When Automation Meets Accountability:

International Evidence from Robotics Adoption and ESG Incidents[*]

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Abstract

We examine whether the adoption of automation technologies influences environmental, social, and governance (ESG) risk in an international setting. Using global industrial robotics data as a proxy for automation and ESG incident measures as a proxy for ESG risk, we find that robotics stock and flow are positively associated with higher firm-level ESG risk, including the frequency of ESG incidents, overall ESG risk index, and severity, reach, and novelty of these incidents. The effect is more pronounced for environmental and social incidents. Using fixed internet broadband subscriptions and population aging measures as instruments, we establish a causal link between automation adoption and increased ESG risk. We further provide evidence that firm-, industry-, and country-level factors can moderate this relationship. Our findings highlight an important yet often overlooked downside of automation—its potential to exacerbate ESG risks and impede corporate sustainability efforts. These results also underscore the importance of integrating ESG risk management into corporate technology transformation strategies.

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1. Introduction

Automation is reshaping how firms operate and compete, generating well-documented gains in productivity, efficiency, and cost reduction (Acemoglu and Restrepo, 2018; Graetz and Michaels, 2018; Autor, 2015; Babina et al., 2024; Babina, 2026). More than just incremental improvements, these technological advancements are transforming competitive dynamics across industries, and a vast and maturing literature in economics and finance has sought to understand the implications for productivity, labor demand, organizational change, capital structure, and financial policy[1]. Yet, there remains a less studied dimension of automation: how it affects firms' environmental, social, and governance (ESG) practices.

Alongside research focused on the economic benefits of automation, concerns about its impact on employment, income inequality, and the environment have also emerged (Acemoglu and Restrepo, 2020; Autor, 2015).[2] For example, although automation creates high-skilled jobs in technology and engineering, it displaces workers in routine, middle-skill occupations, exacerbating wage inequality and social tensions (Acemoglu and Restrepo, 2022; Jaimovich et al., 2021). Moreover, automation technologies require substantial energy and resources, the environmental consequences of which could complicate the narrative that automation is an unambiguously positive force (Masanet et al., 2020; Onat et al., 2023; Schwartz et al., 2020; Strubell et al., 2020). As firms adopt these technologies, they must deal with the broader effects on stakeholders, including employees, communities, regulators, and investors.

Firms face increasing pressure from their stakeholders and the general public to demonstrate accountability on ESG dimensions. ESG lapses have been shown to materially destroy shareholder value (Derrien et al., 2022; He et al., 2023; Hoepner et al., 2023; Krüger, 2015; Li and Wu, 2020), leading investors to price in such risks (Bolton and Kacperczyk, 2021; Engle et al., 2020; Hong and Kacperczyk, 2009; Ilhan et al., 2023; Krüger et al., 2024; Li et al., 2024; Pástor et al., 2022; Sautner et al., 2023; Xu and Kim, 2022). Conversely, firms with stronger ESG profiles enjoy tangible benefits in the capital markets (El Ghoul et al., 2011). In short, ESG-related risks have become financially material, and firms that cannot demonstrate their commitment to sustainability, ethical labor practices, and transparent governance, including during the automation process, risk significant reputational damage, regulatory penalties, and

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[1] For example, Abeliansky and Prettner, 2023; Acemoglu and Restrepo, 2020, 2021; Babina et al., 2024; Bates et al., 2024; Benmelech and Zator, 2025; Bresnahan et al., 2002; Cheng et al., 2025; Díaz Pavez and Martínez-Zarzoso, 2024; Hötte et al., 2024; Ince and Iskenderoglu, 2025; Mann and Püttmann, 2023; McElheran et al., 2024; Oesch and Walser, 2025; Restrepo, 2024; Zolas et al., 2025.

[2] This literature focuses on the task-based model of automation, which conceptualizes technology as reassigning tasks between labor and capital, rather than augmenting labor symmetrically (Acemoglu et al., 2024; Autor and Dorn, 2013; Card and Dinardo, 2002). Automation targets routine and codifiable tasks, leading to a displacement effect as machines substitute for workers and a productivity effect as firms scale up production with fewer inputs. The net outcome hinges on whether firms and economies can create sufficient new tasks or markets to absorb displaced labor. In their seminal study, Acemoglu and Restrepo (2020) find that each additional robot per thousand workers reduces the employment-to-population ratio by 0.34 percentage points and reduces average wages by up to 0.5% in U.S. local labor markets. These effects are especially pronounced in manufacturing-intensive regions, underscoring automation's disruptive potential for blue-collar employment.

financial losses.

Despite the rapidly growing literature on both automation and ESG, empirical evidence on how automation adoption affects firms' exposure to ESG risks is limited.[3] This gap is particularly salient given the growing overlap between technological advancement and sustainability concerns. Automation has theoretically ambiguous implications for realized ESG incidents.[4] On the one hand, automation may reduce ESG risk by improving operational efficiency, precision, consistency, and process standardization. By replacing manual or routine tasks with programmable technologies, firms may reduce production errors, improve product quality, and make operational processes more predictable (Autor et al., 2003; Graetz and Michaels, 2018; Acemoglu and Restrepo, 2018; Babina et al., 2024). Automation may also improve workplace safety when robots substitute for workers in physically intensive or hazardous tasks. Consistent with this view, Gihleb et al. (2022) show that industrial robot exposure reduces workplace injuries. Automation may also improve environmental performance when firms use robotics to raise energy efficiency (Lin and Xu, 2024), facilitate cleaner production, or monitor operational deviations more systematically. From this perspective, automation could reduce firms' exposure to ESG incidents by improving process control, safety, resource efficiency, and monitoring.

On the other hand, automation may increase ESG risk because it reorganizes production rather than simply improving existing processes. The task-based view of automation posits that new technologies reallocate tasks between labor and capital, alter the structure of work, and require complementary changes in organizational routines, skills, monitoring systems, and managerial control (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2020, 2022; Bresnahan, Brynjolfsson, and Hitt, 2002). These changes can create a control-gap channel. During the implementation of automation, firms may need to redesign safety procedures, maintenance systems, worker training, accountability structures, and human-machine interfaces. If these control systems do not adjust as quickly as the technology itself, automation can increase the likelihood of operational failures, compliance lapses, labor disputes, and other events that materialize as ESG incidents. This concern is consistent with evidence that, although robots can reduce physical injuries, robot exposure may also generate broader social and health costs, including mental-health and substance-related problems in affected labor markets (Gihleb et al., 2022). Thus, the same technological transition that improves some dimensions of workplace safety may create new social risks if firms do not manage worker adjustment, communication, and accountability effectively.

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[3] Importantly, ESG incident risk is distinct from ESG ratings or disclosure scores. Incidents capture realized failures or controversies, including regulatory actions, media scandals, NGO reports, and community protests. Unlike ratings, which may reflect static policies or self-reported goals, ESG incidents provide a high-frequency, outcome-based measure of non-financial risk exposure. From the perspective of investors and regulators, ESG incidents often have material consequences that may affect market valuations, corporate policies, product markets, the cost of capital, and access to sustainable finance (e.g., see Chasiotis et al., 2024; Dinner et al., 2019; Li and Wu, 2020; Lin et al., 2025).

[4] The Internet Appendix A develops a stylized reduced-form framework to organize our empirical predictions about automation and ESG incident risk.

A second downside operates through scale and complexity. Automation can lower marginal costs, relax capacity constraints, and allow firms to expand production more rapidly. These efficiency gains may also enlarge the firm's ESG footprint by increasing energy use, resource throughput, emissions, waste, supply-chain exposure, logistics complexity, and labor reallocation. In this case, automation need not create ESG incidents because the technology itself fails. Rather, incidents may arise because the firm's prevention, compliance, and stakeholder-management systems do not scale proportionately with the expanded and more complex automated operation. This scale-and-complexity channel is consistent with evidence that supplier ESG incidents affect downstream firm performance and trigger costly adjustments in global sourcing relationships (Lin et al., 2025; Bisetti et al., 2026).

More generally, this downside reflects a private-social cost wedge: firms may bear some private costs from ESG incidents, including reputational, legal, and financing consequences, but they may not fully internalize the harms borne by workers, communities, suppliers, and the environment. As formalized in Internet Appendix A, automation can therefore increase realized ESG incident risk when the disruption and scale effects of automation exceed firms' privately chosen mitigation efforts. These competing perspectives suggest that the net effect of automation on ESG outcomes is ultimately an empirical question. They also imply that the automation-incident relationship should vary systematically with firm capabilities, industry conditions, and country-level institutions that shape either the risk loading of automation or the effectiveness of firms' mitigation efforts.

We address this question by providing the first systematic international evidence on the impact of automation adoption on firm-level ESG risk outcomes. Our study links firm-level automation exposure to subsequent ESG incidents across a large global sample. For automation, we collect industrial robotics data from the International Federation of Robotics (IFR), which tracks the annual flows and cumulative stocks of industrial robot installations by country and industry. We construct firm-year measures of robotics flow and stock after adjusting the industry-level measure by firm capital intensity. For ESG risk, we collect incident data from RepRisk, a leading global database that aggregates media and stakeholder reports of negative ESG events, including environmental accidents, social controversies, and governance scandals. Our final dataset covers 7,864 publicly traded firms across 37 countries from 2007 to 2022. This wide coverage is an important feature of our research design, allowing us to observe automation and ESG outcomes under a variety of economic and institutional settings and ensuring our results are not driven by any single country or industry.

In our baseline regression analysis, we find that firm-level automation adoption, measured by capital intensity–adjusted robotics flow and stock, is positively correlated with the number of ESG incidents, the ESG risk exposure index, and incident impact as measured by its severity, reach, and novelty. Our findings, which are statistically significant, have a significant economic impact: we document that a 10% increase in automation flow would lead to 825 additional global ESG incidents per year. Moreover, among all types of incidents, we find that our results are stronger for environmental- and social-related incidents.

To alleviate endogeneity, we use two instruments that drive firm-level automation adoption but are plausibly unrelated to idiosyncratic ESG risk shocks. The first is the number of fixed Internet broadband subscriptions per 100 inhabitants at the country-year level. While better internet connectivity facilitates the implementation of advanced manufacturing technologies and robots, thereby promoting automation, broadband diffusion itself should not directly cause ESG incidents. The second instrument is the old-age share of total dependency burden per country-year, which captures the pressure of an aging workforce. An aging workforce is likely to encourage automation as a way to counteract potential labor shortages, but it is unlikely to directly increase firm-level ESG controversies. Using these instruments, which are both strongly correlated with automation adoption but plausibly exogenous to firm-level ESG risk, we establish a causal link between automation adoption and ESG risk. The results from two-stage regressions are consistent with the baseline tests.

To identify the channels through which automation adoption positively influences ESG incidents, we conduct a series of cross-sectional heterogeneity tests. First, at the firm level, we find that the positive relationship between automation and ESG incidents is concentrated among firms with more growth potential or in the early stages of automation. For environmental incidents, we find that green innovation attenuates the positive automation–environmental incident relationship. Second, at the industry level, we document that the positive automation–incident relationship is more pronounced in manufacturing industries, in industries requiring higher labor skills, and in more competitive industries. Third, at the country level, we find that the positive relationship between automation and ESG incidents is less pronounced in countries with stronger environmental policy, employment protection legislation, and social trust.

In the robustness tests, we first show that our results are robust to alternative automation measures developed by recent studies that capture firm-level AI adoption. Next, we use Oster's (2019) coefficient stability test, Lewbel's (2012) heteroskedasticity-based instrumental variables approach, and an alternative instrumental variable to confirm the robustness of the identification. Furthermore, our event-study analysis shows that robotics adoption is negatively associated with cumulative abnormal returns (CARs) around global ESG incidents. Lastly, we conduct subsample regressions to show that our results are not driven by any single country or industry.

Our study makes several distinct contributions to the literature. First, we provide the first systematic, international evidence of automation's impact on ESG by bridging two important strands of research that have evolved largely independently of each other: the technology/automation literature in economics and finance and the sustainable finance/ESG literature. To the best of our knowledge, we are the first to connect these domains by demonstrating that a core technological trend, robotics adoption, has significant implications for ESG risk management. This contribution broadens the understanding of how technological innovation creates new risks for stakeholders, filling a critical gap in the literature.

Second, we contribute to the growing finance literature on the materiality of ESG incidents and corporate sustainability. Recent studies show that ESG incidents (controversies) can destroy shareholder value and that investors increasingly price ESG-related risks. We add to this literature by uncovering an internal driver of ESG incidents: firms' automation choices. By establishing a causal impact of automation on ESG outcomes, we provide new evidence on the determinants of corporate social performance and its trade-offs. Our findings imply that corporate policies on technology and capital-labor substitution can inadvertently lead to higher ESG risk. This insight is relevant for scholars and practitioners interested in the intersection of operational efficiency and stakeholder accountability, and it suggests that sustainability should be considered alongside productivity when evaluating new technologies.

Third, we offer novel evidence on the role of organizational and institutional factors in shaping corporate ESG outcomes. Our international research design allows us to show how firm-level characteristics, industry-level attributes, and country-level institutions can jointly influence the relationship between technology adoption and ESG risk. We demonstrate that the unintended consequences of automation are not universal but vary systematically with organizational characteristics and institutional context, pointing to the value of policies and firm strategies that can mitigate environmental, labor, and community disruptions during technological transitions. This finding thus adds to the literature on the importance of institutions in moderating corporate behavior (e.g., see Dyck et al., 2008, 2019; La Porta et al., 1998).

The remainder of this paper is organized as follows. Section 2 describes our data sources and sample construction. Section 3 discusses our baseline empirical results and identification strategies. Section 4 explores cross-sectional heterogeneity. Section 5 presents robustness checks. Section 6 concludes.

2. Data and Sample

2.1 Industrial Robotics Automation Data

The International Organization for Standardization Standard No. 8373 (ISO 8373:2021) defines a robot as a "programmed actuated mechanism with a degree of autonomy to perform locomotion, manipulation, or positioning".[5] Robots can be further categorized as industrial or service. Whereas service robots perform automated tasks for humans or non-industrial applications (e.g., surgery, logistics, domestic chores), industrial robots perform manufacturing tasks (e.g., assembly, engineering). We focus on the industrial version, defined by the ISO (8373:2021) as an "automatically controlled, reprogrammable multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or fixed to a mobile platform for use in

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[5] According to this definition, a selective compliance assembly robot arm, which transfers parts from one place to another with precision and efficiency, would meet the definition, but a keypad-operated door would not.

automation applications in an industrial environment".

We obtain data on operational industrial robotics from the IFR, which uses two primary measures: 1) stock of robots, which is the number of operational robots currently deployed, by country, industry, and year, and 2) flow of robots, which is the increase in the number of operational robots, by country, industry, and year.[6] We follow Acemoglu and Restrepo (2020) and define 19 industries in the IFR's industrial robotics data. This classification is based on the Revision-4 scheme of the International Standard Industrial Classification (ISIC) of All Economic Activities. We map these data into the NAICS and SIC systems using an industry crosswalk and further integrate our sample with Compustat using SIC industry identifiers.[7] As Acemoglu and Restrepo (2020) note, however, the original IFR data do not classify all robotics into these 19 industries (approximately one-third are unclassified); we therefore follow their methodology and allocate the unclassified portion to industries in the same proportion as in the classified data.

To create the firm-level automation measure, we adjust the IFR industry-level robotics flow and stock measures by the firm-level capital intensity share in a country-industry-year cohort. For firm i in country c, industry j, and year t, we define robotics flow and stock as follows:

$$\text{Robotics}_{i,c,j,t} = \text{Robotics}_{c,j,t} \times \frac{\text{Capital Intensity}_{i,t}}{\text{Cohort Total Capital Intensity}_{c,j,t}} \tag{1}$$

where *Robotics* denotes either flows or stock. *Capital Intensity* is defined in three ways: property, plant, and equipment divided by sales (Version 1); capital expenditure divided by sales (Version 2); and property, plant, and equipment divided by the number of employees (Version 3). We then use the natural logarithm of these adjusted measures in our regressions to mitigate right-skewness in the original variables. The log transformation reduces the leverage of extreme values and facilitates interpretation of the estimates in percentage terms.[8]

2.2 ESG Incident Data

Our ESG risk incident data come from RepRisk. RepRisk uses a rules-based methodology to screen over 100,000 public sources and stakeholders daily in 23 languages. It systematically monitors and collects material ESG risks and violations of international standards that may have reputational, compliance, or financial impacts on a company. Using this methodology, RepRisk provides two important ESG data sources over 2007–2022. The first dataset contains incident-

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[6] According to IFR (2022), operational stock is the sum of robot installations over 12 years, assuming a service life of 12 years for each unit and that units are withdrawn from service immediately with no lag or extension beyond this period.

[7] Based on our matching algorithm, we get 18 IFR industries matched to the Compustat data. The industry P (education/research/development) is not separately listed but is part of industry 90 (all other non-manufacturing branches) in our sample.

[8] Log-transformed robotics measures are computed as Ln(1+x). We confirm that our results are robust to the use of the original, unadjusted industry-level IFR robotics measures (reported in the Internet Appendix Table IA.4).

level data capturing the incident date, associated company name, International Securities Identification Number (ISIN), impact measures, and relevant ESG issues and topic tags.[9]

RepRisk rates the impact of each risk incident based on its severity, reach, and novelty. *Severity* captures the harshness of an incident's ESG consequences and is scored from 1 (least severe) to 3 (most severe). *Reach* measures the influence and importance of the incident, according to news readership and circulation. It is similarly scored from 1 (narrow reach) to 3 (wide reach). *Novelty* indicates whether the incident is the company's first exposure to an ESG issue. It is scored 1 (ongoing issue) or 2 (new issue). From this incident-level dataset, we determine the number of incidents per firm-year; the sum of severity, reach, and novelty per firm-year; the number of incidents by individual E, S, or G pillar, as well as overlapping (i.e., cross-cutting) issues per firm-year; and the number of incidents by the 28 RepRisk-identified ESG issues per firm-year.

The other dataset from RepRisk is the firm-daily-level RepRisk Index (RRI). Constructed using a proprietary algorithm, the RRI captures reputational risk exposure to ESG issues and includes a current, peak, and trend value. *Current RRI* reflects the current level of media and stakeholder attention to ESG issues in a company and ranges from 0 (lowest risk exposure) to 100 (highest risk exposure). *Peak RRI* is the highest RRI value in the past two years. *Trend RRI* is the change in RRI over the past 30 days. We take the annual average of daily RRIs to construct firm-year-level RRI measures. Although the RRI is available for all firms covered in the RepRisk universe, a firm must have at least one incident to appear in the incident-level data. Thus, to ensure that missing values in incident-level data indeed mean no incident and not a lack of coverage by RepRisk, we replace missing values with zero if the firm-year is covered in the RRI data.

[Insert Figures 1 and 2]

Figures 1 and 2 present the average level of ESG incident risk across industries and countries, respectively, as measured by *Current RRI*. Each bar represents the mean current RRI score in a given industry or country, based on firm-year observations over the entire sample period. Industries and countries are sorted in descending order of *Current RRI*, highlighting sectoral variation in exposure to ESG-related incidents. As shown, industries associated with substantially higher ESG incident risk include Automotive; Other Vehicles; and Electricity, Gas, Water Supply. These sectors likely face heightened regulatory scrutiny, operational complexity, or public attention that elevates their ESG exposure. In contrast, industries such as Metal Products, Wood and Furniture, and Industrial Machinery exhibit relatively lower ESG incident risk, reflecting a lower external visibility or incident intensity. At the country level, ESG incident risk is highest in Canada, Russia, and Spain, while countries such as Türkiye, Greece, and New Zealand exhibit

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[9] RepRisk has 28 mutually exclusive ESG issues and 74 topic tags. ESG issues are broad, comprehensive, and defined based on key international standards related to ESG issues and business conduct. Every risk incident in RepRisk's dataset is linked to at least one of these issues. Topic tags are specific and thematic. One topic tag can be linked to multiple ESG issues.

relatively lower average Current RRI. This cross-country variation may reflect differences in firm composition, regulatory environments, media coverage, and stakeholder scrutiny. The industry- and country-level heterogeneity motivates a closer investigation into the structural, operational, and technological factors—such as automation exposure—that may explain or amplify these observed differences in ESG risk profiles.

2.3 Firm-Level Financial Data

Our international firm-level financial data come from Compustat North America and Compustat Global. We construct our sample using the intersection of Compustat and RepRisk coverage and match the data using ISINs.[10] We require that firms have all firm-level control variables available. We categorize each country based on companies' headquarters locations. To ensure sufficient statistical power and reliable cross-country comparisons, we drop countries with fewer than 100 observations during our sample period. Our final sample includes 63,473 observations across 37 economies during 2007–2022.[11] The firm-level control variables include firm size (natural logarithm of total assets), book-to-market ratio (book equity over market equity), leverage ratio (long-term debt over total assets), return on assets (ROA and net income over total assets), current assets ratio (current assets over total assets), natural logarithm of sales, and natural logarithm of number of employees. We winsorize all financial variables at the top 0.5% and bottom 0.5% levels.[12]

2.4 Country-Level Control Variables

We obtain country-year-level macroeconomic measures to control for country-level variations in ESG risk exposures. *Inflation* and *GDP per Capita* (in USD thousands) come from the International Monetary Fund. *GDP Growth Rate* (at market prices based on local currency) comes from the World Bank. *Patent per Capita* (patent applications per million people) is from the World Bank. *Globalization Index* is constructed by the KOF Swiss Economic Institute and measures the economic, social, and political dimensions of globalization. *Political Freedom Index* measures the degree of civil liberties and political rights and is available from Freedom House. *Civil Liberties Index* is developed by the Economist Intelligence Unit and measures the extent to which citizens enjoy civil liberties. Appendix A defines all variables.

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[10] For Compustat global companies, the ISIN is available in the database. For Compustat North America companies, we construct the ISIN from the CUSIP number and country code.

[11] Our full sample includes 58 countries/economies. Our results (unreported) are consistent if we keep all 58 in the sample.

[12] We also winsorize the RepRisk variables and IFR robotics variables at the top and bottom 0.5% levels and find the results (unreported) remain consistent.

2.5 Descriptive Statistics

Table 1 Panel A presents the distribution of our regression sample by year. The number of firm-year observations gradually increases over time, from 2,639 in 2007 to 4,360 in 2022. Panel B shows the sample distribution by headquarters country/economy (top 15 economies by sample size). Out of 37 countries/economies, U.S. companies account for 35% of the sample, followed by Japanese (13%) and Chinese (8%) firms. The top 15 countries account for 86% of the sample. Panel C presents the distribution by industry, following the classification method in Acemoglu and Restrepo (2020). The top three industries are All Other Non-Manufacturing Branches (21%), Plastic and Chemical Products (15%), and Mining and Quarrying (15%).

[Insert Table 1]

Table 2 presents summary statistics for the automation, ESG, firm-level, and country-level variables. The automation measures in Panel A are the natural logarithm of capital intensity-adjusted robotics computed based on formula (1). The mean robotics flow ranges from 0.014 to 0.018 across specifications, whereas the mean robotics stock ranges from 0.067 to 0.086. Panel B shows that ESG risk is economically meaningful in the sample. The average firm records 2.6 ESG incidents per year, with mean *Current RRI* and *Peak RRI* values of 8.1 and 16.3, respectively. Incident impact is also nontrivial, as the average severity, reach, and novelty sums are 3.4, 4.5, and 3.6. Across ESG pillars, cross-cutting and social incidents are the most common on average, followed by environmental and governance incidents. Panels C and D further indicate variation in firm- and country-level variables, consistent with the international and multi-industry scope of our sample. Taken together, these descriptive statistics reveal substantial heterogeneity in both automation adoption and ESG outcomes, which motivates the multivariate tests that follow.

[Insert Table 2]

To further understand the dynamic between the ESG incident risk measures reported in Table 2 and robotics adoption, we present the Pearson correlation coefficients between firm-level *Robotics Flow* and *Current RRI* in Figure 3. These numbers are computed separately by industry. The vertical axis lists industries, and the horizontal axis shows the correlation coefficients. The results reveal considerable variation across sectors. For example, the three industries with the strongest positive correlations are Automotive, Basic Metals, and Wood and Furniture. In these sectors, firms with greater robotics exposure tend to have higher ESG incident risk. In contrast, the three industries with the most negative correlations are Other Vehicles, Electricity, Gas, Water Supply, and Metal Products. Increased automation in these sectors may coincide with lower ESG incident risk. These patterns underscore sector-specific dynamics in how robotics adoption aligns with ESG outcomes.[13]

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[13] In Internet Appendix Figure IA.1, we present a heatmap of Pearson correlation coefficients between firm-level robotics flow and the E, S, G, and cross-cutting pillars, calculated separately by industry. The heatmap reveals meaningful variation across industries and pillars. Several sectors—notably Automotive, Wood and Furniture, and Basic Metals—show consistently positive correlations across all four pillars, with Automotive displaying the highest

[Insert Figure 3]

We turn next to country-level variations in the correlation between robotics adoption and ESG incident risk. Figure 4 presents the correlation between *Robotics Flow* and *Current RRI* by country/economy. Among the 37 countries/economies in our sample, Russia, Germany, and Japan display the most positive correlations, and Thailand, New Zealand, and Greece display the lowest. We observe wide dispersion in correlations, reinforcing that national context plays a critical mediating role in shaping the ESG consequences of robotics adoption.

[Insert Figure 4]

Although the cross-sectional correlations between robotics adoption and ESG incident risk show considerable heterogeneity across industries and countries, these static snapshots do not capture patterns over time. To demonstrate the temporal dimension of this dynamic, Figures 5 and 6 present a panel-based view of industry- and regional-level trajectories in the current RRI and robotics flow.[14] This approach allows us to assess whether changes in automation adoption are followed by systematic shifts in ESG outcomes within sectors and regions, which would complement earlier correlation-based evidence presented in Figures 3 and 4. The patterns in Figures 5 and 6 indicate that automation is not universally ESG risk-enhancing or -reducing but instead interacts with sectoral and country/region characteristics to affect ESG outcomes.

[Insert Figures 5 and 6]

3. Empirical Results

Equation (2) outlines our baseline regression framework:

$$\begin{aligned} \text{ESG Incident}_{i,c,j,t} = \alpha + \beta\, Ln\left(1 + Robotics_{i,t-1}\right) + \text{FLV}_{i,t-1} \\ + \text{CLV}_{c,t-1} + \gamma_c + \delta_j + \theta_t + \varepsilon_{i,c,j,t} \end{aligned} \tag{2}$$

The dependent variable is ESG incident measures, including the total number of ESG incidents, RRI, the severity, reach, novelty of incidents, and the number of incidents by ESG pillar. The main independent variable is the natural logarithm of capital intensity–adjusted robotics flow or stock. Firm-level control variables (*FLV*) include the previously defined firm size, book-to-market ratio, leverage ratio, ROA, current assets ratio, sales, and number of employees. Country-level controls (*CLV*) include inflation, GDP per capita, GDP growth

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overall associations (0.26 with environmental, 0.20 with social, 0.31 with governance, and 0.30 with cross-cutting scores). The results suggest that, in these sectors, greater robotics intensity is linked to overall higher ESG incident risk. In contrast, other industries exhibit negative correlations. For example, modest negative associations between robotics exposure and ESG outcomes are observed for Other Vehicles, Paper, and Electricity, Gas, Water Supply. The results suggest potential ESG risk mitigation or better performance among automated firms in these sectors.

[14] In Figures 5 and 6, the industry-year aggregates of current RRI and robotics flow are min-max normalized within each industry to facilitate within-industry comparison over time, regardless of level differences in raw metrics. The use of consistent normalization and panel-specific faceting allows comparison of dynamic patterns across sectors, highlighting temporal alignment or divergence in ESG risk and automation exposure.

rate, patent per capita, globalization index, political freedom index, and civil liberties index. Dependent variables are computed in year t; independent variables are computed in year $t-1$. We include country (γ_c), industry (δ_j), and year (θ_t) fixed effects, and we cluster standard errors at the firm level.[15] If the number of incidents is the dependent variable, we adopt negative binomial regressions to address the potential overdispersion issue in the non-negative count data (Cohn et al., 2022).

3.1 Baseline Results

The first two columns of Table 3 present the negative binomial regression results, where the dependent variable is the number of ESG incidents per firm-year and the primary independent variable is the capital intensity–adjusted robotics flow or stock using Version 1 of the capital intensity definition.[16] In columns (1) and (2), we show that an increase in robotics flow or stock is associated with a higher number of ESG incidents, and these results are significant at the 5% level. The coefficient of 0.410 in column (1) indicates that a 10% increase in automation flow is associated with an approximately 4.1% increase in the number of ESG incidents, whereas the coefficient of 0.173 in column (2) indicates that a 10% increase in automation stock is associated with an approximately 1.7% increase in the number of ESG incidents. These results are also economically significant. Based on the summary statistics reported in Table 2, if an average firm in our sample has 2.56 incidents per year, then with 7,864 unique firms in our sample, a 10% increase in automation flow would lead to 4.1% × 2.56 × 7,864 = 825 additional ESG incidents per year across the globe. The number of incidents is also positively associated with firm size, current assets ratio, number of employees, inflation, and GDP growth rate, and negatively associated with book-to-market ratio, leverage, ROA, and GDP per capita. We note that the natural logarithm of alpha is approximately 0.47 and significant at 1% level in both columns, indicating that the negative binomial regression is more appropriate than a Poisson regression to address potential overdispersion.[17]

[Insert Table 3]

Next, we regress the RRI on capital intensity–adjusted robotics flow and stock. In columns (3) and (4) of Table 3, we report the OLS results of regressing the annual average of daily *Current RRI* on adjusted robotics flow and stock. We find that the coefficients are significant at 1% in both specifications. Column (3) shows that, holding other factors constant, a 10% increase in *Robotics Flow* is associated with an approximately 0.6-point increase in *Current RRI* (which ranges from 0 to 100, with a mean of 8.1). The magnitude of *Robotics Stock*'s impact is lower—a 10% increase leads to an approximately 0.2-point increase in *Current RRI*. In columns (5) and (6) of Table 3, the

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[15] We confirm consistent results (untabulated) if we cluster standard errors at the firm and year levels.

[16] In all tables, we report regression results using Robotics V1 measures. Results based on V2 and V3 are consistent with those using V1 and are reported in the Internet Appendix Table IA.1 and Table IA.2.

[17] Ln(alpha) = 0.47 indicates alpha = $e^{0.47}$ = 1.6, which confirms the overdispersion and justifies the use of the negative binomial model.

dependent variable is the annual average of daily peak RRI, defined as the highest RRI over the past two years. The effects of robotics flow and stock on *Peak RRI* are similar in both magnitude and significance to those on *Current RRI*.[18]

In Table 4, we examine the relationship between robotics flow and stock and the three measures of ESG incident impact: *Severity*, *Reach*, and *Novelty*. Across all specifications, we find a consistent and significant positive association between automation adoption and incident impact. Columns (1) and (2) show that greater use of robotics is linked to more severe ESG incidents. In columns (3) and (4), where the dependent variable is incident reach, we document that a higher level of robotics adoption is associated with broader readership and circulation of incident news. Columns (5) and (6) show that higher robotics adoption means firms are more likely to be exposed to new rather than recurring ESG issues. To interpret the economic significance of these results, a 10% increase in *Robotics Flow* is associated with an approximately 1.0-point increase in *Severity* (with a mean of 3.4), 1.7-point increase in *Reach* (with a mean of 4.5), and 1.1-point increase in *Novelty* (with a mean of 3.6).

[Insert Table 4]

Figure 7 illustrates the relationship between robotics adoption and the impact of ESG incidents by plotting the average values of the three impact measures (*Severity*, *Reach*, and *Novelty*) across robotics adoption groups. We sort firms into quartiles based on their *Robotics Flow* and compute the mean value of each ESG impact measure within each quartile. The grouped bar chart displays the average value of each measure by the *Robotics Flow* level. As shown, a clear upward trend is observed across all three ESG impact measures as *Robotics Flow* increases. Specifically, the highest quartile of *Robotics Flow* is associated with higher average severity, broader reach, and an increase in novel ESG incidents, compared to the lower robotics quartiles. The consistent increase in these factors across quartiles suggests that firms with higher levels of automation tend to experience ESG incidents that are not only more frequent but also more serious, widespread, and unusual. The results align with the evidence in Table 4.

[Insert Figure 7]

3.2 Identification

To address potential endogeneity concerns, we use two country-year-level instrumental variables in two-stage least squares (2SLS) regressions. The first is the number of fixed internet broadband subscriptions per 100 inhabitants, as reported by the International Telecommunication Union. This measure serves as a proxy for regional digital infrastructure and technological readiness, which plausibly influences the diffusion and adoption of automation technologies at a firm level. Availability and quality of broadband access facilitate data-intensive operations, remote monitoring, and integration with cloud-based robotics systems, lowering the cost and increasing

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[18] In unreported results, we find some weak evidence that robotics stock has a positive impact on trend RRI.

the feasibility of automation. Importantly, fixed broadband penetration is determined by country-level infrastructure investment and policy decisions, which are unlikely to be directly related to firm-specific ESG incidents, particularly after controlling for country and year fixed effects. Therefore, this instrument satisfies the relevance condition by being strongly correlated with firm-level automation. It is plausibly exogenous to unobserved determinants of ESG incidents.

The second instrumental variable is the old-age share of total dependency burden per country-year, defined as the ratio of the population aged 65 and above to the total dependent population (ages 0–14 and 65+). This instrument captures demographic-driven pressures on automation. Population aging is a structural, exogenous force that influences labor market dynamics by reducing the supply of working-age individuals and increasing labor costs. It is particularly salient in sectors that depend on manual or routine tasks, where firms are more likely to adopt robotics and automation technologies as substitutes for scarce or expensive labor. This demographic shift, measured at the country level, manifests slowly and is largely determined by fertility and mortality trends. Thus, it is plausibly exogenous to firm-level ESG outcomes. Moreover, though aging populations may influence broad policy agendas, they are unlikely to directly affect the number of ESG incidents reported by individual firms.

In Table 5, we report the 2SLS results for the number of incidents. In the first stage, we regress *Robotics Flow* and *Robotics Stock* on the two instruments, along with the firm- and country-level control variables used in the baseline regressions. In columns (1) and (2), we show that both instruments are positively associated with robotics flow and that the number of fixed broadband subscriptions is positively associated with robotics stock. In columns (3) and (4), we report the negative binomial results using instrumented robotics flow and stock, respectively, as the independent variable. The second-stage results are consistent with our baseline results in Table 3, indicating that the positive impact of robotics adoption on the number of ESG incidents is likely causal.

To show that the rest of the results in Tables 3 and 4 are also robust to endogeneity concerns, we use the same two instruments. We apply the 2SLS regressions to *Current RRI*, *Peak RRI*, *Severity*, *Reach*, and *Novelty*. 2SLS results reported in columns (5)-(14) in Table 5 are mostly consistent with our baseline results. The first-stage diagnostics indicate that the instruments are relevant and sufficiently strong. The *F*-statistics for the excluded instruments are 20.83 for *Robotics Flow* and 17.89 for *Robotics Stock*, and both the Cragg–Donald and Kleibergen–Paap *F*-statistics exceed the corresponding Stock–Yogo critical values (10% and 15% maximal IV size), suggesting that weak instrument concerns are unlikely. The Kleibergen–Paap underidentification tests strongly reject the null of underidentification (*p*-values = 0.00), confirming that the model is identified. Finally, the Hansen J overidentification tests yield *p*-values that are generally large and fail to reject the null, suggesting that our robotics measures are not overidentified.

[Insert Table 5]

3.3 ESG Incident Categories

To investigate variation among ESG incident categories, we use two groups of measures: the number of incidents in the E, S, G, and cross-cutting pillars by firm-year, and the number of incidents across the 28 ESG issues defined by RepRisk. In Panel A of Table 6, we present the negative binomial regression results by pillar and find that the increase in ESG incidents is driven by the E and S incidents, whereas the effects on G and cross-cutting incidents are not statistically significant. These results confirm our expectations. First, robots could transform production processes, resulting in increased energy consumption, electronic waste, and resource-intensive operations that increase a firm's environmental footprint. Second, automation can lead to large-scale workforce displacement, labor unrest, and deteriorating employee relations, thereby intensifying social risks. In contrast, governance-related incidents (e.g., board independence issues, executive misconduct, audit failures) are generally influenced by institutional structures and leadership behavior, which are less directly affected by a firm's technology adoption. Consequently, the mechanistic and labor-disruptive nature of robotics aligns more closely with environmental degradation and social conflict, making its impact on the E and S pillars more pronounced than on the G pillar.

In Panel B of Table 6, we tabulate the selected regression coefficients of the baseline regressions for the 28 ESG issue types. We find the most pronounced issues in the areas related to local pollution; energy management; discrimination in employment; fraud; product health and environmental issues; supply chain issues; and violations of national legislation.[19] We observe a negative and significant impact of automation on ESG incidents for controversial products and services and for tax optimization issues.

[Insert Table 6]

4. Cross-Sectional Heterogeneity Tests

The baseline results show that automation adoption is positively associated with ESG incident risk. However, this average effect is unlikely to be uniform across firms, industries, and institutional environments. As discussed in the Introduction and formalized in Internet Appendix A, automation can increase ESG incident risk through two related channels: a control-gap channel, in which firms' monitoring, safety, accountability, and stakeholder-management systems lag behind technological change; and a scale-and-complexity channel, in which automation allows firms to expand output and operational scope faster than their ESG-control systems can adjust. The framework also posits a private-social cost wedge: firms may bear some private costs

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[19] Although governance incidents as a whole are not significantly associated with automation adoption, fraud is an exception. Most G incidents, such as board independence, executive misconduct, audit failures, are shaped primarily by institutional and leadership factors that automation does not directly alter. Fraud, however, can be facilitated by algorithmic opacity and weakened human oversight during rapid technological transformation. Its significance at the issue level does not contradict the aggregate G non-result; automation's governance effect is simply concentrated in this one sub-category, whose signal is diluted when aggregated across all governance issues.

from ESG incidents, but they may not fully internalize the broader harms borne by workers, communities, suppliers, and the environment. As a result, the ESG consequences of automation should depend on the extent to which automation increases risk exposure and the extent to which firms, industries, and institutions mitigate that exposure.

4.1 Firm-Level Heterogeneity Tests

4.1.1 Growth Opportunities

One possible factor to moderate our finding is the firm's growth opportunities. As growth firms typically face stronger pressure to scale production, they may apply automation more aggressively and create more ESG incidents during the process. We use the average sales growth rate over the past three years as a measure to capture growth opportunities and test whether firms with more growth opportunities have a stronger automation–ESG incident relationship. [20] We compute the median past-three-year sales growth rate by country-year cohort, then define *High Avg Sales Growth* as equal to one if it exceeds the cohort median, and zero otherwise. In Table 7 Panel A, we interact this high growth indicator with the robotics flow and stock measures. We observe positive and significant interaction terms for all five outcome variables, consistent with our argument that firms with more growth potential tend to use automation more intensively, which in turn amplifies the impact on ESG outcomes.

4.1.2 Automation Experience

Another possible factor is the length of time a firm has been using automation equipment. During the early stages of automation adoption, operational disruptions and implementation challenges can increase the risk of ESG incidents. As the firm becomes more familiar with the equipment and integrates it more effectively into its operations, such risks are likely to diminish. To capture this firm experience, we use the age of property, plant, and equipment (PP&E), defined as the accumulated depreciation divided by the sum of gross PP&E and capital expenditures.[21] We compute the median PP&E age by country-year cohort. *High PPE Age* equals one if it exceeds the cohort median, and zero otherwise. We interact the *High PPE Age* indicator with robotics flow and stock in our baseline regressions. In Table 7 Panel B, we find that seven out of eight interaction terms are negative and significant.[22] The results suggest that the risk of ESG incidents declines as firms gain experience with automation equipment, providing evidence for the control-gap channel.

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[20] Past-three-year sales growth is calculated as the average annual sales growth over years t, t-1, and t-2, where annual sales growth is defined as (Sales_t - Sales_{t-1}) / Sales_{t-1}. We require at least two non-missing annual sales growth observations to compute this measure, leaving 44,923 non-missing observations.

[21] The regression sample has 62,932 observations with non-missing PPE age.

[22] We do not find significant interaction terms for *Peak RRI*.

4.1.3 Green Innovation

To better understand the E pillar, we examine whether a firm's green innovation efforts moderate the relationship between automation and environmental incidents. The rationale is that firms that adopt automation technologies without accompanying innovations may be more prone to environmental issues. We construct two firm-year-level measures of green innovation using the University of Virginia Global Corporate Patent Dataset: the number of green patent filings and the number of forward citations received within five years. Green patents are identified following the approaches of Atta-Darkua et al. (2025), Cohen et al. (2024), Hascic and Migotto (2015), Hege et al. (2025), and Klausmann et al. (2025). As shown in Table 7 Panel C, the positive association between automation and ESG incidents is significantly weaker among firms engaged in green innovation, both in terms of green patent filings and forward citations. These findings suggest that when automation is integrated with broader innovation strategies aimed at sustainability, the potentially adverse environmental impacts of automation are mitigated, which is consistent with evidence that high-value innovation can shape firm outcomes (Kogan et al., 2017).

[Insert Table 7]

4.2 Industry-Level Heterogeneity Tests

4.2.1 Manufacturing and Non-Manufacturing Industries

At the industry level, we first examine whether industry type explains our findings by comparing manufacturing and non-manufacturing firms.[23] Results presented in Panel A of Table 8 suggest that the documented positive relationship between automation and ESG incidents is more pronounced among manufacturing firms. This finding is consistent with the view that manufacturing industries rely more heavily on physical production processes, where the adoption of automation may involve greater operational complexity and disruption, thereby increasing the likelihood of ESG-related incidents.

4.2.2 Labor Skill

We next investigate whether labor skill in an industry explains our findings. We obtain the industry-level labor skill measure from Belo et al. (2017). The measure is defined as the percentage of workers who work in occupations that require a high level of training and preparation. We match this measure to firm-level data using 3-digit NAICS industry codes.[24] *High Labor Skill* is defined as one if the labor skill measure of industry j in year t is above the

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[23] We define manufacturing industries as those with IFR industry code not equal to 90.

[24] Labor skill measure is available at the 4-digit NAICS level. To align with firm-level data where many global firms are only classified at the 3-digit NAICS level, we aggregate the measure by taking the average within each 3-digit NAICS industry. The data from Belo et al. (2017) are available through 2013; for subsequent years, the measure is assumed to remain constant at its 2013 level. The regression sample includes 61,217 observations with matched industry-level labor skill.

country-year median, and zero otherwise. Results presented in Panel B of Table 8 suggest that industries that require higher labor skills are more likely to have a stronger automation-ESG incident relationship. This finding is consistent with the view that automation in skill-intensive industries can cause more complex organizational adjustments and increase the likelihood of operational disruptions and ESG-related incidents.

4.2.3 Competition

Finally, we test whether industry competition explains our findings. To measure industry competition, we compute the Top 4 Concentration Ratio as the sum of market shares of the four largest firms per 3-digit NAICS, country, and year, where market share is defined as a firm's annual sales divided by total industry (3-digit NAICS) sales in the same country-year. A higher ratio indicates a more concentrated and thus less competitive industry. We then define *High Top 4 Concentration Ratio* as one if the Top 4 Concentration Ratio of industry *j* (3-digit NAICS) in year *t* is above the country-year median, and zero otherwise. In Panel C of Table 8, we find that the interaction between *Robotics Flow* and *High Top 4 Concentration Ratio* is negative and significant across five ESG incident measures, indicating that the baseline relationship is stronger (weaker) if an industry is more (less) competitive. One interpretation is that competitive pressure amplifies the operational and reputational risks associated with automation and thereby increases the likelihood of ESG incidents. The interaction term between *Robotics Stock* and *High Top 4 Concentration Ratio* is negative across all specifications but does not appear to have similar statistical significance.

[Insert Table 8]

4.3 Country-Level Heterogeneity Tests

4.3.1 Environmental Policy Stringency

At the country level, we examine whether institutional quality shapes the automation–ESG incident relationship. Jurisdictions with stricter environmental regulations should impose tighter monitoring, higher compliance costs, and stronger enforcement on firms, making these firms more likely to consider environmental risk and to implement risk management systems when adopting automation. To capture the intensity of environmental regulations, we use the Organisation for Economic Co-operation and Development (OECD) Environmental Policy Stringency index and interact it with the robotics flow and stock measures.[25] In Table 9 Panel A, we document significantly negative interaction terms for all three impact measures of environmental incidents, indicating that stricter policies attenuate the automation–incident relationship. This result is consistent with our prediction that effective environmental policy can minimize the negative environmental consequences of automation.

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[25] This index from OECD countries is available until 2016. The regression sample includes 31,174 observations with a non-missing index value.

4.3.2 Employment Protection Legislation

Next, we explore the mechanism from the labor replacement perspective. If firms can more easily replace human labor with robots after events such as mass layoffs, it is plausible that increased automation could lead to more social issues. We measure the difficulty of conducting mass layoffs using the Collective Dismissal component of the OECD Employment Protection Legislation Index.[26] A higher index value indicates stronger employment protection and thus greater constraints on large-scale layoffs. In Table 9 Panel B, we interact *Employment Protection Legislation Index* with robotics flow and stock. We find that for social incidents, stronger employment protection (i.e., a higher OECD *Employment Protection Legislation Index*) attenuates the positive association between robotics and incidents, and this pattern holds for all three impact measures of social incidents. The result is consistent with our prediction that stronger employment protection moderates the social consequence of firms' automation adoption.

4.3.3 Social Trust

We further investigate whether the informal institution of social trust moderates the relationship between automation and ESG incidents. Social trust reflects the degree to which individuals believe others will act in a fair and cooperative manner. In high-trust societies, stakeholders (e.g., employees, customers, and local communities) conduct informal monitoring of firms, which holds firms accountable by shaping their reputational constraints.[27] These firms should be less likely to incur automation-related ESG risk. We obtain trust data from two harmonized, cross-national surveys, the World Values Survey and European Values Study, which collect information on individuals' attitudes and values.[28] Because trust is measured repeatedly across survey waves and varies meaningfully across countries and over time, this setting allows us to test whether the societal trust environment moderates the relationship between automation adoption and ESG incident risk. As presented in Panel C of Table 9, interacting the social trust measure with the robotics flow and stock measures reveals negative and significant interaction terms for all five incident outcomes. This evidence supports our prediction that higher social

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[26] The Collective Dismissal component is available from 2000 to 2019. The regression sample includes 46,058 observations with a non-missing index value.

[27] Social trust is widely used as a summary measure of community-based capital and a country's broader ethical environment (Ahern et al., 2015; Guiso et al., 2004; La Porta et al., 1997). Trust can influence economic and organizational outcomes by affecting cooperation, monitoring intensity, and stakeholders' willingness to extend legitimacy to firms during periods of adjustment (Guiso et al., 2004; Guiso et al., 2008; Pevzner et al., 2015; Brockman et al., 2022; Nguyen, 2026).

[28] The surveys are fielded in seven multi-year waves (1981–1984, 1990–1994, 1995–1998, 1999–2004, 2005–2009, 2010–2014, and 2017–2022). Respondents are selected using probability-based sampling designed to approximate national representativeness, with coverage across key demographic and regional strata (e.g., age, gender, occupation, and geographic area). Following the established approach in the literature, we use the standard generalized-trust question, "Can most people be trusted?" We code affirmative responses as equal to one, and zero otherwise. We then construct country-level trust as the average response for each country and survey wave (Ahern et al., 2015; Guiso et al., 2004; Pevzner et al., 2015). The regression sample has 55,616 observations with a non-missing social trust measure.

trust mitigates the automation–ESG incident relationship.

[Insert Table 9]

5. Robustness Checks

5.1 Cross-Validation Using AI-Based Automation

In this section, we use two firm-level AI adoption measures as alternative proxies for automation. Our main robotics measures capture physical automation through machines that replace manual jobs, while the AI-based measures capture cognitive automation through software and skills. Examining both dimensions allows us to assess whether the ESG risk implications of automation generalize beyond manufacturing robots to the broader technological shift toward intelligent machines.

The first alternative uses the AI workforce measures developed by Babina et al. (2024). These measures capture the investments in AI technologies based on firms' AI-skilled human capital. *AI Employees* is the share of a firm's workforce with AI-specific skills, such as building, training, and deploying AI systems, whereas *AI Knowledge Employees* is a broader measure and is defined as the share of a firm's workforce with AI-adjacent knowledge. In Table 10 Panel A, we present consistent evidence that both measures are positively associated with the *Number of Incidents*, *Current RRI*, and *Peak RRI*, and *AI Employees* is also positively associated with *Severity*, *Reach*, and *Novelty*.[29]

The second alternative is the measure of generative AI (GenAI) adoption in financial reporting developed by Blankespoor et al. (2026). This measure is based on the intensity of GenAI-related language in firms' corporate communications among U.S. firms. It is constructed using disclosures from annual report Item 1A (Risk Factors), Item 7 (Management Discussion and Analysis), conference calls, and press releases. We compute *AI Financial Reporting* as the natural logarithm of the average of these four Gen AI measures per firm-year.[30] In Table 10 Panel B, we show that this measure is positively associated with *Severity*, *Reach*, and *Novelty*.[31]

Together, Table 10 shows a remarkably consistent pattern: firms with greater exposure to

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[29] Industry classifications in Table 10 results are based on 2-digit SIC. Results remain mostly significant after we replace industry fixed effects with firm fixed effects. These results are presented in Internet Appendix Table IA.5.

[30] Although this measure is rooted in the disclosure literature, it still speaks to our broader argument about unintended consequences of automation. Automating financial reporting can improve efficiency and readability, but it can also introduce new risks by weakening human review, amplifying managerial tone management, and increasing the possibility of inaccurate stakeholder communications. As such, this measure should be viewed as capturing a communication- and reporting-oriented dimension of automation. It allows us to assess whether our main results extend to cognitive automation in firms' information environment.

[31] We remove the country-level controls and country fixed effects in Panel B of Table 10, given that the measure is available for US firms only. The results are somewhat weaker than those for industrial robots or the Babina et al. (2024) measures, which is consistent with two features of this sample: the narrower focus on the GenAI that became commercially prominent only after 2018, and the smaller sample for which textual measures are available. Nonetheless, the direction of the effect is consistent across all three incident impact measures.

either AI-skilled labor or GenAI-based reporting also exhibit higher ESG incident risk or more consequential incidents. This convergence across measures supports our main story that the adoption of automation technologies, whether physical or cognitive, can create organizational disruption and stakeholder-related risks that manifest in realized ESG incidents.

[Insert Table 10]

5.2 Additional Identification Strategies

We adopt three additional tests to strengthen our identification strategies. First, to further address omitted variable concerns, we conduct Oster's (2019) coefficient stability test, which assesses the sensitivity of coefficients of the key independent variables (*Robotics Flow* and *Robotics Stock*) to unobserved variables by examining how the coefficients change after adding controls.[32] Panel A of Table 11 shows the stability of the *Robotics Flow* and *Robotics Stock* coefficients. Columns (1) and (4) report results without controls, columns (2) and (5) include firm-level controls, and columns (3) and (6) add country-level controls. Oster's identified set, which provides bounding values for the treatment effect, confirms that the coefficients on *Robotics Flow* and *Robotics Stock* remain robust to including additional controls. Oster's identified set excludes zero, indicating that our results are unlikely to be affected by omitted variable bias.

Second, we address endogeneity concerns using Lewbel's (2012) heteroskedasticity-based instrumental variables approach, which is well-suited for settings where external instruments may be weak or endogenous. In the first stage (unreported), we regress our endogenous variable, *Robotics Flow*, on all exogenous covariates and save the residuals. A Breusch–Pagan test strongly rejects homoskedasticity ($\chi^2(1) = 26{,}872$, $p < 0.001$), providing support for the use of heteroskedasticity as a source of identification. We then interact the residuals with mean-centered covariates to construct the Lewbel instruments. The joint first-stage Sanderson–Windmeijer F-statistic is 25.01 ($p < 0.001$), and the Kleibergen–Paap underidentification test ($\chi^2(14) = 41.61$, $p < 0.001$) rejects the null of underidentification, both indicating that the Lewbel instruments are sufficiently strong and relevant. In the second stage, the results of which are reported in Panel B of Table 11, we regress our outcome *Current RRI* on the predicted values of *Robotics Flow*, controlling for covariates and fixed effects. The Lewbel-IV estimate of the *Robotics Flow* coefficient is 3.213, significant at the 5% level. The Hansen J statistic does not reject instrument exogeneity ($\chi^2(13) = 21.23$, $p = 0.069$). We find similar results and diagnostic statistics for *Robotics Stock*. Taken together, these results reinforce our findings that higher

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[32] Our tests are based on the regressions in columns (3) and (4) of Table 3, where the dependent variable is *Current RRI* and the main independent variables are *Robotics Flow* and *Robotics Stock*, respectively. Following Oster (2019), we define the identified set as $\left[\widetilde{\beta},\ \beta^{*'}\right]$, and obtain $\beta^{*'}$ from: $\beta^{*'} = \widetilde{\beta} - \delta\left[\dot{\beta} - \widetilde{\beta}\right]\frac{R_{\max} - \widetilde{R}}{\widetilde{R} - \dot{R}}$. In our case, $\widetilde{\beta}$ and $\widetilde{R}$ are the coefficients estimated respectively from *Robotics Flow* or *Robotics Stock* and the R-square value of our baseline regression that includes control variables. Similarly, $\dot{\beta}$ and $\dot{R}$ are their counterparts from the regression without control variables, respectively. We set arbitrary values for δ and $\mathrm{R}_{\mathrm{MAX}}$, with δ set at 1, following Oster's (2019) recommendation for an appropriate upper bound. $R_{\max} = min(2.2\widetilde{R}, 1)$, as suggested by Mian and Sufi (2014).

robotics adoption increases ESG incidents.

[Insert Table 11]

Third, we follow Acemoglu and Restrepo (2020) and use the average robotics adoption in five European countries—Denmark, Finland, France, Italy, and Sweden (EURO5)—as the instrumental variable for companies in other countries. European countries are considered pioneers in adopting automation technologies. Focusing on these five countries, which are ahead of other major economies, allows us to isolate the source of variation coming from global technological advances. We use *EURO5 Robotics Flow* to instrument for the rest of the world and report the 2SLS results in Table 12. The first-stage results indicate that the instrument is highly relevant, whereas the second-stage results are mostly consistent with our baseline results.

[Insert Table 12]

5.3 Event Study: Automation and Market Reactions to ESG Incidents

We conduct event studies around impactful ESG incidents and investigate whether robotics adoption affects shareholder returns through these incidents. We first use Datastream to collect daily stock returns for all firms in our sample, and we collect index returns using the widely adopted market index in the respective headquarters country.[33] We then compute the daily market-adjusted return by subtracting the index return from the stock return and aggregate it to the CAR over multiple event windows.

We select impactful ESG incidents in two ways. First, we identify days on which the RRI peaks over the past two years and the peak exceeds 50.[34] Second, we select incidents related to 10 or more countries and compute the CARs over event windows [-1,5] and [-1,10].[35,36] In Table 13, we regress the CARs on *Robotics Flow* and *Robotics Stock* using the same set of control variables and fixed effects as in our baseline regressions. In columns (1)–(4), we find that a higher level of robotics adoption is associated with significantly lower CARs around peak RRI dates. In columns (5)–(8), we find some evidence that *Robotics Flow* is negatively associated with CARs around incident dates with a wide global impact. These event study results suggest an automation-induced, material impact of ESG incidents that can affect market perception, consistent with Krüger (2015) and Hoepner et al. (2023).

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[33] The list of market indexes is available upon request.

[34] We use a threshold of 50 to capture materially severe ESG incidents. Given that the RRI ranges from 0 to 100, values above 50 correspond to high-risk events that are more likely to attract significant stakeholder attention. For a given firm, if multiple peak RRI dates occur in a calendar year, we use the date with the highest RRI.

[35] In the RepRisk raw data, an average incident is related to 2.09 countries, while the standard deviation is 5.75 countries. For a given firm-year, if multiple incidents are related to the same number of countries, we use the earliest incident. Results are qualitatively similar, though slightly weaker, when using alternative thresholds of 5–9 impacted countries.

[36] We choose not to use severity, reach, and novelty measures to capture the impact per incident. This is because these variables have limited variation (severity and reach range from 1 to 3, and novelty is binary). As such, they offer only coarse distinctions and are less effective in identifying truly impactful incidents.

[Insert Table 13]

5.4 Subsample Evidence

Last, we discuss the results using subsamples, and these results are reported in the Internet Appendix. First, we examine the baseline regressions excluding certain countries. In Panel A of Table IA.3, we report the regression results for *Current RRI* after excluding companies in the top three countries (US, Japan, and China) individually, as well as excluding all firms from all top-five countries. The results are consistent with our baseline results reported in Table 3, indicating they are not driven by large countries or economies.

Next, we exclude certain industries. In Panel B of Table IA.3, we report the regression results for *Current RRI* after excluding companies in the top three industries individually, as well as excluding all firms from all top-five industries. The results are again consistent with our baseline results reported in Table 3, indicating they are not driven by large industries.

In unreported results, we explore subsamples excluding one country or one industry at a time and do not find any evidence that our main results are driven by a single country or a single industry.

6. Conclusion

This paper examines a fundamental but underexplored question: does the adoption of automation technologies, while potentially enhancing productivity, create new risks along ESG dimensions? Motivated by growing concerns about the societal consequences of automation, we provide the first systematic international evidence on how robotics adoption shapes firms' exposure to ESG incidents.

Using a global sample of firms across 37 economies from 2007 to 2022, we show that greater adoption of industrial robotics is associated with significantly higher ESG risk, as measured by incident frequency, overall risk exposure, and the severity, reach, and novelty of ESG controversies. These effects are economically meaningful and are driven primarily by environmental and social incidents. Addressing endogeneity concerns through instrumental variable approaches, we provide evidence consistent with a causal interpretation.

We further document important heterogeneity that sheds light on the strength of the relationship. The adverse ESG effects of automation are more pronounced among high-growth firms, firms at earlier stages of automation adoption, and firms operating in manufacturing, higher-skill, and more competitive industries, suggesting that rapid scaling and implementation frictions play a central role. At the same time, these effects are mitigated when firms engage in green innovation, and when they operate in institutional environments characterized by stronger environmental policies, stricter employment protection, and higher social trust. Taken together, these findings indicate that the ESG consequences of automation are not inevitable but depend on firm choices and institutional context.

Our findings have several implications. For corporate managers, the results indicate that automation strategies should be accompanied by investments in risk management, employee transition policies, and sustainable innovation to avoid unintended ESG consequences. For investors, our evidence suggests that automation exposure constitutes a previously underappreciated source of ESG risk that may affect firm valuation and downside risk, particularly around adverse ESG events. For regulators and policymakers, the results point to the importance of complementary institutions, such as environmental regulation and labor protections, in mitigating the negative externalities of technological adoption.

Our results suggest that the productivity gains from robotics adoption are not without cost; firms that automate more aggressively face measurably greater exposure to environmental and social controversies. This tension between operational efficiency and stakeholder accountability is unlikely to diminish as automation spreads across industries and economies. Understanding this trade-off should be a central concern for firms' decision-makers, asset managers pricing ESG risk, and policymakers designing the institutional frameworks that govern the technological change.

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Table 1. Sample Distribution

This table provides the regression sample distribution by year in Panel A, by country/economy in Panel B, and by industry in Panel C. See Appendix A for variable definitions.

Panel A. Sample Distribution by Year				**Panel B. Sample Distribution by Country/Economy**			
Year	N	%	Cumulative %	Country/Economy	N	%	Cumulative %
2007	2,639	4.16	4.16	United States (USA)	22,190	34.96	34.96
2008	3,504	5.52	9.68	Japan (JPN)	7,973	12.56	47.52
2009	3,478	5.48	15.16	China (CHN)	5,193	8.18	55.70
2010	3,556	5.60	20.76	United Kingdom (GBR)	4,191	6.60	62.31
2011	3,706	5.84	26.60	India (IND)	2,787	4.39	66.70
2012	3,833	6.04	32.64	France (FRA)	1,797	2.83	69.53
2013	3,747	5.90	38.54	Germany (DEU)	1,701	2.68	72.21
2014	3,825	6.03	44.57	Australia (AUS)	1,698	2.68	74.88
2015	3,917	6.17	50.74	Hong Kong (HKG)	1,618	2.55	77.43
2016	4,535	7.14	57.88	Switzerland (CHE)	1,042	1.64	79.07
2017	4,618	7.28	65.16	Sweden (SWE)	962	1.52	80.59
2018	4,459	7.03	72.18	Canada (CAN)	890	1.40	81.99
2019	4,462	7.03	79.21	Finland (FIN)	817	1.29	83.28
2020	4,462	7.03	86.24	Italy (ITA)	795	1.25	84.53
2021	4,372	6.89	93.13	Netherlands (NLD)	740	1.17	85.70
2022	4,360	6.87	100.00	All Others	9,079	14.30	100.00
Total	63,473	100.00		Total	63,473	100.00	

Panel C. Sample Distribution by IFR Industry

Industry	IFR Industry	N	%	Cumulative %
All Other Non-Manufacturing Branches	90	13,173	20.75	20.75
Plastic and Chemical Products	19-22	9,594	15.12	35.87
Mining and Quarrying	C	9,248	14.57	50.44
Construction	F	5,311	8.37	58.81
Electricity, Gas, Water Supply	E	4,990	7.86	66.67
Food and Beverages	10-12	3,885	6.12	72.79
Electrical/Electronics	26-27	3,658	5.76	78.55
Industrial Machinery	28	2,559	4.03	82.58
Agriculture, Forestry, Fishing	A-B	2,042	3.22	85.80
All Other Manufacturing Branches	91	1,351	2.13	87.93
Textiles	13-15	1,237	1.95	89.88
Metal Products (Non-Automotive)	25	1,228	1.93	91.81
Glass, Ceramics, Stone, Mineral Products	23	1,195	1.88	93.69
Wood and Furniture	16	990	1.56	95.25
Basic Metals	24	849	1.34	96.59
Automotive	29	812	1.28	97.87
Other Vehicles	30	789	1.24	99.11
Paper	17-18	562	0.89	100.00
Total		63,473	100.00	

Table 2. Summary Statistics

This table provides the regression sample summary statistics of the robotics measures, ESG incident measures, firm-level variables, and country-level variables. See Appendix A for variable definitions.

	N	Mean	SD	Min	Median	Max
Panel A: Automation Measures						
Robotics Flow V1	63,473	0.015	0.079	0.000	0.000	2.809
Robotics Flow V2	63,473	0.014	0.079	0.000	0.000	3.268
Robotics Flow V3	63,473	0.018	0.093	0.000	0.000	2.690
Robotics Stock V1	63,473	0.070	0.251	0.000	0.001	4.539
Robotics Stock V2	63,473	0.067	0.248	0.000	0.001	4.947
Robotics Stock V3	63,473	0.086	0.282	0.000	0.001	4.343
Panel B: ESG Incident Measures						
Number of Incidents	63,473	2.557	10.775	0.000	0.000	505.000
Current RRI	63,473	8.114	10.391	0.000	1.205	72.038
Peak RRI	63,473	16.347	16.209	0.000	16.844	86.000
Trend RRI	63,473	0.060	0.807	-3.839	0.000	6.403
Severity	63,473	3.432	14.322	0.000	0.000	591.000
Reach	63,473	4.531	20.184	0.000	0.000	1044.000
Novelty	63,473	3.560	13.219	0.000	0.000	542.000
Environmental	63,473	0.928	5.151	0.000	0.000	201.000
Social	63,473	1.316	5.873	0.000	0.000	280.000
Governance	63,473	0.901	4.339	0.000	0.000	263.000
Cross-cutting	63,473	1.596	7.082	0.000	0.000	341.000
Panel C: Firm-Level Variables						
Size	63,473	7.745	1.667	1.569	7.710	12.932
Book_Market	63,473	0.650	0.666	-0.488	0.486	5.821
Leverage	63,473	0.191	0.174	0.000	0.161	0.881
ROA	63,473	0.036	0.114	-1.316	0.042	0.352
Current Assets Ratio	63,473	0.435	0.216	0.028	0.429	0.991
Sales	63,473	7.428	1.713	0.005	7.458	11.338
Employees	63,473	2.073	1.269	0.002	1.937	5.575
Panel D: Country-Level Variables						
Inflation	63,473	0.027	0.026	0.000	0.021	0.285
GDP per Capita	63,473	10.348	0.975	6.687	10.741	11.545
GDP Growth Rate	63,473	2.237	3.159	-10.940	2.289	14.520
Patent per Capita	63,473	699.006	662.797	0.463	739.889	2713.480
Globalization Index	63,473	77.040	8.072	51.421	79.060	89.812
Political Freedom Index	63,473	1.918	1.786	1.000	1.000	7.000
Civil Liberties Index	63,473	8.069	2.230	0.880	8.530	10.000
Fixed Broadband Subscription	63,473	27.537	10.381	0.015	30.000	47.943
Aging	63,473	0.450	0.134	0.080	0.445	0.708

Table 3. Number of ESG Incidents, Current RRI, and Peak RRI

This table shows the negative binomial and OLS regression results of the effect of robotics flow and stock on the number of ESG incidents and RRI using the international sample from 2007 to 2022. The dependent variables are the *Number of Incidents*, *Current RRI*, and *Peak RRI* of firm *i* in year *t*. All independent variables are calculated in year *t-1*. See Appendix A for variable definitions. Industry, year, and country fixed effects are as indicated. Standard errors are clustered at the firm level. The *t*-statistics are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

	Number of Incidents		*Current RRI*		*Peak RRI*	
	(1)	(2)	(3)	(4)	(5)	(6)
Robotics Flow	0.410**		5.759***		5.668***	
	(2.145)		(4.107)		(3.728)	
Robotics Stock		0.173**		1.919***		2.190***
		(2.215)		(3.987)		(3.880)
Size	0.663***	0.662***	3.090***	3.086***	4.162***	4.151***
	(22.358)	(22.258)	(23.418)	(23.338)	(24.395)	(24.264)
Book_Market	-0.110***	-0.111***	-0.514***	-0.517***	-0.574***	-0.579***
	(-4.502)	(-4.531)	(-5.425)	(-5.468)	(-4.131)	(-4.164)
Leverage	-0.312**	-0.313**	-3.061***	-3.069***	-2.927***	-2.937***
	(-2.181)	(-2.187)	(-5.972)	(-5.988)	(-3.915)	(-3.929)
ROA	-0.736***	-0.736***	-3.724***	-3.739***	-6.362***	-6.376***
	(-4.325)	(-4.325)	(-7.572)	(-7.603)	(-8.088)	(-8.110)
Current Assets Ratio	0.418***	0.422***	1.705***	1.738***	2.416***	2.459***
	(3.658)	(3.688)	(4.353)	(4.431)	(4.035)	(4.105)
Sales	0.056*	0.057*	-0.154	-0.145	0.075	0.092
	(1.695)	(1.729)	(-1.418)	(-1.329)	(0.455)	(0.561)
Employees	0.211***	0.210***	1.379***	1.372***	1.798***	1.788***
	(6.930)	(6.903)	(11.783)	(11.718)	(11.091)	(11.026)
Inflation	2.069***	2.063***	5.934***	5.887**	10.377**	10.308**
	(3.287)	(3.277)	(2.579)	(2.550)	(2.369)	(2.348)
GDP per Capita	-0.690***	-0.692***	-3.380***	-3.392***	-4.581***	-4.600***
	(-6.416)	(-6.429)	(-8.712)	(-8.743)	(-6.443)	(-6.468)
GDP Growth Rate	0.013***	0.013***	0.050***	0.052***	0.039	0.041*
	(3.616)	(3.702)	(3.478)	(3.590)	(1.637)	(1.706)
Patent per Capita	0.000	0.000	0.001**	0.001**	0.000	0.000
	(0.268)	(0.207)	(2.028)	(1.989)	(0.455)	(0.393)
Globalization Index	0.024	0.025	0.037	0.052	-0.075	-0.062
	(1.403)	(1.462)	(0.643)	(0.885)	(-0.676)	(-0.556)
Political Freedom Index	-0.037	-0.039	-0.234	-0.261	-0.434	-0.457
	(-0.800)	(-0.844)	(-1.391)	(-1.554)	(-1.454)	(-1.533)
Civil Liberties Index	-0.060*	-0.059*	-0.298**	-0.283**	-0.253	-0.237
	(-1.891)	(-1.873)	(-2.484)	(-2.353)	(-1.072)	(-1.001)
Constant	-1.928	-2.014	16.763***	15.658***	35.331***	34.328***
	(-1.111)	(-1.161)	(2.763)	(2.580)	(3.109)	(3.023)
Observations	63,473	63,473	63,473	63,473	63,473	63,473
Ln (Alpha)	0.473***	0.472***				
Adjusted R-Squared			0.406	0.406	0.372	0.372
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4. Severity, Reach, and Novelty of Incidents

This table shows the OLS regression results of the effect of robotics flow and stock on the severity, reach, and novelty of all ESG incidents, using the international sample from 2007 to 2022. The dependent variables are *Severity*, *Reach*, and *Novelty*. All independent variables are calculated in year *t-1*. See Appendix A for variable definitions. Industry, year, and country fixed effects are as indicated. Standard errors are clustered at the firm level. The *t*-statistics are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

	Severity		*Reach*		*Novelty*	
	(1)	(2)	(3)	(4)	(5)	(6)
Robotics Flow	10.286**		16.634**		10.688**	
	(2.170)		(2.265)		(2.257)	
Robotics Stock		3.358**		5.234**		3.412**
		(2.346)		(2.436)		(2.466)
Size	3.664***	3.659***	5.118***	5.116***	3.555***	3.553***
	(8.475)	(8.460)	(8.315)	(8.314)	(9.092)	(9.075)
Book_Market	-0.218	-0.225	-0.384	-0.394	-0.323	-0.329
	(-0.677)	(-0.701)	(-0.875)	(-0.903)	(-1.248)	(-1.279)
Leverage	-6.208***	-6.221***	-8.309***	-8.329***	-5.842***	-5.856***
	(-5.325)	(-5.340)	(-5.197)	(-5.213)	(-5.520)	(-5.536)
ROA	-1.885**	-1.912**	-1.817	-1.861	-1.774**	-1.802**
	(-2.432)	(-2.468)	(-1.544)	(-1.582)	(-2.405)	(-2.445)
Current Assets Ratio	1.958***	2.014***	3.194***	3.278***	2.072***	2.128***
	(3.033)	(3.105)	(3.434)	(3.500)	(3.407)	(3.480)
Sales	-0.970***	-0.957***	-1.541***	-1.525***	-0.959***	-0.948***
	(-4.096)	(-3.987)	(-4.403)	(-4.331)	(-4.412)	(-4.312)
Employees	1.370***	1.360***	1.870***	1.856***	1.407***	1.398***
	(6.226)	(6.161)	(5.970)	(5.919)	(6.807)	(6.748)
Inflation	6.530***	6.450***	9.336***	9.222***	7.451***	7.374***
	(2.619)	(2.593)	(2.613)	(2.587)	(3.240)	(3.209)
GDP per Capita	-2.871***	-2.892***	-3.630***	-3.661***	-2.889***	-2.909***
	(-5.449)	(-5.491)	(-5.136)	(-5.183)	(-6.202)	(-6.242)
GDP Growth Rate	0.008	0.010	0.019	0.023	0.013	0.016
	(0.300)	(0.415)	(0.525)	(0.657)	(0.672)	(0.827)
Patent per Capita	0.001**	0.001**	0.001*	0.001*	0.001**	0.001**
	(2.119)	(2.099)	(1.666)	(1.675)	(2.291)	(2.298)
Globalization Index	-0.029	-0.003	-0.014	0.028	-0.007	0.020
	(-0.520)	(-0.059)	(-0.176)	(0.349)	(-0.131)	(0.385)
Political Freedom Index	0.240	0.190	0.812	0.729	0.111	0.058
	(0.761)	(0.593)	(1.584)	(1.397)	(0.382)	(0.196)
Civil Liberties Index	0.105	0.130	0.415**	0.455**	0.134	0.160
	(0.729)	(0.888)	(2.000)	(2.148)	(1.057)	(1.234)
Constant	9.523	7.529	5.312	2.033	8.708	6.615
	(1.241)	(0.987)	(0.485)	(0.186)	(1.282)	(0.979)
Observations	63,473	63,473	63,473	63,473	63,473	63,473
Adjusted R-Squared	0.187	0.186	0.173	0.172	0.211	0.210
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5. IV 2SLS Regressions

This table shows the 2SLS regression results of the effect of robotics flow and stock on ESG incident measures using the international sample from 2007 to 2022. In columns (1) and (2), the dependent variables are *Robotics Flow* and *Robotics Stock* of firm *i* in year *t*. In columns (3) to (4), the dependent variables are *Number of Incidents* of firm *i* in year *t*, and the results are generated from negative binomial regressions. In columns (5) to (12), the dependent variables are *Current RRI*, *Peak RRI*, *Severity*, *Reach*, and *Novelty* of firm *i* in year *t*, and the results are generated from OLS regressions. All independent variables are calculated in year *t-1*. See Appendix A for variable definitions. Industry, year, and country fixed effects are as indicated. Standard errors are clustered at the firm level. The *t*-statistics are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

	First Stage		Second Stage											
	Robotics Flow	*Robotics Stock*	*Number of Incidents*		*Current RRI*		*Peak RRI*		*Severity*		*Reach*		*Novelty*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Fixed Broadband Subscription	0.001***	0.004***												
	(4.737)	(4.926)												
Aging	0.112**	0.171												
	(2.025)	(1.083)												
Robotics Flow (Predicted)			15.093***		33.006**		59.597**		42.051**		36.865		33.651**	
			(3.600)		(2.127)		(2.098)		(2.202)		(1.544)		(2.018)	
Robotics Stock (Predicted)				5.929***		12.910**		21.551*		19.404**		18.630*		16.672**
				(3.525)		(2.080)		(1.922)		(2.464)		(1.877)		(2.363)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473
Adjusted R-Squared	0.447	0.585			0.382	0.376	0.334	0.335	0.170	0.154	0.169	0.160	0.200	0.184
Ln (Alpha)			0.472***	0.472***										
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J p-value					0.92	0.70	0.26	0.16	0.16	0.24	0.12	0.17	0.05	0.09
F-stat for Excluded Instruments	20.83	17.89												
Cragg-Donald F-stat	71.69	59.18												
Kleibergen–Paap F-stat	20.83	17.89												
Nearest lower critical %	10%	15%												
Nearest lower critical value	19.93	11.59												
Kleibergen-Paap p-value	0.00	0.00												

Table 6. Incident Category

This table shows the regression results of the effect of robotics flow and stock on different ESG incident types, using the international sample from 2007 to 2022. Panel A shows the negative binomial regression results where the dependent variables are the number of environmental incidents of firm *i* in year *t* in columns (1) and (2), number of social incidents in columns (3) and (4), number of governance incidents in columns (5) and (6), and number of cross-cutting incidents in columns (7) and (8). Panel B presents the negative binomial regression coefficients in columns (2) and (3) and OLS regression coefficients in columns (4)–(9) of *Robotics Flow* and *Robotics Stock* by ESG incident issue. All independent variables are calculated in year *t-1*. See Appendix A for variable definitions. Industry, year, and country fixed effects are as indicated. Standard errors are clustered at the firm level. The *t*-statistics are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A. Pillar-Level Results: Environmental, Social, Governance, Cross-Cutting

	Environmental		*Social*		*Governance*		*Cross-Cutting*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robotics Flow	0.438*		0.369*		0.200		0.327	
	(1.713)		(1.717)		(0.885)		(1.619)	
Robotics Stock		0.327***		0.231**		0.114		0.089
		(2.676)		(2.548)		(1.265)		(1.056)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Issue-Level Results and Impact Dimensions

	ESG	*Number of Incidents*		*Severity*		*Reach*		*Novelty*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Positive Impact		Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
Local Pollution	E	0.484*	0.361***	0.138	0.089	0.129	0.078	0.104	0.076
Energy Management	E	3.038**	0.883*	0.009*	0.003**	0.017*	0.006*	0.017*	0.006**
Discrimination in Employment	S	0.481**	0.165*	-0.082	-0.034	-0.155	-0.063	-0.079	-0.032
Fraud	G	0.640***	0.212**	0.921**	0.263**	1.426**	0.425**	0.864**	0.247**
Product Health & Environmental Issues	Cross	0.353	-0.004	4.739***	1.358***	8.050***	2.320***	4.769***	1.339***
Supply Chain Issues	Cross	0.618**	0.235*	0.969*	0.293*	1.564*	0.475*	0.991*	0.293**
Violation of National Legislation	Cross	0.336	0.180**	2.087**	0.913**	3.230**	1.354**	2.005**	0.835**
Negative Impact		Flow	Stock	Flow	Stock	Flow	Stock	Flow	Stock
Controversial Products and Services	Cross	-0.665	-0.505***	-0.265***	-0.145***	-0.280***	-0.160***	-0.257***	-0.131***
Tax Optimization	G	0.006	0.001	-0.046***	-0.017**	-0.046**	-0.019**	-0.048***	-0.018***

Table 7. Heterogeneity Tests: Firm Level

This table shows the OLS regression results of firm-level mechanism tests using the international sample from 2007 to 2022. In Panel A, the dependent variables are *Current RRI*, *Peak RRI*, *Severity*, *Reach*, and *Novelty* of firm *i* in year *t*. *High Avg Sales Growth* is one if the average sales growth rate is above the country-year median, and zero otherwise. In Panel B, the dependent variables are *Current RRI*, *Severity*, *Reach*, and *Novelty* of firm *i* in year *t*. *High PPE Age* is one if the PPE age of firm i in year t is above the country-year median, and zero otherwise. In Panel C, the dependent variables are *Severity*, *Reach*, and *Novelty* of environmental incidents of firm *i* in year *t*. *Green Patent Filings* is the number of green patent filings of firm *i* in year *t*. *Green Patent Citations* is the number of forward five-year citations of green patents of firm *i* in year *t*. All independent variables are calculated in year *t-1*. See Appendix A for variable definitions. Industry, year, and country fixed effects are as indicated. Standard errors are clustered at the firm level. The t-statistics are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A. Growth Opportunities

	Current RRI		*Peak RRI*		*Severity*		*Reach*		*Novelty*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Robotics Flow	3.912***		2.776*		7.503		12.777		8.146	
	(2.764)		(1.652)		(1.421)		(1.544)		(1.557)	
Robotics Stock		1.452***		1.358**		2.497		4.004		2.644*
		(2.765)		(2.009)		(1.488)		(1.559)		(1.666)
High Avg Sales Growth	-0.917***	-0.917***	-1.683***	-1.683***	-0.417*	-0.456*	-0.298	-0.363	-0.407*	-0.440**
	(-7.825)	(-7.647)	(-9.179)	(-8.965)	(-1.681)	(-1.916)	(-0.742)	(-0.960)	(-1.734)	(-1.968)
Robotics Flow × *High Avg Sales Growth*	5.305***		6.168***		10.451***		16.614***		10.223***	
	(3.981)		(3.454)		(3.337)		(3.236)		(3.392)	
Robotics Stock × *High Avg Sales Growth*		1.176**		1.351**		2.856**		4.589**		2.731**
		(2.321)		(2.070)		(2.323)		(2.301)		(2.402)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,923	44,923	44,923	44,923	44,923	44,923	44,923	44,923	44,923	44,923
Adjusted R-Squared	0.426	0.426	0.363	0.363	0.208	0.208	0.193	0.192	0.232	0.231
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. Heterogeneity Tests: Firm Level (Continued)

Panel B. Automation Experience

	Current RRI		*Severity*		*Reach*		*Novelty*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robotics Flow	6.686***		13.663***		22.205***		13.874***	
	(3.961)		(2.802)		(2.908)		(2.899)	
Robotics Stock		2.261***		4.749***		7.618***		4.732***
		(4.075)		(3.172)		(3.300)		(3.316)
High PPE Age	-0.248*	-0.221*	-0.638**	-0.521**	-0.864**	-0.660*	-0.582**	-0.470**
	(-1.895)	(-1.654)	(-2.412)	(-2.036)	(-2.195)	(-1.751)	(-2.356)	(-1.961)
Robotics Flow × High PPE Age	-3.486*		-13.206***		-21.540***		-12.821***	
	(-1.669)		(-2.959)		(-2.796)		(-2.772)	
Robotics Stock × High PPE Age		-1.099		-4.385***		-7.378***		-4.244***
		(-1.618)		(-3.069)		(-3.144)		(-3.021)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	62,932	62,932	62,932	62,932	62,932	62,932	62,932	62,932
Adjusted R-Squared	0.407	0.407	0.188	0.188	0.174	0.174	0.212	0.212
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. Heterogeneity Tests: Firm Level (Continued)

Panel C. Green Innovation

	E		*E*		*E*		*E*		*E*		*E*	
	Severity		*Reach*		*Novelty*		*Severity*		*Reach*		*Novelty*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Robotics Flow	-0.112		-0.127		-0.078		-0.285		-0.313		-0.234	
	(-0.320)		(-0.312)		(-0.233)		(-0.796)		(-0.746)		(-0.683)	
Robotics Stock		0.006		-0.036		0.028		-0.030		-0.075		-0.005
		(0.029)		(-0.153)		(0.143)		(-0.135)		(-0.317)		(-0.026)
Green Patent Filings	0.022*	0.025*	0.023*	0.026*	0.019*	0.022*						
	(1.859)	(1.863)	(1.792)	(1.793)	(1.946)	(1.949)						
Robotics Flow × Green Patent Filings	-0.040**		-0.043**		-0.035**							
	(-2.079)		(-2.063)		(-2.154)							
Robotics Stock × Green Patent Filings		-0.012**		-0.013**		-0.011**						
		(-2.047)		(-2.010)		(-2.123)						
Green Patent Citations							0.002	0.002	0.002	0.002	0.002*	0.002*
							(1.567)	(1.594)	(1.547)	(1.574)	(1.659)	(1.683)
Robotics Flow × Green Patent Citations							-0.003*		-0.004*		-0.003*	
							(-1.738)		(-1.828)		(-1.772)	
Robotics Stock × Green Patent Citations								-0.001*		-0.001*		-0.001*
								(-1.768)		(-1.819)		(-1.813)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473
Adjusted R-Squared	0.072	0.072	0.068	0.068	0.082	0.083	0.071	0.071	0.067	0.067	0.081	0.081
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8. Heterogeneity Tests: Industry Level

This table shows the OLS regression results of industry-level mechanism tests using the international sample from 2007 to 2022. In Panel A, the dependent variables are *Current RRI*, *Peak RRI*, *Severity*, *Reach*, and *Novelty* of all incidents of firm *i* in year *t*. *Manufacturing* is one if the IFR industry code is not 90, and zero otherwise. In Panel B, the dependent variables are *Current RRI*, *Severity*, *Reach*, and *Novelty* of all incidents of firm *i* in year *t*. *High Labor Skill* is one if the labor skill measure of industry *j* (3-digit NAICS) in year *t* is above the country-year median, and zero otherwise. In Panel C, the dependent variables are *Current RRI*, *Peak RRI*, *Severity*, *Reach*, and *Novelty* of all incidents of firm *i* in year *t*. *High Top 4 Concentration Ratio* is one if the Top 4 Concentration Ratio of industry *j* (3-digit NAICS) in year *t* is above the country-year median, and zero otherwise. All independent variables are calculated in year t-1. See Appendix A for variable definitions. Industry, year, and country fixed effects are as indicated. Standard errors are clustered at the firm level. The t-statistics are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A. Manufacturing

	Current RRI		*Peak RRI*		*Severity*		*Reach*		*Novelty*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Robotics Flow	-16.851		-41.306**		-23.502*		-33.445*		-24.590*	
	(-1.382)		(-2.042)		(-1.815)		(-1.958)		(-1.923)	
Robotics Stock		-8.363		-17.396*		-15.874**		-21.571**		-15.774**
		(-1.385)		(-1.790)		(-2.159)		(-2.176)		(-2.191)
Manufacturing	0.839***	0.805***	1.229***	1.200***	0.930***	0.821**	0.714	0.520	0.813***	0.702**
	(4.416)	(4.189)	(4.363)	(4.225)	(2.819)	(2.452)	(1.566)	(1.125)	(2.687)	(2.280)
Robotics Flow × Manufacturing	22.254*		46.089**		34.872***		53.731***		36.566***	
	(1.823)		(2.277)		(2.653)		(3.078)		(2.810)	
Robotics Stock × Manufacturing		9.758		18.648*		19.190***		27.583***		19.247***
		(1.618)		(1.921)		(2.605)		(2.775)		(2.665)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473
Adjusted R-Squared	0.394	0.393	0.363	0.363	0.178	0.178	0.165	0.164	0.202	0.201
Industry FE	No	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8. Heterogeneity Tests: Industry Level (Continued)

Panel B. Labor Skill

	Current RRI		*Severity*		*Reach*		*Novelty*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robotics Flow	2.209		-5.306		-9.733**		-4.944	
	(1.137)		(-1.608)		(-1.969)		(-1.585)	
Robotics Stock		0.434		-1.122		-1.945		-0.958
		(0.785)		(-1.199)		(-1.455)		(-1.083)
High Labor Skill	-0.451***	-0.507***	-0.619**	-0.750**	-0.633*	-0.833**	-0.587**	-0.710***
	(-2.790)	(-3.092)	(-2.034)	(-2.473)	(-1.669)	(-2.180)	(-2.182)	(-2.624)
Robotics Flow × High Labor Skill	3.937*		17.701***		30.085***		17.722***	
	(1.879)		(3.316)		(3.601)		(3.392)	
Robotics Stock × High Labor Skill		1.862***		5.820***		9.415***		5.660***
		(3.025)		(3.574)		(3.819)		(3.571)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,217	61,217	61,217	61,217	61,217	61,217	61,217	61,217
Adjusted R-Squared	0.402	0.402	0.199	0.199	0.192	0.192	0.227	0.227
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8. Heterogeneity Tests: Industry Level (Continued)

Panel C. Competition

	Current RRI		*Peak RRI*		*Severity*		*Reach*		*Novelty*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Robotics Flow	9.230***		8.877***		21.080**		31.091**		21.569***	
	(5.196)		(4.736)		(2.529)		(2.436)		(2.608)	
Robotics Stock		2.533***		2.839***		5.149**		7.389**		5.229**
		(3.858)		(3.841)		(2.250)		(2.113)		(2.278)
High Top 4 Concentration Ratio	0.877***	0.879***	1.028***	1.036***	1.479***	1.469***	2.121***	2.087***	1.461***	1.454***
	(5.854)	(5.722)	(4.844)	(4.771)	(3.950)	(3.860)	(4.207)	(4.071)	(4.290)	(4.186)
Robotics Flow × *High Top 4 Concentration Ratio*	-5.108**		-4.794**		-15.464**		-20.759*		-15.579**	
	(-2.385)		(-1.985)		(-2.006)		(-1.743)		(-2.031)	
Robotics Stock × *High Top 4 Concentration Ratio*		-1.055		-1.131		-2.916		-3.557		-2.955
		(-1.365)		(-1.255)		(-1.321)		(-1.051)		(-1.336)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473
Adjusted R-Squared	0.407	0.407	0.373	0.373	0.190	0.189	0.176	0.174	0.214	0.213
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9. Heterogeneity Tests: Country Level

This table shows the OLS regression results of country-level mechanism tests using the international sample from 2007 to 2022. In Panel A (B), the dependent variables are *Severity*, *Reach*, and *Novelty* of environmental (social) incidents of firm i in year t. *Environmental Policy Stringency Index* is the OECD Environmental Policy Stringency Index of country c in year t. *Employment Protection Legislation Index* is the Collective Dismissal component of the OECD Employment Protection Legislation Index of country c in year t. In Panel C, the dependent variables are *Current RRI*, *Peak RRI*, *Severity*, *Reach*, and *Novelty* of all incidents of firm i in year t. *Social Trust* is the country-level social trust measure constructed following Ahern et al. (2015), Guiso et al. (2004), and Pevzner et al. (2015). All independent variables are calculated in year *t-1*. See Appendix A for variable definitions. Industry, year, and country fixed effects are as indicated. Standard errors are clustered at the firm level. The t-statistics are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A. Environmental Policy Stringency

	E *Severity*		*E* *Reach*		*E* *Novelty*	
	(1)	(2)	(3)	(4)	(5)	(6)
Robotics Flow	1.887*		1.742		1.735*	
	(1.701)		(1.443)		(1.751)	
Robotics Stock		0.789*		0.782*		0.752**
		(1.926)		(1.800)		(2.137)
Environmental Policy Stringency Index	-0.128**	-0.117*	-0.096	-0.084	-0.108**	-0.097*
	(-2.114)	(-1.925)	(-1.462)	(-1.277)	(-2.023)	(-1.800)
Robotics Flow × *Environmental Policy Stringency Index*	-0.957**		-0.973**		-0.874**	
	(-2.457)		(-2.362)		(-2.453)	
Robotics Stock × *Environmental Policy Stringency Index*		-0.285**		-0.307**		-0.272***
		(-2.417)		(-2.445)		(-2.594)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,174	31,174	31,174	31,174	31,174	31,174
Adjusted R-Squared	0.079	0.079	0.079	0.079	0.093	0.093
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 9. Heterogeneity Tests: Country Level (Continued)

Panel B. Employment Protection Legislation

	S *Severity*		*S* *Reach*		*S* *Novelty*	
	(1)	(2)	(3)	(4)	(5)	(6)
Robotics Flow	8.893***		11.706**		8.449***	
	(2.652)		(2.568)		(2.601)	
Robotics Stock		2.792**		3.912**		2.645**
		(2.293)		(2.240)		(2.261)
Employment Protection Legislation Index	-0.285	-0.246	-0.174	-0.115	-0.227	-0.190
	(-0.641)	(-0.555)	(-0.407)	(-0.271)	(-0.613)	(-0.515)
Robotics Flow × *Employment Protection Legislation Index*	-2.743***		-3.568**		-2.569**	
	(-2.652)		(-2.573)		(-2.548)	
Robotics Stock × *Employment Protection Legislation Index*		-0.766**		-1.090**		-0.719**
		(-2.091)		(-2.129)		(-2.050)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,058	46,058	46,058	46,058	46,058	46,058
Adjusted R-Squared	0.091	0.091	0.082	0.082	0.101	0.101
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 9. Heterogeneity Tests: Country Level (Continued)

Panel C. Social Trust

	Current RRI		*Peak RRI*		*Severity*		*Reach*		*Novelty*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Robotics Flow	19.747***		21.343***		40.268***		66.803***		41.229***	
	(4.852)		(4.621)		(3.529)		(3.669)		(3.656)	
Robotics Stock		3.739***		4.655***		8.896**		14.086***		8.518***
		(3.330)		(3.333)		(2.494)		(2.752)		(2.789)
Social Trust	2.388*	2.359*	2.276	2.299	5.336***	5.630***	7.253***	7.663***	5.549***	5.739***
	(1.754)	(1.716)	(0.920)	(0.924)	(3.024)	(3.131)	(3.075)	(3.214)	(3.308)	(3.400)
Robotics Flow × *Social Trust*	-26.947***		-30.173***		-58.953***		-99.065***		-59.949***	
	(-3.990)		(-3.668)		(-3.521)		(-3.664)		(-3.637)	
Robotics Stock × *Social Trust*		-3.807*		-5.273*		-12.493*		-19.987**		-11.400*
		(-1.772)		(-1.903)		(-1.763)		(-1.961)		(-1.851)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	55,616	55,616	55,616	55,616	55,616	55,616	55,616	55,616	55,616	55,616
Adjusted R-Squared	0.401	0.400	0.370	0.370	0.184	0.183	0.168	0.166	0.209	0.206
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10. Robustness Tests: Firm-Level AI Measure

This table shows the regression results using firm-level AI measures. In Panel A, the independent variables are *AI Employees* and *AI Knowledge Employees* developed by Babina et al. (2024). The dependent variables are *Number of Incidents*, *Current RRI*, *Peak RRI*, *Severity*, *Reach*, and *Novelty* of all incidents of firm *i* in year *t*. In Panel B, the independent variable is *AI Financial Reporting* developed by Blankespoor et al. (2026). The dependent variables are *Severity*, *Reach*, and *Novelty* of all incidents of firm *i* in year *t*. All independent variables are calculated in year *t-1*. See Appendix A for variable definitions. Industry, year, and country fixed effects are as indicated. Standard errors are clustered at the firm level. The *t*-statistics are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A. AI Workforce Measures by Babina et al. (2024)

	Number of Incidents		*Current RRI*		*Peak RRI*		*Severity*		*Reach*		*Novelty*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AI Employees	19.705**		70.398***		80.965**		189.797**		366.476**		201.261**	
	(2.364)		(2.635)		(1.992)		(2.236)		(2.379)		(2.403)	
AI Knowledge Employees		1.129**		7.231**		12.011***		2.380		6.679		3.710
		(2.125)		(2.553)		(4.340)		(0.379)		(0.574)		(0.564)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,769	37,769	37,768	37,740	37,768	37,740	37,768	37,740	37,768	37,740	37,768	37,740
Adjusted R-Squared			0.480	0.479	0.438	0.440	0.264	0.261	0.232	0.233	0.284	0.281
Industry FE (SIC2)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. AI in Financial Reporting by Blankespoor et al. (2026)

	Severity (1)	*Reach* (2)	*Novelty* (3)
AI Financial Reporting	0.905*	1.674*	0.964*
	(1.766)	(1.810)	(1.879)
Firm-Level Controls	Yes	Yes	Yes
Country-Level Controls	No	No	No
Observations	13,235	13,235	13,235
Adjusted R-Squared	0.220	0.174	0.234
Industry FE (SIC2)	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country FE	No	No	No

Table 11. Robustness Tests: Additional Identification Strategies

This table shows the robustness tests of the effect of robotics flow and stock on *Current RRI*, using the international sample from 2007 to 2022. Panel A reports the coefficient stability results following Oster (2019). The Oster (2019) Identified Set reports the stability interval of the coefficient estimates when comparing specifications in column (1) with those in columns (2) and (3) or specifications in column (4) with those in columns (5) and (6). Panel B reports the heteroscedasticity-based IV regressions following Lewbel (2012). Columns (1) and (2) report the second-stage result, where *Robotics Flow* and *Robotics Stock* are predicted using the Lewbel (2012) approach in the first stage. All independent variables are calculated in year *t-1*. See Appendix A for variable definitions. Industry, year, and country fixed effects are as indicated. Standard errors are clustered at the firm level. The *t*-statistics are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A. Coefficient Stability Using Oster (2019)

	Current RRI					
	(1)	(2)	(3)	(4)	(5)	(6)
Robotics Flow	9.433***	5.630***	5.759***			
	(4.147)	(3.969)	(4.107)			
Robotics Stock				3.473***	1.834***	1.919***
				(4.499)	(3.806)	(3.987)
Oster Identified Set (δ=1; Rmax=min(2.2R,1))		[5.630,10.236]	[5.759,10.209]		[1.834, 3.820]	[1.919, 3.802]
Includes Zero?	No	No	No	No	No	No
Firm-Level Controls	No	Yes	Yes	No	Yes	Yes
Country-Level Controls	No	No	Yes	No	No	Yes
Observations	63,473	63,473	63,473	63,473	63,473	63,473
Adjusted R-Squared	0.096	0.404	0.406	0.096	0.404	0.406
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Heteroscedasticity-based IV Regressions Following Lewbel (2012)

	Current RRI	
	(1)	(2)
Robotics Flow (Predicted)	3.213**	
	(2.123)	
Robotics Stock (Predicted)		2.141***
		(2.810)
Firm-Level Controls	Yes	Yes
Country-Level Controls	Yes	Yes
Observations	63,473	63,473
Adjusted R-Squared	0.344	0.344
Industry FE	Yes	Yes
Year FE	Yes	Yes
Country FE	Yes	Yes
First-Stage Breusch–Pagan	$p<0.001$	$p<0.001$
First-Stage F	25.01	13.31
Kleibergen–Paap Under-Identification	$p<0.001$	$p<0.001$
Hansen J	$p=0.069$	$p=0.174$

Table 12. Robustness Tests: Alternative Instrumental Variable (EURO5)

This table shows the alternative 2SLS regression results of the effect of robotics flow on the ESG incident measures using the international sample from 2007 to 2022, excluding companies headquartered in Denmark, Finland, France, Italy, and Sweden (EURO5). The first-stage results in column (1) are generated by the OLS regressions. The second-stage results in column (2) are generated by the negative binomial regressions, and columns (3)-(7) are generated by the OLS regressions. In column (1), the dependent variable is *Robotics Flow* of firm *i* in year *t*. In columns (2)–(7), the dependent variables are *Number of Incidents*, *Current RRI*, *Peak RRI*, *Severity*, *Reach*, and *Novelty*, respectively. All independent variables are calculated in year *t-1*. See Appendix A for variable definitions. Industry, year, and country fixed effects are as indicated. Standard errors are clustered at the firm level. The *t*-statistics are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

	First Stage	Second Stage					
	Robotics Flow	*Number of Incidents*	*Current RRI*	*Peak RRI*	*Severity*	*Reach*	*Novelty*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EURO5 Robotics Flow	5.9e-05***						
	(8.589)						
Robotics Flow (Predicted)		15.137***	43.052***	104.690***	46.947***	52.860**	44.268***
		(5.332)	(3.832)	(4.766)	(2.867)	(2.188)	(3.017)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58,670	58,670	58,670	58,670	58,670	58,670	58,670
Adjusted R-Squared	0.454		0.354	0.234	0.160	0.158	0.183
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 13. Robustness Tests: Cumulative Abnormal Returns Analysis

This table shows the OLS regression results of the effect of robotics flow and stock on shareholder returns around incidents using the international sample from 2007 to 2022. The dependent variables are the cumulative abnormal returns (*CAR*) over the event window [t_1,t_2]. In columns (1)–(4), CARs are around the dates when the RRI reaches the peak over the past two years and the peak RRI is greater than 50. In columns (5)–(8), CARs are around the incidents that are related to ten or more countries. All independent variables are calculated in year *t*-1. See Appendix A for variable definitions. Industry, year, and country fixed effects are as indicated. Standard errors are clustered at the firm level. The *t*-statistics are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

	Peak RRI >= 50				Incident Impacts >= 10 Countries			
	CAR[-1,5]		CAR[-1,10]		CAR[-1,5]		CAR[-1,10]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robotics Flow	-0.029*		-0.037*		-0.026**		-0.023**	
	(-1.756)		(-1.706)		(-2.445)		(-2.099)	
Robotics Stock		-0.020***		-0.026**		-0.005		-0.007
		(-2.824)		(-2.518)		(-0.892)		(-1.185)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	658	658	658	658	3,155	3,155	3,155	3,155
Adjusted R-Squared	0.044	0.047	0.080	0.084	0.020	0.020	0.029	0.029
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Figure 1. ESG Incident Risk by Industry

The figure reports the average ESG risk index by industry, measured by the mean value of *Current RRI* across all firm-year observations in the sample. Industries are sorted in descending order of average risk. Data are aggregated at the industry level, and the bar chart is based on unweighted means. Darker shades indicate higher *Current RRI*.

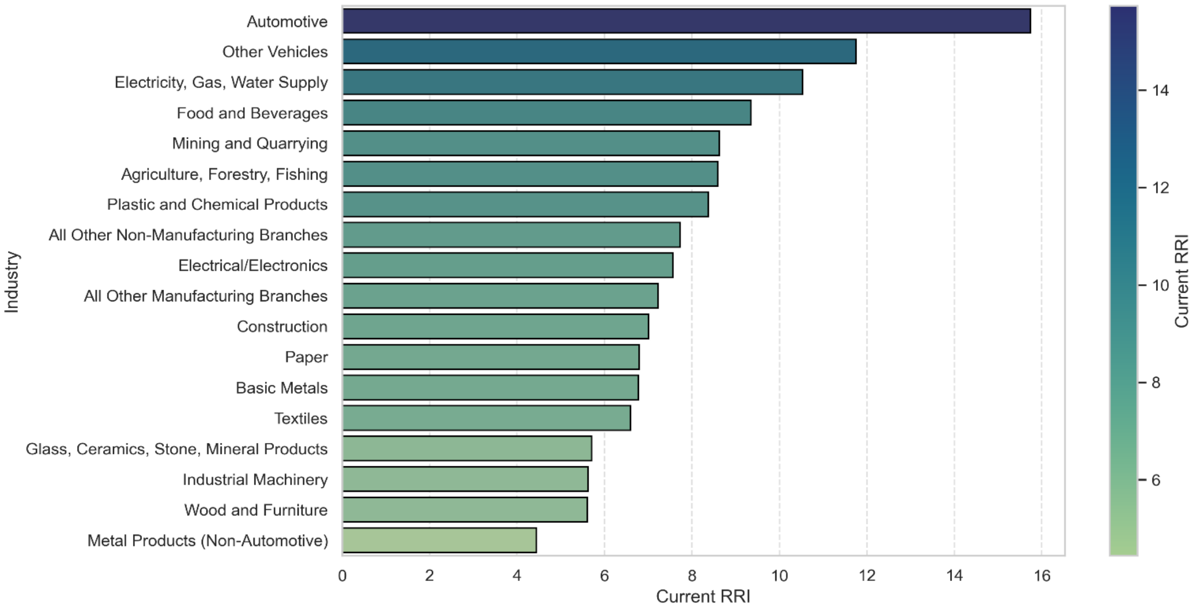


Figure 2. ESG Incident Risk by Country

The figure reports the average ESG risk index by country, measured by the mean value of *Current RRI* across all firm-year observations in the sample. Countries are sorted in descending order of average risk. Data are aggregated at the country level, and the bar chart is based on unweighted means. Darker shades indicate higher *Current RRI*.

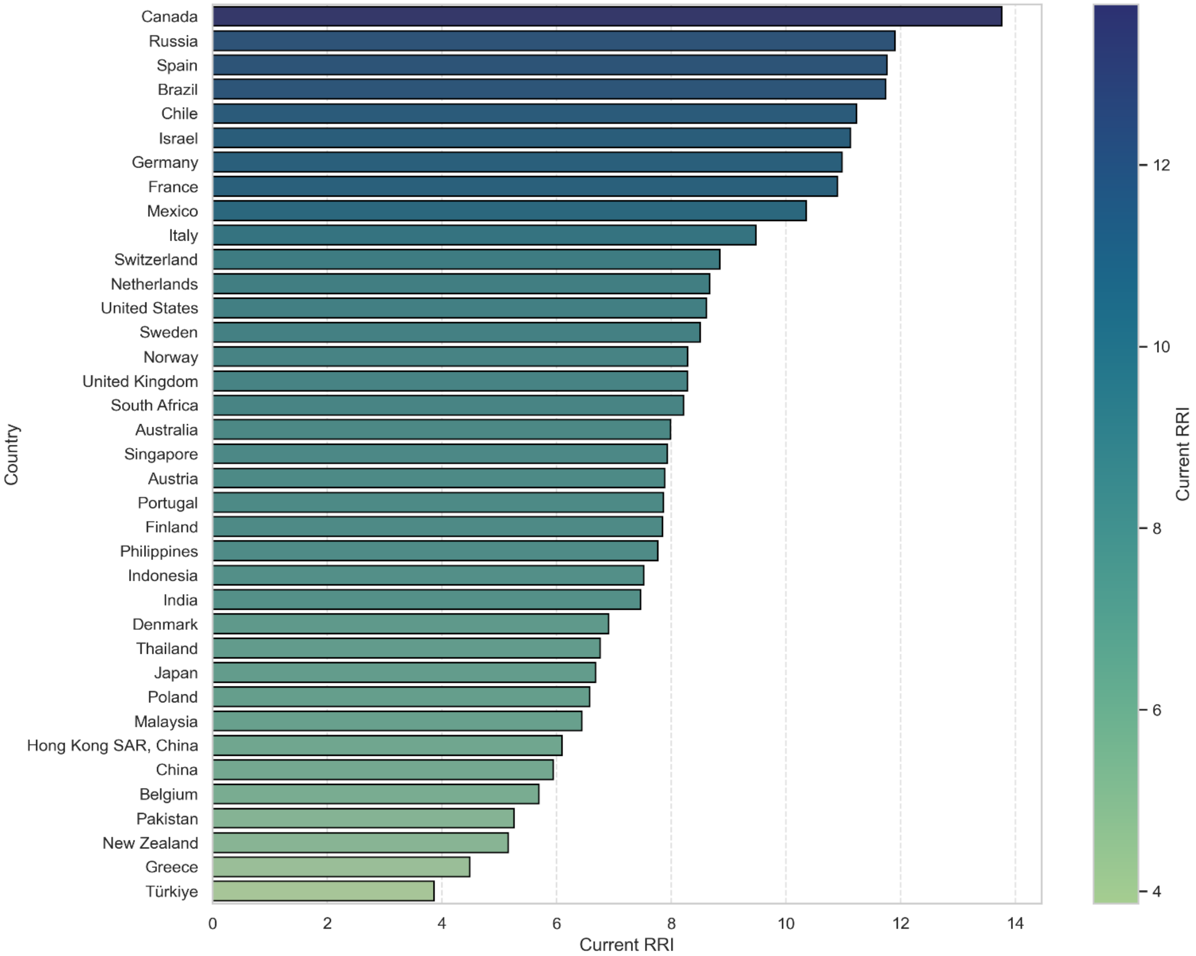


Figure 3. Correlation between ESG Incident Risk and Robotics Adoption by Industry

This figure displays Pearson correlation coefficients between the firm-level *Robotics Flow* and *Current RRI*, computed by industry. Industries are sorted in descending order based on correlation magnitude. Colors indicate the direction and strength of the correlations, with warmer colors representing positive values, cooler colors representing negative values, and darker shades indicating larger absolute magnitudes. Industries with the highest and lowest values are annotated for reference.

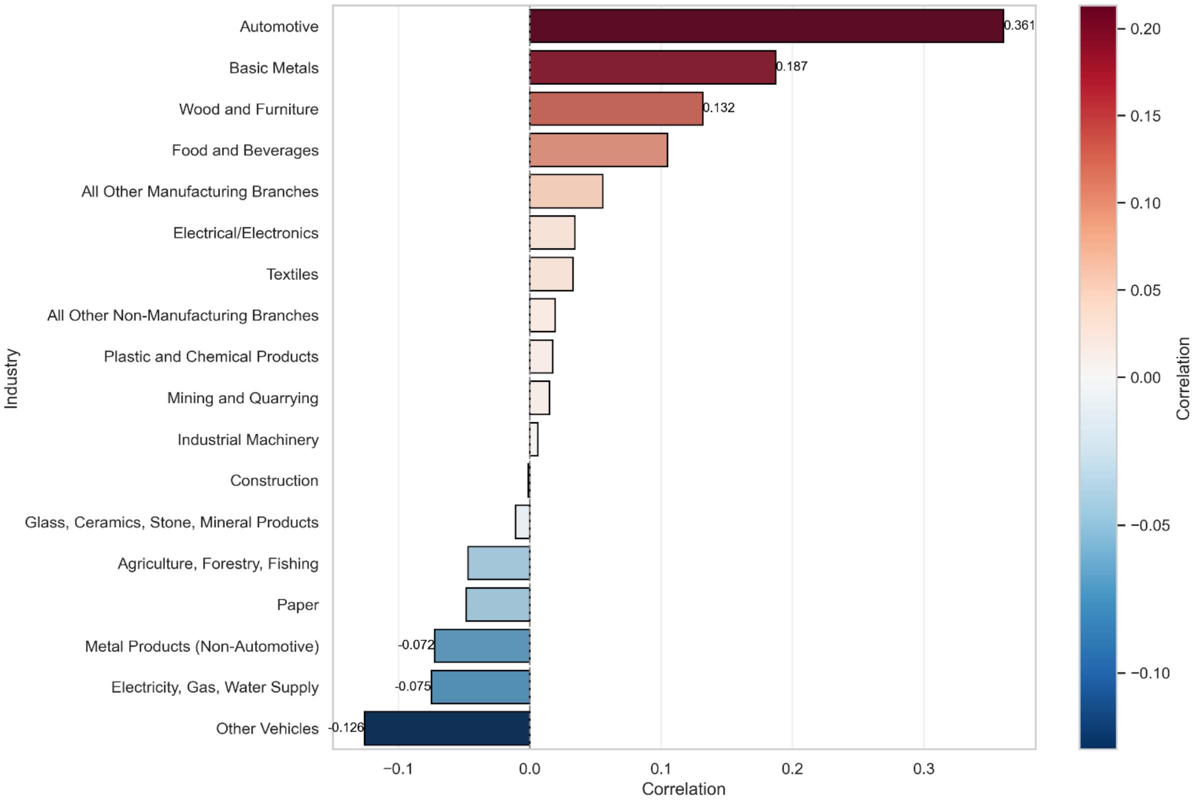


Figure 4. Correlation between ESG Incident Risk and Robotics Adoption by Country

This figure reports Pearson correlation coefficients between firm-level *Robotics Flow* and *Current RRI*, computed by country. Countries are sorted in descending order based on correlation magnitude. Colors indicate the direction and strength of the correlations, with warmer colors representing positive values, cooler colors representing negative values, and darker shades indicating larger absolute magnitudes. Countries with the highest and lowest values are annotated for reference.

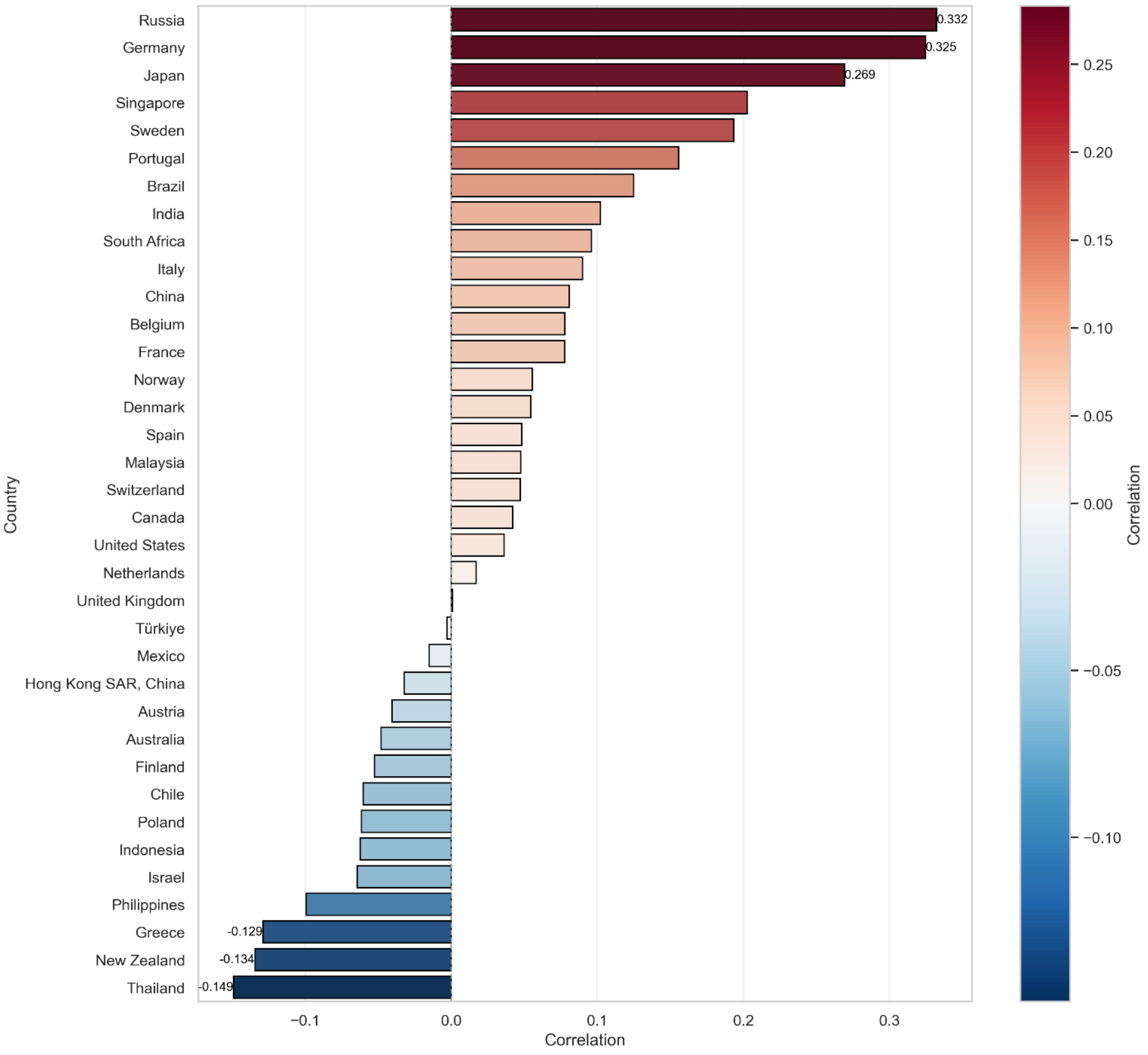


Figure 5. Temporal Dynamics of ESG Incident Risk and Robotics Adoption by Industry

This figure presents the time series evolution of the average of *Current RRI* and *Robotics Flow* by industry. The industry-year aggregates are then min-max normalized within each industry to facilitate within-industry comparison over time, regardless of level differences in raw metrics. The black solid line depicts normalized *Current RRI*, and the red dashed line shows normalized *Robotics Flow*. The "All Industries" panel presents the full-sample trend, computed by averaging across all firms in a given year.

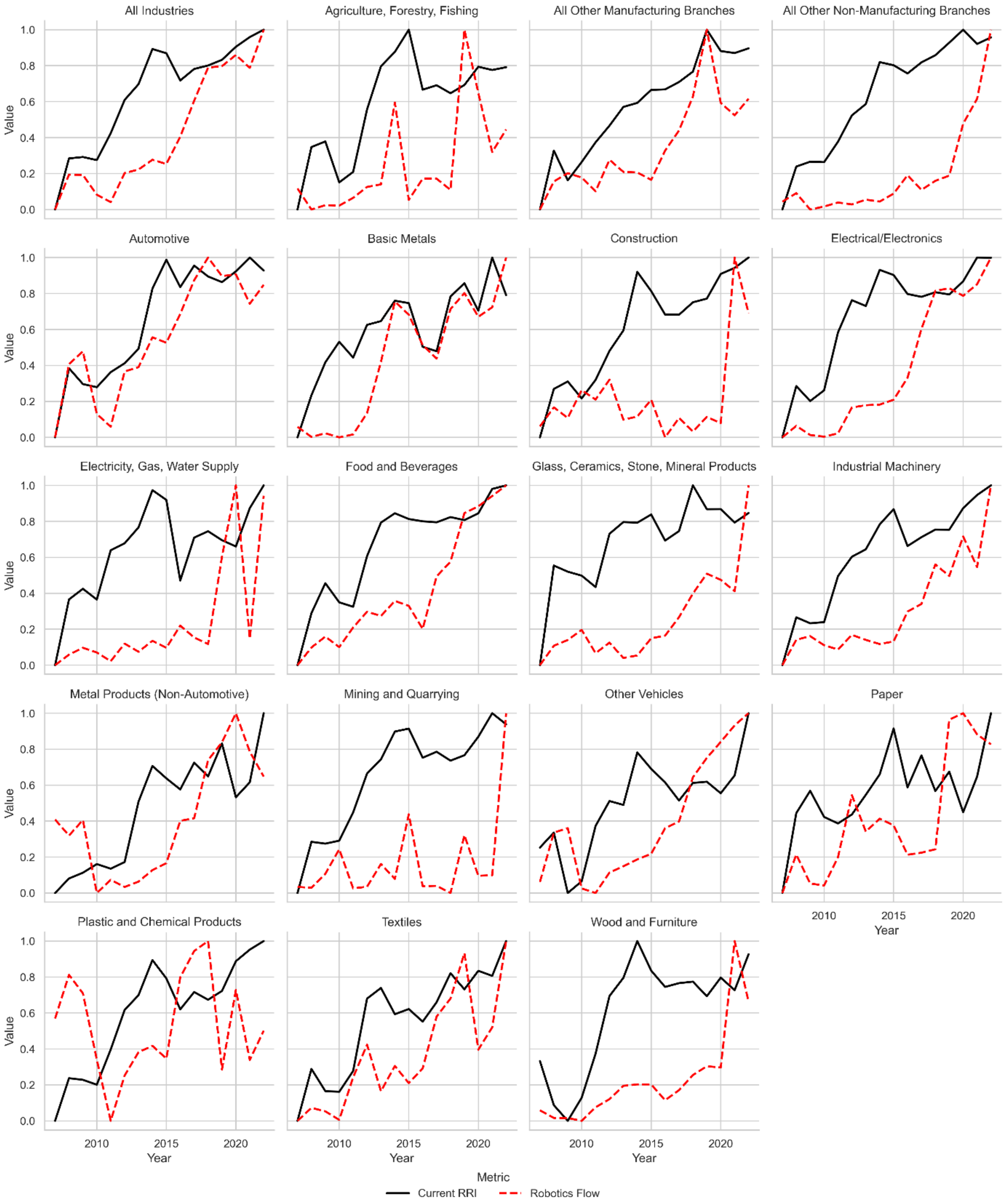


Figure 6. Temporal Dynamics of ESG Incident Risk and Robotics Adoption by Region

This figure presents the time series evolution of the average of *Current RRI* and *Robotics Flow* by region. The region-year aggregates are then min-max normalized within each region to facilitate within-region comparison over time, regardless of level differences in raw metrics. The black solid line depicts normalized C*urrent RRI*, and the red dashed line shows normalized *Robotics Flow*. The "All Continents" panel presents the full-sample trend, computed by averaging across all firms in a given year.

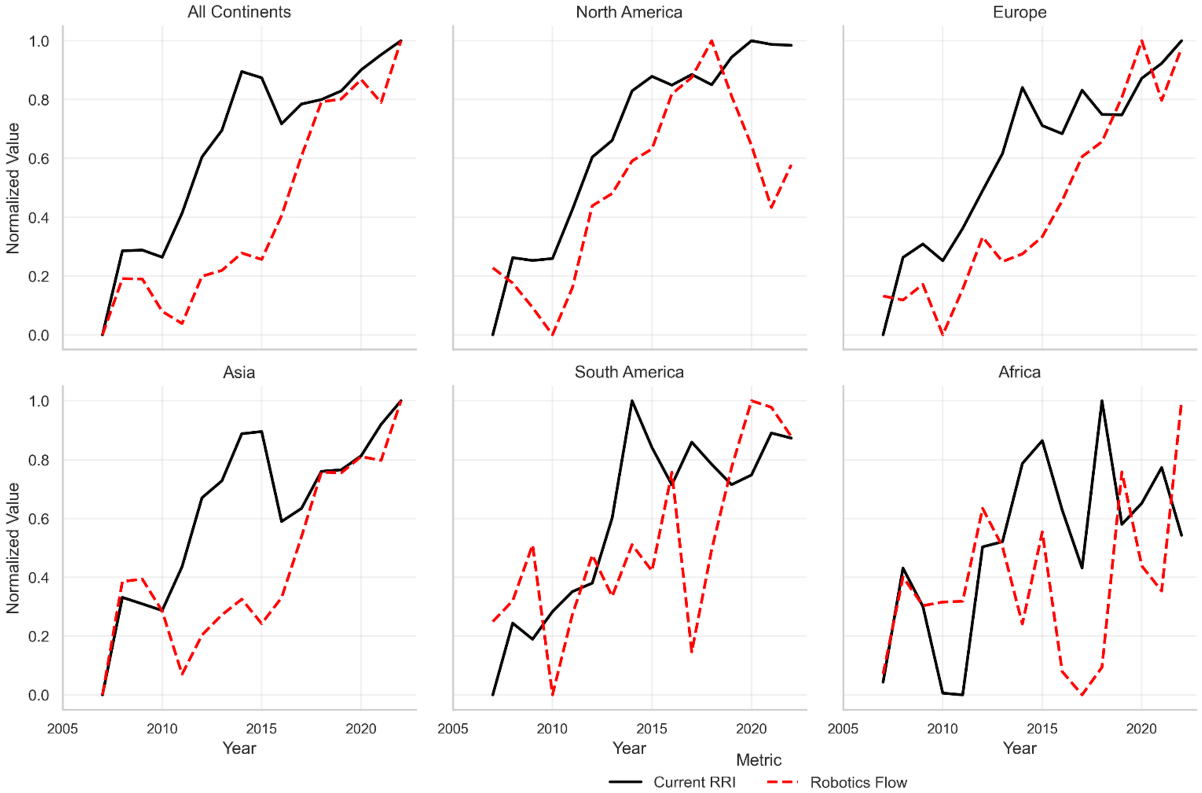
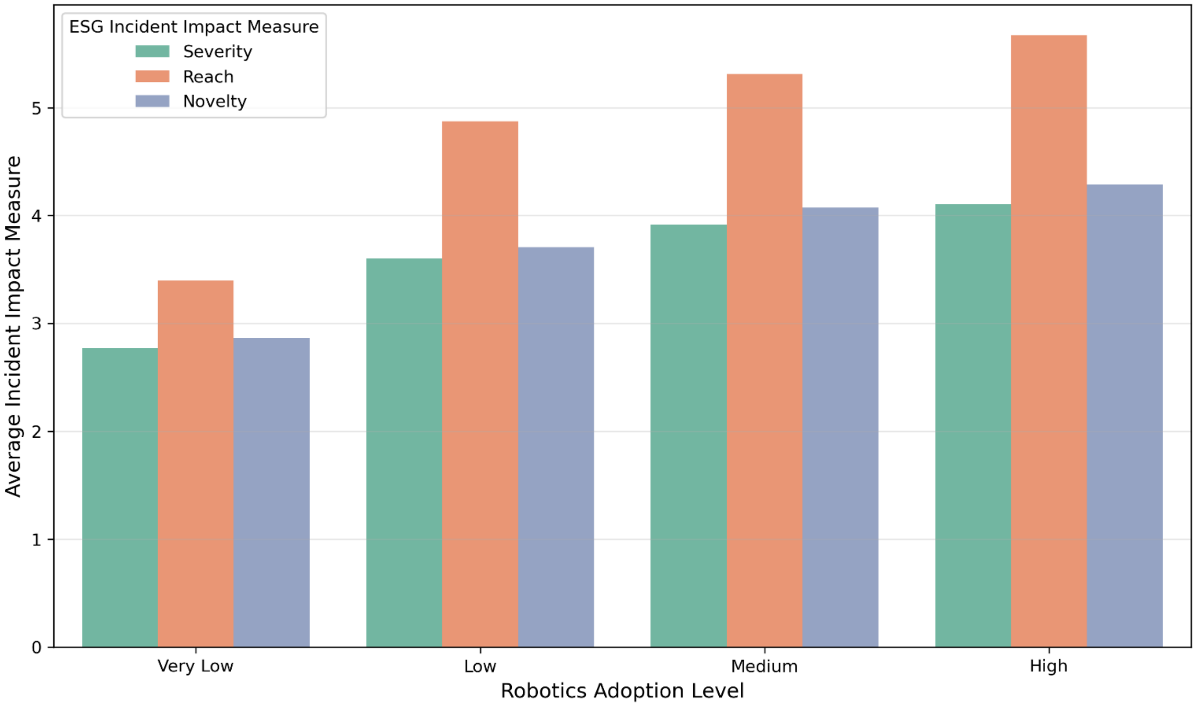


Figure 7. ESG Incident Severity, Reach, and Novelty by Robotics Quartile

This figure displays the average values of three ESG incident impact measures—*Severity*, *Reach*, and *Novelty*—across quartiles of firm-level robotics adoption. Firms are ranked based on their robotics flow and divided into four equally sized groups labeled "Very Low," "Low," "Medium," or "High" adoption. Within each quartile, the mean value of each ESG impact measure is computed across all firm-year observations.



Appendix A. Variable Definitions

Variable Name	Definition	Data Source
Robotics Flow/Stock V1	Natural logarithm of one plus IFR industry-level robotics flow or stock × firm share of capital intensity in the country-industry-year cohort. Capital intensity is PP&E / sales.	IFR, Compustat
Robotics Flow/Stock V2	Natural logarithm of one plus IFR industry-level robotics flow or stock × firm share of capital intensity in the country-industry-year cohort. Capital intensity is CapEx / sales.	IFR, Compustat
Robotics Flow/Stock V3	Natural logarithm of one plus IFR industry-level robotics flow or stock × firm share of capital intensity in the country-industry-year cohort. Capital intensity is PP&E / employees.	IFR, Compustat
Number of Incidents	Number of ESG incidents by firm and year.	RepRisk
Current RRI	Annual average of daily current RRI. Daily current RRI reflects current level of media and stakeholder attention to ESG issues in a company and measures reputational ESG exposure.	RepRisk
Peak RRI	Annual average of daily peak RRI. Daily peak RRI denotes highest level of current RRI over past two years.	RepRisk
Trend RRI	Annual average of daily trend RRI. Daily trend RRI denotes change in current RRI over past 30 days.	RepRisk
Severity	Sum of incident severity by firm and year. Defined by RepRisk, severity of incident is a function of its consequences with respect to ESG issues, extent of its impact, and its type, where 1 = less severe, 2 = severe, and 3 = very severe.	RepRisk
Reach	Sum of incident reach by firm and year. Defined by RepRisk, reach of incident measures reach of information source according to its readership and circulation, where 1 = limited reach, 2 = medium reach, and 3 = high reach.	RepRisk
Novelty	Sum of incident novelty by firm and year. Defined by RepRisk, novelty of incident measures novelty of issues addressed for criticized company (i.e., if this is first time company is exposed to issue), where 1 = reoccurring issue and 2 = new issue.	RepRisk
Environmental	Number of environmental incidents by firm and year.	RepRisk
Social	Number of social incidents by firm and year.	RepRisk
Governance	Number of governance incidents by firm and year.	RepRisk
Cross-Cutting	Number of cross-cutting incidents by firm and year.	RepRisk
Size	Natural logarithm of total assets in $ millions.	Compustat
Book_Market	Book value to market value of equity.	Compustat
Leverage	Leverage ratio, defined as the ratio of long-term debt over total assets.	Compustat
ROA	Net income divided by total assets.	Compustat
Current Assets Ratio	Current assets divided by total assets.	Compustat
Sales	Natural logarithm of total sales in $ millions.	Compustat
Employees	Natural logarithm of the number of employees in thousands.	Compustat
Inflation	Realized inflation rate by country and year.	IMF

GDP per Capita	Natural logarithm of gross domestic product per capita in \$ thousands by country and year.	IMF
GDP Growth Rate	Annual percentage growth rate of GDP at market prices, based on constant local currency. Aggregates are based on constant 2015 prices, expressed in \$.	World Bank
Patent per Capita	Annual patent applications per million people by country and year.	World Bank
Globalization Index	Index of economic, social, and political dimensions of globalization by country and year, ranging from 0 to 100, where higher values indicate a greater degree of global integration.	KOF Swiss Economic Institute
Political Freedom Index	Index of degree of political rights by country and year, ranging from 1 (most politically free) to 7 (least politically free).	Freedom House Freedom in the World (FIW)
Civil Liberties Index	Index of extent to which citizens enjoy civil liberties by country and year, ranging from 0 (fewest liberties) to 10 (most liberties).	Economist Intelligence Unit
Fixed Broadband Subscription	Number of fixed internet broadband subscriptions per 100 inhabitants, reported by the International Telecommunication Union.	International Telecommunication Union
Aging	Old-age share of total dependency burden by country and year, defined as the ratio of the population aged 65 and above to the total dependent population (ages 0–14 and 65+).	World Bank
High Avg Sales Growth	Equals one if the average sales growth rate is above the country-year median, and zero otherwise. Average sales growth rate is computed as the average of the annual sales growth rates from year t-3 to year t.	Compustat
High PPE Age	Equals one if PPE age of firm is above the country-year median, and zero otherwise. PPE age is accumulated depreciation divided by sum of gross PP&E and capital expenditures.	Compustat
Green Patent Filings	Number of green patents that a firm files in a year.	University of Virginia Global Corporate Patent Dataset
Green Patent Citations	Number of citations of green patents a firm accumulates in five years following the filing year.	University of Virginia Global Corporate Patent Dataset
Environmental Policy Stringency Index	OECD Environmental Policy Stringency Index by country and year. Stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behavior. The index ranges from 0 (not stringent) to 6 (highest degree of stringency).	OECD
Employment Protection Legislation Index	Collective Dismissal component of OECD Employment Protection Legislation Index by country and year. The index ranges from 0 (no restrictions) to 6 (very strict regulation).	OECD

Social Trust	Country-level social trust measure constructed following Ahern et al. (2015), Guiso et al. (2004), and Pevzner et al. (2015). We use the standard generalized-trust question, "Can most people be trusted?" in the surveys and code affirmative responses as equal to one, and zero otherwise. Country-level trust is the average response for each country and survey wave. The surveys are fielded in seven multi-year waves (1981–1984, 1990–1994, 1995–1998, 1999–2004, 2005–2009, 2010–2014, and 2017–2022). A higher value indicates stronger social trust.	World Values Survey, European Values Study
Manufacturing	Equals one if the IFR industry code is not 90, and zero otherwise.	IFR
High Labor Skill	*Equals one if the labor skill measure of industry j (3-digit NAICS) in year t is above the country-year median, and zero otherwise. Labor skill measure is obtained from Belo et al. (2017) and defined as the percentage of workers that work on occupations that require a high level of training and preparation. The measure is matched to firm-level data using 3-digit NAICS industry codes. For years after 2013, the measure is held constant at its 2013 level.*	Belo et al. (2017)
High Top 4 Concentration Ratio	*Equals one if the Top 4 Concentration Ratio of industry j (3-digit NAICS) in year t is above the country-year median, and zero otherwise. Top 4 Concentration Ratio is computed as the sum of market shares of the four largest firms in an industry-country-year, where market share is defined as a firm's annual sales divided by total industry sales in the same country-year.*	Compustat
AI Employees	The share of a firm's workforce with AI-specific skills by firm and year, developed by Babina et al. (2024). It captures workers directly involved in building, training, and deploying AI systems.	Babina et al. (2024)
AI Knowledge Employees	The share of a firm's workforce with broader AI-related knowledge by firm and year, developed by Babina et al. (2024). It captures workers who have AI-adjacent knowledge.	Babina et al. (2024)
AI Financial Reporting	Natural logarithm of one plus the average of four Gen AI measures by firm and year, developed by Blankespoor et al. (2026). Four measures include GenAI use scores in annual report Item 1A (Risk Factors), annual report Item 7 (Management Discussion and Analysis), conference calls, and press releases.	Blankespoor et al. (2026)
EURO5 Robotics Flow/Stock	Average of industry-year robotics flow and stock in Denmark, Finland, France, Italy, and Sweden (EURO5).	IFR
CAR[t1, t2]	Cumulative abnormal returns over the event window [t1,t2], where daily abnormal returns are computed as market-adjusted returns, defined as the difference between the stock return and the corresponding market index return.	Datastream

Internet Appendix

When Automation Meets Accountability: International Evidence from Robotics Adoption and ESG Incidents

Internet Appendix A

Theoretical Framework

This section develops a stylized reduced-form framework to organize our empirical predictions about automation and ESG incident risk. The purpose of the framework is not to provide a structural task-assignment model of automation. Instead, we use a parsimonious risk-production framework, informed by the task-based automation literature, to clarify why automation can increase firms' exposure to realized ESG incidents and why this effect should vary across firm, industry, and country characteristics.

The task-based literature suggests that automation reallocates tasks between labor and capital, reorganizes production processes, and changes how firms coordinate workers, machines, information systems, and managerial control (Autor, Levy, and Murnane, 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018, 2020, 2022). This reorganization can produce productivity gains, but it can also generate transitional frictions, operational complexity, and stakeholder disruption. We build on this logic to motivate how automation may affect ESG incident risk, where ESG incidents are realized failures or controversies involving environmental, social, or governance-related externalities.

We focus on ESG incidents rather than ESG policies or disclosure scores because incidents capture realized adverse outcomes. They include events such as environmental accidents, labor controversies, supply-chain misconduct, regulatory violations, community disputes, and governance failures. Prior research shows that such controversies are financially material and can destroy shareholder value, affect reputational capital, and shape investor responses (Krüger, 2015; Li and Wu, 2020; Hoepner et al., 2023; He et al., 2023). Our framework therefore treats ESG incident risk as an outcome-based measure of the extent to which firms' operational and organizational externalities materialize into observable controversies.

1. Two Channels Linking Automation to ESG Incidents

Automation can reduce ESG incident risk through efficiency, standardization, and monitoring. Automated systems may reduce human error, improve process precision, support real-time monitoring, and remove workers from hazardous tasks. These mechanisms imply that automation could improve firms' ESG outcomes by strengthening process control and lowering the probability of some operational failures.

However, automation may also increase ESG incident risk through two distinct channels.

Control-gap channel. Automation changes how production is organized. It reallocates tasks away from workers, introduces new human-machine interfaces, and requires firms to redesign routines, monitoring systems, maintenance procedures, and accountability structures. During implementation, especially in the early stages of adoption, these control systems may lag behind the technological change itself. Safety procedures designed for human-operated processes may not fit automated production lines. Responsibility may become unclear when monitoring shifts from workers to sensors, software, or centralized control systems. Tacit knowledge embedded in experienced workers may be lost before it is fully codified into new routines. These mismatches create control gaps that increase the probability of operational failures, compliance lapses, and stakeholder disputes.

Scale-and-complexity channel. Automation can also increase ESG incident risk by lowering marginal costs, relaxing capacity constraints, and allowing firms to expand output more rapidly. Greater scale can increase energy use, resource throughput, emissions, waste, supplier exposure, logistics complexity, and labor reallocation. Even if the firm implements automation competently, its ESG-control capacity may not expand proportionately with the enlarged operational footprint. In this case, automation increases the number of points at which environmental, social, and governance failures can occur. This mechanism does not require a breakdown in existing controls. It requires only that the firm's prevention, monitoring, and stakeholder-management systems fail to scale as quickly as its automated operations.

These two channels imply that the automation-incident relationship should not be uniform. It should be stronger when automation generates greater disruption, complexity, or stakeholder exposure, and weaker when firms or institutions are better able to prevent, absorb, or discipline these risks.

2. A Reduced-Form Risk-Production Setup

Let A denote a firm's automation intensity. In the empirical analysis, A corresponds to our robotics flow or robotics stock measures. Let e denote the firm's ESG-control effort, broadly defined to include prevention, monitoring, compliance systems, worker adjustment policies, environmental safeguards, supplier oversight, and stakeholder engagement.

Let Z denote a vector of moderators that shape how automation translates into ESG incident risk. These moderators include firm-level characteristics, such as growth opportunities, automation experience, and green innovation; industry-level characteristics, such as manufacturing intensity, labor skill, and competition; and country-level institutions, such as environmental policy stringency, employment protection, and social trust.

We write the firm's realized ESG incident risk as:

$$R\left(A, e; Z\right) = R_0\left(\mathrm{Z}\right) + \theta\left(\mathrm{Z}\right) A - \varphi\left(\mathrm{Z}\right) e + \varepsilon. \tag{A.1}$$

Here, $R(A,e;Z)$ is the firm's latent ESG incident-risk exposure. Empirically, this exposure is proxied by the number of ESG incidents, the RepRisk Index, and incident-impact measures such as severity, reach, and novelty. $R_0(Z)$ captures baseline incident risk that is unrelated to automation. The parameter $\theta(Z)>0$ captures the extent to which automation increases incident exposure through the control-gap and scale-and-complexity channels. The parameter $\varphi(Z)>0$

captures the effectiveness of ESG-control effort in reducing incident risk. The term ε captures unobserved shocks to ESG incident risk.

This formulation is deliberately reduced-form. It does not assume that automation mechanically increases ESG incidents in all settings. Rather, it makes the net effect depend on the balance between the risk exposure created by automation, $\theta(Z)A$, and the firm's mitigation response, $\varphi(Z)e$. Automation increases ESG incident risk when the exposure generated by automation exceeds the firm's ability or willingness to offset that exposure through ESG-control effort.

The marginal effect of automation on ESG incident risk can be written as:

$$\frac{\mathrm{dR}}{\mathrm{dA}} = \theta\left(\mathrm{Z}\right) - \varphi\left(\mathrm{Z}\right)\frac{\mathrm{de}}{\mathrm{dA}}. \tag{A.2}$$

This expression is the central object of the framework. The first term, $\theta(\mathrm{Z})$, captures the gross incident-risk loading of automation. The second term, $\varphi(\mathrm{Z})(\mathrm{de}/\mathrm{dA})$, captures the extent to which firms increase effective ESG-control effort when automation rises. Thus, the automation-incident relationship is stronger when automation has a high risk loading, when mitigation is less effective, or when firms do not increase ESG-control effort sufficiently as automation expands.

3. Private versus Social Costs

The framework also incorporates a private-social cost wedge. Let λ denote the expected private cost borne by the firm when ESG incidents occur. These private costs include fines, litigation, remediation costs, reputational damage, higher financing costs, and loss of investor or customer confidence. Let Λ denote the full social cost of ESG incidents, including harms borne by workers, communities, consumers, suppliers, and the environment. In general,

$$\Lambda > \lambda. \tag{A.3}$$

This wedge is consistent with the classic externality problem in which private decision-makers do not fully internalize the social costs of their actions (Coase, 1960). In this setting, a firm may rationally choose a level of ESG-control effort that is privately optimal but socially insufficient. To see this, suppose the firm chooses ESG-control effort by trading off the private benefits of reducing incidents against the cost of control effort. A simple representation is:

$$e^{p}\left(A, Z, \lambda\right) = arg\ min_{e}\left\{\mathrm{C}\left(e; Z\right) + \lambda R\left(A, e; Z\right)\right\}. \tag{A.4}$$

where $C(e;Z)$ is increasing and convex in e. A social planner would instead choose:

$$e^{s}\left(A, Z, \Lambda\right) = arg\ min_{e}\left\{\mathrm{C}\left(e; Z\right) + \Lambda R\left(A, e; Z\right)\right\}. \tag{A.5}$$

Because $\Lambda>\lambda$, the privately chosen level of control effort will generally be below the socially efficient level:

$$e^p < e^s. \tag{A.6}$$

This private-social wedge explains why automation can increase realized ESG incident risk even when firms respond rationally to private incentives. Firms may bear meaningful costs from ESG incidents, but they do not necessarily internalize the full social costs of environmental damage, worker displacement, community disruption, or supply-chain misconduct. As a result, automation can create an overlooked downside: it may increase operational and stakeholder exposure faster than firms' privately chosen ESG-control systems adjust.

Institutional environments can narrow this wedge. Stronger regulation, enforcement, stakeholder monitoring, and informal social discipline can raise the private costs of ESG failures and improve firms' incentives to invest in prevention. Institutions can also affect the risk-production technology itself by reducing $\theta(Z)$, increasing $\varphi(Z)$, or increasing the responsiveness of control effort to automation, $\frac{\mathrm{de}}{\mathrm{dA}}$.

4. Interpretation of the Framework

The framework generates three key implications.

First, automation increases ESG incident risk when its gross risk-loading effect exceeds the firm's mitigation response:

$$\theta\left(\mathrm{Z}\right) > \varphi\left(\mathrm{Z}\right)\frac{\mathrm{de}}{\mathrm{dA}}. \tag{A.7}$$

This condition is more likely to hold when automation creates substantial disruption or complexity, when ESG-control systems are weak, or when the private costs of ESG incidents are below their social costs.

Second, the effect of automation on ESG incident risk depends on the characteristics of firms, industries, and countries. These characteristics shape the automation risk loading, $\theta(Z)$; the effectiveness of mitigation, $\varphi(Z)$; and the degree to which firms increase ESG-control effort as automation rises.

Third, moderators may affect the automation-incident relationship through different mechanisms. Some moderators primarily change the risk loading of automation. Others primarily change mitigation effectiveness. Still others affect both. This distinction is important for interpreting the empirical cross-sectional tests.

5. Empirical Predictions

The baseline prediction follows directly from the framework. Automation can increase ESG incident risk because the control-gap and scale-and-complexity channels may outweigh firms' privately chosen mitigation responses, especially when firms do not fully internalize the broader social costs of ESG failures.

Automation and ESG incident risk. Firms with higher automation adoption experience greater ESG incident risk, as reflected in incident frequency, ESG risk exposure, and incident-impact measures.

The framework also generates empirical predictions about the conditions under which this positive relationship should be stronger or weaker.

5.1 Firm-Level Moderators

Growth opportunities. Firms with stronger growth opportunities face greater pressure to scale output, expand production, and exploit automation-enabled capacity. Rapid expansion can magnify coordination problems, supply-chain strain, stakeholder tensions, and environmental externalities. In the model, growth opportunities increase the risk loading of automation, $\theta(Z)$, because each unit of automation creates greater disruption or complexity. Therefore, the positive automation-incident relationship should be stronger among high-growth firms.

Automation maturity and experience. The control-gap channel should be strongest during the early stages of adoption, when firms are still redesigning routines, maintenance systems, accountability structures, and human-machine workflows. As firms gain experience with automated equipment, they become better able to integrate automation into existing operations and governance systems. In the model, automation experience reduces $\theta(Z)$ and may increase $\varphi(Z)$, because automation becomes less disruptive and ESG-control systems become better adapted to the automated environment. Therefore, the positive automation-incident relationship should be stronger during early adoption and weaker among firms with greater automation experience.

Green innovation. Green innovation can reduce the environmental consequences of automation by improving energy efficiency, reducing waste, supporting cleaner production processes, and strengthening environmental monitoring. In the model, green innovation lowers the environmental component of $\theta(Z)$ and/or increases the environmental component of $\varphi(Z)$. Therefore, green innovation should attenuate the positive relationship between automation and environmental incidents.

5.2 Industry-Level Moderators

Manufacturing industries. Automation should have stronger ESG consequences in manufacturing industries because industrial robots are more directly embedded in physical production processes. In these settings, automation changes production lines, maintenance systems, workplace safety procedures, energy use, emissions, waste generation, and worker-task allocation. These changes increase the probability of control gaps and the scope for scale-related externalities. In the model, manufacturing industries have a higher automation risk loading, $\theta(Z)$, because each unit of automation is more closely tied to operational processes that can generate environmental and social incidents. Therefore, the positive automation-incident relationship should be stronger in manufacturing industries.

Labor skill. Automation in skill-intensive industries can require more complex coordination among technical workers, engineers, software systems, production workers, and managers. It can also require more extensive redesign of workflows, training systems, and accountability structures. Although high-skill industries may have stronger capabilities, the complexity of integrating automation into skill-intensive production can increase the likelihood of temporary control gaps and organizational disruption. In the model, high labor skill increases $\theta(Z)$ during the transition to automation because automation creates more complex human-machine coordination problems. Therefore, the positive automation-incident relationship should be stronger in industries requiring higher labor skill.

Industry competition. Competition can intensify the ESG risks of automation by increasing pressure to adopt new technologies quickly, reduce costs, scale output, and accelerate production cycles. When firms automate under strong competitive pressure, they may expand operations faster than their ESG-control systems can adjust, or they may underinvest in costly prevention and monitoring systems. In the model, competition increases $\theta(Z)$ by amplifying the scale-and-complexity channel and may reduce $\frac{\mathrm{de}}{\mathrm{dA}}$ if firms are less willing or able to expand ESG-control effort proportionately with automation. Therefore, the positive automation-incident relationship should be stronger in more competitive industries.

5.3 Country-Level Moderators

Environmental policy stringency. Stronger environmental policy can reduce the environmental risk loading of automation by imposing stricter standards, increasing monitoring, and requiring firms to internalize more of the environmental costs of production. It can also increase mitigation effectiveness by encouraging firms to adopt better environmental-control systems. In the model, environmental policy stringency lowers the environmental component of $\theta(Z)$, increases the environmental component of $\varphi(Z)$, or increases the responsiveness of environmental-control effort to automation. Therefore, the positive relationship between automation and environmental incidents should be weaker in countries with stricter environmental policy.

Employment protection. Automation can generate social risks when it displaces workers, accelerates restructuring, or creates labor-relations tensions. Stronger employment protection can reduce the extent to which automation translates into layoffs, worker conflict, and restructuring-related controversies. In the model, employment protection lowers the social component of $\theta(Z)$

and may increase the effectiveness of worker-adjustment and labor-relations controls. Therefore, the positive relationship between automation and social incidents should be weaker in countries with stronger employment protection.

Social trust. Social trust can mitigate the ESG consequences of automation by supporting cooperative adjustment, informal monitoring, reputational discipline, and stakeholder engagement during technological change. In high-trust societies, employees, communities, customers, and other stakeholders may be more willing to cooperate during adjustment periods, while firms may face stronger informal constraints against opportunistic behavior. In the model, social trust can lower $\theta(Z)$ by reducing the probability that automation-related frictions escalate into controversies, and it can increase $\varphi(Z)$ by making mitigation and stakeholder coordination more effective. Therefore, the positive automation-incident relationship should be weaker in countries with higher social trust.

6. Summary

The framework clarifies why automation can have ambiguous ESG consequences in theory but a positive association with ESG incident risk in the data. On the one hand, automation may improve efficiency, precision, and monitoring. On the other hand, it can create control gaps and expand operational complexity. The net effect depends on whether firms' mitigation responses keep pace with the disruption and scale enabled by automation. Because firms do not fully internalize the social costs of ESG failures, privately chosen controls may be insufficient, allowing automation-related risks to materialize as ESG incidents.

The framework also clarifies why the automation-incident relationship should vary across firms, industries, and countries. The relationship should be stronger when automation creates greater disruption or complexity, as in high-growth firms, early-stage adopters, manufacturing industries, skill-intensive industries, and competitive industries. It should be weaker when firms or institutions reduce automation's risk loading or strengthen mitigation capacity, as in firms with green innovation and countries with stronger environmental policy, stronger employment protection, and higher social trust.

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Internet Appendix B

Robustness Check Tables

Table IA.1. Number of ESG Incidents, Current RRI, and Peak RRI (V2 and V3)

This table shows the negative binomial and OLS regression results of the effect of robotics flow and stock on the number of ESG incidents and RRI using the international sample from 2007 to 2022. The dependent variables are the *Number of Incidents*, *Current RRI*, and *Peak RRI* of firm *i* in year *t*. Robotics V2 measures are adjusted by CapEx/Sales. Robotics V3 measures are adjusted by PP&E/Employees. All independent variables are calculated in year *t-1*. See Appendix A for variable definitions. Industry, year, and country fixed effects are as indicated. Standard errors are clustered at the firm level. The *t*-statistics are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Dependent Variable:	*Number of Incidents*				*Current RRI*				*Peak RRI*			
	Robotics V2		Robotics V3		Robotics V2		Robotics V3		Robotics V2		Robotics V3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Robotics Flow	0.494***		0.383**		6.271***		6.463***		6.237***		5.676***	
	(2.702)		(1.968)		(4.611)		(4.714)		(4.098)		(3.991)	
Robotics Stock		0.232***		0.238***		2.146***		2.847***		2.379***		2.743***
		(3.102)		(3.085)		(4.698)		(5.535)		(4.413)		(4.673)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473
Ln(alpha)	0.472***	0.472***	0.473***	0.471***								
Adjusted R-Squared					0.406	0.406	0.407	0.407	0.372	0.372	0.372	0.373
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.2. Severity, Reach, and Novelty of Incidents (V2 and V3)

This table shows the OLS regression results of the effect of robotics flow and stock on the severity, reach, and novelty of all ESG incidents, using the international sample from 2007 to 2022. The dependent variables are *Severity*, *Reach*, and *Novelty* of firm *i* in year *t*. Robotics V2 measures are adjusted by CapEx/Sales. Robotics V3 measures are adjusted by PP&E/Employees. All independent variables are calculated in year *t-1*. See Appendix A for variable definitions. Industry, year, and country fixed effects are as indicated. Standard errors are clustered at the firm level. The *t*-statistics are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Dependent Variable:	*Severity*				*Reach*				*Novelty*			
	Robotics V2		Robotics V3		Robotics V2		Robotics V3		Robotics V2		Robotics V3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Robotics Flow	10.997***		15.280***		18.238***		23.939***		11.431***		15.060***	
	(2.766)		(3.474)		(2.830)		(3.596)		(2.801)		(3.493)	
Robotics Stock		3.638***		7.437***		5.840***		10.964***		3.703***		7.082***
		(2.857)		(4.429)		(2.934)		(4.721)		(2.952)		(4.616)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473	63,473
Adjusted R-Squared	0.187	0.187	0.191	0.194	0.173	0.173	0.177	0.180	0.211	0.210	0.215	0.218
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.3. Robustness: Subsample Results

This table shows the subsample OLS baseline regression results where the dependent variable is *Current RRI* of firm *i* in year *t*. All independent variables are calculated in year *t-1*. See Appendix A for variable definitions. Industry, year, and country fixed effects are as indicated. Standard errors are clustered at the firm level. The *t*-statistics are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A. Excluding Certain Countries

Dependent Variable:	*Current RRI*							
	Excl. USA		Excl. JPN		Excl. CHN		Excl. Top 5 Countries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robotics Flow	5.419***		4.541***		9.640***		9.929***	
	(3.463)		(3.097)		(5.451)		(4.631)	
Robotics Stock		1.967***		1.639***		2.209***		2.733***
		(3.531)		(3.044)		(3.932)		(3.201)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,283	41,283	55,500	55,500	58,280	58,280	21,139	21,139
Adjusted R-Squared	0.394	0.395	0.411	0.412	0.419	0.418	0.428	0.427
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Excluding Certain Industries

	Excl. Industry 90		Excl. Industry 19-22		Excl. Industry C		Excl. Top 5 Industries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robotics Flow	5.512***		5.779***		5.888***		6.179***	
	(3.979)		(4.027)		(4.167)		(4.073)	
Robotics Stock		1.857***		1.900***		2.010***		2.255***
		(3.867)		(3.876)		(4.132)		(4.348)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,300	50,300	53,879	53,879	54,225	54,225	21,157	21,157
Adjusted R-Squared	0.417	0.417	0.392	0.392	0.411	0.411	0.404	0.403
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.4. Robustness: Industry-Level Unadjusted Measure

This table shows the regression results of the effect of robotics flow and stock on ESG incident measures, using the international sample from 2007 to 2022. *Robotics Flow* and *Robotics Stock* are the industry-level measures provided by the IFR without firm-level capital intensity adjustment. The dependent variables are *Number of Incidents, Current RRI,* and *Peak RRI* at firm *i* in year *t*. All independent variables are calculated in year *t-1*. See Appendix A for variable definitions. Industry, year, and country fixed effects are as indicated. Standard errors are clustered at the firm level. The *t*-statistics are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Dependent Variable:	*Number of Incidents*		*Current RRI*		*Peak RRI*	
	(1)	(2)	(3)	(4)	(5)	(6)
Robotics Flow *(Industry-Level Unadjusted Measure)*	8.8e-06**		3.4e-05**		4.1e-05*	
	(2.392)		(2.518)		(1.878)	
Robotics Stock *(Industry-Level Unadjusted Measure)*		2.1e-06**		8.2e-06**		9.5e-06*
		(2.530)		(2.460)		(1.862)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63,473	63,473	63,473	63,473	63,473	63,473
Ln(alpha)	0.472***	0.472***				
Adjusted R-Squared			0.405	0.405	0.372	0.372
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.5. Robustness: Firm-Level AI Measure with Firm Fixed Effects

This table shows the regression results using firm-level AI measures. In Panel A, the independent variables are AI Employees and AI Knowledge Employees developed by Babina et al. (2024). The dependent variables are *Number of Incidents*, *Current RRI*, *Peak RRI*, *Severity*, *Reach*, and *Novelty* of all incidents of firm i in year t. In Panel B, the independent variable is AI Financial Reporting developed by Blankespoor et al. (2026). The dependent variables are *Severity*, *Reach*, and *Novelty* of all incidents of firm i in year t. Results in panel A columns (1)-(2) are generated from Poisson regressions, and other results are generated from OLS regressions. All independent variables are calculated in year t-1. See Appendix A for variable definitions. Firm, year, and country fixed effects are as indicated. Standard errors are clustered at the firm level. The t-statistics are in parentheses. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A. AI Workforce Measures by Babina et al. (2024) – Firm Fixed Effects

Dependent Variable:	*Number of Incidents*		*Current RRI*		*Peak RRI*		*Severity*		*Reach*		*Novelty*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AI Employees	1.235		15.945		-0.881		231.299*		456.159**		236.095**	
	(0.122)		(0.549)		(-0.017)		(1.951)		(2.094)		(2.064)	
AI Knowledge Employees		1.548*		10.005*		-1.667		19.411*		33.875*		20.468*
		(1.745)		(1.844)		(-0.233)		(1.648)		(1.686)		(1.815)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,647	33,791	37,081	37,376	37,081	37,376	37,081	37,376	37,081	37,376	37,081	37,376
Adjusted R-Squared			0.685	0.691	0.613	0.622	0.736	0.733	0.685	0.689	0.751	0.751
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. AI in Financial Reporting by Blankespoor et al. (2026) – Firm Fixed Effects

Dependent Variable:	*Severity* (1)	*Reach* (2)	*Novelty* (3)
AI Financial Reporting	0.370	0.778*	0.398*
	(1.441)	(1.768)	(1.669)
Firm-Level Controls	Yes	Yes	Yes
Country-Level Controls	No	No	No
Observations	13,235	13,235	13,235
Adjusted R-Squared	0.220	0.174	0.234
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country FE	No	No	No

Figure IA.1. Robotics Adoption and ESG Incident Risk by Industry and by ESG Pillars

This heatmap displays Pearson correlation coefficients between the firm-level *Robotics Flow* and *Current RRI* by industry and by the four ESG pillars, environmental, social, governance, and cross-cutting. Industries (ESG pillars) are listed along the vertical (horizontal) axis. The color scale represents both the sign and magnitude of the correlations, centered at zero, with annotated values for interpretability. Darker colors represent stronger correlations.

Industry	Environment	Social	Governance	Cross-Cutting
Automotive	0.26	0.20	0.31	0.30
Wood and Furniture	0.19	0.18	0.05	0.04
Basic Metals	0.14	0.16	0.09	0.13
Food and Beverages	0.04	0.04	0.04	0.03
Metal Products (Non-Automotive)	0.04	-0.01	-0.06	-0.07
Plastic and Chemical Products	0.04	0.05	0.07	0.06
All Other Manufacturing Branches	0.03	0.04	0.03	0.04
All Other Non-Manufacturing Branches	0.02	0.00	0.00	-0.00
Construction	0.01	-0.01	-0.00	-0.00
Mining and Quarrying	-0.01	-0.01	-0.02	-0.01
Industrial Machinery	-0.01	0.00	-0.01	-0.02
Textiles	-0.02	-0.01	-0.01	-0.00
Electrical/Electronics	-0.02	-0.01	-0.00	-0.01
Agriculture, Forestry, Fishing	-0.04	-0.04	-0.04	-0.04
Glass, Ceramics, Stone, Mineral Products	-0.04	-0.05	-0.06	-0.03
Electricity, Gas, Water Supply	-0.05	-0.05	-0.04	-0.04
Paper	-0.07	-0.06	0.02	-0.01
Other Vehicles	-0.10	-0.09	-0.08	-0.09