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Abstract: Do high-tech startups benefit from developing more ethical AI? AI startups implement policies and take actions to manage ethical issues associated with data collection, storage, and usage and adapt to the norms of their industry. This paper describes these startups' ethics-related actions, including ethical AI policy adoption, and examines how these actions relate to startup performance. We find that merely adopting an ethical AI policy (i.e., a less costly signal) does not relate to increased performance. However, there is evidence that investors reward startups that take more costly preventative pro-ethics actions, like seeking expert guidance, training employees about unconscious bias, and hiring certain types of programmers. We use signaling theory to interpret these results, which suggest that ethical AI policies are a low-cost signal of quality to investors.

1. Introduction

AI is considered by many to be a general-purpose technology with the potential to increase labor productivity and enable macroeconomic growth (Acemoglu and Restrepo, 2020; Brynjolfsson et al., 2018; Bresnahan and Trajtenberg, 1995; Furman and Seamans, 2019). Training data are the lifeblood of artificial intelligence (AI) production. There is growing evidence that firms with higher-quality data perform better than those without (Bajari et al., 2019; Bessen et al., 2022; Brynjolfsson et al., 2011; Nagaraj, 2022). However, there are growing concerns about how much data firms control and how they use it. These include concerns about increasing industry concentration, which may in part be due to data (Aghion et al., 2019, Bessen, 2020), concerns about privacy (Barocas and Nissenbaum, 2014; boyd and Crawford, 2012), and concerns about outcome fairness (Cowgill, Dell'Aqua, Deng, et al., 2020; Martin, 2019; Teodorescu et al., 2021). Issues around outcome fairness may stem from algorithmic bias (Barocas et al., 2018; Lambrecht and Tucker, 2019; Mittelstadt, 2019; Mitchell et al., 2021), coder bias (Cowgill, Dell'Aqua, Deng, et al., 2020), unrepresentative training data (Cowgill and Tucker, 2019), or manager's use of AI in decision making (Cowgill, Dell'Aqua, and Matz, 2020; Martin, 20; Teodorescu et al., 2021).

One way to address risks associated with these concerns is formal government regulation. For instance, the European Union (EU) General Data Protection Regulation (GDPR) and California Consumer Protection Act (CCPA) govern data privacy issues. As an example of how regulation can address market structure concerns, the UK's Open Banking regulations mandate interoperability for the largest UK banks. Potential regulations in the US, such as the Consumer Financial Protection Bureau's[1] proposed rulemaking on data interoperability and explainable algorithms are focused on addressing market structure and bias, respectively. In many of these cases, small firms are exempt from or face less stringent formal government regulation.[2]

[1]https://www.consumerfinance.gov/compliance/circulars/circular-2022-03-adverse-action-notification-requirements-in-connection-with-credit-decisions-based-on-complex-algorithms/

[2] For example, firms with less than 1M Euros in annual revenue or less than 250 employees are exempt from many aspects of GDPR. https://gdpr-info.eu

Industry self-regulation – a process in which business communities develop codes of practice, rules, or standards for those in their community (Gunningham and Rees, 1997) – may be another way to complement formal regulation and address potential risks associated with collecting and using data in production. Many studies suggest positive benefits for firms developing and adhering to industry self-regulation (Barrett and King, 2008; Berchicci and King, 2020). Yet, others caveat this by noting that industry self-regulation is challenging to maintain over extended periods and is subject to the negative impacts of opportunism from larger, more powerful firms (Lenox, 2006; King and Lenox, 2000; Short and Toffel, 2010). Self-regulation may be particularly important for small firms, which are often unfamiliar with or exempt from formal government regulation, by acquainting them with their industries' norms. Additionally, despite the importance of AI to macroeconomic growth and the potential risks of using personal data in product development, we know little about how AI startups approach the numerous ethical issues associated with using large amounts of personal data in the algorithms underlying their products and services.

In this paper, we create a unique dataset of AI startups to study the extent to which these startups adopt and apply ethical principles. We use this dataset to document several patterns in the data. First, approximately 58% of startups report having an ethical AI policy. Second, there is substantial heterogeneity in the adoption of ethical AI policy depending on the downstream industry to which the startup sells its product or services; however, this heterogeneity does not appear due to the relative CSR ratings for these downstream industries. Third, startups with a relationship with a large technology firm are more likely to adopt ethical AI principles. Fourth, almost 80% of startups report taking ethical actions, such as offering bias training and engaging in other pro-ethics actions, which include seeking expert guidance, training employees about unconscious bias, and hiring certain types of programmers. These startups are more likely to report having an ethical AI principle and more likely to have a relationship with a large technology firm. Fifth, adopting an ethical AI policy does not relate to increased venture capital funding; however, taking ethical actions does relate to increased venture capital funding.

We believe the patterns we find in the data are consistent with signaling theory (Spence, 1973). Even in situations when information asymmetries exist (i.e., the startup knows more about the ethicality of their products than external stakeholders), investors can observe actions, certifications, or relationships that signal whether a firm is of a higher or lower quality type (Davila et al., 2003; Higgins and Gulati, 2006). Prior research suggests that certifications (Cihon et al., 2021) and patents (Leland and Pyle, 1976; Long, 2002) can resolve some information asymmetries. Moreover, patents are discussed in the entrepreneurship literature as providing a signal to investors of the venture's higher quality (Conti et al., 2013; Hsu and Zeidonis, 2008). However, high-tech startups at the forefront of AI development are less likely to patent because patenting code is difficult, and disclosure requirements may release valuable information to competitors. Alternatively, data-centric startups encounter many ethical issues in product development. Their costly and verifiable[3] actions to prepare for and mitigate ethical issues signal their higher quality to stakeholders (King et al., 2005; Terlaak and King, 2006). As such, we anticipate that investors will provide capital to startups that signal their higher quality through safeguarding data, mitigating biases in data sources, coders, and algorithms, training employees about potential biases, and developing fairer products. Adopting AI ethics policies without these more costly actions may be perceived by investors as a weaker signal of a startup's higher quality, providing limited benefits.

Our research contributes to several streams of research. First, we contribute to a growing literature on the role of data for AI-producing firms (Bessen et al., 2022; Brynjolfsson et al., 2019; Hartmann and Henkel, 2020). Next, we contribute to important literature on ethics in AI development (Cowgill and Tucker, 2019; Martin, 2019; Ali et al., 2023; Raisch and Krakowski, 2021; Silva and Kenney, 2019; Teodorescu et al., 2021) by collecting and analyzing novel survey data and providing a first glimpse into the antecedents of more ethical AI development. Third, we address a gap in the corporate social responsibility literature by focusing on an entrepreneurial context and examining performance outcomes. Moreover, we continue this literature's discussion of industry self-regulation (Barrett and King, 2008;

[3]These actions may not need to be visible if they are verifiable. For instance, investors can easily verify many of these pro-ethics actions, like engaging an ethics expert or offering bias training, even if they are not directly observed.[3]

Berchicci and King, 2020; King and Lenox, 2000; Locke, 2013; Short and Toffel, 2010) and CSR practices as potential signals to investors (Davila et al., 2003; King et al., 2005; Terlaak and King, 2006) within the context of data-centric startups. Prior literature mainly focuses on larger firms in mature industries (Burke and Logsdon, 1996; Husted and Allen, 2007; King et al., 2005), and the studies of startups that do exist primarily focus on environmental issues and "green" product development (Demirel et al., 2019; Truong and Nagy, 2021; Berrone et al., 2013). By examining the link between more ethical digital product development and venture performance outcomes, we contribute by adding to the debate over whether investors value social responsibility more than the cost of implementing more ethical actions (Bansal, 2005; Bansal and Roth, 2000; Hull and Rothenberg, 2008; Wang and Bansal 2012).

This paper proceeds as follows. Section 2 introduces the academic literature on responsible development and usage of AI, highlighting gaps in the research on how ethics interplays with data access issues. Next, Section 3 discusses the data collected from our survey of AI startups, including several potential data limitations. Section 4 explains our cross-sectional research design, including Heckman's (1979) selection approach. Section 5 presents our findings and robustness analyses. Section 6 describes how these findings are consistent with a signaling model in which merely having an ethical AI policy is a weaker (i.e., lower cost) signal to investors of ethical responsibility than investing in pro-ethics actions. Lastly, Section 7 discusses the broader implications of our findings and concludes.

2. Startup relationships with technology firms and prior investments in pro-ethics actions

Even though AI is a relatively new technology, the generalizability of its application suggests that its economic impact will be far-reaching and proliferate to downstream industries, similar to the personal computer. However, these expected gains do not exist without risks to consumers. Privacy and fairness risks will increase as technologies evolve, and algorithms will become more sophisticated, requiring firms to collect and use more data to fuel development.[4] At the same time, access to representative training data,

[4] For instance, many discuss neural network algorithms as being more sophisticated than earlier types of algorithms but requiring more data and computational power to work appropriately.

which often entails having granular data across demographic groups, increases outcomes fairness. Collecting and storing more granular individual-level data could increase privacy risks but may also enable firms to control for specific subgroup demographics, reducing potential fairness issues.

Technology firm suppliers

The inherent tradeoff between privacy and outcome fairness and the lack of regulation creates a situation where startups may heed the advice of technology firms that supply their IT resources. Incumbent technology firms are more visible to regulators and are under greater public scrutiny. Their stakeholders hold them to a higher standard, expecting them to conduct their business responsibly (Bansal and Roth, 2000). They also have experience in dealing with prior ethical dilemmas that startups lack (Harris et al., 2009). The largest technology firms' (i.e., Apple, Amazon, Google, Microsoft, Meta) actions are highly visible. And as such, stakeholders often hold them to an even higher standard, and their failure to comply with these standards is costly, creating legal liabilities and harming their brand image (e.g., scandalous data-sharing practices[5], data breaches[6], facial recognition issues[7]). Their prior experience in the established Information Technology (IT) industry, combined with scale benefits from the size of their operations and breadth of their business holdings, uniquely positions them to establish AI development norms.

AI-producing startups face the same ethical challenges as larger technology firms, and their AI products pose similar potential risks to outcome fairness. Yet, in addition to decoding the ethical norms in their swiftly growing industry and navigating regulatory grey areas, these startups must quickly develop their initial product to raise funds and survive. Regulators' failure to act has given these large firms more power in shaping norms of smaller firms than was likely intended or desired. Resource-strapped startups often already rely on their supplier relationships for important initial resources, including technical and ethical guidance, training data, and discounted access to cloud computing, which benefits product

[5]https://www.nytimes.com/2018/04/04/us/politics/cambridge-analytica-scandal-fallout.html
[6]https://www.wired.com/story/amazon-failed-to-protect-your-data-investigation/
[7]https://www.forbes.com/sites/glenngow/2020/06/23/why-are-technology-companies-quitting-facial-recognition/?sh=4bbe13786994 & https://www.technologyreview.com/2021/08/13/1031836/ai-ethics-responsible-data-stewardship/

development (Impink, 2022; Jin and McElheran, 2017; Stuart, 2000). These larger firms are uniquely positioned to disseminate information on ethical issues associated with big data's use, best practices on reducing bias and training algorithms with appropriately representative data, and documents codifying ethical AI development principles through their IT supplier relationship. Relationships with technology firms can guide startups to develop more responsible AI products. Moreover, technology firms can disseminate this information through existing online portals or their startup programs, making materials easily accessible. Given startups' resource constraints, they likely lack the policy expertise and legal advice to knowledgeably depart from the guidance provided or visible norms within the industry.

Training data is critically important to developing a functional AI product. Startups must collect training data that fit their production needs to train their initial products. However, training data that is unrepresentative of the underlying population, over-indexing on specific subgroups and omitting others, may bias products making resulting subgroup outcomes less fair (Barocas et al., 2018).[8] Startups could develop products that produce fairer outcomes across demographic subgroups by accessing training data more representative of their product's targeted population.

Potential antecedents to more ethical AI product development: preventative pro-ethics actions and training

Two mechanisms enable more ethical AI development when coupled with adequate training data resources. First, startups could engage in preventative pro-ethics actions, including seeking expert ethics advice, recruiting more diverse programmers, and attempting to collect more diverse and representative training data. If training data are biased, then the resulting products will reflect that bias. The decision to spend time and scarce resources on collecting additional training data may delay product development, but a product's ethicality likely benefits from these investments. Other actions, such as hiring an ethics consultant or placing an ethics expert on the firm's board, suggest that founders are aware of potential ethical issues in

[8] Several news agencies report two well-known examples of this. First, many technology firms' facial recognition training data underrepresented black women's faces, and their resulting AI product had trouble recognizing black women (https://www.nytimes.com/2022/06/21/technology/microsoft-facial-recognition.html). Second, minorities may receive unfair outcomes in loan applications when the training data is unrepresentative of black home ownership (https://www.forbes.com/sites/korihale/2021/09/02/ai-bias-caused-80-of-black-mortgage-applicants-to-be-denied/?sh=6a0d5ad536fe).

store for them and have the forethought to address them head-on. These actions are visible to investors and easily verifiable.

Even if training data are fully representative, access to additional guidance and best practices from larger firms in the industry could provide a rubric for more ethical product development. For instance, many larger technology firms stress the importance of employing female and underrepresented minority programmers to reduce programmer-induced bias because programmers with shared backgrounds or experiences may develop AI more similarly (Cowgill and Tucker, 2019; Cowgill et al., 2020). The iterative nature of AI, which relies on initial data and subsequent feedback loops, may exacerbate biases that are small initially (Cowgill and Tucker, 2019). Startups that focus on hiring more diverse talent may benefit from reduced algorithmic bias and fairer products.

Second, startups could train employees to recognize biases and fairness issues. The need for awareness and education will only increase as AI becomes more prevalent in organizations (Teodorescu et al., 2021). These risks are present for all firms, but smaller firms have fewer resources to combat these risks. AI product ethicality benefits from training programmers and other non-technical decision makers, like managers, in the firm. Guidance from technology firms reinforces the need to train programmers to recognize algorithmic bias and to educate managers about the potential risks of using AI outcomes in decision-making.[9] Some larger technology firms even provide bias-related training materials.

Training programmers to recognize potential biases stemming from under-representative training data or from how the AI is coded enables startups to develop fairer products (Athey, 2017). Granted, this is not always an easy task. Algorithmic bias issues are even difficult for experienced programmers to recognize, and even if they are aware of a problem, they may be unable to diagnose it accurately (Selbst and Barocas, 2018).[10] Next, training non-technical employees creates an awareness of potential fairness

[9] Though we cannot fully account for the intensity of the resources sharing through this relationship with our data, we anticipate these relationships will enable startups to access more data, become aware of ethical issues, implement additional pro-ethics actions, and train employees to recognize potential biases.
[10] The difficulties in understanding the algorithm's inner workings and dissecting its bias's source have led to discussions of more sophistical algorithms as a "black box" where it is hard to map inputs to the results (Athey, 2017; Donnelly et al., 2018).

issues. Managers benefit from education on recognizing and overcoming unconscious biases in their decisions making processes (Martin, 2019; Rambachan et al., 2020). Even if the data are more representative and algorithms are less biased, employees may introduce their own cognitive biases when interpreting the AI's outcome (Tversky and Kahneman, 1985). Training managers to focus on outcome accuracy by demographic subgroup can reduce biases in decision-making even if the underlying training data or algorithms are flawed (Cowgill and Stevenson, 2020).

However, there are numerous caveats to these actions, as they may not be fully aligned with the goals of the organization. Recent literature points to the decoupling between the firm's stated ethical goals and the apparent goals on the ground in the firm, particularly highlighting risk for whistleblowers (Ali et al., 2023; Mittelstadt, 2019; Metcalf et al., 2019). Potentially, we are capturing "ethics washing" in organizations instead of using policies to align employees' actions to an authentic goal of increasing the product's ethicality.[11]

3. Data and measures

We use data from a survey of AI startups, including questions on the development and use of ethical AI principles, to determine the effect of data-sharing relationships between technology firms and AI startups. We pretested the survey with several academics and practitioners associated with startups and then administered it through Qualtrics yearly for two years (2021-2022). Respondents to our survey come from several sampling frames, including Crunchbase, Pitchbook, Creative Destruction Labs, and an incubator at Technische Universität München (TUM). From Crunchbase and Pitchbook, we identify firms associated with the keyword "artificial intelligence" that are currently operating yet have not experienced an initial public offering (IPO). Additionally, we received a contact list of AI startups from the Creative Destruction Lab, a startup incubator based in Toronto, and another contact list from Philipp Hartmann and Joachim

[11] Khari Johnson. 2019. How AI companies can avoid ethics washing. https://venturebeat.com/ai/how-ai-companies-can-avoid-ethics-washing/
Publisher: VentureBeat.

Henkel at TUM (Hartmann and Henkel 2018). To develop a more homogenous sample of firms for our analysis, we exclude larger (i.e., more than 500 employees) or older (i.e., more than ten years old) firms.

We sent a digital survey via email to founders, chief technology officers, or executives who know their firm's business model and technologies at 4,593 AI-producing startups.[12] Responding firms confirmed they develop AI products in the first survey question. We received 376 responses[13] from AI startups in our sample, and our response rate of startups is about 8%. We pair the survey data with employee-level skills data sourced from LinkedIn profiles, firm-level demographic, funding, and investor data from Crunchbase[14] and Pitchbook[15], and firm-level data on cloud providers from BuiltWith[16]. Our analyses include industry-level data on socially responsible product development from Thompson Refinitiv[17], which captures responsible use of data and consumer data privacy practices at the industry level. More specifically, our product responsibility score reflects an industry's capacity to produce quality goods and services, integrating the customer's health and safety, integrity, and data privacy. If a startup sells into multiple industries, we calculate this score as the mean of the product responsibility score across those industries.

Firms responding to our survey are about five years old and employ 25 employees (mean), with almost half having ten or fewer employees. Even though we administered the survey worldwide, most of our responses are from more developed countries, with nearly 80% of responses from the United States,

[12] We exclude firms where email addresses bounce back, assuming that they are no longer in business or that data provided by third parties is incorrect.

[13] We only included the first observation for the 27 startups that responded in both years. Some startups in our sample are listed in Crunchbase and Pitchbook with nothing more than a description. These startups are likely small, nascent ventures that will have additional data paired in the future as they grow. Startups missing firm locations or founding data are not included in our analyses.

[14] Crunchbase is a platform for finding business information about private and public companies. It provides intelligent prospecting software powered by live company data.

[15] Pitchbook Data, Inc. is a SaaS company that delivers data, research, and technology covering private capital markets, including venture capital, private equity, and M&A transactions.

[16] BuiltWith is a data service that determines the technologies connected to a web domain.

[17] Thompson/Refinitiv is one of the world's largest providers of financial markets data and infrastructure. The product responsibility score reflects a company's capacity to produce quality goods and services, integrating the customer's health and safety, integrity, and data privacy. These industry-level measures are developed using transparency weights methodology and are adequate for comparing across industries using Boolean data points. These Boolean data points are measures with a value of "Yes" or "No." Magnitude weights are based on the level of disclosure of each data point in each industry group. The question of materiality, or in other words, the relative importance, is determined based on the disclosure of the relative level in that industry group. The disclosure percentage for each industry group to which the data point is material is identified. Then decile ranks are assigned. The decile rank determines the relative weight given to that data point in determining the industry weight – from 1 to 10.

Canada, and Europe. Our third-party data suggest that 14% of startups license healthcare products, and 6% license finance products. Additionally, we create indicator variables for if a startup has a female founder (0.12 SD 0.33), a minority founder (0.06 SD 0.24), or a Master of Business Administration degree (MBA) graduate (0.44 SD 0.05). In Table 1.A. we report firm-level descriptive statistics.

Our survey instrument collects information on data-sharing relationships between startups and technology firms (0.45 SD 0.50).[18] In 2021 and 2022, we used the survey instrument to collect information on ethical AI development. From these data, we created dummy variables for if the firm had established an ethical AI policy (0.58 SD 0.49). These policies are often quite different. However, most policies cover fundamental issues around data privacy, training data representativeness, and algorithmic biases and address the potential for unfair AI to harm subgroups. Suppose the firm does not take policies seriously, and these policies do not align with the organization's actual goals (i.e., ethics washing). In that case, these policies may not indicate more ethical product development, potentially existing as a signal to external stakeholders. From our data, 85 of the 218 startups responded that they have never evoked their policies in a way that led to a costly outcome, such as dropping data, firing an employee, or turning down sales.[19] Ethical AI policies are only effective if the firm abides by those principles, enabling them to develop more ethical products.

Many startups have undertaken pro-ethics actions not necessarily connected with the adoption of ethical AI principles, such as considering diversity when selecting training data (0.42 SD 0.49), seeking expert advice (0.35 SD 0.47), or hiring a minority or female programmer (0.61 SD 0.49). These actions are preventative measures that set up the organization to develop more ethical products, and almost 80% of

[18] As a limitation of our survey mechanism, we cannot gauge the intensity or nature of the sharing relationship between the startup and the technology firm.

[19] To build this measure, we also collect data on common but costly business outcomes, which include dismissing an employee that did not adhere to the ethics policy (0.07 SD 0.26), dropping more biased training data (0.22 SD 0.41), or turning down business (0.24 SD 0.41). Though this is not an exhaustive list of outcomes, responses provide insight into it the policy exists as a signal or is being used to hold the startup accountable, even when costs are high. As a limitation to our signaling measure, we only capture data on three more costly business outcomes that startups commonly cite as ethical issues (i.e., dropping less representative data, firing an employee in breach of the policy, and turning down business due to the policy). This is not a fully exhaustive list, but it captures many outcomes compelled by strict adherence to an ethical AI policy.

startups take at least one action. We create an index that captures the similar nature of several pro-ethics actions. This index ranges from 0 to +3, with firms receiving a point for each action: considering diversity when selecting, hiring a minority or female, seeking expert advice (mean 1.43 SD 1.06). Some startups respond in the survey that they offer bias training (0.23 SD 0.42). We provide summary statistics for survey responses in Table 1.B. and for the indexes in Table 1.C. We report survey questions in Appendix A.1 and correlations in Appendix Table A.2.

To validate the survey, we compare data on startup location from the survey with objectively obtained data from Crunchbase. In Appendix A.3, we show the comparison between these data sources for the top five countries and top six US states[20] and report no significant differences for either using a Pearson Chi-squared test. As a second validation, we collect data from LinkedIn data for employees working for these startups, and we create an indicator variable for firms where employees report ethics skills (0.04 SD 0.2) or training skills (0.54 SD 0.5). In Appendix Table A.4., we correlate LinkedIn measures with our survey measures and find a positive and significant relationship between startups responding that their firm engages in pro-ethics action and employing workers reporting ethics skills on LinkedIn (model (1): +0.18 SD 0.07). Similarly, there is a positive relationship between startups responding they provide unconscious bias training and employing worker reporting training skills on LinkedIn (model (2): +0.07 SD 0.04). As a final validation, we compare firm size (i.e., categories of firm size from the survey) with firm size from Crunchbase and find a strong positive relationship (model (3): 0.78 SD 0.06). These checks provide additional confidence in our survey data and the validity of the survey measures.

4. Research Design

4.1. Main specification

We use the following firm-level regression specification for our initial cross-sectional analyses to examine the relationship between having a data-sharing relationship with a technology firm and the antecedents to

[20] Only 127 of the 137 startups reporting to be in the USA provided zip code data in the survey, so ten were omitted from this analysis.

more ethical product development.[21] We control for firm demographics, including firm size, region, and age, which relate to outcomes product development and performance outcomes. As examples, older firms may have more time to enact and enforce ethics policies, or norms and regulations may differ across regions. We also control for if a founder has an MBA as a step toward overcoming concerns that some firms are better managed than others and that product ethicality is related to better management abilities. Lastly, we control for prior funding, as on the one hand, prior ethical product development may beget earlier funding, and on the other hand, earlier funding may provide resources that facilitate startups following their policies more closely.

(1) $$\boldsymbol{ethical\_action_i = \beta_0 + \beta_1 tech\_datasharing_i + \beta_2 \lambda_i + \beta\chi + \mu}$$ [main specification]

where, $\boldsymbol{ethical\ action_i}$ refers to an indicator variable for if the firm: (a) has a set of ethical AI principles, (b) invests in costly pro-ethics actions, or (c) provides biases training; $\boldsymbol{tech\_datasharing_i}$ refers to an indicator variable if a firm has a data sharing relationship with a technology firm; $\boldsymbol{\chi}$ includes controls for downstream industry-level social product development norms, age, age^2, region (NA, EU, MEA, and Asia), founder MBA degree, and prior funding (log, before 2021). For models including the two-stage Heckman selection procedure, $\boldsymbol{\lambda_i}$ is the firm-level inverse of the Mill's ratio (IMR), used to adjust the estimate for potential selection issues in the second stage stemming from non-response.

Lastly, our performance specification examines the link between having an ethics policy or taking pro-ethics actions and future fundraising (i.e., funding after we administered the survey in 2021). Given that these are high-growth startups, we have a particular interest in their ability to raise the capital and follow-on funding needed to scale.

(2) $$\boldsymbol{performance_i = \beta_0 + \beta_1 ethical\_action_i + \beta\chi + \mu}$$ [main specification]

where, $\boldsymbol{performance_i}$ refers to the log of funds raised in or after 2021 or an indicator variable for receiving follow-on funding in or after 2021; $\boldsymbol{ethical\_action}$ refers to an indicator variable for having an ethic policy but not enacting it; $\boldsymbol{\chi}$ includes controls for age, age^2, founder MBA, prior funding, and region.

[21] In situations where the firm responds twice, we include the first response from the 2021 survey.

4.2. Selection specification

In addition to collecting data on a relatively homogenous group of startups, we examine survey responses to determine if startups responding to the survey are similar to the broader startup population in Crunchbase and Pitchbook, which have excellent coverage of startups in developed countries. From initial t-tests, we find that responses from California, where many startups are based, are underrepresented. Moreover, younger firms are less likely to respond to our survey. To confirm this, we use a probit regression model to estimate the likelihood of response (Appendix Table A.5, selection specification below).[22]

$$(3) \qquad \boldsymbol{response_i} = \boldsymbol{w_i}\boldsymbol{\gamma} + \boldsymbol{\mu} \quad \text{[selection specification]}$$

where, $\boldsymbol{response}$ takes the value of 1 if a firm in the population responds to the survey and otherwise 0; $\boldsymbol{w_i}$ refers to a vector of variables related to non-response: an indicator variable for location in California, continuous measures of age and age^2 plausibly correlated with sample response, and an indicator variable for if the founder had prior work experience at a larger technology firm. This probit model is the first stage of the Heckman (1979) selection approach, which we use to adjust estimates of our model for potential respondent selection issues.

5. Findings

Ethical AI policies

Of responding firms, 58% have an ethical AI policy. Table 2 adds a series of controls to determine if other factors correlate with ethical AI policy adoption. We find heterogeneity by industry, suggesting that certain industries are more likely to have policies than others (model (2)). These differences across industries are exacerbated by when we scale industry indicator variables by industry-level CSR scores (model (3)). Next, we add controls for age and age^2 (model (4)), region, size, founder MBA (model (5)), and prior performance

[22] We look at responses to the survey against the total population of AI startups matching our criteria, currently available in Crunchbase and Pitchbook.

(model (6)), which account for some of the variation, lowering the constant from +0.58 SD 0.025 in the base model to +0.45 SD 0.123 in model (6).

Data-sharing relationship and ethical actions

Using cross-sectional data, we explore the relationship between having a data-sharing relationship with a technology firm and adopting an ethical AI policy. In Table 3 model (1), we find a positive correlation (+0.18 SD 0.05). Next, using a similar build-up as in Table 2, in Table 3 model (2), we include industry indicator variables, noting heterogeneity by industry. This heterogeneity persists when scaling industry indicator variables by industry-level CSR scores (model (3))[23], suggesting that the trade and healthcare industries are more likely to have ethical AI policies. In models (3)-(6) we include other firm-level control variables, which do not significantly affect the coefficient describing the relationship between having a technology firm data-sharing relationship and adopting an ethical AI policy (+0.21 SD 0.05).[24]

In Table 4, we examine data on the correlation between having an ethical AI policy and engaging in ethical actions and training. Using the prior firm controls (i.e., age, age^2, region, size, founder MBA, and prior funding), we find a positive relationship (model (1): +0.66 SD 0.1) between having an ethical AI policy and engaging in a higher number of costly pro ethics actions (i.e., Ethics index [0-3]: hiring more diverse programmers, collecting more diverse data, or consulting with an ethics expert). Even when adding a firm-level measure of downstream CSR scores[25], this relationship persists (+0.65 SD 0.01). Next, we examine the relationship between having an ethical AI policy and conducting bias training (model (3): +0.17 SD 0.04), which slightly increases when controlling for firm-level CSR scores (model (4): +0.18 SD 0.04). We find a positive relationship between firms that consider diversity in training data selection and having a female founder (model (7), *Female x Ethical AI policy*: +0.258 SD 0.135), aligning with our

[23] Scaling the industry indicator variable does not change the coefficient of the independent variable; instead, it changes the by-industry coefficients to describe the effect of downstream industry-level CSR practice above and beyond controlling for the industry.
[24] To support this result, in Appendix Table B.1. we rerun Table 3 using a probit specification instead of OLS since the dependent variable is a binary indicator variable for having an ethical AI policy and find a similarly positive and significant relationship.
[25] Note that many startups sell products to multiple industries. In these cases, the firm-level CSR score is an average across all the industries where a firm sells its products.

intuition that females may be more aware of how unrepresentative training data impacts outcome fairness for demographics subgroups.[26]

In Appendix Table B.2. we examine the relationship between having a data-sharing relationship with a tech firm and a single aspect of the Ethics index, collecting more diverse training data, which also has a significant and positive correlation. In Table B.3., we use a multinomial probit, with industry fixed effects, to show that having a data-sharing relationship with a tech firm relates to taking a higher number of pro-ethics actions (base = no action taken). And given that we are using cross-sectional data, in Table B.4. we include a LASSO model to support that observable omitted variables do not nullify results. This approach chooses 17 controls from more than 60 variables on these startups' relationships, prior performance, and technologies from the survey data and other paired demographic data. These results support a positive correlation between having an ethical AI policy and having a data-sharing relationship (model (1)), taking a pro-ethics action (model (2)), and collecting more diverse data (model (3)).

In Appendix Table B.5., we share a version of the main results from Table 3 with an added control for respondent selection, the Inverse Mill's ratio. This added control is not significant, suggesting that the observable respondent selection biases do not significantly impact our results. The probit results from specification (3), from which we calculate IMR (Appendix Table A.5.), enable us to examine which attributes of startups in the sample are related to higher or lower response rates. We find that startups in California (-0.35 SD 0.09) and with founders that previously worked at Amazon, Google, or Microsoft (-0.2 SD 0.08) are less likely to respond to the survey. There is a non-linear relationship with age. Younger and older startups are less likely to respond to the survey (age (log): -17.4 SD 0.82; age^2 (log): +6.3 SD 0.3).

<u>Link with fundraising</u>

Table 5 examines the correlation between having an ethical AI policy and funds raised since the survey was administered in 2021 (log). Model (1) is the base model with no added controls (-0.94 SD 0.66). In model

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[26] Moreover, prior literature points to females making more ethical decisions than men (Malinowski and Berger, 1996; Peterson et al., 1991).

(2) we add CSR-scaled industry indicators variables, and in model (3) we add additional firm-level demographic controls, including indicator variables for if a startup located in a location with a high proportion of VCs (New York, San Francisco Bay Area, London, and Boston) or a startup's founder has an MBA, both which could plausibly be correlated to raising additional funds. We also include a continuous control variable for age and age^2, but our results remain similar to the prior models. In model (4) we also include a measure from prior funding performance (i.e., the log of funding before 2021, when the survey was administered), which reduces the coefficient (-0.61 SD 0.67).

In Table 5 model (5) we include an interaction between adopting an AI policy (indicator variable) and the continuous Ethics index [0,3], which captures the number of pro-ethics actions taken, and find that the interaction coefficient is slightly negative and not significant (*AI policy x Pro ethics action (cont.)*: -0.21 SD 0.72). Then we split the sample into two groups: lower (2 or fewer pro-ethics actions, 307 firms) and higher (3 pro-ethics actions, 67 firms) pro-ethics actions. In model (6), the lower ethics index group, we report a slightly significant ($p<=0.1$) negative correlation between having an ethical AI policy and future funding (-1.21 SD 0.69). On the other hand, in model (7) we report a positive yet insignificant correlation between having an ethical AI policy and future funding (+3.3 SD 2.8). These findings, taken together, support that there is no correlation or a slightly negative correlation between having an ethical AI policy and future funding.[27]

Table 6 examines the correlation between startups taking pro-ethics actions and future fundraising performance, using the same specification and model by model build up as in Table 5 models (1)-(4). The first set of regressions reports a positive relationship between taking a least one pro-ethics action (dummy) and future funding (model (4): +1.23 SD 0.7). The next set of regressions examines this relationship by

[27] In Appendix Table B.6., we rerun the specifications used in Table 5 with a slightly different IV to capture firms that had an ethical AI policy but did not respond that they used that policy in three key ways: dropping data, firing an employee in breach of the policy, or turning down a sale due to the policy. We acknowledge other possibly costly outcomes that the firm could have encountered due to the policy that are not covered by the questions. Additionally, it is possible that the firm has not encountered any of these ethically dubious situations and that proactively managing ethical issues prevents them from dealing with these costly outcomes. Results from these analyses show a slightly more negative relationship between having an "unused" ethical AI policy and future funding.

analyzing pro-ethics actions as a categorical variable, reporting that coefficient of the positive relationship with future funding is higher as the number of pro-ethics actions increases (model (8): 1 action: +.57 SD 0.78; 2 actions: +1.6 SD 0.89; 3 actions +1.9 SD 1.04). These findings support that pro-ethics actions, including hiring minority programmers, searching for more representative data, and engaging with experts, are valued by and visible to investors and relate to greater performance. Lastly, we find a positive relationship between raising future funding and offering bias training (model (12): +1.09 SD 0.85; *insignificant*).

To better understand if taking more costly ethical actions leads to better or worse future fundraising, we consider changes to the startup's data resources. Of these firms, those using more sophisticated algorithms (i.e., neural networks) will require more data to train their AI product. Alternatively, those that use other algorithms will likely require less robust data. In Appendix Table B.7, we show the interaction between firms that have to collect more data and the scenario where that data is likely more costly to collect (i.e., when they are using neural networks), and find a positive relationship between the interaction term and future funding (model (4), *NN x Collect more diverse data*: +1.1 SD 0.43). We use a similar analysis for firms that have an ethical AI policy and drop data due to that following their policy, and find a similarly significant relationship between the interaction term and future funding (model (8) *NN x Policy + dropped data*: 1.21 SD 0.66).

As robustness for the performance relationship, we examine an alternative fundraising DV. In Table B.8. we analyze a dummy variable for follow-on funding (i.e., additional funding beyond the first funding round) after 2021. Since the dependent variable is a binary indicator variable, we rerun these analyses using a probit regression (Table B.9.). In these iterations, results remain similar to the main performance analyses reported in Table 6. Next, we examine our alternate proxies for ethics and training from LinkedIn data on employee skills, which shows similar trends (Table B.10).

6. Interpretation of findings in alignment with signaling

Information asymmetries about the startup's practices make it difficult for investors to determine which startups are better investments (Leland and Pyle, 1976). This has likely only been exacerbated in recent years by the onset of "spray and pray" investing, where venture capital firms are less well-connected to startups than previously. Prior literature points to the importance of patents in reducing information asymmetries (Long, 2002) and signaling quality to venture capital investors (Hsu and Zeidonis, 2008; Conti et al., 2013). Similar to how college degrees enable employers to differentiate between higher- and lower-productivity employees on the labor market (Spence 1973), a costly and visible signal of ethical production could aid investors in determining which startups take ethical AI development seriously.

Patents are less commonly used by high-tech startups developing AI products, as code-based operating systems and software are difficult to protect under current IP regimes. In lieu of patenting, startups are looking for ways to signal their quality. As the survey suggests, there are numerous ways that startups can invest their scarce resources into preparing their firms for the ethical issues that lie ahead in a way that is visible to investors. It seems plausible that investors value startups that take data privacy and ethical development more seriously. For instance, investors could worry about PR-related issues or reduced exit opportunities for startups with ethical issues or products that facilitate discriminatory behavior. Furthermore, as potential algorithmic bias and resulting discrimination are more universally acknowledged as a risk, there could be increased liability related to product usage once judicial rulings are established. In addition to this, it is also plausible that investors view these ethics-related investments as signals of startup quality and differentiate startups based on this information.

The adoption of an ethical AI policy is not a particularly costly way for startups to signal their willingness and ability to adopt the extant ethical norms in their industry. They could copy stock language from the publicly accessible policies of other firms, or they could choose not to enforce or abide by their policy (Hawn and Ioannou, 2016). Even if this policy is a talking point with investors, it seems unlikely that investors would value this action. This theory aligns with our analysis and interpretation that there are limited returns to having an ethical AI policy in and of itself. Even if you enact the policy, your startup is in a situation where the costs of mistakes are detrimental. For instance, dropping training data, firing a programmer, or turning down an initial sale may threaten the startup's existence, particularly in its first few years.

On the other hand, investors may be more inclined to invest in AI startups that take more costly preventative actions exemplifying their prioritization of ethical AI development. Though some of these actions remain unseen, it is easy for investors to gauge if the startup is hiring more diverse talent, including female or minority programmers or employees with a background in data privacy, ethical data usage, or training. Moreover, it is not difficult for investors to access information on whether the firms offer bias training, have hired an ethics consultant, or have added an ethics or privacy expert to their board. These actions are more costly than adopting an ethical AI policy but could aid in preventing substantially more costly business outcomes. The ethical AI policy may only create awareness of these issues without readying the firm to encounter the ethical grey area that is likely to be encountered.

Data sharing relationships with technology firms may be two-fold, enabling startups to access needed resources (i.e., more representative data, ethical AI development guidance) and signal their quality to investors. For instance, these larger firms have legal affairs and policy teams, abreast of data privacy and fairness issues, that guide the business when regulations are lacking. Given the lack of regulatory oversight, many large technology firms have developed ethical AI guidance, which codifies their stances on data privacy and ethical AI development (Guo et al., 2019; Smith and Browne, 2019). These ethical AI guidelines focus on how to use big data more ethically, creating awareness around algorithmic transparency, bias, and fairness issues and suggesting remedies to those issues (Jobin et al., 2019).[28] Without these interfirm relationships, startups lack access to many in-house resources that these larger firms have in abundance (Dodge and Robbins, 1992; Evans and Leighton, 1990; Katz and Gartner, 1988; Zott and Huy,

[28] For example, Intel, IBM, Microsoft, Sony, SAP, and Google have all developed ethical AI policies that provide their stance and guidance on data-related issues affecting AI development. Many of these policies considerably overlap in the guidance they prescribe.

2007). Alternatively, these technology firms are capable of evaluating the startup's contributions and may choose to only partner with startups that are more likely to succeed.

7. Discussion and conclusion

Responses from our AI startup survey enable us to take an initial step toward understanding issues impacting startups relying on big data in AI product development. Given the value of AI to the economy, more broadly, these firms' products are anticipated to be important for labor productivity and future macroeconomic growth. This study provides early insight into how AI startups address ethical issues and into which actions map to greater performance.

In almost all scenarios explored, a data-sharing relationship with a technology firm relates to startups engaging in behaviors commonly seen as antecedents to more ethical product development. In the absence of regulation, large technology firms, for better or worse, play a large role in setting norms and guiding more ethical AI development. Startups may find it difficult to navigate complex ethical issues without these relationships or may not have robust enough data resources in-house to develop their products or drop less representative data. These technology firms have invested in codifying their data privacy and ethical AI guidance, which startups often cite and follow. However, there are potential long-run risks of this arrangement if this form of industry self-regulation makes startups more reliant on technology firms. For instance, these larger firms have more power in norm-setting, creating an environment conducive to opportunistic behavior. AI regulation could incentivize firms to develop more ethically while potentially reducing the need for startups to rely on technology firms, benefiting startups competing with large technology firms in downstream markets.

Though these survey data enable us to describe a novel setting, using cross-sectional survey data presents numerous limitations. We control for startup age, region, founder's education, prior fundraising performance, and industry-level CSR norms; however, we cannot rule out unobservable variables. We attempt to address these issues by detailing and testing plausible alternative explanations (Spector, 2019).

Given our data limitations and research design, we cannot fully rule out reverse causality (i.e., the alternate interpretation that more ethical firms are more likely to partner with high-technology firms).

Adding to the literature on corporate social responsibility, our results further suggest that investing in costly pro-ethics actions and training employees on biases relates to greater future fundraising performance, even when controlling for industry-level CSR norms and prior fundraising. Granted, with our data in this setting, we are unable to parse whether investments in more ethical products equate to more sought-after products or are signals of a startup's higher quality to investors. These actions can signal to investors that a startup abides by the norms of the industry or "knows the rules of the game," reducing liabilities associated with creating harmful or unfair AI products. It also signals to investors that they can attract higher-quality employees that are aware of ethical issues and are interested in working at a startup that takes those issues seriously. Startups investing in the pro-ethics preventative actions and hiring labor with skills conducive to more ethical product development may prevent these firms from situations where they incur an exceedingly costly business outcome. These are small firms with uncertain futures that may be unable to sustain these costs. Lastly, in alignment with signaling, less costly actions, such as adopting an ethical AI policy, do not relate to increased fundraising performance. Adopting a policy may merely be a form of ethics washing, or the policy content may not map to the firm's goals or actions.

As startups use more sophisticated algorithms that require even more data, the conversation around the risks of responsible AI development becomes even more important. Startups may need more robust data resources when they use neural networks, making it even more costly to drop unrepresentative data and source new data. Our results show that when using these more sophisticated algorithms (i.e., when data is more valuable to the startups), having to drop training data or collect additional training data relates to increased funding, supporting our interpretation of costly and verifiable pro-ethics actions as a signal to investors.

Tables and Figures

Table 1.A. – Firm summary

Measure	Mean	SD	Min	Max
Age	5.2	2.2	1	10
Employee	25	35	1	375
Small, < 11 emp.	0.48	0.50	0	1
Healthcare	0.14	0.35	0	1
Finance	0.06	0.23	0	1
US	0.41	0.49	0	1
UK	0.05	0.21	0	1
France	0.02	0.15	0	1
Germany	0.04	0.19	0	1
Canada	0.04	0.2	0	1
Founder MBA	0.44	0.5	0	1
Founder big tech experience	0.2	0.4	0	1
Founder female	0.12	0.33	0	1
Two funding rounds, dummy	0.38	0.48	0	1
Second funding in/after 2021, d	0.12	0.33	0	1
Prior funding (2019, 2020)	0.23	0.42	0	1
Funding in/after 2021, log	3.22	6.14	0	18.42
Funded in/after 2021, d	0.2	0.4	0	1.0

Table 1.B. – Survey measure summary

Measure	Mean	SD	Min	Max	
Relationship with tech firm	0.64	0.48	0	1	
Data sharing relationship w/ tech firm	0.48	0.50	0	1	
Data sharing relationship w/ AM,GO,MS	0.14	0.35	0	1	
Cloud services connected to web domain	0.29	0.45	0	1	
Do you have ethical AI principles?	0.58	0.49	0	1	a
Due to these principles, has your firm:					
Dismissed employee	0.13	0.34	0	1	b
Dropped data	0.37	0.48	0	1	c
Turned down business	0.43	0.50	0	1	d
Has your firm done the following:					
Considered diversity in data selection	0.43	0.50	0	1	e
Sought expert advice	0.35	0.48	0	1	f
Hired minority/female programmer	0.60	0.49	0	1	g
Offered unconscious bias training	0.23	0.42	0	1	h
Employee skills (ethics)	0.04	0.20	0	1	i
Employee skills (training)	0.54	0.50	0	1	j

Table 1.C. – Index Summary

Measure	Mean	SD	Min	Max
Pro ethics actions index (e+f+g)	1.38	1.04	0	3
Ethics policy + costly outcomes index (b+c+d)	0.93	0.92	0	3
Signal (ethics policy + no costly outcomes)	0.20	0.40	0	1

Table 2 – Ethical AI principles

	(1)	(2)	(3)	(4)	(5)	(6)
DV, Dummy:	Ethical AI policy					
Constant	0.580	0.492	0.492	0.450	0.447	0.452
	(0.025)	(0.046)	(0.046)	(0.118)	(0.122)	(0.123)
Industries:		*Industry indicator*		*CSR scaled industry ind.*		
Agriculture		0.049	0.104	0.087	0.087	0.090
		(0.075)	(0.159)	(0.160)	(0.161)	(0.160)
Manufacturing		-0.082	-0.121	-0.085	-0.084	-0.085
		(0.064)	(0.094)	(0.097)	(0.098)	(0.098)
Communication		0.003	0.005	0.014	0.014	0.015
		(0.066)	(0.112)	(0.114)	(0.114)	(0.114)
Utilities/transport		-0.087	-0.174	-0.148	-0.148	-0.146
		(0.061)	(0.122)	(0.125)	(0.125)	(0.125)
Trade		0.111	0.270	0.281	0.280	0.284
		(0.061)	(0.148)	(0.151)	(0.151)	(0.151)
Finance		0.003	0.010	0.006	0.006	-0.000
		(0.057)	(0.174)	(0.179)	(0.179)	(0.180)
Software/IT		0.011	0.029	-0.001	-0.001	-0.001
		(0.059)	(0.150)	(0.155)	(0.156)	(0.156)
Education		0.059	0.177	0.171	0.171	0.172
		(0.059)	(0.178)	(0.182)	(0.183)	(0.183)
Healthcare		0.084	0.163	0.194	0.194	0.196
		(0.052)	(0.102)	(0.103)	(0.103)	(0.102)
Other. Services		0.070	0.138	0.119	0.119	0.116
		(0.056)	(0.111)	(0.112)	(0.112)	(0.113)
Firms	376	376	376	376	376	376
Adj R2	0.000	0.013	0.013	0.009	0.006	0.004
Age, Age^2	No	No	No	Yes	Yes	Yes
Region (4)	No	No	No	Yes	Yes	Yes
Size (<11 emps.)	No	No	No	Yes	Yes	Yes
Founder MBA	No	No	No	No	Yes	Yes
Prior funding (<2021)	No	No	No	No	No	Yes

Notes: SD reported in parentheses under the coefficient.

Table 3 – Tech firm relationship and ethical AI principles

	(1)	(2)	(3)	(4)	(5)	(6)
DV, Dummy:	Ethical AI policy					
Tech firm data sharing relationship	0.184	0.190	0.190	0.207	0.207	0.206
	(0.050)	(0.050)	(0.050)	(0.051)	(0.051)	(0.051)
Industries:		*Industry indicator*	*CSR-scaled industry indicator*			
Agriculture		0.062	0.132	0.110	0.110	0.111
		(0.071)	(0.152)	(0.152)	(0.152)	(0.151)
Manufacturing		-0.098	-0.144	-0.104	-0.104	-0.105
		(0.063)	(0.093)	(0.095)	(0.096)	(0.096)
Communication		-0.007	-0.013	-0.005	-0.006	-0.005
		(0.065)	(0.110)	(0.111)	(0.111)	(0.111)
Utilities/transport		-0.092	-0.184	-0.152	-0.152	-0.151
		(0.060)	(0.120)	(0.123)	(0.123)	(0.123)
Trade		0.113	0.275	0.291	0.291	0.293
		(0.060)	(0.146)	(0.148)	(0.149)	(0.149)
Finance		0.015	0.046	0.048	0.048	0.044
		(0.055)	(0.169)	(0.174)	(0.174)	(0.175)
Software/IT		0.022	0.056	0.023	0.023	0.022
		(0.059)	(0.149)	(0.153)	(0.154)	(0.154)
Education		0.049	0.146	0.137	0.137	0.138
		(0.058)	(0.176)	(0.179)	(0.179)	(0.180)
Healthcare		0.090	0.174	0.214	0.215	0.216
		(0.052)	(0.101)	(0.102)	(0.102)	(0.102)
Other. Services		0.065	0.127	0.102	0.102	0.100
		(0.055)	(0.108)	(0.110)	(0.110)	(0.110)
Constant	0.492	0.402	0.402	0.360	0.362	0.365
	(0.036)	(0.051)	(0.051)	(0.117)	(0.121)	(0.121)
Firms	376	376	376	376	376	376
Adj R2	0.032	0.048	0.048	0.051	0.048	0.046
Age, Age^2	No	No	No	Yes	Yes	Yes
Region (4)	No	No	No	Yes	Yes	Yes
Size (<11 emps.)	No	No	No	Yes	Yes	Yes
Founder MBA	No	No	No	No	Yes	Yes
Prior funding (<2021)	No	No	No	No	No	Yes

Notes: SD reported in parentheses under the coefficient.

Table 4 – Ethical AI policies and pro ethics actions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DV:	Ethics index		Bias training		Collect more diverse data		
Ethical AI Policy	0.660	0.645	0.173	0.175	0.224	0.214	0.181
	(0.102)	(0.103)	(0.041)	(0.040)	(0.051)	(0.051)	(0.055)
Tech firm data sharing relationship	0.073	0.081	0.021	0.020	0.047	0.053	0.056
	(0.101)	(0.101)	(0.042)	(0.042)	(0.051)	(0.051)	(0.051)
Firm level CSR		-1.272		0.159		-0.859	-0.895
		(0.749)		(0.341)		(0.339)	(0.333)
Female							-0.037
							(0.097)
Female x Ethical AI policy							0.258
							(0.135)
Firms	376	376	376	376	376	376	376
Adj R2	0.140	0.144	0.072	0.070	0.066	0.077	0.085
Age, Age^2	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region (4)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size (<11 Emps., dummy)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founder MBA	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prior funding (<2021, log)	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: SD reported in parentheses under the coefficient.

Table 5 – Performance and Ethical AI policies

DV:	Funding in and after 2021 (log)						
Sample:	All					L. Ethics Index	H. Ethics Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ethical AI policy	-0.941	-0.901	-0.915	-0.612	-0.974	-1.210	3.301
(dummy)	(0.656)	(0.678)	(0.681)	(0.668)	(0.952)	(0.686)	(2.750)
Pro ethics action					1.015		
index (cont.)					(0.605)		
AI policy x					-0.206		
Pro ethics action (cont.)					(0.716)		
Observations	376	376	376	376	376	307	69
Adj R2	0.003	-0.004	-0.004	0.028	0.047	0.051	-0.070
CSR weighted ind. dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
VC Location	No	No	Yes	Yes	Yes	Yes	Yes
Age	No	No	Yes	Yes	Yes	Yes	Yes
Age^2	No	No	Yes	Yes	Yes	Yes	Yes
Founder MBA	No	No	Yes	Yes	Yes	Yes	Yes
Funding b/f 2021 (log)	No	No	No	Yes	Yes	Yes	Yes

Notes: SD reported in parentheses under the coefficient.

Table 6 - Performance and more costly ethical actions

DV:	Funding in and after 2021 (log)			
	(1)	(2)	(3)	(4)
Pro ethics action	1.302	1.459	1.358	1.226
(dummy)	(0.671)	(0.705)	(0.714)	(0.700)
Adj R2	0.005	0.001	0.001	-0.002
	(5)	(6)	(7)	(8)
No pro ethics action (base)				
Pro ethics action (1)	0.697	0.848	0.774	0.568
	(0.769)	(0.800)	(0.800)	(0.782)
Pro ethics action (2)	1.691	1.843	1.734	1.673
	(0.883)	(0.904)	(0.912)	(0.888)
Pro ethics action (3)	1.846	2.136	2.007	1.914
	(0.984)	(1.018)	(1.041)	(1.040)
Adj R2	0.006	0.002	0.002	-0.001
	(9)	(10)	(11)	(12)
Employee ethics skill	3.673	3.823	4.167	3.198
(dummy)	(1.965)	(2.005)	(2.024)	(2.011)
Adj R2	0.012	0.007	0.007	0.004
	(13)	(14)	(15)	(16)
Bias trainings	1.508	1.530	1.475	1.244
(dummy)	(0.842)	(0.848)	(0.869)	(0.855)
Adj R2	0.008	0.002	0.002	-0.001
	(17)	(18)	(19)	(20)
Employee training skill	1.871	1.883	2.046	1.674
(dummy)	(0.614)	(0.635)	(0.675)	(0.664)
Adj R2	0.020	0.014	0.014	0.011
Observations	376	376	376	376
CSR weighted ind. dummies	No	Yes	Yes	Yes
VC Location	No	No	Yes	Yes
Age	No	No	Yes	Yes
Age^2	No	No	Yes	Yes
Founder MBA	No	No	Yes	Yes
Funding b/f 2021 (log)	No	No	No	Yes

Notes: SD reported in parentheses under the coefficient.

References

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6), 2188-2244.

Aghion, P., Bergeaud, A., Boppart, T., Klenow, P. J., & Li, H. (2019). A theory of falling growth and rising rents (No. w26448). National Bureau of Economic Research.

Athey, S. (2017). Beyond Prediction: Using big data for policy problems. *Science,* 355, no. 6324, 483-485.

Bajari, P., Chernozhukov, V., Hortaçsu, A., & Suzuki, J. (2019). The impact of big data on firm performance: An empirical investigation. In *AEA Papers and Proceedings*, Vol. 109, pp. 33-37.

Bansal, P. (2005). Evolving sustainably: A longitudinal study of corporate sustainable development. *Strategic Management Journal*, 26(3), 197-218.

Bansal, P., & Roth, K. (2000). Why companies go green: A model of ecological responsiveness. *Academy of Management Journal*, 43(4), 717-736.

Barnett, M. L., & King, A. A. (2008). Good fences make good neighbors: A longitudinal analysis of an industry self-regulatory institution. *Academy of Management Journal*, 51(6), 1150-1170.

Barocas, S., and Nissenbaum, H. (2014). Big data's end run around anonymity and consent. Privacy, big data, and the public good: Frameworks for engagement, 1, 44-75.

Barocas, S., Hardt, M., and Narayanan, A. (2018). *Fairness and Machine Learning*. URL: http://www. fairmlbook.org. 2018.

Berchicci, L., & King, A. A. (2022). Building knowledge by mapping model uncertainty in six studies of social and financial performance. *Strategic Management Journal*, 43(7), 1319-1346.

Berrone, P., Fosfuri, A., Gelabert, L., & Gomez-Mejia, L. R. (2013). Necessity as the mother of 'green'inventions: Institutional pressures and environmental innovations. *Strategic Management Journal*, 34(8), 891-909.

Bessen, J. (2019). Automation and jobs: When technology boosts employment. *Economic Policy*, 34(100), 589-626.

Bessen, J. (2020). Industry concentration and information technology. The Journal of Law and Economics, 63(3), 531-555.

Bessen, J., Impink, S. M., Reichensperger, L., & Seamans, R. (2022). The role of data for AI startup growth. *Research Policy*, 51(5), 104513.

boyd, D., and Crawford, K. (2012). Critical Questions for Big Data: Provocations for a cultural, technological, and scholarly phenomenon. Information, Communication and Society 15, no. 5: 662-679.

Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies 'Engines of growth'?. *Journal of Econometrics*, 65(1), 83-108.

Brynjolfsson, E., Hitt, L. M., & Kim, H. H. (2011). Strength in numbers: How does data-driven decision-making affect firm performance?. Working paper, SSRN 1819486.

Brynjolfsson, E., Rock, D., & Syverson, C. (2018). "Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics." In The economics of artificial intelligence: An agenda (pp. 23-57). University of Chicago Press.

Burke, L., & Logsdon, J. M. (1996). How corporate social responsibility pays off. *Long Range Planning*, 29(4), 495-502.

Conti, A., Thursby, M., & Rothaermel, F. T. (2013). Show me the right stuff: Signals for high-tech startups. *Journal of Economics & Management Strategy*, 22(2), 341-364.

Cowgill, B., and Tucker, C. E. (2019). Economics, Fairness and Algorithmic Bias. Working Paper.

Cowgill, B., Dell'Acqua, F., Deng, S., Hsu, D., Verma, N., and Chaintreau, A. (2020). Biased Programmers? or biased data? A field experiment in operationalizing ai ethics. In *Proceedings of the 21st ACM Conference on Economics and Computation*, pp. 679-681.

Cowgill, B., Dell'Acqua, F., and Matz, S. (2020). The Managerial Effects of Algorithmic Fairness Activism. In *AEA Papers and Proceedings*, vol. 110, pp. 85-90.

Cihon, P., Kleinaltenkamp, M. J., Schuett, J., & Baum, S. D. (2021). AI certification: Advancing ethical practice by reducing information asymmetries. IEEE Transactions on Technology and Society, 2(4), 200-209.

Davila, A., Foster, G., & Gupta, M. (2003). Venture capital financing and the growth of startup firms. *Journal of Business Venturing*, 18(6), 689-708.

Demirel, P., Li, Q. C., Rentocchini, F., & Tamvada, J. P. (2019). Born to be green: new insights into the economics and management of green entrepreneurship. *Small Business Economics*, 52(4), 759-771.

Donnelly, R., Ruiz, F. R., Blei, D., and Athey, S. (2019). Counterfactual Inference for Consumer Choice Across Many Product Categories. arXiv:1906.02635.

Evans, D. S., & Leighton, L. S. (1990). "Some empirical aspects of entrepreneurship". In The Economics of Small Firms (pp. 79-99). Springer, Dordrecht.

Friedman, B., and Nissenbaum, H. (1996). Bias In Computer Systems. *ACM Transactions on Information Systems* (TOIS) 14, no. 3, 30-347.

Gunningham, N., & Rees, J. (1997). Industry self-regulation: an institutional perspective. *Law & Policy*, 19(4), 363-414.

Harris, J. D., Sapienza, H. J., and Bowie, N. E. (2009). Ethics and Entrepreneurship. *Journal of Business Venturing*, 24(5), 407-418.

Hawn, O., & Ioannou, I. (2016). Mind the gap: The interplay between external and internal actions in the case of corporate social responsibility. Strategic Management Journal, 37(13), 2569-2588.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the Econometric Society*, 153-161.

Higgins, M. C., & Gulati, R. (2006). Stacking the deck: The effects of top management backgrounds on investor decisions. *Strategic Management Journal*, 27(1), 1-25.

Hull, C. E., & Rothenberg, S. (2008). Firm performance: The interactions of corporate social performance with innovation and industry differentiation. *Strategic Management Journal*, 29(7), 781-789.

Husted, B. W., & Allen, D. B. (2007). Strategic corporate social responsibility and value creation among large firms: lessons from the Spanish experience. *Long Range Planning*, 40(6), 594-610.

Impink, S. M. (2022). Outsourcing IT and Technological Differentiation: Evidence from Digital Startups. NYU Stern Working Paper.

Jin, W., & McElheran, K. (2017). Economies before scale: survival and performance of young plants in the age of cloud computing. Rotman School of Management Working Paper, (3112901).

Jobin, A., Ienca, M., and Vayena, E. (2019). The Global Landscape of AI Ethics Guidelines. *Nature Machine Intelligence,* vol. 1, no. 9: 389-399.

Katz, J., & Gartner, W. B. (1988). Properties of emerging organizations. *Academy of Management Review*, 13(3), 429-441.

King, A. A., & Lenox, M. J. (2000). Industry self-regulation without sanctions: The chemical industry's responsible care program. *Academy of Management Journal*, 43(4), 698-716.

King, A. A., Lenox, M. J., & Terlaak, A. (2005). The strategic use of decentralized institutions: Exploring certification with the ISO 14001 management standard. *Academy of Management Journal*, 48(6), 1091-1106.

Lambrecht, A., and Tucker, C. (2019). Algorithmic bias? An empirical study of apparent gender-based discrimination in the display of STEM career ads. *Management Science*, 65(7), 2966-2981.

Leland, H. E., & Pyle, D. H. (1977). Informational asymmetries, financial structure, and financial intermediation. The journal of Finance, 32(2), 371-387.

Lenox, M. J. (2006). The role of private decentralized institutions in sustaining industry self-regulation. *Organization Science*, 17(6), 677-690.

Locke, R. M. (2013). "The promise and limits of private power: Promoting labor standards in a global economy". Cambridge University Press. Cambridge, UK.

Long, C. (2002). Patent signals. *The University of Chicago Law Review*, 625-679.

Martin, K. E. (2019). Designing ethical algorithms. *MIS Quarterly Executive*, June.

Martin, K. E. (2020). Ethical issues in the big data industry. In *Strategic Information Management*, pp. 450-471

Metcalf, J., & Moss, E. (2019). Owning ethics: Corporate logics, silicon valley, and the institutionalization of ethics. *Social Research: An International Quarterly*, 86(2), 449-476.

Mitchell, S., Potash, E., Barocas, S., D'Amour, A., & Lum, K. (2021). Algorithmic fairness: Choices, assumptions, and definitions. *Annual Review of Statistics and Its Application*, 8, 141-163.

Mittelstadt, B. (2019). Principles alone cannot guarantee ethical AI. *Nature Machine Intelligence*, 1(11), 501-507.

Nagaraj, A. (2022). The private impact of public data: Landsat satellite maps increased gold discoveries and encouraged entry. *Management Science*, 68(1), 564-582.

Raisch, S., and Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, 46(1), 192-210.

Rambachan, A., Kleinberg, J., Ludwig, J., & Mullainathan, S. (2020). An economic perspective on algorithmic fairness. In *AEA Papers and Proceedings* (Vol. 110, pp. 91-95).

Sanna Jamila Ali, Angèle Christin, Riitta Katila, and Andrew Smart. 2023. Walking the Walk of AI Ethics: An Ethnographic Study of Ethics Workers in Technology Companies. Working Paper.

Short, J. L., & Toffel, M. W. (2010). Making self-regulation more than merely symbolic: The critical role of the legal environment. *Administrative Science Quarterly*, 55(3), 361-396.

Silva, S., and Kenney, M. (2019). Algorithms, platforms, and ethnic bias. *Communications of the ACM*, 62(11), 37-39.

Smith, B., and Browne, C.A. “Tools and weapons: The promise and the peril of the digital age.” Penguin. 2019.

Stuart, T. E. (2000). Interorganizational alliances and the performance of firms: a study of growth and innovation rates in a high-technology industry. *Strategic Management Journal*, 21(8), 791-811.

Teodorescu, M. H., Morse, L., Awwad, Y., and Kane, G. C. (2021). Failures of fairness in automation require a deeper understanding of human-ML augmentation. *MIS Quarterly*, 45(3), 1-17.

Terlaak, A., & King, A. A. (2006). The effect of certification with the ISO 9000 Quality Management Standard: A signaling approach. *Journal of Economic Behavior & Organization*, 60(4), 579-602.

Truong, Y., & Nagy, B. G. (2021). Nascent ventures’ green initiatives and angel investor judgments of legitimacy and funding. *Small Business Economics*, 57(4), 1801-1818.

Tversky, A., & Kahneman, D. (1985). “The framing of decisions and the psychology of choice” (pp. 25-41). Springer US.

Wang, T., & Bansal, P. (2012). Social responsibility in new ventures: profiting from a long-term orientation. *Strategic Management Journal*, 33(10), 1135-1153.

Zott, C., & Huy, Q. N. (2007). How entrepreneurs use symbolic management to acquire resources. *Administrative Science Quarterly*, 52(1), 70-105.

Appendix

Appendix A.1 – Question summary

Q50. Has your firm taken any of the following actions?

	Yes (1)	No (2)	I don't know or N/A (3)
Offered unconscious bias training	○	○	○
Hired an under-represented minority or female programmer	○	○	○
Considered gender or racial diversity as criteria for selecting training data	○	○	○
Sought expert advice on navigating ethical issues	○	○	○

51. Does your firm have a set of ethical AI principles?

○ Yes

○ No

○ I don't know

52. If your firm has ethical AI principles, has your firm ever:

	Yes (1)	No (2)	I don't know or N/A (99)
Turned down business due to a conflict with these ethical AI principles	○	○	○
Dismissed an employee that did not follow these ethical AI principles	○	○	○
Stopped using certain training data that did not align with these ethical AI principles	○	○	○

Table A.2. – Correlations

Table A.2.A. – Tech firm data sharing and demographics

		[1]	[2]	[3]	[4]	[5]	[6]
[1]	Tech data sharing relationship	1					
[2]	Age	0.12+	1				
[3]	Employees	0.12+	0.25+	1			
[4]	Founder MBA	0.031	0.0037	0.0093	1		
[5]	Founder female	-0.015	-0.0026	-0.051	0.097+	1	
[6]	Founder diversity	0.023	0.031	0.0057	0.044	0.21+	1

Table A.2.B. – Tech firm data sharing, industry and location

		[1]	[2]	[3]	[4]	[5]	[6]
[1]	Tech data sharing relationship	1					
[2]	Healthcare	-0.012	1				
[3]	Finance	0.046	-0.097+	1			
[4]	US	0.040	0.042	-0.038	1		
[5]	UK	0.023	0.061	0.059	-0.18+	1	
[6]	France	-0.0099	0.038	-0.038	-0.13+	-0.034	1

Table A.2.C. – Tech firm data sharing and survey measures

		[1]	[2]	[3]	[4]	[5]	[6]
[1]	Tech data sharing relationship	1					
[2]	AI principles	0.19+	1				
[3]	Dropped biased data	0.12+	0.24+	1			
[4]	Turned down business	0.21+	0.45+	0.37+	1		
[5]	Fire employee breaking policy	0.19+	0.49+	0.23+	0.38+	1	
[6]	Ethical prep. actions (>2)	0.12+	0.37+	0.18+	0.34+	0.26	1

Notes: SD omitted for space; significance at p<0.1 denoted by +.

Appendix A.3. – Validating survey with external data source (Crunchbase)

Table A.3.A. – Comparison of survey and CB data on location (top country)

	Canada	France	Germany	UK	US
Canada	12				
France		9			
Germany			12		1
UK				14	
US	1		2		137

Pearson Chi2 = 693, p=0, not independent

Figure A.3.A. - Comparison survey and CB (top countries)

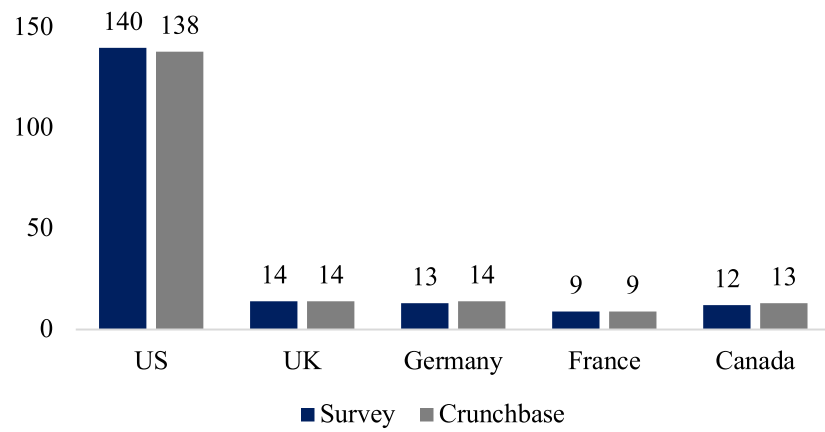

Table A.3.B. – Comparison of survey and CB data on US state

	Survey	Crunchbase	Difference	% Difference
CA	43	40	-3	7%
CO	4	5	1	-25%
CT	2	1	-1	50%
DC	3	1	-2	67%
FL	6	7	1	-17%
GA	1	1	0	0%
IL	2	3	1	-50%
MA	6	6	0	0%
MI	2	3	1	-50%
MN	1	1	0	0%
MO	1	2	1	-100%
NE	1	1	0	0%
NJ	7	9	2	-29%
NY	19	17	-2	11%
NC	2	2	0	0%
OH	1	1	0	0%
PA	8	8	0	0%
TN	2	2	0	0%
TX	10	9	-1	10%
UT	1	1	0	0%
VA	2	2	0	0%
WA	2	2	0	0%
WI	2	2	0	0%

Pearson Chi2 = .00027, p=0, not independent
Data for 127 of 137 firms based in the USA

Figure A.3.B. - Comparison survey and CB (top US states)

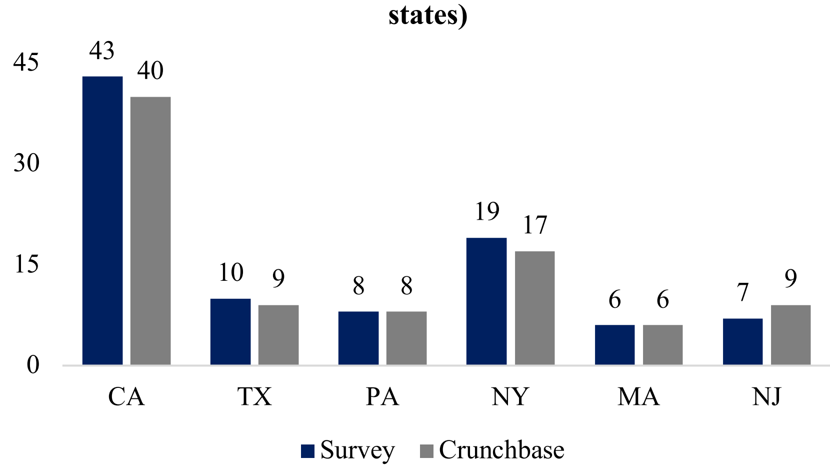

Table A.4. – Ethical AI policies and pro ethics actions

	(1)	(2)	(3)
DV:	Ethics index	Training Capability	Employees
Ethics Skills (LinkedIn)	0.182		
	(0.065)		
Training Skills (LinkedIn)		0.074	
		(0.043)	
Employees (5 buckets)			0.784
			(0.058)
Firms	376	376	376
Adj R2	0.005	0.005	0.438

Notes: SD reported in parentheses under the coefficient.

Table A.5. – Respondent selection bias (probit)

	(1)
DV, dummy:	Response
California (dummy)	-0.347
	(0.087)
Age (log)	-17.462
	(0.820)
Age^2 (log)	6.325
	(0.300)
Founder big tech	-0.201
experience	(0.078)
Firms	4593

Notes: SD reported in parentheses under the coefficient. 4593 startups were contacted to participate in the survey.

Appendix B – Additional Analyses

Table B.1. – Tech firm relationship and ethical AI principles (Probit)

	(1)	(2)	(3)	(4)	(5)	(6)
DV, Dummy:	Ethical AI policy					
Tech firm data sharing relationship	0.476	0.509	0.509	0.558	0.559	0.556
	(0.132)	(0.135)	(0.135)	(0.137)	(0.137)	(0.138)
Industries:		*Industry indicator*	*CSR-scaled industry indicator*			
Agriculture		0.190	0.406	0.345	0.345	0.353
		(0.210)	(0.448)	(0.454)	(0.454)	(0.454)
Manufacturing		-0.316	-0.467	-0.349	-0.351	-0.354
		(0.172)	(0.253)	(0.260)	(0.261)	(0.261)
Communication		-0.026	-0.044	-0.023	-0.025	-0.020
		(0.173)	(0.294)	(0.296)	(0.297)	(0.297)
Utilities/transport		-0.244	-0.486	-0.415	-0.415	-0.414
		(0.164)	(0.328)	(0.333)	(0.333)	(0.333)
Trade		0.357	0.865	0.893	0.893	0.903
		(0.159)	(0.385)	(0.391)	(0.391)	(0.392)
Finance		0.054	0.165	0.181	0.181	0.168
		(0.153)	(0.471)	(0.475)	(0.475)	(0.476)
Software/IT		0.067	0.169	0.085	0.085	0.085
		(0.156)	(0.397)	(0.402)	(0.402)	(0.402)
Education		0.136	0.410	0.397	0.397	0.401
		(0.158)	(0.476)	(0.482)	(0.482)	(0.482)
Healthcare		0.249	0.483	0.597	0.599	0.606
		(0.139)	(0.270)	(0.277)	(0.277)	(0.278)
Other. Services		0.135	0.267	0.220	0.219	0.212
		(0.148)	(0.291)	(0.293)	(0.293)	(0.293)
Constant	-0.019	-0.268	-0.268	-0.382	-0.373	-0.362
	(0.089)	(0.136)	(0.136)	(0.339)	(0.350)	(0.350)
Firms	376	376	376	376	376	376
Age, Age^2	No	No	No	Yes	Yes	Yes
Region (4)	No	No	No	Yes	Yes	Yes
Size (<11 emps.)	No	No	No	Yes	Yes	Yes
Founder MBA	No	No	No	No	Yes	Yes
Prior funding (<2021)	No	No	No	No	No	Yes

Notes: SD reported in parentheses under the coefficient.

Table B.2. – Tech firm relationship and collecting more diverse training data

	(1)	(2)	(3)	(4)	(5)	(6)
DV, Dummy:	Collect more diverse training data					
Tech firm data sharing relationship	0.084	0.099	0.099	0.103	0.103	0.106
	(0.051)	(0.050)	(0.050)	(0.051)	(0.051)	(0.051)
		Industry indicator	*CSR-scaled industry indicator*			
Industries:						
Agriculture		0.013	0.027	0.032	0.032	0.027
		(0.075)	(0.160)	(0.161)	(0.162)	(0.163)
Manufacturing		-0.243	-0.358	-0.327	-0.327	-0.326
		(0.058)	(0.086)	(0.089)	(0.089)	(0.089)
Communication		-0.039	-0.067	-0.063	-0.064	-0.066
		(0.066)	(0.111)	(0.112)	(0.113)	(0.112)
Utilities/transport		0.032	0.063	0.103	0.103	0.100
		(0.061)	(0.121)	(0.122)	(0.122)	(0.122)
Trade		0.087	0.211	0.206	0.206	0.200
		(0.060)	(0.146)	(0.148)	(0.149)	(0.150)
Finance		0.020	0.062	0.022	0.022	0.034
		(0.057)	(0.176)	(0.176)	(0.176)	(0.177)
Software/IT		0.015	0.039	0.042	0.043	0.044
		(0.058)	(0.148)	(0.151)	(0.151)	(0.152)
Education		0.117	0.353	0.319	0.319	0.317
		(0.060)	(0.182)	(0.183)	(0.184)	(0.184)
Healthcare		0.114	0.221	0.232	0.232	0.228
		(0.052)	(0.102)	(0.104)	(0.105)	(0.105)
Other. Services		-0.076	-0.151	-0.155	-0.155	-0.150
		(0.056)	(0.110)	(0.110)	(0.110)	(0.110)
Constant	0.391	0.345	0.345	0.287	0.289	0.279
	(0.035)	(0.050)	(0.050)	(0.122)	(0.126)	(0.126)
Firms	376	376	376	376	376	376
Adj R2	0.005	0.049	0.049	0.058	0.055	0.056
Age, Age^2	No	No	No	Yes	Yes	Yes
Region (4)	No	No	No	Yes	Yes	Yes
Size (<11 emps.)	No	No	No	Yes	Yes	Yes
Founder MBA	No	No	No	No	Yes	Yes
Prior funding (<2021)	No	No	No	No	No	Yes

Notes: SD reported in parentheses under the coefficient.

Table B.3. – Multinomial probit (Pro ethics actions and policy)

	(1)		
Number of pro ethics actions:	One	Two	Three
Tech firm data sharing rel.	-0.238	0.595	1.187
	(0.216)	(0.217)	(0.257)
Industries:			
Agriculture	0.196	0.255	0.825
	(0.698)	(0.714)	(0.762)
Manufacturing	-0.037	-0.681	-0.915
	(0.393)	(0.406)	(0.465)
Communication	-0.162	-0.624	-0.358
	(0.461)	(0.467)	(0.496)
Utilities/transport	0.232	0.154	-0.330
	(0.517)	(0.514)	(0.582)
Trade	0.233	0.164	0.045
	(0.610)	(0.605)	(0.667)
Finance	-0.238	0.517	0.407
	(0.756)	(0.743)	(0.781)
Software/IT	0.168	0.184	0.429
	(0.629)	(0.624)	(0.678)
Education	-1.087	-0.042	0.747
	(0.769)	(0.737)	(0.795)
Healthcare	0.292	0.776	0.875
	(0.436)	(0.423)	(0.460)
Other. Services	0.769	0.063	0.444
	(0.463)	(0.464)	(0.492)

Notes: SD reported in parentheses under the coefficient.

Table B.4. – LASSO Model

	(1)	(2)	(3)
	Ethical AI policy		
Tech firm data sharing relationship	0.217		
	(0.055)		
Pro ethics actions (dummy)		0.222	
		(0.069)	
Collect more diverse data			0.205
			(0.056)
Firms	334	334	334
Controls	45	45	45

Notes: SD reported in parentheses under the coefficient.

Table B.5. – Tech firm data sharing relationship and ethical AI principles (IMR)

	(1)	(2)	(3)	(4)	(5)	(6)
DV, Dummy:	Ethical AI policy					
Tech firm data sharing relationship	0.182	0.189	0.189	0.202	0.203	0.202
	(0.050)	(0.050)	(0.050)	(0.051)	(0.051)	(0.051)
IMR	-0.014	-0.021	-0.021	-0.034	-0.034	-0.034
	(0.027)	(0.027)	(0.027)	(0.034)	(0.034)	(0.035)
Industries:		*Industry indicator*	*CSR-scaled industry indicator*			
Agriculture		0.067	0.143	0.129	0.129	0.129
		(0.072)	(0.153)	(0.152)	(0.153)	(0.153)
Manufacturing		-0.120	-0.178	-0.128	-0.129	-0.129
		(0.063)	(0.093)	(0.095)	(0.096)	(0.096)
Communication		-0.011	-0.019	-0.005	-0.006	-0.006
		(0.065)	(0.110)	(0.112)	(0.112)	(0.112)
Utilities/transport		-0.093	-0.186	-0.156	-0.156	-0.156
		(0.060)	(0.120)	(0.122)	(0.123)	(0.123)
Trade		0.134	0.325	0.326	0.326	0.327
		(0.060)	(0.146)	(0.148)	(0.148)	(0.148)
Finance		0.023	0.071	0.076	0.076	0.075
		(0.055)	(0.169)	(0.174)	(0.174)	(0.175)
Software/IT		0.027	0.068	0.032	0.033	0.033
		(0.059)	(0.150)	(0.153)	(0.154)	(0.154)
Education		0.048	0.145	0.126	0.125	0.125
		(0.059)	(0.177)	(0.182)	(0.182)	(0.183)
Healthcare		0.097	0.188	0.228	0.229	0.229
		(0.052)	(0.101)	(0.102)	(0.102)	(0.102)
Other. Services		0.049	0.097	0.078	0.078	0.078
		(0.054)	(0.107)	(0.109)	(0.110)	(0.110)
Constant	0.507	0.422	0.422	0.323	0.327	0.328
	(0.046)	(0.057)	(0.057)	(0.124)	(0.128)	(0.131)
Firms	376	376	376	376	376	376
Adj R2	0.030	0.051	0.051	0.054	0.052	0.049
Age, Age^2	No	No	No	Yes	Yes	Yes
Region (4)	No	No	No	Yes	Yes	Yes
Size (<11 emps.)	No	No	No	Yes	Yes	Yes
Founder MBA	No	No	No	No	Yes	Yes
Prior funding (<2021)	No	No	No	No	No	Yes

Notes: SD reported in parentheses under the coefficient.

Table B.6. – Performance and "unused" ethical AI policies

DV:	Funding in and after 2021 (log)						
Sample			All			L. Ethics Index	H. Ethics Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ethical AI policy, outcomes	-1.246	-1.213	-1.186	-1.135	-2.452	-1.841	0.545
not influenced (dummy)	(0.705)	(0.735)	(0.744)	(0.750)	(1.295)	(0.766)	(2.267)
Pro ethics action					0.645		
index (cont.)					(0.349)		
AI policy x					0.655		
Pro ethics action (cont.)					(0.821)		
Observations	376	376	376	376	376	307	69
Adj R2	0.004	-0.003	-0.003	0.031	0.046	0.056	-0.098
Industry dummy	Yes	No	No	No	No	No	No
CSR weighted ind. dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
VC Location	No	No	Yes	Yes	Yes	Yes	Yes
Age young (<2)	No	No	Yes	Yes	Yes	Yes	Yes
Founder MBA	No	No	Yes	Yes	Yes	Yes	Yes
Funding b/f 2021 (log)	No	No	No	Yes	Yes	Yes	Yes

Notes: SD reported in parentheses under the coefficient.

Table B.7. – Performance and more costly ethical actions (Int. w/ Neural Net.)

DV:	Funding in and after 2021 (log)			
	(1)	(2)	(3)	(4)
Neural networks	-0.275	-0.334	-0.346	-0.447
	(0.209)	(0.213)	(0.216)	(0.222)
Collect more diverse data	-0.571	-0.591	-0.609	-0.677
	(0.363)	(0.376)	(0.376)	(0.390)
NN x	0.895	0.971	0.976	1.118
Collect more diverse data	(0.399)	(0.410)	(0.410)	(0.426)
Observations	376	376	376	376
Adj R2	0.008	0.005	0.005	0.002
	(5)	(6)	(7)	(8)
Neural Networks	-0.369	-0.483	-0.490	-0.476
	(0.276)	(0.293)	(0.302)	(0.305)
Policy + dropped data	-0.922	-1.003	-0.924	-0.801
	(0.551)	(0.581)	(0.600)	(0.608)
NN x	1.172	1.336	1.312	1.214
Policy + dropped data	(0.594)	(0.633)	(0.652)	(0.659)
Observations	218	218	218	218
Adj R2	0.006	0.019	0.019	0.020
Industry dummy	Yes	No	No	No
CSR weighted ind. dummies	No	Yes	Yes	Yes
VC Location	No	No	Yes	Yes
Age young (<2)	No	No	Yes	Yes
Founder MBA	No	No	Yes	Yes
Funding b/f 2021 (log)	No	No	No	Yes

Notes: SD reported in parentheses under the coefficient.

Table B.8. – Performance and more costly ethical actions, follow on funding

DV:	Follow-on funding after 2021(dummy)			
	(1)	(2)	(3)	(4)
Pro ethics action	0.559	0.570	0.526	0.576
(dummy)	(0.165)	(0.169)	(0.178)	(0.200)
Adj R2	0.005	0.001	0.001	-0.002
	(5)	(6)	(7)	(8)
No pro ethics action (base)				
Pro ethics action (1)	0.157	0.157	0.131	0.094
	(0.063)	(0.064)	(0.061)	(0.050)
Pro ethics action (2)	0.228	0.230	0.202	0.192
	(0.068)	(0.070)	(0.069)	(0.059)
Pro ethics action (3)	0.225	0.230	0.192	0.176
	(0.075)	(0.076)	(0.072)	(0.064)
Adj R2	0.006	0.002	0.002	-0.001
	(9)	(10)	(11)	(12)
Bias trainings	0.260	0.259	0.219	0.178
(dummy)	(0.060)	(0.060)	(0.059)	(0.054)
Adj R2	0.008	0.002	0.002	-0.001
Observations	376	376	376	376
CSR weighted ind. dummies	No	Yes	Yes	Yes
VC Location	No	No	Yes	Yes
Age	No	No	Yes	Yes
Age^2	No	No	Yes	Yes
Founder MBA	No	No	Yes	Yes
Funding b/f 2021 (log)	No	No	No	Yes

Notes: SD reported in parentheses under the coefficient.

Table B.9. – Performance and more costly ethical actions, follow on funding (probit)

DV:	Follow-on funding after 2021 (dummy)			
	(1)	(2)	(3)	(4)
Pro ethics action (dummy)	0.559	0.570	0.526	0.576
	(0.165)	(0.169)	(0.178)	(0.200)
	(5)	(6)	(7)	(8)
No pro ethics action (base)				
Pro ethics action (1)	0.456	0.465	0.406	0.357
	(0.187)	(0.190)	(0.200)	(0.226)
Pro ethics action (2)	0.637	0.657	0.641	0.767
	(0.196)	(0.201)	(0.210)	(0.235)
Pro ethics action (3)	0.629	0.656	0.593	0.715
	(0.211)	(0.220)	(0.232)	(0.259)
	(9)	(10)	(11)	(12)
Bias trainings (dummy)	0.671	0.689	0.643	0.676
	(0.157)	(0.160)	(0.166)	(0.183)
Observations	376	376	376	376
CSR weighted ind. dummies	No	Yes	Yes	Yes
VC Location	No	No	Yes	Yes
Age	No	No	Yes	Yes
Age^2	No	No	Yes	Yes
Founder MBA	No	No	Yes	Yes
Funding b/f 2021 (log)	No	No	No	Yes

Notes: SD reported in parentheses under the coefficient.

Table B.10. – Performance and more costly ethical actions

DV:	Funding in and after 2021 (log)			
	(1)	(2)	(3)	(4)
Employee ethics skill	3.673	3.823	4.167	3.198
(dummy)	(1.965)	(2.005)	(2.024)	(2.011)
Adj R2	0.012	0.007	0.007	0.004
	(5)	(6)	(7)	(8)
Employee training skill	1.871	1.883	2.046	1.674
(dummy)	(0.614)	(0.635)	(0.675)	(0.664)
Adj R2	0.020	0.014	0.014	0.011
Observations	376	376	376	376
CSR weighted ind. dummies	No	Yes	Yes	Yes
VC Location	No	No	Yes	Yes
Age	No	No	Yes	Yes
Age^2	No	No	Yes	Yes
Founder MBA	No	No	Yes	Yes
Funding b/f 2021 (log)	No	No	No	Yes

Notes: SD reported in parent4
heses under the coefficient.