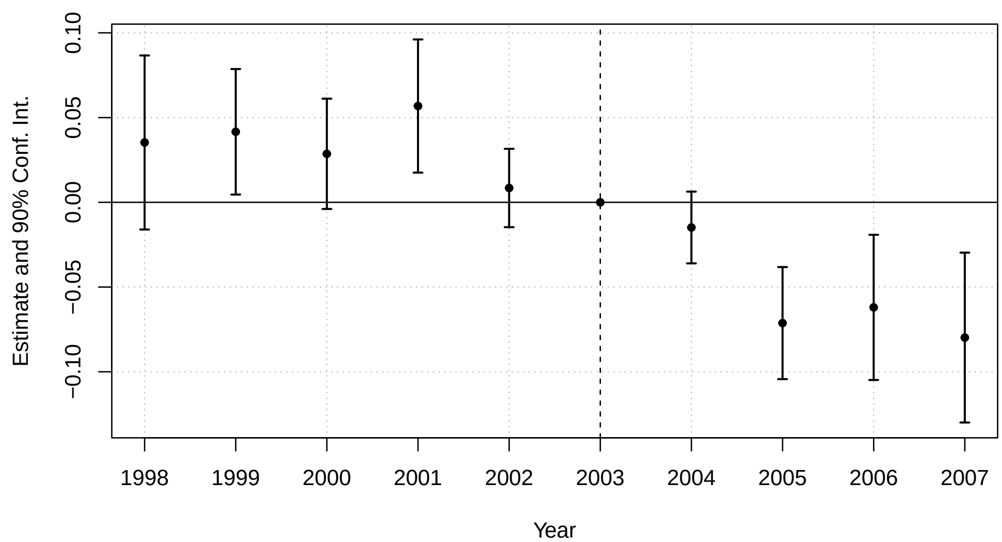
	Dep. Variable: $\mathbb{1}$(Exit to Firm with PF)			
	(1)	(2)	(3)	(4)
Post 1–4 × $\mathbb{1}$(Had Foundation)	-0.0570**	-0.0662**	-0.0285	-0.0231
	(0.0232)	(0.0281)	(0.0212)	(0.0194)
$\mathbb{1}$(Had Foundation)	0.0209	0.0179	0.0024	
	(0.0213)	(0.0239)	(0.0197)	
Observations	15,200	15,200	15,200	15,200
R^2	0.1368	0.0991	0.1430	0.2414
Relative Time FE	✓	✓	✓	✓
Year × GIC4 FE	✓		✓	✓
Year FE		✓		
GIC4 FE		✓		
GIC4:Event FE			✓	
Firm × Event FE				✓
Firm Controls	✓	✓	✓	✓
Inventor Controls	✓	✓	✓	✓

Figure IA.1: Dividend Tax Cut 2003 — Donations and Dividends

(a) Effect on Dividends

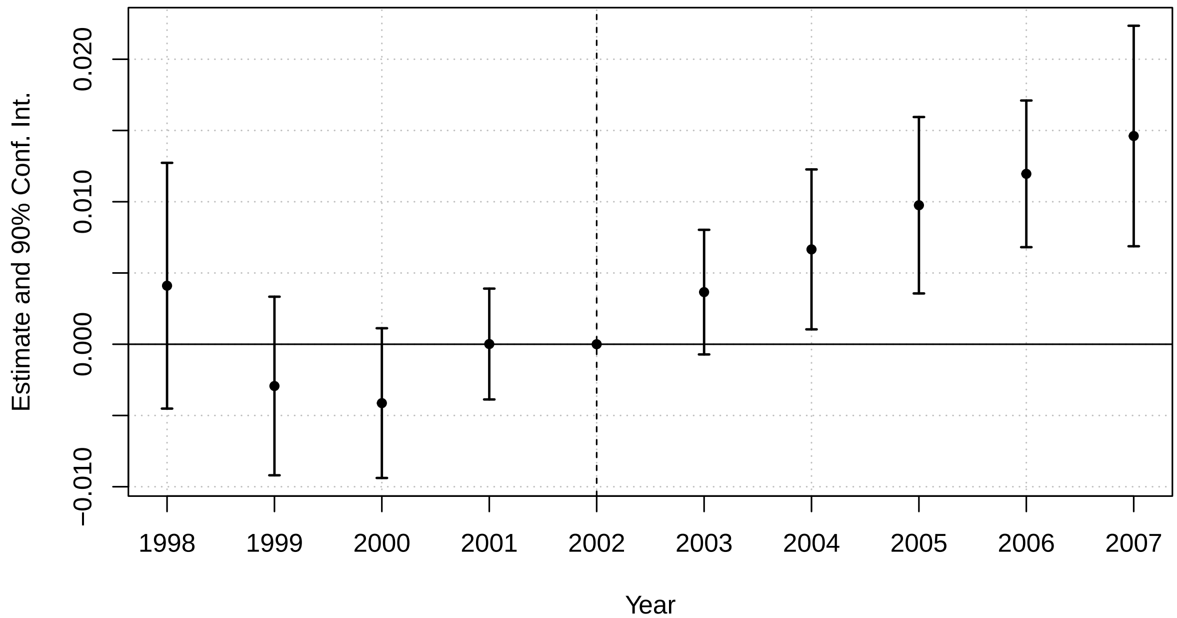


(b) Effect on Donations



Notes: These figures plot the evolution of firms' Dividends (Panel IA.1a) and charitable donations (Panel IA.1b) around the 2003 dividend tax cut. Specifically, each figure plots the coefficient estimates and corresponding 90% confidence intervals for a regression of the respective firm-level outcome on interaction terms of year dummy variables with an indicator for treated firms. Firms are considered to be 'treated' if the CEO's percentage of ownership was in the top quartile prior to 2003. The estimation includes year-by-industry- ('Year × GIC4 FE'), and firm-by-CEO fixed effects, as well as controls for "log(1+Mkt. Capitalization)", "Mkt. Leverage", "Cash Flow/Assets", "ROA", "log(1+Market-to-Book)" and the "Whited-Wu Index".

Figure IA.2: Dividend Tax Cut 2003 — Inventor Turnover



Notes: This figure plots the evolution of inventor turnover in the years before and after the 2003 dividend tax cut. 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. "Inventor Exit (0/1)") on interaction terms of dummy variables indicating the distance (in years) to 2003 with an indicator for treated firms, i.e. firms where CEO ownership in the top quartile. The estimation is at the inventor-year level. The estimation includes year-by-industry- ('Year × GIC4 FE') and firm-by-CEO fixed effects, as well as firm-level controls for 'Employment', 'Employment^2', 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'), and inventor-level controls for 'Cumulative Patents', 'Career Length (Years)', and 'Gender (Male=1)'.

Table IA.7: The 2003 Dividend Tax Cut and Other Firm-Level Outcomes

Notes: This table presents OLS regression results for the effect of the 2003 dividend tax cut on several firm outcomes, analogous to Table 9. Specifically, the dependent variables are the overall CSR score from KLD, and the number of employees, CAPX, R&D expenses, and sales, all scaled by total assets. '$\mathbb{1}$(CEO Own. High)' is an indicator variable that takes the value of one if the CEO's share ownership ('CEO Own (%)') is in the top quartile of the sample, and '$\geq$ 2003' takes the value of one if the year observation is after 2003. The data is organized at the firm-year level. We include similar firm-level control variables as in Table 4. Year $\times$ GIC4 fixed effects, and firm- and firm-by-CEO fixed effects are included as indicated. Standard errors are clustered at the firm level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Dep. Variable	CSR (KLD)	Empl./Assets	Capx/Assets	R&D/Empl.	Sales/Assets	CSR (KLD)	Empl./Assets	Capx/Assets	R&D/Empl.	Sales/Assets
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbb{1}(\geq 2003) \times \mathbb{1}$(CEO Own. High)	-0.1834	-0.5997	-0.0058*	1.724	-0.0234					
	(0.1606)	(0.6258)	(0.0032)	(2.181)	(0.0505)					
CEO Own. (%) Sq.						-0.0002	-0.0005	0.00002**	0.0039	0.00010
						(0.0004)	(0.0021)	(0.000010)	(0.0038)	(0.00010)
$\mathbb{1}(\geq 2003) \times$ CEO Own. (%)						-0.0076	-0.0746	-0.0002	0.1203	-0.0010
						(0.0131)	(0.0910)	(0.0002)	(0.0892)	(0.0029)
Observations	4,600	8,243	7,952	4,363	8,347	4,532	8,098	7,818	4,305	8,200
R^2	0.8404	0.9851	0.7891	0.8008	0.8992	0.8411	0.9860	0.7902	0.7997	0.8984
Year $\times$ GIC4 FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm $\times$ CEO FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table IA.8: The 2003 Dividend Tax Cut — Robustness

Notes: This table presents analogous to Table 10, including additional controls for CSR. The dependent variable in Panel IA.8a is an indicator that takes the value of one if an inventor leaves their employer after the current year (t). '𝟙(CEO Own. High)' and '$\geq$ 2003' are indicators for high CEO ownership and years after 2003, respectively. We additionally include the CSR category scores for Environment, Community, Human Rights, Employee relations, Product, Diversity, and Governance from KLD. Panel IA.8b implements a similar 2SLS-IV estimation as Table 10b, including the overall CSR from KLD as an additional control. The data is organized at the inventor-year level. We include similar firm-level and inventor-level control variables as in Table 3. Year-by-industry- ('Year × GIC4 FE'), firm-, and firm-by-CEO fixed effects are included as indicated. In Panel IA.8b, F-test (IV only) reports the Cragg-Donald F-statistic for the first-stage (columns 1, 3, 5) and second-stage (columns 2, 4, 6) estimation. Standard errors are clustered at the firm level and reported in parentheses. Standard errors are clustered at the firm level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) DiD Setting

Dep. Variable	𝟙(Inventor Exit)		
	(1)	(2)	(3)
𝟙($\geq$ 2003) × 𝟙(CEO Own. High)	0.0065***	0.0047*	0.0058***
	(0.0019)	(0.0026)	(0.0019)
𝟙(CEO Own. High)	-0.0040	-0.0046*	
	(0.0028)	(0.0024)	
𝟙($\geq$ 2003)	-0.0091***		
	(0.0019)		
CSR Env. (t-1)	0.0015	0.0019*	-0.0003
	(0.0010)	(0.0011)	(0.0009)
CSR Comm. (t-1)	-0.0012	-0.0017*	0.0018
	(0.0010)	(0.0009)	(0.0011)
CSR Hum. (t-1)	-0.0005	-0.0039*	0.0034
	(0.0021)	(0.0021)	(0.0029)
CSR Emp. (t-1)	-0.0008	-0.0014	-0.0003
	(0.0007)	(0.0009)	(0.0007)
CSR Prod. (t-1)	-0.0033**	-0.0034***	0.0003
	(0.0014)	(0.0012)	(0.0007)
CSR Div. (t-1)	0.0014**	0.0020***	0.00005
	(0.0007)	(0.0007)	(0.0004)
CSR Gov. (t-1)	-0.0003	0.0010	-0.0005
	(0.0019)	(0.0016)	(0.0014)
Observations	702,704	702,704	702,704
R^2	0.0042	0.0084	0.0146
Year × GIC4 FE		✓	✓
Firm × CEO FE			✓
Firm Controls	✓	✓	✓
Inventor Controls	✓	✓	✓

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(b) Shock-IV Setting

Dep. Variable	Log Grants	$\mathbb{1}$(Inv. Exit)	Log Grants	$\mathbb{1}$(Inv. Exit)	Log Grants	$\mathbb{1}$(Inv. Exit)
IV Stages	1st	2nd	1st	2nd	1st	2nd
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}(\geq 2003) \times \mathbb{1}$(CEO Own. High)	-0.4796***		-0.5041***		-0.2200**	
	(0.1729)		(0.1571)		(0.1073)	
$\mathbb{1}(\geq 2003)$	0.4311***		0.3988***			
	(0.1108)		(0.1053)			
$\mathbb{1}$(CEO Own. High)	-0.3740				0.6742	
	(0.2360)				(262,761.8)	
$log(1+\widehat{Grants})(t)$		-0.0091**		-0.0137***		-0.0261*
		(0.0043)		(0.0045)		(0.0138)
CSR Env. (t-1)	-0.0987*	0.0005	-0.0254	-0.0020	-0.0195	-0.0009
	(0.0575)	(0.0011)	(0.0635)	(0.0015)	(0.0863)	(0.0023)
CSR Comm. (t-1)	-0.0227	-0.0014	-0.0101	0.0021	-0.0352	0.0008
	(0.0926)	(0.0014)	(0.0916)	(0.0017)	(0.0602)	(0.0019)
CSR Hum. (t-1)	0.0379	-0.0019	0.1244	0.0055	0.2405	0.0096
	(0.1966)	(0.0034)	(0.2269)	(0.0049)	(0.1510)	(0.0065)
CSR Emp. (t-1)	-0.1097	-0.0012	-0.0633	-0.0003	-0.0976	-0.0027
	(0.0690)	(0.0011)	(0.0586)	(0.0013)	(0.0641)	(0.0023)
CSR Prod. (t-1)	0.1423	-0.0019	0.1197*	0.0028**	0.0466	0.0017
	(0.1120)	(0.0014)	(0.0616)	(0.0013)	(0.0590)	(0.0017)
CSR Div. (t-1)	0.1713***	0.0032**	0.0994**	0.0014	0.1003**	0.0026*
	(0.0650)	(0.0013)	(0.0504)	(0.0009)	(0.0404)	(0.0015)
CSR Gov. (t-1)	-0.0143	-0.0011	-0.0268	0.000009	-0.1355	-0.0042
	(0.1736)	(0.0023)	(0.1358)	(0.0025)	(0.1004)	(0.0029)
Observations	711,964	711,964	711,964	711,964	711,964	711,964
R^2	0.5879	0.0024	0.8652	0.0108	0.9087	0.0086
Cragg-Donald F-Stat	20874.307		30416.280		1049.496	
Kleibergen-Paap Wald F-Stat	6.931		7.171		2.133	
Firm × CEO FE			✓	✓	✓	✓
Year × GIC4 FE					✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓
Inventor Controls	✓	✓	✓	✓	✓	✓