Artificial Intelligence and Firm Resilience: Evidence from Firm Performance under Natural Disaster Shocks

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Forthcoming: *Information Systems Research*

Abstract

Artificial intelligence (AI) has been increasingly deployed in business operations over the past decade. While AI productivity in normal times has been extensively studied, direct evidence of its effectiveness in uncertain contexts is limited. Our work fills this gap by examining the contribution of AI to corporate resilience under natural disaster shocks, particularly concentrating on AI-using and goods-producing firms. We measure firm AI investment by the cumulative AI-relevant skills extracted from a comprehensive job posting database. We gauge firm resilience with the changes in corporate valuation in response to operational shocks induced by natural disasters. Using a pooled event study approach, we provide evidence that AI generates resilience: an average firm that equips 2.4% of total jobs to be AI-related could approximately recover the full damage of disasters reflected in corporate valuation over a short event window. Then, we discuss mechanisms under the framework of an adapted production function model. Combined with an instrumental variable that integrates baseline firm-specific task structure and task-specific AI suitability over time, we find consistent evidence that, during turbulent periods, AI deployment moderates the decreased responsiveness of firm output to both labor and capital inputs in the production process. An array of sub-sample analyses reveals a pressing phenomenon: although underperforming firms could benefit more from an additional unit of AI investment, the realized productivity is notably restrained due to a lack of complementary organizational designs. Overall, our study makes a distinct contribution compared to prior literature that focuses on AI productivity while assuming certainty or homogeneous factor elasticity. Our findings provide managerial implications regarding the interplay between environmental conditions and firm investments in both AI technology and complementary infrastructures.

Keywords: artificial intelligence, firm resilience, uncertainty, natural disasters, job posting, market return, production function

1 Introduction

With the rapid development of computing power, data availability, and breakthroughs in mathematical models and algorithms, artificial intelligence (AI) has become increasingly popular within corporate organizations in various industry sectors. In addition to the tech giants at the forefront of this revolution, such as Google and Microsoft, companies in traditional industries are also gradually participating in the revolution. They have recruited and utilized AI in product manufacturing and business operations. For instance, General Motors analyzes camera images of assembly robots to discover signs and indications of malfunctioning robotic components to prevent unplanned outages. Danone Group, a French multinational food producer, uses machine learning systems to improve coordination across marketing, sales, supply chain, and finance management, obtaining a 30% reduction in lost sales and product obsolescence.[1]

This new wave of AI-related concepts has drawn tremendous attention from both the capital market and academia. According to GlobalData estimates, the AI market could generate sales of $190 billion by 2025, up from $67 billion in 2021, with an increase of 184% and a compound annual growth rate of 38%.[2] With such a large amount of money poured into this market, it is crucial to understand the impact of AI investments on economics and business. An extensive literature studies this question from different aspects, including labor market (Felten et al. 2019, Agrawal et al. 2019, Acemoglu and Restrepo 2020, Acemoglu et al. 2022), innovation performance (Cockburn et al. 2019, Babina et al. 2024), investment management (D'Acunto et al. 2019, Hendershott et al. 2021), retail operations (Bajari et al. 2019), and so on. Most existing literature focuses on AI value in normal times (Aghion et al. 2018, Haltiwanger 2019). However, given the current high-velocity environment characterized by disruptive upheavals from pandemics, political upheavals, military operations, or climate changes, a better understanding of how to deal with such unrest becomes more urgent. Nevertheless, our understanding is still limited in this respect.

In this paper, we specifically investigate AI effectiveness on firm resilience under natural disaster-induced uncertainty shocks to fill this gap. Firm resilience — the ability of a firm to successfully confront the unforeseen,[3] and to restore normal operations within an acceptable period of time after being disturbed (Christopher et al. 2004) — becomes more and more important in today's ever-changing environment (Chakravarty et al. 2013, Ambulkar et al. 2015, Bai et al. 2021). As algorithms advance, in comparison to traditional data techniques and platforms, AI (represented by machine learning, natural language processing, computational intelligence, etc.)

[1] https://www.forbes.com/sites/louiscolumbus/2020/05/18/10-ways-ai-is-improving-manufacturing-in-2020/?sh=cd0f7391e85a

[2] https://www.bankrate.com/investing/emerging-technology-investing/

[3] https://hbr.org/2007/08/building-a-resilient-supply-ch

is endowed with promises to adapt to and overcome the challenges. On the one hand, despite the hype around AI, some might question its usefulness for aiding firm operations, especially in the context of high uncertainty where the information on which AI is dependent is largely unknown or imperfect. Due to the inherent noise, incompleteness, and inconsistency along the process of conducting operational-relevant tasks, the effect of AI might be undermined. Sources of threat lie in the data generation (e.g., variance in environmental conditions), data collection (e.g., concerns related to survival bias), objective identification (e.g., the ever-changing purpose and objective functions), or task integration (e.g., the complexity of organizing sub-tasks into complete process). These various aspects of uncertainty render a lack of confidence in the resulting analytic process and decisions made thereof.

On the other hand, AI incorporates flexible modeling architectures and is able to learn from examples and form statistical reasoning to find associations in data. With the help of advanced computational theories (e.g., active learning for finding better training labels, reinforcement learning for automatically refining objectives and goals, fuzzy theory for dealing with large spaces of possibilities), AI-based learning is potentially an advantageous tool for prediction and decision-making support, especially under great uncertainty. A survey of AI startups documents that the most applicable and advantageous practice of AI is to make predictions and aid decisions (Bessen et al. 2018). Researchers have also suggestively implied that AI could improve forecast accuracy, mitigate prediction biases and uncertainties, and thus enhance resource deployment and operational efficiency (Brynjolfsson et al. 2011, Mihet and Philippon 2019, Agrawal et al. 2018, 2019). Industrial examples of AI battling uncertainty include pharmaceutical firms using AI to predict whether an ingredient will arrive on time and how the delay will affect production, or retail industries using AI to take into account data from weather forecasts and other disruptions to usual shipping patterns to find alternate routes and make new plans that won't disrupt normal business operations. A specific case in point is Biogen's recovery from the impact of Hurricane Maria on its production plan in Puerto Rico. Applying the prediction algorithm learned from prior experience of natural disasters, Biogen successfully forecasted the landfall in advance, promptly created a war room to pinpoint the supply-chain threats, and therefore secured productions in due time. As a result, its stock price recovered and even surpassed the prestorm price within 15 days of Hurricane Maria's strike.[4]

Combining these equivocal arguments, we aim to empirically assess AI's impact on firm resilience during challenging periods and identify specific conditions. Focusing on goods-producing

[4]https://www.mckinsey.com/industries/life-sciences/our-insights/four-ways-pharma-companies-can-make-their-supply-chains-more-resilient

sectors where AI serves as an auxiliary technology support rather than a direct profitable output, our goal is to measure the influence of uncertainty on firm performance and explore AI's role in alleviating disruptions caused by uncertainty. Essentially, our research questions cover: 1) how firms are affected by uncertainty shocks, and 2) whether AI helps mitigate uncertainty-induced disruptions, and through what channel.

To measure the level of uncertainty, we exploit a near-universe record of natural disasters and generate a continuous variable of firm-exposure-weighted uncertainty induced by these exogenous events. Notably, unlike previous studies that use a firm's headquarter location to determine if it is exposed to disasters, we carefully look into county-level operating sites, enabling us to better identify both extensity and intensity of disaster shocks. To measure firm-level AI investments, we employ a comprehensive dataset of online job postings and identify the ones requiring AI-relevant skills. In addition, through job postings with complementary requirements or in different occupations, we offer more discussions on granularity and dynamics.

We start with the test for AI injecting resilience among firms undergoing disaster-induced uncertainty shocks. Since natural disasters normally happen within a few days, ideally we need an identification strategy that captures high-frequency dynamics. Changes in the firm's stock return in the financial market provide an appropriate setting. Financial return symbolizes readjustments in the general expectation towards a firm's future performance in the incidence of unexpected events such as natural disasters as we focus, thus well reflecting the firm's ability to confront the unforeseen (Bai et al. 2021). During three short windows before, in, and after the disaster befallen, we compare return performances between firms with different levels of uncertainty exposures and different levels of AI intensity. Our evidence suggests that firms with higher AI intensity have more moderate loss, as well as more positive returns compared to peers with lower AI intensity. An intensity of 2.4% (out of 100 cumulative job postings, 2.4 being AI-related) could approximately recover the full slides in shareholder return in the event of severe shocks.

After presenting the evidence of AI-empowered resilience with high-frequency analyses at the firm-by-date level, we next explore the working mechanisms under the framework of an adapted production function with a firm-by-year-by-quarter panel. By allowing the factor elasticity to vary across contexts, we find that conditional on uncertainty level, firms with higher AI intensity generate more production outputs in response to each unit of labor or capital. Such elasticity-enhancing effect stays consistent after controlling for alternative explanation variables and strictly fixed effects at the level of NAICS2-by-year-by-quarter and firms. To address the endogeneity concern of AI investment being self-selective among firms, we construct an instrumental variable that combines the baseline firm-specific task structure with the task-relevant AI growth among peers. To further remove the confounding impact from general IT investment, we specifically control for skills regarding data analytics, cloud computing, and robotics. Results are replicated with the same directions and similar magnitudes.

In an effort to pin down essential channels that matter for both theory and practices, we attempt to explore ways of deploying AI-relevant skills in real operations. However, we acknowledge a major limitation in our study thus far that we are vague about how these skills are practically used in each position for each task, and how these skill-aided tasks contribute to the performance outcome. To tackle this challenge, we resolve to provide more granularity in understanding AI deployments by digging into various contingencies, including the specific occupations that require such skills, firm fundamental characteristics, operational conditions, and complementary hiring strategies. Split-sample analyses reveal a thought-provoking finding. Firms with poorer performance or larger constraints in previous periods could potentially benefit from greater responsiveness of production outputs to each unit of AI injection. However, due to a lack of complementary investment, the actual realized productivity of these firms appears to be consistently lower than their counterparts. These findings together imply a promising future of AI especially for under-performing businesses, reaping the benefits of which, however, requires more systematic and strategic input designs.

From untabulated results, we recognize that our findings of AI injected resilience do not persist through all contexts, two of which are worth attention. First, while we present AI-enabled resilience among a sample of firms that are primarily using AI for goods production in the paper, we do not find similar effects among firms that are in the services industries or that are inventing AI. Second, while we present consistent evidence of AI-enabled resilience under the uncertainty shocks induced by natural disasters, we do not find similar effects for uncertainty shocks induced by technological disasters such as cybersecurity attacks and industrial accidents. Plausible explanations are that, for these other contexts, our measurement of job posting-based geographic composition is not sufficiently indicative as discussed later in Section 3.3, or that the general operations and recovery processes are inherently different. A thorough investigation is beyond the scope of this paper.

Overall, this study connects to the literature on the productivity of IT especially emerging technologies, encompassing three main contributions. First, we spotlight AI in the context of uncertain environments, which is operationalized by our identification of natural disasters. Second, we present evidence of resilience with a financial market-based measure of firm performance from a high-frequency firm-by-date panel and an accounting-based measure of firm performance from a fundamental firm-by-quarter panel. Results from both sets of analyses corroborate each other, providing a complete picture of market reaction on firm production. Third, we propose an instrumental variable that combines and adapts two widely used instruments in extant literature for AI investment or AI adoption at the firm level. Through extensive analyses, we echo some tentative results from previous literature, while offering new perspectives regarding corporate valuations and management practices.

2 Related Literature

In this section, we review three related research streams in the literature. We start from our overall research context regarding environmental uncertainty and firm resilience. We then review the productive value of general information technology and data-driven decision-making. We discuss their respective characteristics, the existing findings, and how our focus on AI differs from the concerns in extant literature. We finally provide a comprehensive review of the burgeoning literature specific to AI.

2.1 Environmental Uncertainty and Firm Resilience

Environmental uncertainty generally refers to the volatility and unpredictability of the changes that a business has to deal with (Miller and Friesen 1983, Keats and Hitt 1988). Multiple sources and measurements of external uncertainty have been considered in previous literature. Keats and Hitt (1988) exploit different levels of dynamism, competitiveness, and complexity to conceptualize the uncertainty degree in a firm's market environment. Baker et al. (2016) uses the natural language from mainstream media to quantify the uncertainty in aggregate economics. These characterizations of uncertainty are undoubtedly important and relevant to business management. One common concern, however, is whether and to what extent such uncertainty is endogenous to firm operations. Since these measurements somewhat embed firm actions, it could be challenging to tease out the true origin of volatility and unpredictability.

Our study contributes by operationalizing the external environmental condition with a continuous measure of uncertainty induced by exogenous shocks from natural disasters. In addition to providing a new perspective on the definition of environmental uncertainty, this way of construction offers a clean and exogenous cause that is less likely to be reversely or simultaneously affected by firm production choices. Such natural-disaster-based indices have been constructed to study the firm-level idiosyncratic shocks. Limitation resides in prior literature that some only select one disaster event, such as the 2011 Japan Earthquake (Hendricks et al. 2020), and some only use a firm's headquarter location to identify whether it is impacted by disasters (Barrot and Sauvagnat

2016). These two approaches are undesirable due to a lack of generality and lack of preciseness in the measurement. In our paper, we aim to provide a new and more accurate identification strategy that is based on the universe of natural disasters on record and firms' recruitment locations at the county level.

Under the various measurements of environmental uncertainty, previous literature unanimously defines resilience as the ability to maintain the original function despite internal or external disruptions (Kitano 2004) or to return to normal operating performance within an acceptable period of time after being disturbed (Christopher et al. 2004). For example, Toyota was able to resume production at 29 plants just 3–4 days after the Kobe earthquake of 1995 (Fujimoto 2011). The measure of resilience in the existing literature is either focused on supply chain-specific indices or elicited from corporate surveys and interviews (Reichhart and Holweg 2007). Our study differs in this dimension by statistically exploring the concept of "resilience" from stock return analyses. Under the assumption that financial market return reflects real-time forward-looking information about firm operations, the dynamics of stock returns during uncertainty-intensive periods present a chance to quantitatively gauge the market-perceived firm's capability of handling disruptions.

Following the general practice in the literature of environmental uncertainty and firm performance, our testing logic starts by investigating if the proposed measure of uncertainty does cause a materially negative impact on the proposed measure of firm operations, then proceeds to ask whether our crucial variable, AI investment, help mitigate the negative influence of uncertainties.

2.2 Value of IT and Data-driven Decision Making

Our paper belongs to the enormous literature on the value of information technology (IT): IT-enabled knowledge networks improve worker performance (Aral et al. 2012); IT-enabled innovations create value at an intermediate stage of production (Kleis et al. 2012); IT-enabled capability reshapes firm boundaries horizontally and vertically (Hitt 1999). Among the literature on general productivity, some studies have focused on IT effectiveness in dealing with dynamic and uncertain contexts. It is well documented that IT can enhance organizational resilience through speeding up decision-making (Oh and Lucas Jr 2006), facilitating entrepreneurial and adaptive actions (Lu and Ramamurthy 2011, Chakravarty et al. 2013), and enabling digital options (Sambamurthy et al. 2003).

We contribute to the literature with a particular interest in an emerging technology, Artificial Intelligence (AI). Although they share some similarities, AI differs from general IT in major aspects. The function of IT is to reduce costs and to improve efficiency in coordinating, communicating, and monitoring a wide range of economic activities within and between firms (Hitt 1999), whereas the function of AI mainly concentrates on generating predictions and aiding decision-making. While the benefit of reducing costs is proven to be the dominant advantage of IT, that of AI is by no means conclusive. In addition to the aspect of cost-reduction, a growing literature has delved into the potential of AI in creating larger premiums and opportunities for firm productions (Agrawal et al. 2022). We aim to contribute towards this direction and uncover the possibility of using AI in the face of rising turbulence and volatility.

Our paper also contributes to the burgeoning research in data-driven decision-making (DDD, hereafter). Despite the many similarities between AI and DDD, there are some nuanced differences that could make an impact in generating conclusions and managerial implications. First, DDD refers to the general use of data in firm practices, measured by the extent of data availability and data usage within a firm (Brynjolfsson and McElheran 2016), whereas AI leans towards applications where machines, normally as a combination of data and algorithms, learn to perceive, analyze, determine response and act accordingly in their environment (a standard definition of AI (Zolas et al. 2021). With less human discretion and behavioral biases, this improved automatic learning capability of machines foresees larger potential in handling turbulence and uncertainty. Second, regarding the adoption, empirical evidence consistently suggests rapid and widespread diffusion of DDD (Brynjolfsson and McElheran 2016), whereas the diffusion of AI in firm practices is found to be rare and generally skewed towards larger and older firms (Zolas et al. 2021). Third, DDD is unanimously proven to be beneficial for firm management, whereas AI is still undergoing debates regarding the contextual dependencies varying from human, organizational, to environmental factors.

In this paper, we borrow the framework of studying general DDD with a specific focus on emerging AI-based technology. Instead of trying to draw the boundary between DDD and AI or quantify the productivity differences between DDD and AI, we aim to explore empirically valid patterns among large-scale public firms and discuss some nuanced findings that might spur future research.

2.3 Effects of AI

Prior literature on the effects of AI has been mostly theoretical and has largely focused on the level of an aggregate economy. Using structured models, past researchers have discussed the potential implications of AI on income distribution and labor demand (Korinek and Stiglitz 2017, Acemoglu and Restrepo 2018), economic growth process (Aghion et al. 2018), and long-term impact on future societies (Sachs and Kotlikoff 2012). Although AI has the potential to be an innovation that can lead to breakthroughs, Brynjolfsson et al. (2019b) find that since the late 1990s, measured productivity growth has declined, and real income has stagnated. There are two types of empirical studies in this debate on whether AI can increase productivity. One focuses on a specific AI skill and investigates its effectiveness in a particular business. For example, Brynjolfsson et al. (2019a) specifically focus on machine translation and provide causal evidence that introducing AI applications significantly increased international trade on a digital platform. The other stream studies the general AI value across industrial sectors. For example, Babina et al. (2024) study the economic impact of AI technology investments among U.S. firms and showed a product innovation channel through which AI facilitates firm growth. Our research supplements this discussion by focusing on the general AI value on a firm's resilience, or the effectiveness of AI in firms facing severe natural disasters.

By revealing AI effects on firm performances under turbulent environments, we contribute to firm resilience literature. Gupta (2020) finds that innovation capability makes a firm more resilient by providing product differentiation. Bai et al. (2021) show that public firms with higher work-from-home feasibility perform significantly better during the COVID-19 pandemic. Pavlou and El Sawy (2010) reveal that IT enables competitive advantage in turbulence through better resource management and team collaboration. Our paper adds AI investments as another factor that can improve firm resilience by providing prediction power and helping efficient decision-making.

The rest of the paper proceeds as follows. In Section 3, we describe the data sources for constructing the measure of AI intensity and uncertainty shocks and provide summary statistics of major variables and features of our analytical sample. Section 4 presents the evidence of AI-empowered firm resilience in a high-frequency firm-by-date setting. Specifically, we detail the construction of a pooled event study to examine the changes of the firms' stock returns. Section 5 offers the mechanism explanation regarding channels through which AI injects resilience: an adapted production function is built in Section 5.1, robustness tests whereby an instrumental variable is used and the general IT investment is controlled for are respectively discussed in Section 5.2 and Section 5.3. Section 6 explores heterogeneity across firms, and Section 7 concludes.

3 Data and Measures

In this section, we describe our sample inclusion process, the datasets, and the construction of key variables – AI intensity and uncertainty shock. Summary statistics are provided.

3.1 Sample

In this study, we focus on U.S. publicly traded firms with two-digit North American Industry Classification System (NAICS2, hereafter) codes equal to or less than 49, including sectors of agriculture, mining, utilities, construction, manufacturing, wholesale trade, retail trade, transportation, and warehousing. Our rationale for this sample inclusion is three-fold. First, to achieve our goal of studying the impact of AI on AI-using firms rather than AI-producing firms, common practices are specifically excluding professional and business services and information technology sectors (Acemoglu et al. 2022), or only including manufacturing companies (Brynjolfsson et al. 2021). We strike a balance between avoiding AI-producing firms and maintaining more observations by considering the classification based on economic activities. Second, data on production inputs and outputs in these sectors have been well established over time, supporting a rich exploration of productivity dispersion in a well-understood setting (Bartelsman and Doms 2000, Syverson 2011). Third, we are implicitly constrained by our employment-based measurement of the geographical risk exposure of a firm. Further explanations are provided in Section 3.3.

Regarding the sample construction process, we start from the full sample of firms in BGT (details in next section) and exclude those that have fewer than ten job posts through the whole data period (January 2010 to December 2019). Then, we merge with the dataset from the Center for Research in Security Price (CRSP) and from S&P Compustat to obtain stock price and firm fundamentals for U.S. publicly traded firms. We exclude observations with missing values in concerning variables [5] and exclude firms with NAICS2 code equal to or greater than 50 to obtain the sample of interest.[6] In total, we obtain 3137 firms.

We provide summary statistics in Table 1. The distributions of major characteristics for the firms in our data are presented in Panel A and compared against that for all publicly traded firms in the Compustat dataset in Appendix A. The comparison indicates that our in-analysis firms over-sample larger and more profitable firms. In addition to the selection bias of posting online among different-sized firms (Acemoglu et al. 2022), removing firm observations with missing key production inputs (such as assets, working capital, and employees) also leads to slightly biased representativeness. However, the industry composition, as reflected by NAICS2 distribution, suggests good coverage of the U.S. economy. The distributions of job posting-related variables

[5] Since our concerned variables are all fundamental indices, the total number of firm-quarter observations with missing values thus being excluded is small. In untabulated results, we impute missing values with the average among firms in the same NAICS2 industry. Results are consistent.

[6] In later analysis of pooled event-study, we provide estimation results for firms in sectors with NAICS2 code equal to or greater than 50. Null effects support our precondition that natural disaster tends to be a source of disruptive uncertainty for firms with tangible operations, i.e., inputs and/or outputs are material and subject to environmental situations.

Table 1: Summary statistics

Panel A: Characteristics of in-sample firms (N=3137)	Min	P25	P50	P75	Max	Std. Dev.
Asset	2.42	128.11	593.72	2969.45	416073.70	21507.76
Cash	0.01	19.40	62.04	204.11	24051.03	1491.97
Sales	0.00	15.30	128.95	615.70	121759.40	4890.35
Cost of goods sold	0.00	12.58	78.20	391.95	89117.22	3895.34
R&D expense	0.00	1.56	7.07	21.51	6855.56	264.41
# employees	0.00	0.16	1.22	6.33	2222.22	49.98
Working capital	-11298.44	24.37	111.06	368.79	42480.80	1937.54
Revenue-to-asset	-50.04	-0.11	0.00	0.04	23.26	1.56
Book-to-market	0.05	0.53	0.97	1.78	345416.30	6278.39
Debt-to-asset	0.00	0.10	0.21	0.35	5.37	0.26
# total posts	0.00	0.33	2.86	28.22	20079.33	683.05
# AI posts	0.00	0.00	0.00	0.11	101.44	3.17
AI intensity (%)	0.00	0.00	0.00	0.23	15.23	1.01
# bachelor posts	0.00	0.11	1.22	9.78	1572.78	87.78
# master posts	0.00	0.00	0.00	0.33	604.00	12.17
Master intensity (%)	0.00	0.00	0.00	2.22	34.78	5.89
# doctoral posts	0.00	0.00	0.00	0.11	427.44	10.97
Min required experience	0.00	0.26	0.63	1.20	15.00	1.25
Panel B: Temporal changes of key variables	# firms	# total posts	# AI posts	AI intensity (%)	Firms with AI (%)	Master Intensity (%)
2011	2563	63.32	0.30	0.16	8.12	2.55
2012	2629	54.69	0.22	0.25	7.38	2.24
2013	2650	89.88	0.36	0.25	8.42	2.09
2014	2619	152.71	0.44	0.31	9.74	1.87
2015	2581	140.22	0.48	0.37	10.46	1.89
2016	2537	140.21	0.57	0.40	11.55	2.21
2017	2484	150.39	0.92	0.58	14.49	2.61
2018	2384	169.19	0.93	0.72	13.42	2.39
2019	2253	162.61	1.16	0.79	16.42	2.18
Panel C: Characteristics of in-sample disasters (N=141)	Min	P25	P50	P75	Max	Std. Dev.
Duration (days)	1	3	4	7	47	6.69
Total damage (Thousands USD)	7.81	12.31	13.83	14.71	18.55	1.93
Insured damage (Thousands USD)	10.95	12.43	13.77	14.43	17.39	1.30
Uninsured damage (Thousands USD)	0.00	0.30	0.45	0.69	2.25	0.46
# firms affected	56	88	453	562	872	188.26

Notes: Panel A presents characteristics of in-sample firms. The industry distribution categorized by NAICS2 code is: 11 (0.38%), 21 (7.81%), 22 (3.60%), 23 (2.10%), 31-33 (71.09%), 42 (4.18%), 44-45 (7.01%), 48-49 (3.83%). Panel B presents the time series of key variables. Panel C presents the characteristics of in-sample disasters. The frequency of each disaster type is: storm (116), flood (17), wildfire (4), extreme temperature (2), earthquake (1), volcanic activity (1).

(details in next section), including the number of any posts or AI-related posts, the number of posts requiring at least a bachelor's, master's, or doctorate degree, and the minimum required working experiences, suggest great dispersion among in-analysis firms, offering a large enough variation to make meaningful statistical inferences about the effects of AI across firms.

3.2 AI Intensity

We use an online job vacancy dataset provided by Burning Glass Technologies (BGT, hereafter)[7] that covers the time from January 2010 to December 2019. BGT tracks a near-universe of all websites that contain job postings in the United States and records the postings in a machine-readable form after parsing and removing duplicate postings. It covers about 60-70% of job vacancies in the U.S., either online or offline. Each post contains detailed information about the standard occupation classification (SOC) code, county-level geographical location, detailed skill requirements, education and experience requirements, and firm identifiers. The BGT dataset has been used in several recent studies to analyze occupational demand and labor market outcomes (Modestino et al. 2020, Deming and Kahn 2018, Hershbein and Kahn 2018, Acemoglu et al. 2022, Braxton and Taska 2023). In particular, Carnevale et al. (2014) conduct a comprehensive examination and conclude that BGT's online job postings correlate strongly with job openings in the entire job market and provide a good measure of employment demand.

Since human capital is an input into technology development and diffusion, skills listed in job posts should reflect firms' intentions to engage with emerging technologies (Goldfarb et al. 2023). Therefore, we consider a job posting as an AI job if it requires at least one AI-related skill. To identify AI-related skills in nearly 17,000 unique skills that are presented in job postings, we use a skill taxonomy developed by BGT. This taxonomy identifies AI-related skills based on a job description's skill requirement. Specifically, the taxonomy looks for the presence of words and phrases that are commonly associated with AI knowledge (e.g., deep learning, image processing, speech recognition, etc.) or AI-related tools (e.g., TensorFlow, Random Forests, etc.). The same identification of AI-related jobs is also used in Goldfarb et al. (2023) and Alekseeva et al. (2021). Appendix B provides a complete list of AI-related skills. Note that although job posts are not equivalent to actual labor recruitment, previous literature has well established that emergent technology diffusion can be measured using labor demand data (Tambe and Hitt 2012a,b).

We measure the intensity of AI investment at the firm-date level by calculating the number of AI-related posts (#*AI_Posts*) normalized by the number of total posts (#*Total_Posts*) announced by

[7] Burning Glass Technologies is renamed to Lightcast (`https://lightcast.io/`) after a recent acquisition.

firm i within the one-year rolling period ($\tau = 365$)[8] before the start date $d(e)$ of disaster e, as shown in the following expression:

$$AI\_Intensity_{i,e} = \frac{\sum_{t=d(e)-\tau}^{d(e)-1} \#AI\_Posts_{i,t}}{\sum_{t=d(e)-\tau}^{d(e)-1} \#Total\_Posts_{i,t}} \times 100 \tag{1}$$

It is worth noting that this construction of AI intensity measured with job posts is a good proxy for comparing AI investment and adoption across firms (Acemoglu et al. 2022, Alekseeva et al. 2021, Babina et al. 2024). One may have concerns about the job nature of the hiring postings and worry that the AI investment calculated from job postings can be overestimated since job vacancies posted are not necessarily fulfilled, or underestimated since AI job postings do not capture AI capital gain through M&A. Babina et al. (2024) show that the AI postings align well with the actual hiring of AI talent, validated by a resume dataset.[9] Another concern might relate to the potential discrepancy between this flow-type measure (i.e., only considering the past rolling periods) and a stock-type measure (i.e., considering all skills ever demanded during the whole period). We calculate a set of stock-type measurements with the perpetual inventory method in Appendix G and the coefficient estimates are robust. Based on the cross-sectional distribution in Panel A and inter-temporal changes in Panel B, we conclude although AI-related posts are rare and AI intensity is generally low, there is notable variation across firms and over the years, with the portion of firms having at least one AI-related posts increases from 8.12% in 2010 to 16.41% in 2019, and the intensity increases nearly five times. This rising trend in AI differs from job posts requiring general high education, such as a master's degree, implying that the effect of AI-related posts is less susceptible to the confounding variation from high-education-related investment.

3.3 Uncertainty Shock

We operationalize the uncertainty shocks with exogenous occurrences of natural disasters. We obtain the universe of natural disasters archived in the EM-DAT, the International Disaster Database that was created with the support of the Centre for Research on the Epidemiology of Disasters (CRED) and the World Health Organization (WHO).[10] It documents essential core data on over 22,000 mass disasters worldwide from 1900 to the present day, collected from various sources,

[8]In the main text, we present results with one-year rolling AI-intensity, i.e. $\tau = 365$. As robustness checks, we additionally present regression results using 3-month ($\tau = 90$), 6-month ($\tau = 180$), 18-month ($\tau = 540$), and 24-month ($\tau = 720$) rolling periods in Appendix E.

[9]Another widely-used AI investment measure is the AI-related patents. However, such measurement is not suitable for our study since it is very likely to overlook firms that are exploiting AI during operations but not inventing AI as outputs.

[10]See https://www.emdat.be for more details.

including the United Nations agencies, non-governmental organizations, insurance companies, research institutes, and news presses. It is widely used in climate research (Thomalla et al. 2006) and economic studies (Klomp 2014).

We start with 233 disaster events that occurred in the U.S. from January 2010 to December 2019. For identification and measurement purposes, we focus on well-defined sudden-impact disasters by filtering out disaster records that have missing values in start or end dates (such as droughts that develop gradually over a longer time period), in affected locations, or in estimated economic damages. Combining firms' exposure to each disaster event, we further remove the events that no firms have been exposed to. After filtration, we have 141 disasters in our analyzed sample, consisting mainly of storms and floods. Panel C of Table 1 presents the characteristics of in-sample disasters, including the disaster duration, the inflation-adjusted damages, the number of people affected, and the count of events under each categorical type.

We construct a continuous index of uncertainty shocks at the firm-by-disaster level with the following expression:

$$Shock_{i,e} = DisasterSeverity_e \times \sum_{c \in C(e)} FirmExposure_{i,e,c} \tag{2}$$

where $DisasterSeverity_e$ is measured with the inflation-adjusted total economic damages of disaster e renormalized to have the highest value of 1.[11] To address the concern that some disasters can be easily predicted and managed, thus not contributing to more uncertainty, we run robustness checks using only the uninsured portion of total economic damage as a proxy for disaster severity (shown in Table 3). Then, for each firm i, we weight the severity by $FirmExposure_{i,e,c}$, i.e., the firm's varying exposure to disaster-struck counties $C(e)$.[12] Specifically, we use the geographic distribution of firm job posts across counties in the one-year rolling period to gauge the extent of firm exposure, as expressed below:

[11] The raw damages are divided by the maximal value, hence the largest value of re-scaled disaster severity is 1. This normalization has no influence on coefficient estimates since the scaled factor is only a constant number. In addition, we should note a caveat regarding our data limitation that the documented economic damage is largely under-reported. As quoted from the EM-DAT documentation, "figures tend to be available only for high-impact disasters in countries with insurance and reinsurance coverage. The insured damage is usually reported by reinsurance companies that publish figures about disaster losses, e.g., MunichRe, SwissRe, or AON. When insured damage is reported, the total damage is generally reported from the same source for consistency". Such under-reported statistics presumably have limited impact on our estimated effects, because we focus on the United States where majority of the regions are covered by insurance and reinsurance, and because we include fixed effects at the disaster level to account for disaster-specific conditions throughout all analyses.

[12] Due to the dataset limitation, we cannot specify county-level severity for each disaster. Instead, we use the total damage and consider each affected county equally shocked.

$$FirmExposure_{i,e,c} = \frac{\sum_{t=d(e)-\tau}^{d(e)-1} \#Total\_Posts_{i,c,t}}{\sum_{c \in C} \sum_{t=d(e)-\tau}^{d(e)-1} \#Total\_Posts_{i,c,t}} \tag{3}$$

where $d(e)$ indicates the start date of event e, τ indicates the number of days in the rolling period,[13] C indicates all counties, $\#Total\_Posts$ indicates the total count of all job posts. By considering firm exposure before event occurrence, we alleviate the concern of firm strategic hiring in response to disasters. As robustness checks, instead of job posts from the BGT dataset, we use establishment-level sales and employees from the NETS dataset (details in Appendix D) to calculate the geographic exposure variable. We illustrate our construction with a numerical example as follows. Suppose, over a rolling period of one year (i.e., 365 days before the landfall date t of a disaster event), firm i has 10 job posts in county c_1 (among which 1 is AI-related), 20 job posts in county c_2 (among which 3 is AI-related), 30 job posts in county c_3 (among which 5 is AI-related). The disaster event e hits county c_1 and county c_3, and has a damage severity of 0.5. By our construction, $AI\_Intensity_{i,t} = (1+3+5)/(10+20+30) \times 100 = 15$, $FirmExposure_{i,e,c} = (10+30)/(10+20+30) = 0.66$, and $Shock_{i,e} = 0.5 \times 0.66 = 0.33$. In the extreme case, $Shock_{i,e}$ equals to 1, indicating that the entire operational sites of a company are exposed to the most severe disaster. For one instance of in-analysis disaster, Hurricane Sandy (October 22, 2012 to November 2, 2012) caused the largest economic damage measured by US dollar, with 392 firms being affected and 76 being fully exposed. For another instance, the tornado outbreak in late April 2014 caused the most widespread impact measured by geographical area, with 842 firms being affected and 369 being fully exposed.

Our measure of uncertainty shocks captures full-spectrum variations from both event severity and firm exposure. Compared to previous literature where firm headquarters are used to identify whether or not the firm is affected, our continuous measure of the firm exposure degree at the county level offers a more granular picture.[14] This granularity enhances the intention of measuring "uncertainty". Although the timing of some disaster landfalls is predictable,[15] the exact magnitude and affected area are hard to specify in advance. However, since both the measurements of

[13] In the main text, we present results with one-year rolling AI-intensity, i.e. $\tau = 365$. As robustness checks, we additionally present regression results using 3-month ($\tau = 90$), 6-month ($\tau = 180$), 18-month ($\tau = 540$), and 24-month ($\tau = 720$) rolling periods in Appendix E.

[14] This measurement comes with a caveat: in order for it to accurately capture geographical risk-exposure, the distribution of employees across locations should be aligned with the distribution of value-added. Though not fully secured, our focal sample (i.e., the product-concentrated sectors with NACIS 2-digit ≤ 49) is less likely to suffer from this measurement error compared to the excluded sample (i.e., the services-concentrated sectors with NACIS 2-digit $>$ 50). For instance, mining outputs align physically with miners, and goods produced align physically with workers at factory sites; whereas insurance services could be remotely provided by brokers, and transactions between home sellers and buyers could be enabled by real estate agents located in another county.

[15] Even when the event timing is predictable, our measurement that considers geographical distribution over one or more years' rolling period could relieve the concern since firms are not likely to predict future disasters years ahead.

uncertainty shock and of AI intensity are factoring in posting-related variation, the concern of collinearity issues between these two key variables might arise. For example, firms that anticipate higher threats of uncertainty exposure might take precautionary management practices, leading to concomitant investment in emerging technologies and AI; or firms that appear to have larger exposure might naturally be different from peers and demand higher skilled labor. To probe into this issue, we conduct correlation tests between uncertainty shock and post-based intensity measures in Appendix C and find no systematic relations. We later conduct our estimation with the fixed-effect panel analysis, an instrumental variable, and a variety of robustness checks to formally address measurement error concerns and to add support for a causal interpretation of the results.

In the following sections, we establish formal estimations with a pooled event specification. We then explore mechanisms with an adopted production function and heterogeneity tests. To enhance the causality explanation, we further develop an instrumental variable.

4 Empirical Evidence of AI Resilience

We define "resilience" as the ability to withstand or quickly recover from an exogenous shock that affects a firm's normal operations. In order to capture the dynamic changes at a relatively higher frequency level, we rely on the event study approach to reveal the impact of shocks and AI on a firm's daily stock return. Changes in stock return in the financial market reflect a real-time readjustment of public perception toward firm operations and aggregate performance. If the market negatively responds to a firm's stock under disasters, we can conclude that the uncertainty from shocks has hindered the firm's development to some extent. If investors value the affected firms differently with respect to AI intensity, it suggests supporting evidence on AI's contribution to firm resilience.

We formally estimate the effect of AI with a pooled event study approach in which each disaster is considered as an event. For each event, we adopt the difference-in-differences framework and make an adaptation to include three short time windows: before, during, and after the disaster shock.[16] We pool together all disasters as multiple events and estimate coefficients with the

[16]For this approach (i.e., using changes in stock return to capture dynamics around disasters) to be valid, we rely on an assumption that the "disruptive impact" could be timely reflected by the changes in investors' valuation towards the firm (thus the changes in the stock market returns). Under the efficient market hypothesis, this assumption normally holds because natural disasters and the following consequences are public information that could be accessed by the public with little friction. However, in cases where the firm valuation metrics are very complex, or the damage of disasters on firm operation takes longer to materialize, the changes of stock prices could lag behind the disaster event. By referring to previous studies that also use stock return to capture unexpected damages induced by natural disasters (Chen et al. 2023, Huynh and Xia 2023), and by referring to the fact that our focal sample mainly consists of product-

following regression specification:[17]

$$Return_{i,e,t} = \sum_{T=0,1,2} I\{t=T\}(\alpha_t Shock_{i,e} + \beta_t AI_{i,e} + \gamma_t Shock_{i,e} \times AI_{i,e}) + X_{i,e}\phi + \mu_i + \theta_e + \varepsilon_{i,e,t} \tag{4}$$

where $Return_{i,e,t}$ is the stock return of firm i at disaster event e in window T, $T \in (0 : "before", 1 : "in", 2 : "after")$. The window length for $T = 1$ matches the actual duration of disaster e, while the window lengths for $T = 0/2$ are set as seven trading days over which markets are likely to have incorporated changing expectations.[18] $Shock_{i,e}$ is the continuous measure of uncertainty level from firm i in disaster e. $AI_{i,e}$ (shorthand for $AI\_Intensity_{i,e}$, hereafter) is the continuous measure of AI investment of firm i before the disaster e. $X_{i,e}$ is a series of control variables for time-varying firm basics, including log-transformed assets, revenue-to-asset ratio, book-to-market ratio,[19] and financial leverage, all at the pre-disaster periods.[20] For each event, we maintain the same set of explanatory variables and only allow changes in coefficient estimates by including dummy indicators for different time windows. The coefficients α_t and β_t respectively measure baseline effects of shock severity and AI investment of firm stock return. The coefficients of interest are γ_t, representing the mitigating effect of AI over the event windows. We include fixed effects for each firm i and each disaster e to control for time-invariant firm unobservables and disaster-specific unobservables. Since firm fundamental variables vary at the quarter level, we cluster standard errors within NAICS2-by-year-by-quarter.

, and column (9) considers a sample with the same variable constructions but for firms from AI-producing and services-oriented sectors as selected by NAICS2 code equal to or greater than 50.

We present the main results in Table 2 for our focal sample (firms from AI-using and goods-

centered companies for whom the evaluation metrics (such as inventory turnover rate, gross margins, etc) are easily materialized and thereby observed in a shorter time window, we believe such concern is limited in our setting. If the impact indeed takes longer time to realize, any effects we find from a short time window would potentially serve as a lower bound of the true aggregate impact.

[17] We acknowledge that this identification and specification may suffer from potential issues about multiple treatment periods and continuous dosage in DID design. We discuss these issues in Appendix K and provide evidence to show the low heterogeneity in our treatment effects.

[18] As robustness checks, we provide results in Appendix E with window lengths being three, seven, ten, and fifteen trading days. The short length tends to generate volatile results and the longer length tends to smooth out potential variations, though the sign and magnitude of coefficient estimates stay consistent.

[19] Book-to-market ratio roughly equals to the inverse of Tobin's Q, which is widely studied in previous literature to measure firm performance (Cheng et al. 2021). Since it is a forward-looking measure that accounts for the intangible and long-term impact of some explanatory factor (Bharadwaj et al. 1999), we consider it as a control variable, while using the high-frequent stock return as the dependent variable.

[20] In execution, since we only have firm quarterly fundamental variables, we consider the pre-disaster period to the last quarter before the disaster occurrence.

oriented sectors as selected by NAICS2 less than or equal to 49) and a sample of remaining public firms (firms from AI-producing and services-oriented sectors as selected by NAICS2 equal to or greater than 49). Columns (1, 6) is our most parsimonious specification, showing baseline stock returns across three event windows. Columns (2, 7) includes the measurement of shocks, depicting baseline impacts of the varying severity of disasters. Columns (3, 8) further includes AI intensity and its interaction with shocks, exploring the baseline and mitigating role of AI. A concern is that AI may be proxying for investment in general high technology. We address this issue by additionally controlling for the firm's investment in general high technology, measured by either the intensity of job posts requiring at least a master's degree (columns 4, 9), or the ratio of R&D expense to total sales (columns 5, 10).[21] Through regressions for both firm samples, we find little significance in the coefficient estimates from the before-disaster windows, justifying parallel trends before the disaster treatment. From the during-disaster and after-disaster windows, we find a significantly negative impact of shocks and a positive mitigating impact of AI in our focal sample (i.e., firms with NAICS2 less than or equal to 49), but nearly null impact in the sample of other firms (i.e., firms with NAICS2 equal to or greater than 50). The contrast supports our aforementioned arguments that AI-using firms, compared to AI-producing firms, are more likely to subject to interruptions by natural disasters. Another possible explanation is the measurement error in our employment-based variable constructions, particularly in the services-producing sectors (as detailed in Section 3.3 and footnote 14). In this paper, instead of identifying a conclusive explanation for the contrast between the two sets of firms, we drill down into our focal sample in all following analyses, aiming to establish the robust evidence of AI resilience and understand the working mechanisms for these AI-using and goods-producing firms.

We also provide an array of robustness exercises and tests of the validity of our empirical strategy in Table 3 with our focal sample. We find consistent and robust results when we use the geographical distribution of lagged one- or two-year sales (columns 1, 2) or employees (columns 3, 4) across establishments to measure firm exposure to each disaster, when we consider only insured (column 5) or uninsured (column 6) part of economic damage caused by the disaster. Additionally, in order to test if any sub-sample drives the results, we separately consider three most common types of disasters (storms in column 7, floods in column 8, and wildfires in column 9), or exclude the largest firms (column 10). We find consistent estimates with similar magnitude, albeit slightly lower significance among wildfires that have happened only four times during our sample period. We find null effects in placebo tests when we randomly set the disaster event dates (column 11).

[21] Due to the widely documented selection bias in the self-reported R&D expense (Koh and Reeb 2015), we do not use this measure in our preferred specification.

Table 2: Evidence of AI resilience from the pooled event study

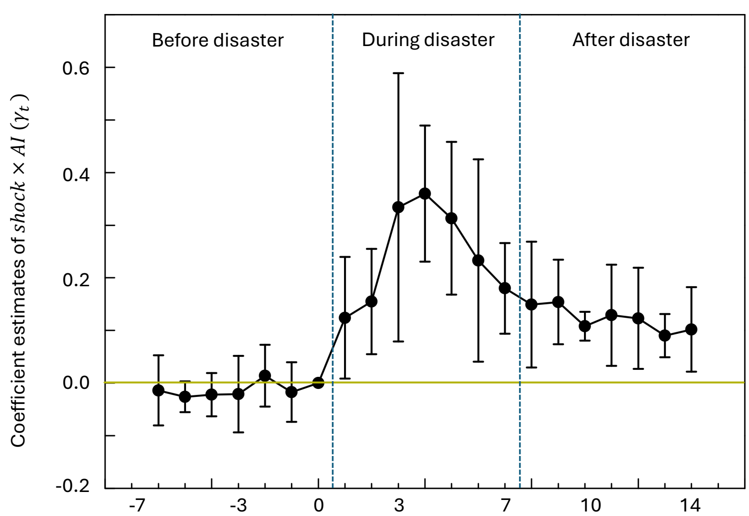
	Stock Return									
Sample	NAICS2 <= 49					NAICS2 >= 50				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Before-disaster window										
$\mathbb{1}(t=0)$	-0.225	-0.232	-0.204	-0.205	0.225	-0.570	-0.576	1.243	1.222	2.188
	(0.626)	(0.626)	(0.628)	(0.628)	(0.893)	(0.596)	(0.595)	(2.229)	(2.432)	(3.210)
$\mathbb{1}(t=0) \times$ Shock		-0.045	-0.019	0.014	-0.185*		0.219	0.204	0.130	0.023
		(0.071)	(0.070)	(0.072)	(0.105)		(0.331)	(0.135)	(0.145)	(0.124)
$\mathbb{1}(t=0) \times$ AI			0.012	0.012	0.014*			-0.003	-0.004	-0.007
			(0.009)	(0.009)	(0.009)			(0.006)	(0.006)	(0.006)
$\mathbb{1}(t=0) \times$ Shock $\times$ AI			**-0.044**	**-0.037**	**-0.035**			**-0.007**	**-0.016**	**-0.012**
			(0.035)	**(0.034)**	**(0.053)**			**(0.022)**	**(0.023)**	**(0.021)**
$\mathbb{1}(t=0) \times$ HighTech				-0.001	-0.091*				0.004	0.174
				(0.004)	(0.050)				(0.007)	(0.552)
$\mathbb{1}(t=0) \times$ Shock $\times$ HighTech				-0.019	0.103				0.040	-1.392
				(0.014)	(0.156)				(0.038)	(1.612)
During-disaster window										
$\mathbb{1}(t=1)$	-0.016	0.012	0.009	0.005	-0.018	-0.016	-0.005	-0.031	-0.032	-0.178
	(0.034)	(0.036)	(0.036)	(0.035)	(0.045)	(0.032)	(0.034)	(0.039)	(0.041)	(0.221)
$\mathbb{1}(t=1) \times$ Shock		-0.398***	-0.552***	-0.551***	-0.462***		-0.196	-0.265	-0.216	0.072
		(0.123)	(0.123)	(0.126)	(0.154)		(0.152)	(0.167)	(0.178)	(0.164)
$\mathbb{1}(t=1) \times$ AI			0.007	0.006	0.006			0.001	0.001	-0.006
			(0.008)	(0.008)	(0.010)			(0.007)	(0.007)	(0.010)
$\mathbb{1}(t=1) \times$ Shock $\times$ AI			**0.236*** **	**0.236*** **	**0.219** **			**0.031**	**0.038**	**0.067* **
			(0.074)	**(0.070)**	**(0.105)**			**(0.042)**	**(0.042)**	**(0.039)**
$\mathbb{1}(t=1) \times$ HighTech				0.002	0.021				0.000	0.532
				(0.004)	(0.060)				(0.006)	(0.752)
$\mathbb{1}(t=1) \times$ Shock $\times$ HighTech				0.000	0.232				-0.026	0.900
				(0.026)	(0.260)				(0.021)	(2.381)
After-disaster window										
$\mathbb{1}(t=2)$	-0.026	-0.011	-0.010	-0.014	-0.016	-0.011	-0.016	-0.021	-0.012	-0.072*
	(0.031)	(0.035)	(0.034)	(0.033)	(0.045)	(0.028)	(0.030)	(0.034)	(0.036)	(0.039)
$\mathbb{1}(t=2) \times$ Shock		-0.211**	-0.291***	-0.270***	-0.139		-0.094	-0.129	-0.089	-0.005
		(0.095)	(0.094)	(0.096)	(0.127)		(0.132)	(0.146)	(0.156)	(0.128)
$\mathbb{1}(t=2) \times$ AI			-0.001	-0.002	-0.004			0.001	0.000	0.001
			(0.006)	(0.006)	(0.008)			(0.006)	(0.006)	(0.006)
$\mathbb{1}(t=2) \times$ Shock $\times$ AI			**0.122** **	**0.127*** **	**0.132* **			**-0.008**	**-0.003**	**-0.000**
			(0.049)	**(0.047)**	**(0.079)**			**(0.026)**	**(0.027)**	**(0.023)**
$\mathbb{1}(t=2) \times$ HighTech				0.002	-0.022				0.005	-0.363
				(0.002)	(0.053)				(0.005)	(0.745)
$\mathbb{1}(t=2) \times$ Shock $\times$ HighTech				-0.011	-0.284				-0.021	0.884
				(0.018)	(0.216)				(0.018)	(2.330)
Obs	417897	417897	417897	417897	210703	268422	268422	268422	268422	134259
R^2	0.42	0.42	0.42	0.42	0.48	0.36	0.36	0.37	0.37	0.38
Control: Time-varying basics	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE: Firm + Disaster	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table presents the empirical evidence of AI resilience as reflected by stock return changes over three disaster windows: before (T=0), during (T=1), and after (T=2). We run regressions respectively on firms with NAICS2 less than or equal to 49 (columns 1 to 5) and firms with NAICS2 equal to or greater than 50 (columns 6 to 10). The dependent variable *Return* and the independent variable *AI_Intensity* are measured by percentages. The main body of the table can be read as follows: respectively at time $T = 0/1/2$, the first section of rows shows the base level of return in the absence of any shock and AI; the second section of rows shows the impact of shock severity on return; the third section of rows shows the impact of AI on return; the last section of rows shows the impact of AI on mitigating the relation between shock severity and return. Independent variables are progressively added through columns (1) to (3) and columns (6) to (8). We further include the firm's investment in general high technology, measured by either the intensity of job posts requiring at least a master's degree (columns 4, 9) or the ratio of R&D expense to total sales (columns 5, 10). All specifications control for time-varying firm basics, including log-transformed assets, revenue-to-asset ratio, book-to-market ratio, and financial leverage. Fixed effects are at the firm and disaster levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In addition, we also vary the choices in event window lengths, the rolling period for computing firm exposure, and AI intensity. Results are consistent and provided in Appendix E. Collectively, these robustness tests provide strong evidence that our event-study specification and construction of shocks capture the first-order effect of uncertainty shocks on firms, and the construction of AI intensity captures the second-order variation defined as "resilience".

From our preferred identification (column 4 of Table 2)[22], an AI intensity level of 2.4% – out of 100 cumulative job posts, 2.4 being AI-related, could approximately recover the full damage of uncertainty shocks on stock returns. To conduct a more granular examination, we plot the dynamic coefficient estimates of interest in Figure 1 by expanding the observation frequency from windows to days. The figure suggests that the mitigating effect of AI on shocks is greater in the during-disaster period than after-disaster period, with a peak in the middle of the disaster event. Additionally, we further investigate the heterogeneous effects at different levels of AI with a dose-response function approach (detailed in Appendix L). The results imply that the benefits of AI increase with its intensity of use and the superstar AI-using firms gain the largest market premium.

Figure 1: Plot of coefficient estimates of the interaction term between *shock* and *AI*



Notes: This figure presents the coefficient estimates for the interaction term between *shock* and *AI* (i.e., the mitigating effect of AI on disaster-shocked stock return) and their 95% confidence intervals. The regression specification follows column 4 of Table 2 with the observation frequency expanded from windows to days. Horizontal axis denotes relative days to the start of the disaster (0 being the day prior to the start). Vertical dotted lines separate before, during, and after disaster periods.

[22] Since R&D expense variable suffers from the issue of a serious selection bias when firms file the report (Koh and Reeb 2015), plus the inclusion of which leads to almost one-half decrease in available observations, we do not consider this variable as our preferred identification.

Table 3: Robustness checks

Robustness	Stock Return										
	Firm exposure measure				Disaster severity measure		Sample selection				Placebo test
	Employee 1yr	Employee 2yrs	Sales 1yr	Sales 2yrs	Insured	Uninsured	Only storms included	Only floods included	Only wildfires included	Largests firms removed	Random event-dates
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Before-disaster window											
𝟙(t=0)	-0.201	-0.200	-0.202	-0.201	0.111	0.106	-0.180	0.333	-0.952	0.106	0.003
	(0.628)	(0.628)	(0.628)	(0.628)	(0.730)	(0.730)	(0.646)	(1.067)	(3.475)	(0.730)	(0.730)
𝟙(t=0) × Shock	0.458	0.453	0.485	0.484	-0.089	-0.055	0.046	-0.062	0.089	-0.055	-0.160
	(0.439)	(0.531)	(0.399)	(0.500)	(0.091)	(0.061)	(0.080)	(0.238)	(0.431)	(0.061)	(0.112)
𝟙(t=0) × AI	0.012	0.012	0.011	0.012	0.015	0.015	0.010	0.026	0.032	0.015	0.022**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.023)	(0.038)	(0.010)	(0.011)
𝟙(t=0) × Shock × AI	**-0.063**	**-0.083**	**-0.044**	**-0.073**	**0.004**	**0.002**	**-0.032**	**0.039**	**-0.336***	**0.002**	**0.089**
	(0.077)	**(0.080)**	**(0.078)**	**(0.084)**	**(0.043)**	**(0.027)**	**(0.038)**	**(0.110)**	**(0.176)**	**(0.027)**	**(0.143)**
During-disaster window											
𝟙(t=1)	-0.007	-0.007	-0.006	-0.006	-0.181	-0.175	-0.008	-0.132	0.012	-0.175	0.022
	(0.032)	(0.032)	(0.032)	(0.032)	(0.232)	(0.192)	(0.040)	(0.093)	(0.099)	(0.329)	(0.022)
𝟙(t=1) × Shock	-1.034***	-1.034***	-1.054***	-1.051***	-0.270*	-0.232**	-0.555***	-0.433***	-0.925*	-0.232***	-0.019
	(0.273)	(0.278)	(0.273)	(0.277)	(0.158)	(0.104)	(0.142)	(0.102)	(0.518)	(0.654)	(0.087)
𝟙(t=1) × AI	0.013*	0.013*	0.013*	0.013*	0.002	0.001	0.010	-0.037*	0.019	0.001	-0.009
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.019)	(0.040)	(0.009)	(0.008)
𝟙(t=1) × Shock × AI	**0.189***	**0.202***	**0.188***	**0.203****	**0.257*****	**0.178*****	**0.236*****	**0.209*****	**0.280**	**0.178*****	**-0.030**
	(0.106)	**(0.107)**	**(0.102)**	**(0.103)**	**(0.068)**	**(0.046)**	**(0.078)**	**(0.033)**	**(0.180)**	**(0.046)**	**(0.058)**
After-disaster window											
𝟙(t=2)	-0.015	-0.015	-0.015	-0.014	-0.107	-0.106	-0.024	-0.045	0.185	-0.106	0.009
	(0.032)	(0.032)	(0.032)	(0.032)	(0.211)	(0.201)	(0.033)	(0.086)	(0.185)	(0.222)	(0.020)
𝟙(t=2) × Shock	-0.705***	-0.726***	-0.723***	-0.744***	-0.141*	-0.109***	-0.322***	-0.390**	-0.960	-0.109**	-0.001
	(0.221)	(0.223)	(0.221)	(0.223)	(0.702)	(0.029)	(0.097)	(0.201)	(0.823)	(0.495)	(0.089)
𝟙(t=2) × AI	-0.001	-0.001	-0.000	-0.001	-0.004	-0.005	0.002	-0.029	-0.015	-0.005	-0.014
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.022)	(0.058)	(0.007)	(0.009)
𝟙(t=2) × Shock × AI	**0.206****	**0.220****	**0.191****	**0.212****	**0.116****	**0.078****	**0.125****	**0.111****	**0.465****	**0.078****	**0.025**
	(0.097)	**(0.099)**	**(0.097)**	**(0.100)**	**(0.056)**	**(0.038)**	**(0.052)**	**(0.050)**	**(0.222)**	**(0.038)**	**(0.043)**
Obs	417897	417897	417897	417897	296841	296841	346607	49382	9393	296841	296841
R^2	0.42	0.42	0.42	0.42	0.43	0.43	0.42	0.47	0.61	0.43	0.43
Control: HighTech	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Control: Time-varying basics	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE: Firm + Disaster	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table reports robustness tests for evidence of AI resilience as reflected by stock return changes over disaster windows. In this table and thereafter, only firms with NAICS2 less than or equal to 49 are included. Columns (1, 2) and columns (3, 4) replace job-post-based firm exposure with operation-size-based geographical distribution of sales or employees average over lagged one or two years from the NETS dataset. Columns (5, 6) separately measure the shock severity with only insured or uninsured portion. Columns (7) to (9) only use storms, floods, or wildfires. Column (10) removes the largest firms characterized by having a total asset of the top 20%. Column (11) assigns random disaster dates, serving as the placebo test. The dependent variable *Return* and the independent variable *AI_Intensity* are measured by percentage levels. All specifications control for the firm's investment in general high technology measured by the intensity of job posts requiring at least a master's degree, and the time-varying firm basics including log-transformed assets, revenue-to-asset ratio, book-to-market ratio, and financial leverage. Fixed effects are at the firm and disaster levels. Only coefficients for shock severity and its interaction with AI intensity are presented in the table. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5 Mechanism Tests

The previous section establishes the evidence of AI resilience from a high-frequency stock return identification. This section examines the mechanism through which AI empowers firm resilience. First, we present the estimation function, which is aligned with widely used models of productivity of technology but accounts for technology-dependent factor elasticity. Then, we discuss identification concerns due to possible endogeneity and confounding impact of general IT investment, as well as the methodologies employed to address these concerns. Finally, we explore heterogeneity and gauge the varying potential of AI across firms.

5.1 Production Function

To study the contribution of AI to firm operations under uncertainty, ideally we would want to conduct analysis within the exact corresponding time frame, i.e., firm-by-disaster data panel. However, we are not aware of any dataset that tracks firm inputs and outputs at such a high frequency. Thus, we turn to the firm-by-quarter panel retrieved from Compustat that documents reliable measures of firm accounting variables.[23] As for the empirical identification, we refer to methods from production economics in which relationships between various production inputs, such as working capital and human labor, and firm output are estimated via a production function. The productivity test is widely used to study the value of IT, in particular emerging technologies, in that it theoretically embeds allocative efficiency, directly ties to an important firm outcome (i.e., performance measured by value added), and the estimates from which are most powerful statistically when not all firms have made the optimal match (i.e. when firm choices on inputs and outputs are not fully self-conscious and endogenous) (Wu et al. 2019). To be comparable and compatible with the bulk of research on the productivity test, we adopt the Cobb–Douglas specification as the underlying functional form. In the existing literature, the IT component is either considered as one part of human labor (Tambe and Hitt 2012b) or financial capital (Dhyne et al. 2020). However, AI is arguably having a broader impact on firms due to its role of making predictions and aiding decisions at all levels of firm operation (Agrawal et al. 2022). This motivates us to consider the AI component being integrated with both existing inputs, labor and capital. With further empirical evidence suggesting significant variation in factor elasticity among firms with different risk exposures (Dewan et al. 2007), with different combinations of practices (Tambe et al. 2012), in different economic circumstances (Tambe and Hitt 2012b), or in different

[23]We present suggestive argument that our firm-by-quarter panel is able to identify the variation induced by disaster shocks based on the finding that across-industry heterogeneity is well aligned between firm-by-disaster analysis and firm-by-quarter analysis. More details are provided in Appendix H.

market competitiveness conditions (Chang and Gurbaxani 2013), we directly model the elasticity of production factors to be dependent on uncertainty shocks and AI intensity.[24] The specification is as follows:

$$VA_{i,q} = C * K_{i,q}^{\alpha} * L_{i,q}^{\beta} \tag{5}$$

where the analysis unit is at the firm-by-year-by-quarter level due to the data availability of major variables. $VA_{i,q}$ is the value-added (equal to production outputs less cost of production inputs).[25] $K_{i,q}$ and $L_{i,q}$ are respectively working capital and human labor capital of firm i in year-quarter q. C is the efficiency multiplier that captures intangible assets such as management skill, institutional knowledge, and learning. We introduce variation of uncertainty shock and AI intensity into the elasticity of two production inputs:

$$\begin{aligned} \alpha =& \alpha_0 + \alpha_1 Shock_{i,q} + \alpha_2 AI_{i,q} + \alpha_3 Shock_{i,q} AI_{i,q} \\ \beta =& \beta_0 + \beta_1 Shock_{i,q} + \beta_2 AI_{i,q} + \beta_3 Shock_{i,q} AI_{i,q} \end{aligned} \tag{6}$$

where $Shock_{i,q}$ is the averaged $Shock_{i,e}$ for disasters happened in quarter q; $AI\_Intensity_{i,q}$ is the $AI\_Intensity_{i,d}$ in which d is set as the start date of quarter q, so that $AI\_Intensity_{i,q}$ measures the rolling AI intensity before this current quarter. Note that we include potential variation in elasticity for both factors, agnostic in advance about whether AI should contribute to capital or labor productivity. After taking log transformation, we estimate the following regression model:

$$\begin{aligned} LnVA_{i,q} =\ & \alpha_0 LnK_{i,q} + \alpha_1 Shock_{i,q} LnK_{i,q} + \alpha_2 AI_{i,q} LnK_{i,q} + \alpha_3 Shock_{i,q} AI_{i,q} LnK_{i,q} \\ & + \beta_0 LnL_{i,q} + \beta_1 Shock_{i,q} LnL_{i,q} + \beta_2 AI_{i,q} LnL_{i,q} + \beta_3 Shock_{i,q} AI_{i,q} LnL_{i,q} \\ & + LnC + \theta_{naics(i),q} + \varepsilon_{i,q} \end{aligned} \tag{7}$$

[24] Our motivation for building the variables of interest into factor elasticity in the production function also comes from a set of reduced-form regressions with the firm-year-quarter panel. We provide details in Appendix F. Various outcome measures, such as sales, costs, and expense, are regressed on the level of shock severity, AI intensity, and other independent variables that are argued to be relevant from previous literature. We find null effects from our variables of interest for explaining the level of inputs (i.e., the amount of costs of goods sold, the amount of expenses) or the level of outputs (i.e., the amount of sales, the gross margin of goods sold). Rather, we find some notable impact from AI for mitigating the weakened inventory turnover and asset turnover during shock periods. Therefore, we are motivated to take a structural approach, i.e., production function, to formally investigate our speculation that AI mitigates uncertainty through adjusting the efficiency and responsiveness of input usage.

[25] We used standard methods from the micro-productivity literature to calculate value-added (Dewan et al. 2007). Price deflators for inputs and outputs are taken from the Bureau of Labor Statistics (BLS) and Bureau of Economic Analysis (BEA) websites.

where we include fixed effects at the NAICS2-by-year-by-quarter level to account for time-varying unobservables across industries. We cluster standard errors at NAICS2 to address possible serial correlation within the industry.

Table 4 presents the results. We start from the plain version of Cobb–Douglas specification in column 1, modify the elasticity by adding uncertainty shock and AI intensity in column 2, and further control for general advanced skills (measured by the intensity of job posts requiring master's degree or higher) in column 3 and strong innovations (measured by the ratio of R&D to sales) in column 4. Several observations emerge. First, the unconditional estimates of factor elasticity are consistent in magnitude and significance across different specifications, proving the validity of the Cobb-Douglas function. Second, there is a significantly negative impact of uncertainty shock on the elasticity of working capital, some on the elasticity of human labor but with volatile estimations across different inclusions of competing variables. Third, AI has a small, if any, baseline effect on factor elasticity, but rather consistent mitigation effect when firms are struck by uncertainty shocks. Fourth, we find no evidence of benefits from general advanced skills, implying that the effect of AI is separated from employees having higher educations or general skills, but specific to the AI-related functions. Fifth, we find some evidence from R&D that higher such expense contributes to greater elasticity of human labor in baseline periods, and greater elasticity of working capital in uncertain periods, consistent with previous literature that strong innovations can facilitate employee productivity on average and firm use of working capital in unexpected situations (Cardona et al. 2013, Hottman et al. 2016, Babina et al. 2024).

By rough estimation, an average firm has an AI-intensity 0.79%, which contributes to approximately 14.15% higher elasticity on working capital and 8.22% higher elasticity on human labor during uncertainty shocks in the most severe decile, calculated by the coefficients in column 2 as an example. To absorb more variation in firm-specific total factor productivity, we additionally add firm fixed effects in columns 5-8. On one hand, the coefficient estimate of unconditional elasticity decreases substantially (a 28.39% decline in labor elasticity, and a 77.11% decline in capital elasticity), but is now more precisely estimated. On the other hand, the interaction term between uncertainty shock and AI remains consistent with comparable magnitude and significance, suggesting a non-firm-specific positive effect of AI on improving the responsiveness of firm value-added to each unit of capital input.[26] We present the analyses across different sectors at NAICS2 level and find the effects most significant among firms in the manufacturing and the retail

[26] The results in Columns (1-4) are unconditional on firms, allowing for the elasticity coefficients to absorb some unobserved firm heterogeneity, consistent with prior work that suggested a source of productivity contribution being slow-changing firm-specific organizational practices (Bresnahan et al. 2002). The results in Columns (5-8) are conditional on firms, removing elasticity components that are persistent at the firm level over time, thus presenting more conservative econometrically but also likely to substantially underestimate actual impacts of AI-relevant technology.

Table 4: Production function analyses

	Log value added							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Labor input								
Log labor	0.652***	0.743***	0.739***	0.712***	0.480***	0.544***	0.542***	0.759***
	(0.047)	(0.052)	(0.052)	(0.048)	(0.052)	(0.046)	(0.046)	(0.079)
Shock × log labor		-0.176***	-0.178***	-0.066*		-0.095**	-0.092**	-0.086***
		(0.051)	(0.051)	(0.032)		(0.040)	(0.041)	(0.024)
AI × log labor		0.019	0.016	0.005		-0.004	-0.005	0.012
		(0.013)	(0.012)	(0.018)		(0.009)	(0.009)	(0.018)
Shock × AI × log labor		**0.116*** **	**0.115*** **	**0.041**		**0.081*** **	**0.082*** **	**0.055**
		(0.030)	**(0.029)**	**(0.064)**		**(0.013)**	**(0.014)**	**(0.048)**
Capital input								
Log capital	0.431***	0.442***	0.434***	0.495***	0.093***	0.136***	0.136***	0.198***
	(0.052)	(0.051)	(0.051)	(0.044)	(0.026)	(0.029)	(0.029)	(0.031)
Shock × log capital		-0.178***	-0.174***	-0.232***		-0.220***	-0.214***	-0.232***
		(0.022)	(0.022)	(0.027)		(0.016)	(0.017)	(0.027)
AI × log capital		0.009*	0.007	0.008*		0.003	0.003	0.000
		(0.004)	(0.004)	(0.004)		(0.003)	(0.002)	(0.005)
Shock × AI × log capital		**0.102*** **	**0.105*** **	**0.122*** **		**0.110*** **	**0.113*** **	**0.119*** **
		(0.018)	**(0.018)**	**(0.037)**		**(0.017)**	**(0.017)**	**(0.033)**
Const.	-0.577**	-0.579**	-0.557**	-1.068***	1.512***	1.413***	1.416***	0.866***
	(0.232)	(0.209)	(0.207)	(0.165)	(0.179)	(0.169)	(0.170)	(0.136)
Obs	51146	51146	51146	26335	51003	51003	51003	26178
R^2	0.61	0.66	0.67	0.73	0.79	0.83	0.83	0.85
Control: HighTech	N	N	Y	Y	N	N	Y	Y
FE: naics2*year*quarter	Y	Y	Y	Y	Y	Y	Y	Y
FE: firm	N	N	N	N	Y	Y	Y	Y

Notes: This table reports the productivity test of AI using the firm-by-quarter panel, aiming to investigate the mechanism through which AI enhances the contribution of each production factor. The dependent variable *value added* and the independent variables *employee* and *capital* are log-transformed. *Shock severity* and *AI intensity* are aggregated at the firm-quarter level, i.e., the average shock uncertainty from all disasters faced by a firm in each quarter and the average AI intensity for a firm in each quarter. The main body of the table can be read as follows: respectively for the input factor being labor or capital, the first row shows baseline input elasticity; the second row shows the impact of shock severity on altering the baseline elasticity; the third row shows the impact of AI on altering the baseline elasticity; the last row shows the impact of AI on altering the relation between shock severity and input elasticity. The firm's investment in general high technology is controlled for and measured by the intensity of job posts requiring at least a master's degree (columns 3, 7) or the ratio of R&D expense to total sales (columns 4, 8). Fixed effects are at the NAICS2-by-year-by-quarter level and additionally at the firm level through columns (5) to (8). Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

trade industries. More details and discussions are documented in Appendix H.

5.2 Instrumental Variable

Measurement of AI intensity using a rolling period of AI-related post intensity will be biased if there are unobserved factors influencing AI investment that are correlated with the responsiveness of firm operations to capital, conditional on the included fixed effects. One source of endogeneity is self-selection, wherein, for example, firms with better management practices or simply with larger size tend to adopt more AI and meanwhile be more resilient towards uncertainty thanks to the sagacious management team or the comprehensive support from organizational resources. Another source of endogeneity is simultaneity or reverse causation, wherein firms dynamically adjust their level of investment since the elasticity of production factors changes under varying environmental conditions. Besides endogeneity, the problem of measurement error arises due to limitations in our job posting dataset that the realized fulfillment rate of AI-related job posts is unclear and might differ across samples, resulting in our post-based measure being misaligned with actual AI investment. Although our inclusion of industry-by-time and firm-fixed effects can absorb systematic errors at these levels, the time-varying fulfillment rates at the firm and occupation levels cannot be addressed.

To mitigate these firm-level endogeneity concerns, we attempt to isolate the firm-specific variation that is less vulnerable to the above-mentioned issues and couple it with aggregate changes in AI-related factors to account for the temporal dynamics. We follow previous literature (Acemoglu et al. 2022, Felten et al. 2021) and construct a firm structure-based AI exposure as an instrumental variable for our post-based AI intensity. Their approach calculates an ability-AI score that considers the compatibility between AI applications and worker abilities (e.g., depth perception, number facility, and written comprehension), then uses the importance and prevalence of each work ability across O*NET occupations to construct occupational-level AI exposure, finally, uses the composition of occupations across firms to construct firm-level AI-exposure. We adopt this general framework while making two improvements. First, instead of a static measure of ability-AI scores elicited from subjective surveys, we employ a data-driven method that tracks the temporal changes in ability-AI scores revealed from aggregate job posts. Second, instead of characterizing firms with their composition of six-digit occupations, we directly look at their composition of abilities. By reducing the dimension from 774 (i.e., the number of categories at the six-digit occupation level) to 52 (i.e., the number of total abilities), we mitigate the volatility introduced by different posting conducts at the firm-by-occupation level.

With this ability-based AI exposure, two related concerns are still pending, albeit with a small probability: if the ability-AI scores seldom vary across time, then the variation in our instrument could be dominated by firm baseline structure, thus accounting for little changes in AI investment; if the ability-AI scores indeed vary but managers somewhat foresee the suitability dynamics, firms might alter its hiring strategy to embrace the changes in advance. Therefore, we run another set of specifications in which we replace the level of ability-AI scores with the abrupt changes in ability-AI scores induced by exogenous shocks. As execution, we exploit the sudden releases of the first major open-source machine learning platform, TensorFlow, that significantly facilitates AI-related tasks, reduces AI-related skill training costs, and boosts AI-related skill supply. Our evidence in Appendix J Figure A3 shows that this enhancement of AI varies across abilities, providing an effective source of exogenous changes in ability-AI scores. Correspondingly, a Bartik-style shift-share regression using the firm structure-weighted exogenous changes provides robust results in direction and significance, as shown in Appendix J.

We illustrate the process of instrument construction and the results of corresponding regressions. As the first step, we rearrange the occupation-level job posts to ability-level job posts using the O*NET 24.1 database released in November 2019:

$$\#Posts_{i,a,q} = \sum_{o \in O} \#Posts_{i,o,q} \times \frac{L_{o,a} \times K_{o,a}}{\sum_{a \in A} L_{o,a} \times K_{o,a}} \tag{8}$$

where a indexes the ability, o indexes the occupation, and $\#Posts_{i,,q}$ indexes the number of job posts for firm i in year-quarter q measured at either ability- or occupation-level. Following Felten et al. (2021), we decompose each occupation into 52 abilities based on each ability's share within that occupation. The share is calculated by multiplying the prevalence ($L_{o,a}$) and importance ($K_{o,a}$) for each ability-occupation pair, scaled so that shares of all abilities within each occupation sum to one. These prevalence and importance scores, as provided by O*NET, allow us to properly characterize each occupation by the embedded abilities. Then, we obtain ability-level job posts $\#Posts_{i,a,q}$ by summing over all occupations $o \in O$.

With the rearranged dataset with ability-level job posts, our instrumental variable is constructed as follows:

$$IV_{i,q} = \sum_{a \in A} BaseShare_{i,a,q_0} \times AI\_Score_{-i,a,q} \tag{9}$$

where $BaseShare_{i,a,q_0}$ denotes the baseline (q_0 includes 2010Q1 to 2012Q4)[27] ability structure for firm

[27]The selection of baseline being three years is in reference to Acemoglu et al. (2022).

i, as measured by:

$$BaseShare_{i,a,q_0} = \frac{\#Posts_{i,a,q_0}}{\sum_{a \in A} \#Posts_{i,a,q_0}} \tag{10}$$

and $AI\_Score_{-i,a,q}$ denotes the compatibility between ability a and AI (ability-AI score, hereafter) for peer firms $-i$ in the same NAICS2 industry with focal firm being left out at year-quarter q. Different from Felten et al. (2021) where the ability-AI score is a static measure elicited from subjective surveys, we proxy for a continuous time-series ability-AI score with ability-level AI intensity averaged among peer firms, as presented below:

$$AI\_Score_{-i,a,q} = MEAN\left(\frac{\#AI\_Posts_{-i,a,q}}{\#Posts_{-i,a,q}}\right) \tag{11}$$

where $\#AI\_Posts_{-i,a,q}$ and $\#Posts_{-i,a,q}$ respectively denote the count of AI-related or general posts at the *ability* level. Thus, higher $AI\_Score_{-i,a,q}$ means the ability a is more compatible with AI-related skills in this industry. For example, the ability of mathematical reasoning has the highest average AI score, while the ability of dynamic flexibility has a low AI score. Note that this measure of ability-AI scores does not attempt to measure whether AI is a complement to or a substitute for this ability, but rather how likely it is that the ability is exposed to AI in some way.

We provide evidence showing that our way of constructing the ability-AI score is consistent with previous literature, in that the ability-AI scores averaged over time series are highly correlated with the static ability-AI scores from Felten et al. (2021) ($\rho = 0.76, p < 0.001$). Meanwhile, our construction of baseline ability structure appears to be more suitable for characterizing a firm's inherent task composition than the occupation-based structure used in Acemoglu et al. (2022). The ability-based structure explains more variation across firms while remaining stable over time within a firm.[28]

To prove the validity of our instrumental variable, we first discuss the relevance condition. We document that it is highly correlated with post-based AI intensity as measured in Expression 1. The first stage regression in Table 5 shows an F-statistic of 319.54, suggesting large predictive power from the instrument. In addition, referring to the conclusion from Brynjolfsson et al. (2021), time-invariant workplace characteristics strongly shape returns to predictive analytics. Moreover, such contingency may be beyond managerial control, thus creating an inherent and lasting link between firm structure measured by the workforce and firm adoption of emerging technologies.

We then discuss the exclusion conditions. Note that our instrument contains two sources of

[28]For each firm-year, we compute a vector representing shares of abilities (or occupations). We then calculate the correlation of within-firm pairs and across-firm pairs. The higher ratio of within-firm correlation to between-firm correlation suggests more stability in characterizing the same firm while differentiating from other firms. Such a ratio equals 1.64 for the ability-based vector and 1.13 for the occupation-based vector.

variation: the baseline mix of abilities for each focal firm, and the time-series changes of ability-AI scores averaged among peer firms (with the focal firm being removed). The former variation is fixed at the baseline years (2010-2012, same as Acemoglu et al. (2022)), thus not susceptible to confounding the within-firm changes over time. The latter variation comes from leave-one-out aggregate movements, thus cannot explain the cross-section differences after including NAICS2-by-year-by-quarter fixed effects. Given that we define peer firms as those in the same NAICS2 code, and it is not likely for firms to flexibly select into certain peer groups in response to performance changes, the concern of reverse causality is relieved. However, we provide formal evidence in Appendix I where we adopt the stricter rule than normal and test if firm fixed effects (considering both observable and unobservable firm-specific factors) could predict the instrumented AI exposure. Following the suggestion by Bertrand and Schoar (2003), we first regress firm performances on generic control variables such as firm size as well as fixed effects at the firm level. Then we retrieve the fitted value of firm fixed effects from above and use it as an explanatory factor for our instrument. The non-significance of firm fixed effects (as shown in Appendix I) supports no sign of a reverse causality problem.[29]

With the instrumental variable, we estimate a two-stage regression model and present the results in Table 5. The first stage regression (column 1) shows the significant predictive power of our instrument to AI intensity measured with Expression 1, and generates an estimated AI intensity for the second stage regression where the specifications follow those in Table 4.[30]

Table 5 presents that results from instrumented regressions are consistent and robust in terms of the coefficient magnitude. One notable observation is that the impacts of uncertainty shocks on factor elasticity and how AI mitigates the negative impacts differ in regressions with fixed effects only at the industry-by-year level (columns (2)-(4)) versus regressions with additional fixed effects at the firm level (columns (5)-(7)). This suggests that the mitigating advantage of AI on improving capital elasticity is only detectable conditional on firm-specific total factor productivity. Given the empirical evidence of great heterogeneity in total factor productivity across firms (Brynjolfsson and Hitt 1995, Stiroh 2002, Dhyne et al. 2020), we argue that regressions in columns (5)-(7) are closer to actual production function forms,[31] and that AI brings resilience to uncertainty-struck

[29] Despite these arguments and tests for exclusion conditions, we should caution that IT-shift correlating with AI-shift at the ability level is still a valid concern. In the next section, we discuss and explicitly control for IT-related variables in the hope of partially relieving this concern.

[30] We standardize the raw and instrumented AI intensity by dividing them by their respective standard deviation. Hence, coefficients in Table 5 and Table 4 could be interpreted comparably, in that the estimates imply a change in the outcome variable associated with a standard deviation difference in the explanatory variable.

[31] We provide another reason why regressions with firm fixed effects contribute to more precise estimations. Compared to the raw measure of AI intensity that considers time-varying firm-specific variation, our instrument variable considers only time-invariant firm-specific variation. Therefore, the additional inclusion of firm fixed effect under instrumented regressions fully teases out the potential correlation between explanatory variable and omitted variables,

Table 5: Causal identification with instrumental variable

	AI	Log value added					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Instrument variable	0.489***						
	(0.027)						
Labor input							
Log labor		0.765***	0.773***	0.716***	0.502***	0.506***	0.702***
		(0.081)	(0.079)	(0.075)	(0.072)	(0.073)	(0.080)
Shock × log labor		-1.367***	-1.272***	-1.029***	-0.570**	-0.547**	-0.462**
		(0.352)	(0.322)	(0.118)	(0.224)	(0.222)	(0.187)
AI × log labor		-0.002	-0.008	0.002	0.020	0.023	0.037*
		(0.028)	(0.028)	(0.031)	(0.013)	(0.014)	(0.020)
Shock × AI × log labor		**0.412****	**0.384*****	**0.307*****	**0.157***	**0.154****	**0.115**
		(0.134)	**(0.120)**	**(0.063)**	**(0.072)**	**(0.067)**	**(0.072)**
Capital input							
Log capital		0.404***	0.396***	0.460***	0.124***	0.124***	0.214***
		(0.060)	(0.058)	(0.054)	(0.027)	(0.027)	(0.024)
Shock × log capital		-0.201*	-0.226*	-0.291**	-0.389***	-0.396***	-0.428***
		(0.105)	(0.107)	(0.108)	(0.043)	(0.047)	(0.085)
AI × log capital		0.014	0.012	0.014	-0.004	-0.004	-0.016**
		(0.009)	(0.009)	(0.010)	(0.004)	(0.004)	(0.005)
Shock × AI × log capital		**0.033**	**0.036**	**0.046**	**0.091*****	**0.089*****	**0.097*****
		(0.041)	**(0.042)**	**(0.040)**	**(0.015)**	**(0.014)**	**(0.027)**
Const.	0.297***	-0.526**	-0.483*	-1.051***	1.544***	1.538***	1.010***
	(0.006)	(0.236)	(0.225)	(0.193)	(0.165)	(0.165)	(0.146)
Obs	46649	38894	38894	19874	38722	38722	19701
R^2	0.01	0.63	0.63	0.70	0.82	0.82	0.83
Control: HighTech	N	N	Y	Y	N	Y	Y
FE: naics2*year*quarter	N	Y	Y	Y	Y	Y	Y
FE: firm	N	N	N	N	Y	Y	Y

Notes: This table reports the productivity test of AI using the instrumental variable approach. Column (1) shows the first-stage regression of AI intensity on the instrumental variable. Columns (2) to (7) show the second-stage regressions of fitted AI intensity on concerning variables. The main body of the table can be read as follows: respectively for the input factor as labor or capital, the first row shows baseline input elasticity; the second row shows the impact of shock severity on altering the baseline elasticity; the third row shows the impact of AI on altering the baseline elasticity; the last row shows the impact of AI on altering the relation between shock severity and input elasticity. The firm's investment in general high technology is controlled for and measured by the intensity of job posts requiring at least a master's degree (columns 3, 6) or the ratio of R&D expense to total sales (columns 4, 7). Fixed effects are at the NAICS2-by-year-by-quarter level and additionally at the firm level through columns (5) to (7). Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

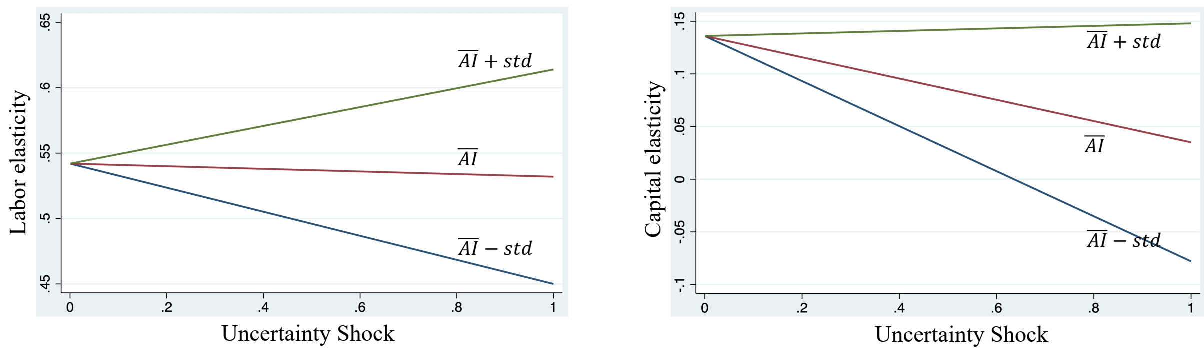
firms mainly through an increase in production responsiveness to one additional unit of financial capital. This is consistent with results from Table 4 that the coefficients of AI impact on capital elasticity increase in magnitude and decrease in variance (i.e., more precisely estimated) after adding firm fixed effects, opposite to the coefficients of that on labor elasticity. Combining these observations, we conclude that AI benefits on labor-wise productivity are slightly more specific to firms, while that on capital-wise go beyond the firm-specific features.

Under the preferred specification from Column (6) in Table 5, we calculate the elasticity of production factors at varying levels of shocks across three different groups of observations that have an AI intensity at mean, and one standard deviation below or above mean. We visualize

leading to a smaller variance in coefficient estimations.

the estimations in Figure 2. Two main observations arise. First, conditional on the level of shock, higher AI investment positively lifts the elasticity of both production factors, with the boosting effect more significant as the level of shock increases. Second, in response to increasing shocks, as opposed to the downward slope among low-AI samples, we observe a slight upward trend among high-AI firms.

Figure 2: Elasticity estimation on different AI intensity levels



Notes: The figure visualizes the estimated elasticity of input factors from the production function specification. The y-axis on the left (right) figure denotes the estimated elasticity of labor (capital), i.e., α (β) in Expression 6. The x-axis denotes a varying level of uncertainty shocks. Three lines mark observations that have an AI intensity at mean, one standard deviation below mean, and one standard deviation above mean.

5.3 IT as Confounding Factors

While AI-based decision-making is conceptually different from general IT, as discussed in the section 2.2, we also acknowledge the potential benefits from general IT in handling emergencies. Some examples might include firms remaining accessible during disrupted events if their data and systems are hosted in the cloud, or firms being able to function remotely if mobile phones, laptops, videoconferencing tools, and file-sharing services are properly deployed.[32] Hence, given the fact that AI adoption largely goes hand-in-hand with IT adoption,[33], our results could be a proxy for the value of deploying general IT, instead of AI in specific. In this section, we conduct a battery of robustness checks to show that our estimates are not driven by these confounders.

First, we explicitly control for general IT-related variables. We leverage our detailed data to develop measures of investments in non-AI technologies: for each firm, we measure the percentage of job postings in the past rolling year requiring general IT or specific IT (including robot-, data analytic-, or cloud-related skills) that are not specific to AI.[34] We include these IT-related variables

[32]We gratefully thank the review team for providing these examples.

[33]The correlated shift between AI and IT is also evidenced in previous literature (McElheran et al. 2024) and observed from the time-series trends we plot with our job-posting data in Appendix C

[34]We refer to Babina et al. (2024) and define a job post as general IT-related if at least 10% of the required skills are in the "Information Technology" skill cluster; as robot-related if any of the required skills has the keyword "Robotics";

in the production-function specification, with results shown in Table 6. Panel A uses the raw AI intensity measurement, and Panel B uses the instrumented AI intensity measurement. The estimated relationship between AI intensity and responsiveness of input factors during shock periods remains similar with the addition of these controls. Notably, the coefficients for instrumented AI almost stay unchanged across different sets of additional control, meanwhile are consistently more accurately estimated (as implied by smaller standard errors and larger t-values) compared to that for raw AI. This provides additional support for the validity of our causal identification: the instrumented variation of AI shift is not confounded with that of general IT shifts. Nevertheless, it is worth mentioning that we do find some significant impact of general IT for the overall operations, but not particularly for shocked periods. We also spot some positive effects of specific robot-, data analytic-, and cloud-related technologies, despite being less consistent and smaller in magnitude.

Second, we probe into the potential channels through which AI and IT might contribute to firm production. If AI is indeed distinct from IT, we should expect to observe differences in terms of the scenarios where the value of each could surface. As gathered from the existing literature, the merits of AI potentially stem from its aiding role for cognitive tasks such as decision-making (Alekseeva et al. 2020, Boyacı et al. 2023), and its preemptive and optimizing capability in operational processes such as supply chain coordination (Hu et al. 2024, Senoner et al. 2022). Hence, we are motivated to further distinguish AI- and IT-related posts across different job positions. Specifically, we consider if a job requires cognitive-related tasks, if a job sits in a decision-maker role, or if a job deals with supply chain-related matters.[35] We run the production function models with both AI and general-IT measurements, respectively in conditions that only consider cognitive-related jobs, non-cognitive-related jobs, decision-making jobs, non-decision-making jobs, supply-chain-related jobs, and non-supply-chain-related jobs. Results are presented in Table 7. The positive impacts of AI on factor responsiveness are more significant when such AI skills are used in cognitive tasks, with decision-making roles, and for supply-chain issues, whereas the impact of IT is roughly indistinguishable across these conditions (if any, slightly higher in non-cognitive tasks, at non-manager roles, and for non-supply-chain issues).

Combining the models that control for IT-related measurements and the models that sort out

as data-analytic-related if skills are required from both data-related skill clusters and from "Analysis" skill cluster; as cloud-related if any of the required skills has the keyword "cloud computing" or cloud-computing related software. AI-related posts are exclusive to being IT-related: if a post requires both AI-related and general IT-related skills, it is deemed as an AI-related post.

[35]We refer to Hershbein and Kahn (2018) and define a job position as requiring cognitive abilities if any listed skills include at least one of the following terms: "research," "analy-," "decision," "solving," "math," "statistic," or "thinking." We define a job with a decision-making function if its O*NET two-digit code is 11 (i.e., all types of manager-related occupations). We define a job in charge of supply-chain-related matters by first looking up the O*NET code for "supply chain managers" (11-3071), and then collecting the top ten related occupations provided on the official website https://www.onetonline.org/link/summary/11-3071.04.

Table 6: Controlling for General- and Specific-IT

	Log value added							
"AI" =	Raw AI intensity				Instrumented AI intensity			
"IT" =	General IT	Robot	Analytic	Cloud	General IT	Robot	Analytic	Cloud
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Labor input								
Log labor	0.511***	0.506***	0.506***	0.505***	0.552***	0.542***	0.545***	0.532***
	(0.073)	(0.073)	(0.073)	(0.071)	(0.049)	(0.045)	(0.048)	(0.043)
Shock × log labor	-0.552**	-0.528**	-0.572**	-0.489**	-0.113**	-0.103**	-0.101**	-0.092**
	(0.225)	(0.206)	(0.236)	(0.218)	(0.043)	(0.041)	(0.041)	(0.041)
"AI" × log labor	0.027	0.023	0.026*	0.019	-0.004	-0.005	-0.004	-0.008
	(0.016)	(0.013)	(0.014)	(0.013)	(0.009)	(0.009)	(0.009)	(0.009)
Shock × "AI" × log labor	**0.154***	**0.144****	**0.161***	**0.129***	**0.080*****	**0.079*****	**0.078*****	**0.079*****
	(0.073)	**(0.062)**	**(0.075)**	**(0.067)**	**(0.015)**	**(0.015)**	**(0.014)**	**(0.014)**
"IT" × log labor	0.04***	0.003	0.025**	0.031	0.05***	0.001	0.021**	0.029**
	(0.012)	(0.021)	(0.011)	(0.020)	(0.011)	(0.012)	(0.016)	(0.011)
Shock × "IT" × log labor	0.006	0.002	0.011	0.049*	0.015	0.027	0.014	-0.001
	(0.023)	(0.022)	(0.023)	(0.026)	(0.011)	(0.017)	(0.011)	(0.011)
Capital input								
Log capital	0.124***	0.124***	0.124***	0.124***	0.134***	0.136***	0.136***	0.137***
	(0.027)	(0.027)	(0.027)	(0.028)	(0.029)	(0.029)	(0.029)	(0.029)
Shock × log capital	-0.391***	-0.394***	-0.366***	-0.410***	-0.215***	-0.212***	-0.215***	-0.214***
	(0.053)	(0.045)	(0.047)	(0.048)	(0.016)	(0.017)	(0.017)	(0.016)
"AI" × log capital	-0.005	-0.004	-0.005	-0.003	0.003	0.003	0.003	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
Shock × "AI" × log capital	**0.086*****	**0.087*****	**0.075*****	**0.095*****	**0.113*****	**0.113*****	**0.113*****	**0.114*****
	(0.019)	**(0.014)**	**(0.014)**	**(0.016)**	**(0.020)**	**(0.018)**	**(0.017)**	**(0.017)**
"IT" × log capital	0.01**	0.003	0.004	-0.010	0.007**	0.002	0.002	0.007**
	(0.004)	(0.007)	(0.005)	(0.007)	(0.003)	(0.004)	(0.005)	(0.003)
Shock × "IT" × log capital	0.001	0.014**	0.019**	-0.010	0.003	0.001	0.008	0.004
	(0.007)	(0.006)	(0.007)	(0.009)	(0.005)	(0.006)	(0.006)	(0.005)
Const.	1.538***	1.538***	1.537***	1.541***	1.416***	1.416***	1.416***	1.423***
	(0.167)	(0.164)	(0.166)	(0.163)	(0.170)	(0.169)	(0.170)	(0.170)
Obs	51003	51003	51003	51003	38722	38722	38722	38722
R^2	0.82	0.82	0.82	0.82	0.83	0.83	0.83	0.83
Control: HighTech	Y	Y	Y	Y	Y	Y	Y	Y
FE: naics2*year*quarter	Y	Y	Y	Y	Y	Y	Y	Y
FE: firm	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table reports the productivity test of AI while controlling for the intensity of IT investment. Columns (1) to (4) consider the raw measures of AI, and columns (5) to (8) consider the instrumented measures of AI. IT variables refer to general IT-related (columns 1,5), robotic-related (columns 2,6), data-analytic-related (columns 3,7), and cloud-computing-related (columns 4,8) job posts. The main body of the table can be read as follows: respectively for the input factor as labor or capital, the first row shows baseline input elasticity; the second row shows the impact of shock severity on altering the baseline elasticity; the third (fourth) row shows the impact of AI (IT) on altering the baseline elasticity; the fifth (sixth) row shows the impact of AI (IT) on altering the relation between shock severity and input elasticity. The firm's investment in general high technology is controlled for and measured by the intensity of job posts requiring at least a master's degree. Fixed effects are at the NAICS2-by-year-by-quarter level and the firm level. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: AI/IT Skills across Positions

	Log value added					
{Positions} =	Cognitive	Non-cognitive	Decision-making	Non-decision-making	Supply chain	Non-supply-chain
	(1)	(2)	(3)	(4)	(5)	(6)
Labor input						
Log labor	0.549***	0.563***	0.552***	0.558***	0.551***	0.561***
	(0.050)	(0.053)	(0.050)	(0.052)	(0.049)	(0.053)
Shock × log labor	-0.089	-0.063	-0.080	-0.058	-0.082	-0.040
	(0.051)	(0.053)	(0.055)	(0.051)	(0.057)	(0.044)
AI-in-{positions} × log labor	-0.011	0.001	-0.010	0.009	-0.008	-0.027*
	(0.018)	(0.009)	(0.017)	(0.019)	(0.017)	(0.013)
Shock × AI-in-{positions} × log labor	**0.080*** **	**-0.022**	**0.075*** *	**0.031**	**0.076*** **	**0.060*** **
	(0.026)	**(0.069)**	**(0.032)**	**(0.061)**	**(0.021)**	**(0.017)**
IT-in-{positions} × log labor	0.030**	0.025**	0.020**	0.029***	0.012	0.022**
	(0.014)	(0.013)	(0.011)	(0.009)	(0.010)	(0.014)
Shock × IT-in-{positions} × log labor	0.000	0.013	-0.007	0.002	-0.001	-0.044**
	(0.012)	(0.017)	(0.012)	(0.014)	(0.014)	(0.018)
Capital input						
Log capital	0.134***	0.129***	0.132***	0.131***	0.132***	0.131***
	(0.028)	(0.028)	(0.029)	(0.028)	(0.029)	(0.028)
Shock × log capital	-0.193***	-0.196***	-0.194***	-0.198***	-0.193***	-0.202***
	(0.014)	(0.012)	(0.012)	(0.014)	(0.012)	(0.015)
AI-in-{positions} × log capital	0.005	0.001	0.003	-0.003	0.003	0.008**
	(0.006)	(0.004)	(0.006)	(0.008)	(0.006)	(0.003)
Shock × AI-in-{positions} × log capital	**0.082*** **	**0.024**	**0.077*** **	**0.043**	**0.083*** **	**0.008**
	(0.021)	**(0.031)**	**(0.023)**	**(0.028)**	**(0.020)**	**(0.016)**
IT-in-{positions} × log capital	0.011**	0.015***	0.010***	0.019***	0.000	0.011**
	(0.005)	(0.005)	(0.004)	(0.003)	(0.004)	(0.006)
Shock × IT-in-{positions} × log capital	-0.008	0.007	-0.005	0.007	-0.008	0.028**
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.010)
Const.	1.429***	1.433***	1.432***	1.428***	1.433***	1.427***
	(0.171)	(0.167)	(0.168)	(0.172)	(0.171)	(0.166)
Obs	51003	51003	51003	51003	51003	51003
R^2	0.82	0.82	0.82	0.82	0.82	0.82
Control: HighTech	Y	Y	Y	Y	Y	Y
FE: naics2*year*quarter	Y	Y	Y	Y	Y	Y
FE: firm	Y	Y	Y	Y	Y	Y

Notes: This table reports the productivity test of AI and IT measured with relevant job posts from different positions: cognitive or non-cognitive (columns 1,2), decision-making or non-decision-making (columns 3,4), supply-chain-related or non-supply-chain-related (columns 5,6). The main body of the table can be read as follows: respectively for the input factor as labor or capital, the first row shows baseline input elasticity; the second row shows the impact of shock severity on altering the baseline elasticity; the third (fourth) row shows the impact of AI (IT) on altering the baseline elasticity; the fifth (sixth) row shows the impact of AI (IT) on altering the relation between shock severity and input elasticity. The firm's investment in general high technology is controlled for and measured by the intensity of job posts requiring at least a master's degree. Fixed effects are at the NAICS2-by-year-by-quarter level and the firm level. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

granular scenarios, we confirm that AI, beyond general IT, has systematic and specific impact on the documented higher factor elasticity during shocks.

6 Heterogeneity Tests

In Table 5, we reveal an interesting dynamic between different production factors: the uncertainty disruption and the AI mitigation divert from influencing labor elasticity to influencing capital elasticity after controlling for firm fixed effects. This implies that the outcome responsiveness to capital varies mainly inter-temporally within the firm, while that to labor varies mostly at the cross-section level. Motivated by the hint of cross-sectional heterogeneity, we resolve to examine the firm characteristics that drive the above-mentioned findings with a series of sub-sample studies. To keep consistent with the definition of the section (i.e., the fixed effects at NAICS2-by-year-by-quarter level), we categorize observations into two sub-samples based on the median value of concerning variables within each NAICS2-by-year-by-quarter cell. Then, we run the specification of Column (6) of Table 5 respectively for the two sub-samples.[36]

We characterize firms from multiple aspects, including financial leverage (measured by the ratio of liabilities to assets), financial flexibility (measured by the ratio of cash holdings to assets), operating flexibility (measured by the ratio of working capital to operating expense), supporting expenses (measured by the ratio of selling, general, and administrative expense to revenue), and inventory turnover (measured by the ratio of cost of goods sold to average inventory). To alleviate the concern of reverse causality, we consider the variable at a one-quarter lagged period. Table 8 presents the results. The responsiveness of production outcome to labor input varies greatly among different samples: the uncertainty shock is more disruptive and the AI is more defensive for firms with smaller leverage, lower flexibility financially and operationally, less supporting expense, and poorer inventory turnover. In contrast, the responsiveness of production outcome to capital input stays consistent throughout samples, corroborating the results in Table 5 that the variation on capital elasticity resides mainly inter-temporally within the firm.

The heterogeneous results imply some *potential* of AI in helping underperforming and constrained firms to catch up with high-performers or even to gain a competitive advantage in the production process. However, the coefficient estimates are independent of the units used to measure the inputs and outputs, thus they cannot be easily compared across different samples that have different average levels of factor input shares. In other words, after considering actual inputs

[36] We maintain the fixed effects at the firm level to remove unobserved firm heterogeneity. Compared to the one-sample analysis, the split-sample analysis allows the firm fixed effects to vary when the same firm is divided into different types based on changing dynamics within firms and within cells.

Table 8: Heterogeneity across major firm characteristics

	Liabilities / Assets		**Cash / Assets**		**Working cap. / Operating exp.**		**SGA exp. / Revenue**		**Inventory turnover**	
Sample	Lower	Higer	Lower	Higer	Lower	Higer	Lower	Higer	Lower	Higer
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Coefficients										
Log labor	0.595***	0.391***	0.430***	0.688***	0.407***	0.510***	0.420***	0.602***	0.602***	0.437***
Shock × log labor	-0.998**	-0.319	-0.604***	-0.490	-0.585***	-0.279	-0.529***	-0.210	-0.656**	-0.546
Fitted AI × log labor	0.014	0.036*	0.030*	0.019	0.023	0.064*	0.034**	0.026*	0.024	0.031**
Shock × Fitted AI × log labor	0.297**	0.072	0.172***	0.119	0.165**	0.031	0.148**	0.024	0.178*	0.151
Log capital	0.116***	0.126***	0.094***	0.184**	0.077***	0.292**	0.117***	0.149***	0.137***	0.112***
Shock × log capital	-0.285**	-0.443***	-0.387***	-0.389***	-0.408***	-0.443***	-0.399***	-0.423***	-0.397***	-0.367**
Fitted AI × log capital	0.000	-0.008	-0.005	-0.003	-0.002	-0.013	-0.007	-0.005	-0.005	-0.005
Shock × Fitted AI × log capital	0.050	0.108***	0.087***	0.089***	0.094***	0.113**	0.090***	0.104***	0.090***	0.081
Elasticity										
$E(labor)$	0.597	0.448	0.470	0.704	0.430	0.614	0.469	0.636	0.623	0.479
$E(capital)$	0.096	0.077	0.052	0.159	0.042	0.245	0.068	0.117	0.098	0.387
Marginal product										
$MP(labor)$	29.380	14.068	18.083	26.951	13.745	21.418	15.866	22.404	19.204	20.828
$MP(capital)$	0.034	0.029	0.024	0.044	0.021	0.054	0.026	0.035	0.027	0.029

Notes: This table presents heterogeneity tests of AI productivity under shocks across major firm characteristics: lower or higher liability-to-asset ratio (columns 1, 2), lower or higher cash-to-asset ratio (columns 3, 4), lower or higher working capital-to-operating expense ratio (columns 5, 6), lower or higher expenses-to-revenue ratio (columns 7, 8), and lower or higher inventory turnover ratio (columns 9, 10). In the section of *Coefficients*, numbers refer to the estimates of parameter coefficients from sub-sample analyses, and stars denote the significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. In the section of *Elasticity* and *Marginal product*, numbers refer to the calculated values of output elasticity with Expression 6 and marginal product with Expression 12 in each sub-sample.

in firm productions, the *realized* productivity gain could differ from the aforementioned latent benefit. Hence, in addition to reporting coefficients, we also report output elasticity calculated with Expression 6, and follow Brynjolfsson and Hitt (1996) and Tambe and Hitt (2012b) to compute the marginal product (*MP*), the increase in value-added associated with one additional unit of production factor (i.e., one thousand dollar working capital or one human labor). The calculation is equal to the output elasticity of factor input multiplied by the ratio of output to that factor input (with an example of capital input K):

$$MP_K = \frac{\partial VA}{\partial K} = \frac{\partial VA}{\partial K}\frac{K}{VA}\frac{VA}{K} = \alpha\frac{VA}{K} \tag{12}$$

where, following Dhyne et al. (2020), we calculate the factor input share for each observation and take the mean of the resulting distribution after winsorizing at the 1% level to avoid biases from outliers. In Table 8, we present the elasticity and marginal product computed with firm actual input shares. The comparison suggests that under-performing and constrained firms which could potentially benefit more from AI investment in aggregate do not generate higher production gain per unit of input. Among many conjectures, one key explanation could be the under-investment in focal AI or complementary infrastructure, rendering a lower rate of accruing marginal return from production inputs.

Motivated by the conjecture, we further explore firm characteristics that depict the level of complementary investments. Previous literature finds that benefits from advanced technologies such as AI are accentuated for firms with a larger portion of general-IT skills, higher level of

Table 9: Heterogeneity across levels of complementary investment

Sample	IT / Non-IT posts		Educated workers		AI positions	
	Lower	Higer	Lower	Higer	Technical	Managerial
	(1)	(2)	(3)	(4)	(5)	(6)
Coefficients						
Log labor	0.725***	0.601**	0.616***	0.244*	0.585**	0.983***
Shock × log labor	-1.175***	-0.460	-0.487**	-0.375	-1.926**	-1.295
Fitted AI × log labor	-0.048	-0.050	-0.024	0.103**	0.077	-0.097
Shock × Fitted AI × log labor	0.357***	0.136	0.146**	0.069	0.536**	0.317
Log capital	0.012	0.033	0.055	0.138***	0.244**	0.135**
Shock × log capital	-0.194	-0.447**	-0.389***	-0.462***	0.199	-0.019
Fitted AI × log capital	0.002	0.012	0.006	-0.014	-0.010	0.089**
Shock × Fitted AI × log capital	0.016	0.103*	0.081***	0.120***	-0.062	0.003
Elasticity						
$E(labor)$	0.434	0.525	0.457	0.525	0.429	0.605
$E(capital)$	0.009	0.042	0.081	0.019	0.025	0.065
Marginal product						
$MP(labor)$	13.471	13.869	14.430	17.393	12.788	24.893
$MP(capital)$	0.002	0.021	0.005	0.028	0.013	0.044

Notes: This table presents heterogeneity tests of AI productivity under shocks across major firm characteristics: lower or higher ratio of IT-related job posts (columns 1, 2), lower or higher ratio of education-demanding job posts (columns 3, 4), and AI-posts concentrated more in technical-knowledge-demanding positions or managerial-knowledge-demanding positions (columns 5, 6). In the section of *Coefficients*, numbers refer to the estimates of parameter coefficients from sub-sample analyses, and the stars denote the significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. In the section of *Elasticity* and *Marginal product*, numbers refer to the calculated values of output elasticity with Expression 6 and marginal product with Expression 12 in each sub-sample.

educated workers, and more skill-aligned management teams (Tambe 2014, Brynjolfsson and McElheran 2016, Rock 2019). In our analyses, we measure the three aspects respectively with the ratio of IT-related job posts accrued over the past three years,[37] the average requirement on educational background for job posts over the past three years, and the ratio of number of AI-posts in technical-knowledge-demanding positions to that in managerial-knowledge-demanding positions.[38] Then, we calculate the median value within the NAICS2-by-year-by-quarter cell and run sub-sample regressions accordingly. Table 9 presents the results. Echoing the results from Table 8, firms currently with lower levels of complementary investment tend to have potentially greater benefits from AI investment, all else being equal. However, after considering the practical input share of capital and labor chosen by firms, the calculated elasticity and marginal product are consistently lower than firms with stronger complements.

Overall, the evidence on heterogeneous effects suggests that there is a great potential for leveraging AI to achieve enhanced performance in turbulent contexts, especially for currently under-performing firms or firms with larger constraints. In practice, however, the under-investment in complementary infrastructure seems to render the realized benefits lower than expected.

[37] We use the same way of identifying general-IT-related job posts as that from Table 6. Combining results from Table 6 and Table 9 implies that, although general-IT itself appears to be less capable of mitigating disruptions, it provides a supportive role for AI to better unleash the potential.

[38] We observe the level of knowledge-demand by referring to the importance and prevalence of management-relevant or technique-relevant knowledge as identified by O*NET. If a job requires more management-relevant knowledge than technique-relevant knowledge, it is regarded as a managerial-knowledge-demanding position.

7 Conclusion and Implications

The primary objective of this paper is to conduct an empirical investigation to evaluate whether and how investment in AI can improve firms' performance when faced with uncertainty shocks. After controlling for various company characteristics and risk factors and using a comprehensive dataset on online job vacancy postings, we find that corporate AI investments can generate considerable resilience as reflected by the mitigated stock value loss caused by disruptive uncertainty. Such mitigated loss in the stock market can be explained by the improved production as identified from an adapted Cobb-Douglas function: investment and accumulation of AI relieve the disturbed elasticity of firm outputs to production inputs among conditions of abnormality. The proposed mechanism of AI empowering resilience is further confirmed with an instrumental variable and an array of robustness tests that control for IT-related investment and explore various potential channels.In addition, the split-sample heterogeneity tests suggest greater potential for employing AI among under-performing firms. However, the actual realized gain being smaller among these firms implies a pressing need for complementary investments and management designs. Overall, our paper identifies an important aspect of AI effectiveness - by increasing labor productivity and capital responsiveness, AI furnishes resilience for firms during rough times.

We acknowledge a major limitation in this paper that the exact practice underlying firm productions is not well discussed. Due to the complexity and variability of production processes across firms and the lack of detailed measurements and datasets, exploration on this end is beyond the scope of our current study. A related caveat is that we do not provide a thorough understanding of all of our results, such as the nuanced differential impact on labor versus capital or whether the impact is specific within firms or general across industries. Qualitative interviews and surveys would help with a further understanding of granular mechanisms. We hope that these findings spark interest in researchers and practitioners to explore in future efforts. Rather than digging deeper into the precise functioning, our goal in this paper is to take an aggregate perspective on the common usage of AI, studying the value and the cost, thus achieving the goal of weighing allocative efficiency. With our broader coverage of firms, solid measures of key variables and instruments, and robust empirical analyses from the firm-date panel and firm-quarter panel, we establish the causal facts and shed light on future research regarding AI effectiveness.

Our research contributes to both academia and industry. It not only enhances our understanding of corporate AI investments as IS researchers but also provides new insights regarding corporate resilience by offering practical managerial guidance on what kind of firms should rely on AI more during shocks. Although natural disasters are difficult to predict, our evidence indicates that if AI is invested in the right setting and used to perform the correct functions, a firm can mitigate the adverse impacts that the disasters bring. Furthermore, the investment in AI should be made by those who can make the most out of the technology, at least at uncertain times. For example, though previous literature found firms with higher liquidity or more cash holdings invest in AI more (Babina et al. 2024, Alekseeva et al. 2021), our results show AI investments have a larger positive effect on income performance under disasters for firms with stronger financial constraints. It suggests that those financially constrained firms should seriously consider AI investments, especially in today's uncertain environment. This makes smart manufacturing and Industry 4.0 technologies more important than ever before.

During the past few years, the pandemic has negatively struck many companies, and corporate resilience has never been as important as it is now. As such, the evolution of AI competence can be thought of as a type of insurance policy that helps companies brace for uncertainty and turbulence. If crisis is the new norm, infusing AI into firm productions is no longer a luxury - it's a necessity. With forewarnings about critical events, AI can help create a semblance of stability and, at the same time, improve efficiencies to get the most out of installed capital investments. As a recent example, AI has already been deployed to assess food supply disruption caused by COVID-19 in real time.[39] Our results indicate that an enhanced benefit of AI investments is that they function like insurance premiums, a new notion that goes beyond the traditional understanding of AI's productivity and performance.

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Appendix

A Sample Comparison

We present here the characteristics of all firms from Compustat before our process of merging with other datasets and filtering with missing variables. Compared to the universe of public firms in Compustat (with NAICS2 < 50), our in-analysis sample covers firms that are slightly larger in size and better in performance, while similar in financial ratios and aggregate standard deviations.

Table A1: Summary statistics of Compustat firms

	Characteristics of Compustat firms (N=7889)					
	Min	P25	P50	P75	Max	Std. Dev.
Asset	0.00	19.54	139.23	1223.29	440707.20	18038.05
Cash	-0.99	1.93	16.61	82.60	27700.55	1187.59
Sales	-200.11	0.23	17.45	217.42	121759.40	3877.02
Cost of goods sold	-87.13	0.68	12.68	140.18	94866.58	3131.20
R&D expense	-0.01	0.19	2.63	12.31	7343.56	255.20
# employees	0.00	0.03	0.29	2.83	2222.22	40.73
Working capital	-40421.78	-0.10	17.38	129.35	42480.80	1582.83
Revenue-to-asset	-5417.78	-0.45	-0.06	0.02	294.03	85.38
Book-to-market	-1.45	0.47	1.02	2.13	435341.80	6787.37
Debt-to-asset	0.00	0.08	0.21	0.37	967.87	15.72

Notes: The industry distribution categorized by NAICS2 code is: 11 (0.61%), 21 (24.67%), 22 (4.49%), 23 (1.89%), 31-33 (55.39%), 42 (3.71%), 44-45 (5.02%), 48-49 (4.21%).

B List of AI Skills

Table A2: AI Skills

List of AI Skills			
1	AI KIBIT	36	Mlpy
2	ANTLR	37	Modular Audio Recognition Framework
3	Apertium	38	Moses
4	Artificial Intelligence	39	Mxnet
5	Automatic Speech Recognition(ASR)	40	Natural Language Processing
6	Caffe Deep Learning Framework	41	Natural Language Toolkit
7	Chatbot	42	ND4J
8	Computational Linguistics	43	Nearest Neighbor Algorithm
9	Computer Vision	44	Neural Networks
10	Decision Trees	45	Object Recognition
11	Deep Learning	46	Object Tracking
12	Deep Learning4j	47	OpenCV
13	Distinguo	48	OpenNLP
14	Google Cloud Machine Learning Platform	49	Pattern Recognition
15	Gradient Boosting	50	Pybrain
16	H2O	51	Random Forests
17	IBM Watson	52	Recommender Systems
18	Image Processing	53	Semantic Driven Subtractive Clustering Method
19	Image Recognition	54	Semi-Supervised Learning
20	IPSoft Amelia	55	Sentiment Analysis / Opinion Mining
21	Ithink	56	Sentiment Classification
22	Keras	57	Speech Recognition
23	Latent Dirichlet Allocation	58	Supervised Learning
24	Latent Semantic Analysis	59	Support Vector Machine
25	Lexalytics	60	TensorFlow
26	Lexical Acquisition	61	Text Mining
27	Lexical Semantics	62	Text To Speech
28	Libsvm	63	Tokenization
29	Machine Learning	64	Torch
30	Machine Translation (MT)	65	Unsupervised Learning
31	Machine Vision	66	Virtual Agents
32	Madlib	67	Vowpal
33	Mahout	68	Wabbit
34	Microsoft Cognitive Toolkit	69	Word2Vec
35	Mlpack	70	Xgboost

C Correlation Tests between Uncertainty Shocks and Key Constructs

We check the correlations between uncertainty shock and key constructs, including AI intensity, Master-degree intensity, and value-added at the firm-by-year-by-quarter level in Table A3. This model-free description shows no systematic relation between uncertainty shock and other post-based intensity measures, suggesting the non-existence of collinearity issue, but a significantly negative relation with value-added, suggesting the validity of this uncertainty shock capturing firm-specific impacts from various disasters.

Table A3: Model-free statistics per uncertainty shock bin

Uncertainty shock decile	Uncertainty shock	AI intensity (%)	Master intensity (%)	Value-added ('000 US$)
0~10%	0.01	0.93	2.30	971.93
10~20%	0.02	0.76	1.91	636.70
20~30%	0.04	0.69	1.65	571.57
30~40%	0.07	0.59	1.47	578.16
40~50%	0.11	0.57	1.44	562.56
50~60%	0.17	0.51	1.43	397.66
60~70%	0.27	0.57	1.52	436.04
70~80%	0.40	0.67	2.05	466.29
80~90%	0.54	0.72	2.33	391.11
90~100%	0.70	0.56	2.11	293.22

Notes: We rank uncertainty shocks from the firm-by-year-by-quarter panel into ten bins, and present the corresponding average value of the uncertainty shock, AI intensity, Master intensity, and value-added of firm outputs.

D Time Series Trends of IT-related Demands

In this section, we present the time-series demands of AI and several IT-related skills that are arguably also creating resilience. To increase the relevance of our concerning samples, we only depict firms that have ever posted AI-related skills. We construct IT-related intensity by referring to that of AI-related intensity, i.e., the share of job posts that require IT-related skills among a total number of all job posts. Following Babina et al. (2024), we include and measure four non-exclusive IT-related job posts: a general IT-related job defined as a job in which at least 10% of the required skills are in the "Information Technology" skill cluster; a robot-related job defined as a job that requires any skills containing the keyword "Robotics"; a data-analytic-related job defined as a job that requires skills from both data-related skill clusters and the "Analysis" skill cluster; a cloud-related job defined as a job that requires any skills containing the keyword "cloud computing" or cloud-computing related software. We plot the time-series changes of each intensity measure compared to AI-intensity in Figure A1. Despite a few divergences at some time points, the overall correlation between AI and IT adoption is notable.

Figure A1: Time-series trend of firms demanding AI and IT

Notes: The figure presents time-series changes of AI intensity and four other intensity measures: general IT-related jobs, cloud-computing-related jobs, data-analytic-related jobs, and robotic-related jobs.

E The NETS Dataset

As a robustness check for our variable construct, we use the NETS dataset to measure the geographical distribution of firm operations and calculate the extent of firm exposure to each disaster event. NETS (the National Establishment Time-Series) is a time-series database of establishment information. We use the release of the 2021 NETS Database, which includes thirty-two annual snapshots (taken every January) of the full Duns Marketing Information (DMI) file that follows over 82.4 million establishments between January 1990 and January 2021. The time-series variables include the total number of employees and the estimated annual sales at the establishment level. Thus, we consider these two variables as indicators of the level of economic activity across facilities from different counties. To reduce reverse causality, we use the records from lagged one or two year(s) as the measure of exposure in the present year. Table A4 presents the time-series changes in the distribution of employee counts and estimated sales at the firm level.

Table A4: Time-series summary statistics from the NETS dataset

Year	Min	P25	P50	P75	Max	Std. Dev.
# Employees						
2010	0	23	353	3181.5	350702	20944.34
2011	0	30	385	3235.5	351463	21786.39
2012	0	34.5	413.5	3262.5	353251	22711.57
2013	0	35	432.5	3374	362350	23086.57
2014	0	33	421.5	3308	372673	22637.27
2015	0	37	432	3347.5	394592	23068.28
2016	0	42	468.5	3268.5	414217	23180.7
2017	0	44	505.5	3213	419576	22691.24
2018	0	44	487.5	3034.5	429361	21343.95
2019	0	46	500.5	3083.5	430862	21161.85
Sales						
2010	0	3009892	1.120E+08	1.020E+09	3.360E+11	1.200E+10
2011	0	4588750	1.140E+08	9.770E+08	4.480E+11	1.370E+10
2012	0	5007041	1.210E+08	9.900E+08	5.590E+11	1.590E+10
2013	0	5308888	1.290E+08	1.080E+09	6.700E+11	1.990E+10
2014	0	5037462	1.210E+08	1.020E+09	6.420E+11	1.860E+10
2015	0	5657406	1.250E+08	1.000E+09	6.130E+11	1.840E+10
2016	0	6321709	1.320E+08	9.990E+08	3.610E+11	1.220E+10
2017	0	6828103	1.280E+08	9.440E+08	2.220E+11	9.420E+09
2018	0	6998873	1.240E+08	8.410E+08	1.660E+11	7.960E+09
2019	0	8076352	1.360E+08	9.000E+08	2.590E+11	9.230E+09

F Different Constructs in a Pooled Event-Study

We show in Table A5 the robustness tests with different considerations on event window length (i.e., the considered number of days before and after disasters) (Columns 1-4), on rolling periods over which the firm's geographic exposure (Columns 5-8) and the firm's AI intensity (Columns 9-12) are calculated. Our results largely persist.

Table A5: Different constructs in pooled event-study

Robustness	Return											
	Event window length (days)				Firm exposure rolling period (months)				AI intensity rolling period (months)			
	3	5	9	14	3	6	18	24	3	6	18	24
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Before-disaster window												
𝟙(t=0)	-0.065	-0.136	-0.091	-0.162	-0.207	-0.206	-0.203	-0.204	0.518	0.087	0.146	0.178
	(0.645)	(0.653)	(0.644)	(0.624)	(0.628)	(0.628)	(0.628)	(0.628)	(0.757)	(0.724)	(0.636)	(0.681)
𝟙(t=0) × Shock	-0.034	-0.010	-0.006	0.090	0.041	0.018	0.018	0.025	0.020	0.027	0.079	0.056
	(0.122)	(0.084)	(0.067)	(0.056)	(0.078)	(0.074)	(0.073)	(0.074)	(0.071)	(0.072)	(0.074)	(0.077)
𝟙(t=0) × AI	0.004	0.012	0.011	0.014*	0.012	0.012	0.012	0.012	0.007	0.002	0.015	0.019*
	(0.011)	(0.010)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.006)	(0.006)	(0.009)	(0.010)
𝟙(t=0) × Shock × AI	**-0.005**	**-0.043**	**-0.023**	**-0.009**	**-0.040**	**-0.038**	**-0.042**	**-0.044**	**-0.033**	**-0.033**	**-0.046**	**-0.038**
	(0.053)	**(0.040)**	**(0.029)**	**(0.020)**	**(0.036)**	**(0.035)**	**(0.034)**	**(0.034)**	**(0.027)**	**(0.026)**	**(0.043)**	**(0.056)**
During-disaster window												
𝟙(t=1)	-0.068	-0.003	0.024	0.022	0.005	0.003	0.005	0.005	0.025	0.020	0.016	0.035
	-0.655	(0.036)	(0.034)	(0.031)	(0.035)	(0.035)	(0.035)	(0.035)	(0.036)	(0.035)	(0.034)	(0.033)
𝟙(t=1) × Shock	-0.506***	-0.524***	-0.552***	-0.333***	-0.598***	-0.540***	-0.535***	-0.533***	-0.554***	-0.557***	-0.596***	-0.574***
	(0.180)	(0.143)	(0.120)	(0.108)	(0.135)	(0.129)	(0.123)	(0.121)	(0.129)	(0.128)	(0.133)	(0.137)
𝟙(t=1) × AI	0.014	0.006	0.006	0.003	0.008	0.007	0.006	0.006	-0.012	-0.007	0.004	0.007
	(0.010)	(0.009)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)
𝟙(t=1) × Shock × AI	**0.204****	**0.242*****	**0.220*****	**0.037**	**0.227*****	**0.229*****	**0.238*****	**0.239*****	**0.195*****	**0.218*****	**0.208****	**0.203****
	(0.082)	**(0.077)**	**(0.066)**	**(0.056)**	**(0.068)**	**(0.068)**	**(0.070)**	**(0.070)**	**(0.058)**	**(0.066)**	**(0.090)**	**(0.097)**
After-disaster window												
𝟙(t=2)	-0.174	-0.027	0.008	-0.003	-0.014	-0.014	-0.014	-0.014	0.001	-0.001	-0.016	-0.017
	-0.231	(0.039)	(0.028)	(0.022)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.035)
𝟙(t=2) × Shock	-0.054**	-0.171**	-0.308***	-0.164**	-0.301***	-0.277***	-0.263***	-0.264***	-0.241***	-0.276***	-0.233***	-0.217**
	(0.250)	(0.854)	(0.090)	(0.065)	(0.099)	(0.098)	(0.096)	(0.096)	(0.092)	(0.094)	(0.089)	(0.095)
𝟙(t=2) × AI	0.004	-0.002	0.001	0.001	-0.002	-0.002	-0.002	-0.002	-0.011	-0.010	-0.001	0.000
	(0.011)	(0.008)	(0.005)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.008)
𝟙(t=2) × Shock × AI	**0.059**	**0.132****	**0.131*****	**0.019**	**0.135*****	**0.122****	**0.127*****	**0.126*****	**0.051**	**0.088****	**0.120****	**0.111***
	(0.084)	**(0.065)**	**(0.040)**	**(0.031)**	**(0.050)**	**(0.048)**	**(0.047)**	**(0.047)**	**(0.038)**	**(0.037)**	**(0.056)**	**(0.058)**
Obs	414399	417887	417900	417910	417897	417897	417897	417897	353630	384682	387672	366230
R^2	0.29	0.38	0.44	0.47	0.42	0.42	0.42	0.42	0.44	0.43	0.43	0.43
Control: HighTech	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Control: Time-varying basics	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE: Firm + Disaster	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The table shows results from the pooled event study testing the evidence of AI resilience. The dependent variable is stock return. Different considerations include varying the event window length (i.e., the considered number of days before and after disasters) (Columns 1-4), the rolling periods over which the firm's geographic exposure (Columns 5-8) and the firm's AI intensity (Columns 9-12) are calculated. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

G Structure-Free Regressions with Firm-Year-Quarter Panel

In this section, we present a set of structure-free regressions with the firm-year-quarter panel. We consider various outcome measurements, including log-transformed sales, log-transformed cost of goods sold, gross margin (sales minus cost of goods sold, divided by sales), log-transformed expenses, log-transformed income (sales minus costs of goods sold and expenses), inventory turnover (cost of goods sold divided by the average inventory between year-start and year-end), and asset turnover (sales divided by the average total assets between year-start and year-end). We regress each outcome variable on the level of shock severity, AI intensity, and other independent variables that are argued to be relevant from previous literature.

We find some baseline negative impact of disaster shocks, though not statistically significant, as reflected by lower sales, higher expenses, and lower income. With regard to our variable of interest, AI, we find some positive effect on sales and gross margin, meanwhile some negative effects on total income. Considering the low significance and weak consistency, we cannot conclude any effects from AI for explaining the level of inputs (i.e., the amount of costs of goods sold, the amount of expenses) and the level of outputs (i.e., the amount of sales, the gross margin, and the total income). This echos previous literature on the complex nature of AI productivity, that the potential benefits on sales and potential downsides on cost and expenses might offset each other, with the ultimate impact undetermined.

However, we find some notable and interesting impact from AI for mitigating the weakened inventory turnover and asset turnover during shock periods. Therefore, we are motivated to take a structural approach, i.e., production function, as our main research framework to formally investigate our speculation that AI mitigates uncertainty through adjusting the efficiency and responsiveness of input usage.

Table A6: Structure-free regressions with firm-year-quarter panel

	Log sales		Log costs of goods sold		Gross margin		Log expense		Log income		Inventory turnover		Asset turnover	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Shock	-0.004	-0.011	-0.006	-0.027	0.003	0.009	0.006	0.012	-0.003	-0.095	-0.009	-1.235***	-0.010***	-0.033***
	(0.005)	(0.028)	(0.006)	(0.028)	(0.002)	(0.014)	(0.004)	(0.018)	(0.023)	(0.115)	(0.053)	(0.376)	(0.002)	(0.013)
AI	0.002**		-0.001		-0.000		0.000		0.005		0.082***		0.000	
	(0.001)		(0.001)		(0.000)		(0.001)		(0.005)		(0.019)		(0.000)	
Shock × AI	-0.001		-0.000		-0.002		-0.000		0.001		-0.018		0.001	
	(0.001)		(0.002)		(0.001)		(0.001)		(0.009)		(0.033)		(0.001)	
Fitted AI		0.003		0.002		0.003*		0.002		-0.037**		-0.063*		-0.003*
		(0.002)		(0.002)		(0.002)		(0.002)		(0.018)		(0.035)		(0.001)
Shock × Fitted AI		0.002		0.008		-0.003		-0.004		0.031		0.467***		0.008*
		(0.011)		(0.010)		(0.005)		(0.006)		(0.043)		(0.142)		(0.005)
Lag return-to-asset	-0.028*	0.009	-0.002	0.015	0.043**	0.023**	0.017	0.020**	0.439**	0.238**	-0.258	-0.490***	0.014	0.037***
	(0.017)	(0.014)	(0.023)	(0.012)	(0.020)	(0.012)	(0.011)	(0.008)	(0.200)	(0.103)	(0.287)	(0.179)	(0.009)	(0.004)
Lag log asset	0.083***	0.084***	0.060***	0.062***	0.005	0.001	0.023***	0.024***	-0.114*	-0.069	-0.550***	-0.544***	-0.240***	-0.218***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.064)	(0.066)	(0.120)	(0.098)	(0.009)	(0.008)
Lag asset-to-debt	0.004***	0.003**	0.003*	0.002	-0.000	-0.001	0.001	-0.001	0.034***	0.045***	-0.061***	-0.041***	0.003***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.008)	(0.009)	(0.013)	(0.010)	(0.001)	(0.000)
Lag log employee	0.009**	0.013***	0.028***	0.031***	0.005***	0.008***	0.018***	0.018***	0.289***	0.233***	-0.379***	-0.333***	-0.026***	-0.016***
	(0.004)	(0.003)	(0.005)	(0.004)	(0.001)	(0.002)	(0.003)	(0.004)	(0.073)	(0.074)	(0.074)	(0.076)	(0.002)	(0.002)
Lag book-to-market	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.015*	0.014*	-0.000	-0.001	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)
Lag R&D-sales	-0.450***	-0.282***	-0.091	-0.055*	-0.009	-0.015	0.091***	0.047***	-7.356***	-1.536**	0.150	0.343	-0.023*	-0.008
	(0.044)	(0.025)	(0.056)	(0.028)	(0.025)	(0.019)	(0.016)	(0.009)	(0.959)	(0.661)	(0.702)	(0.364)	(0.013)	(0.006)
Lag log sales	0.690***	0.707***	-0.097***	-0.079***	0.216***	0.245***	0.053***	0.048***	1.427***	1.148***	-0.328	-0.049	0.129***	0.121***
	(0.019)	(0.018)	(0.022)	(0.016)	(0.017)	(0.018)	(0.010)	(0.008)	(0.172)	(0.163)	(0.368)	(0.213)	(0.009)	(0.007)
Lag log cogs	-0.057***	-0.021**	0.912***	0.925***	-0.154***	-0.188***	-0.018***	-0.025***	-0.687***	-0.612***	0.239*	0.241**	-0.052***	-0.046***
	(0.010)	(0.008)	(0.014)	(0.012)	(0.007)	(0.008)	(0.005)	(0.005)	(0.133)	(0.156)	(0.123)	(0.107)	(0.005)	(0.005)
Lag log cash	-0.000	-0.003*	-0.007***	-0.008***	0.002**	0.001	0.002	0.005***	0.017	0.007	0.330***	0.348***	-0.002*	-0.004***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.018)	(0.019)	(0.036)	(0.036)	(0.001)	(0.001)
Lag log operating expense	0.287***	0.227***	0.140***	0.104***	-0.158***	-0.136***	-0.044***	-0.031**	-0.136	0.193	1.187***	0.841***	0.220***	0.196***
	(0.021)	(0.019)	(0.024)	(0.017)	(0.011)	(0.014)	(0.011)	(0.012)	(0.260)	(0.268)	(0.292)	(0.147)	(0.012)	(0.013)
Lag log general expense	-0.006	0.002	-0.034***	-0.032***	0.087***	0.075***	0.959***	0.955***	-0.058	-0.244***	-0.595***	-0.605***	-0.027***	-0.031***
	(0.006)	(0.005)	(0.008)	(0.008)	(0.002)	(0.003)	(0.006)	(0.006)	(0.094)	(0.091)	(0.084)	(0.078)	(0.003)	(0.004)
Const.	-0.092***	-0.085***	-0.069***	-0.064***	0.346***	0.310***	0.008	0.003	0.097	-0.225	1.175***	1.477***	0.475***	0.485***
	(0.015)	(0.014)	(0.018)	(0.014)	(0.007)	(0.007)	(0.011)	(0.010)	(0.406)	(0.353)	(0.191)	(0.152)	(0.010)	(0.007)
Obs	38722	38722	38722	38722	38722	38722	38722	38722	38722	38722	38722	38722	38722	38722
R^2	0.99	0.99	0.99	0.99	0.77	0.58	0.99	0.99	0.88	0.89	0.12	0.09	0.77	0.75
FE: naics2*year*quarter	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE: firm	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The table shows structure-free regression with the firm-by-year-by-quarter panel. Dependent variables include log-transformed sales (columns 1,2), log-transformed cost of goods sold (columns 3,4), gross margin (sales minus cost of goods sold, divided by sales) (columns 5,6), log-transformed expenses (columns 7,8), log-transformed income (sales minus costs of goods sold and expenses) (columns 9,10), inventory turnover (cost of goods sold divided by the average inventory between year-start and year-end) (columns 11,12), and asset turnover (sales divided by the average total assets between year-start and year-end) (columns 13,14). Odd columns consider the raw measure of AI intensity, and even columns consider the instrumented AI intensity. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

H Stock-Type AI Using the Perpetual Inventory Method

Using the flow-type AI-share (i.e., only considering the AI-related skills in the past rolling period) as a proxy for AI demand and adoption for each firm across time points is a widely adopted practice in this literature (Felten et al. 2021, Acemoglu et al. 2022, Babina et al. 2024). Nevertheless, there remains a concern regarding the potential discrepancy between flow-type and stock-type (i.e., considering AI-related skills ever demanded during the whole period). We address this concern with a simulation test and a sensitivity check.

We first conduct a simulation test to compare our flow-type AI measure and the stock-type AI measure. Note that AI-related skills and general other skills can either depreciate or appreciate over time; hence, we try various combinations of depreciation/appreciation factors. We focus on firms that have ever posted AI-related jobs during our sample period to increase the variation in AI measurement. The flow-type AI is calculated using Equation 1, and the stock-type AI is calculated by following the perpetual inventory method:

$$AI\_Stock_{i,\tau} = \frac{\sum_{t=0}^{\tau} a^{[\frac{\tau-t}{12}]} \#AI\_Post_{\tau}}{\sum_{t=0}^{\tau} b^{[\frac{\tau-t}{12}]} \#Total\_Post_{\tau}} \tag{13}$$

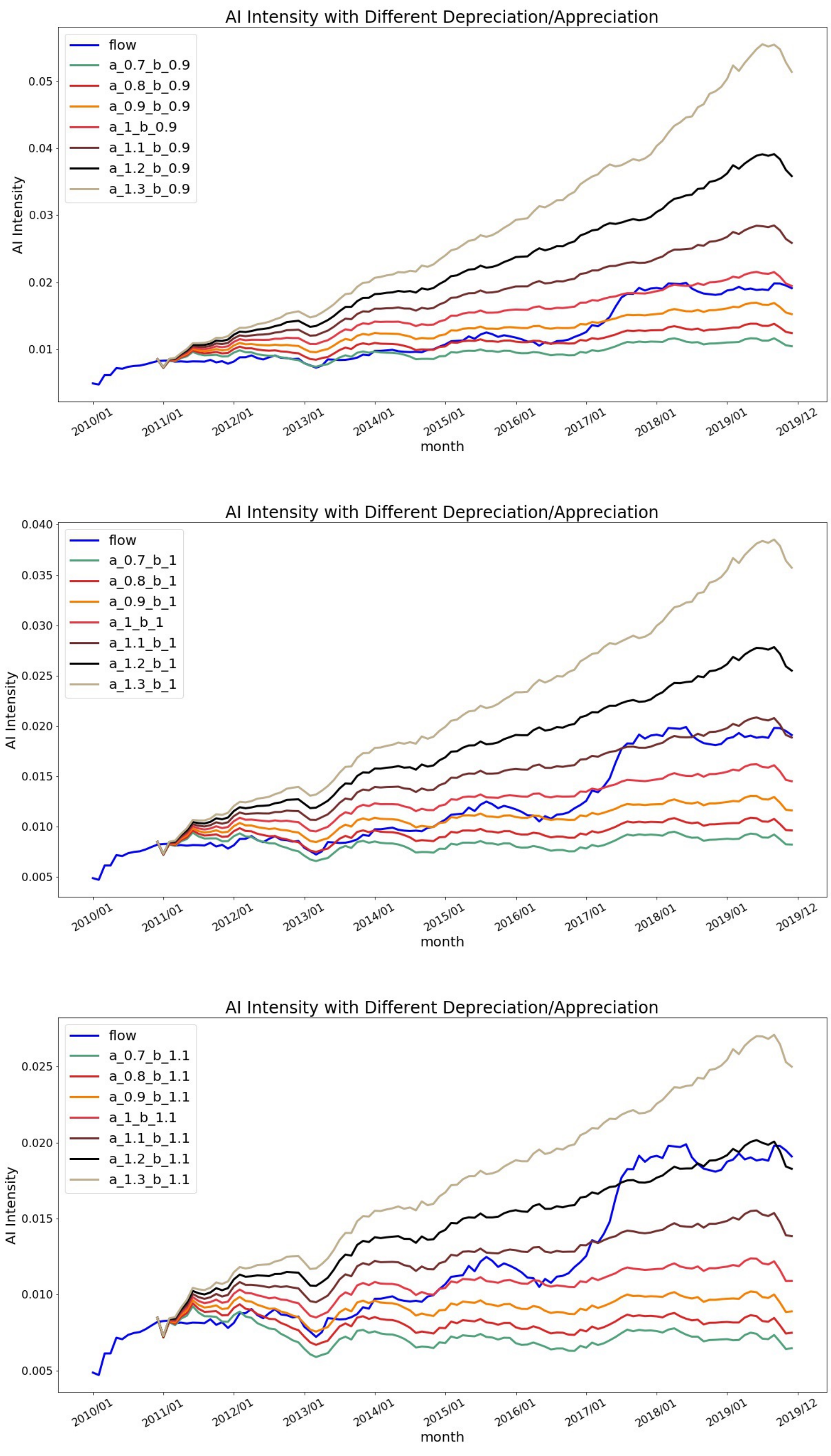
where τ indicates the current month, and a and b respectively indicate the depreciation (or appreciation) factors for AI-related posts and all posts. We impose depreciation (or appreciation) over years, instead of over months, by using the floor division $[\frac{\tau-t}{12}]$[A.1]. We tried seven choices of a (i.e., $a = 0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3$) and three choices of b (i.e., $b = 0.9, 1.0, 1.1$). Figure A2 shows the simulation results. Each sub-graph corresponds to a different value of b. The horizontal axis marks the time series. Lines mark different values of a. We have two major observations.

First, our flow-type AI measure fluctuates on a rising trend. The fluctuation reflects largely secular patterns in the aggregate demand towards AI. This systematic variation is not likely to explain the variation in our outcome variables, since we include fixed effects at industry-by-year-by-quarter level (or even more granular in the stock return analyses, as we included fixed effects at disaster level that is usually within one month).

Second, as the rolling period becomes longer (i.e., approaching the most recent years), our flow-type AI measure approximates the line where $a > b$, implying that it actually aligns with the scenario where AI-related skills from earlier days appreciate throughout the past decade as compared to general other skills. This finding hints at the fact that it is not discounting (or appreciating) AI skill itself, but the comparative speed of discounting (or appreciating) relative to

[A.1] For example, former posts within one year ($\tau - t < 12$) give a power of 0; over one year but within two years ($12 \leq \tau - t < 24$) give 1; etc..

Figure A2: Flow- and stock-type AI measurements



Notes: The figure shows a simulation of flow-type and stock-type AI measurements. For stock-type AI measurements, we simulate various combinations of depreciation/appreciation factors, including seven choices of a (i.e., $a = 0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3$) and three choices of b (i.e., $b = 0.9, 1.0, 1.1$).

that of all other skills, matters.

We finally run regressions that replace the flow-type AI measure with stock-type AI measures, using the same specification as that in Table 4 Column (3) (i.e., only control for industry-year-quarter fixed effects) and Column (7) (i.e., additionally control for firm fixed effects). Coefficient estimates of our main interest, i.e., the mitigation impact of AI on the shock-induced decline in input elasticity, are shown in Table A7. We observe expected consistency in the sign and significance of coefficients between flow-type and stock-type AI measures, and across different pairs of a and b. The differences in magnitude mainly come from the differences in absolute levels of stock-type AI measures. We should caution that these robust results can not argue for the conceptual validity of one measurement over another; instead, they provide support that our choice of measurement is not likely to threaten the identification in which the relation between AI and firm outcomes is the primary interest.

Table A7: Coefficient estimates across stock-type AI measurements with different parameter values

	b = 0.9									
a =	0.8		0.9		1		1.1		1.2	
Shock × stock-type AI × log employee	0.292***	0.241***	0.203***	0.165***	0.144***	0.115***	0.102***	0.081***	0.074***	0.058***
	(0.065)	(0.019)	(0.048)	(0.014)	(0.036)	(0.011)	(0.027)	(0.009)	(0.020)	(0.007)
Shock × stock-type AI × log capital	0.129***	0.135***	0.087***	0.092***	0.059***	0.063***	0.041***	0.044***	0.029**	0.032***
	(0.032)	(0.023)	(0.023)	(0.016)	(0.017)	(0.011)	(0.013)	(0.008)	(0.010)	(0.006)
	b = 1									
a =	0.8		0.9		1		1.1		1.2	
Shock × stock-type AI × log employee	0.421***	0.348***	0.293***	0.239***	0.207***	0.166***	0.148***	0.117***	0.107***	0.084***
	(0.092)	(0.024)	(0.068)	(0.018)	(0.051)	(0.014)	(0.038)	(0.011)	(0.029)	(0.009)
Shock × stock-type AI × log capital	0.186***	0.195***	0.126***	0.133***	0.086***	0.092***	0.060***	0.065***	0.042**	0.046***
	(0.046)	(0.032)	(0.033)	(0.022)	(0.024)	(0.016)	(0.018)	(0.011)	(0.014)	(0.008)
	b = 1.1									
a =	0.8		0.9		1		1.1		1.2	
Shock × stock-type AI × log employee	0.596***	0.495***	0.415***	0.339***	0.293***	0.236***	0.210***	0.167***	0.152***	0.120***
	(0.127)	(0.032)	(0.094)	(0.023)	(0.070)	(0.017)	(0.053)	(0.013)	(0.040)	(0.011)
Shock × stock-type AI × log capital	0.263***	0.275***	0.178***	0.189***	0.122***	0.131***	0.085***	0.092***	0.060***	0.066***
	(0.064)	(0.044)	(0.046)	(0.031)	(0.034)	(0.022)	(0.025)	(0.016)	(0.019)	(0.012)
FE: naics2*year*quarter	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE: firm	N	Y	N	Y	N	Y	N	Y	N	Y

Notes: This table shows the coefficient estimates of our main interest in the production function regressions, i.e., the mitigation impact of AI on the shock-induced decline in input elasticity. AI is measured with stock-type variables, considering three choices of b (i.e., $b = 0.9, 1.0, 1.1$ and five choices of a (i.e., $a = 0.8, 0.9, 1.0, 1.1, 1.2$). Odd columns include fixed effects at the NAICS2-by-year-by-quarter level. Even columns additional include fixed effects at the firm level. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

I Heterogeneity across Industries

In this section, we present the resilience test from stock-return analysis (Table A8) and the mechanism test from production function analysis (Table A9) separately across industry sectors as defined by the NAICS2 code.

We find robust evidence of AI resilience with nuanced differences across industries: manufacturing (NAICS2 = 31-33) and retail trade (NAICS2 = 44-45) sectors enjoy the most notable benefits of AI as reflected by strongly mitigated production elasticity for both labor and capital inputs, and resilient stock price during both in- and after-disaster periods; whereas utilities (NAICS2 = 21), construction (NAICS2 = 23), wholesale trade (NAICS2 = 42), and transportation and warehousing (NAICS2 = 48-49) sectors witness partial benefits of AI as reflected from higher elasticity for either labor or capital inputs, and weaker impact on stock returns.

It is worth noting that, despite the heterogeneity among industry groups, we find two pieces of evidence useful from the across-industry analyses. First, such effects are most significant among firms in the manufacturing and retail trade sectors that rely heavily on their operations along the supply chain, echoing our proposed mechanism that AI mitigates unexpected disruptions potentially by handling the supply chain-related difficulties (e.g., sourcing raw materials and components in due time, or scheduling the purchase of finished goods based on forecasts about downstream sales). Second, the resilience test (i.e., stock return analyses at the firm-disaster level) and the mechanism test (i.e., production function analyses at the firm-year-quarter level) correspond to each other in a way that the most resilient industries tend to also be the most responsive industries. This suggests that, despite two sets of analyses drawn from different panels, the underlying connections largely stand.

Table A8: Stock return analysis across industry groups

	Stock return							
NAICS 2-digit =	11	21	22	23	31-33	42	44-45	48-49
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Before-disaster window								
𝟙(t=0)	1.716	-4.666	-13.397**	-2.846***	1.116	-7.394***	-10.202***	0.792
	(3.359)	(3.895)	(6.242)	(0.859)	(0.729)	(2.106)	(1.868)	(1.581)
𝟙(t=0) × Shock	-0.103	0.514	0.574**	0.200	-0.153*	0.326	-0.068	0.267
	(0.578)	(0.377)	(0.263)	(0.205)	(0.091)	(0.231)	(0.148)	(0.377)
𝟙(t=0) × AI	0.025	-0.066*	-0.226***	0.002	0.026**	0.126***	-0.001	-0.065*
	(0.058)	(0.037)	(0.061)	(0.027)	(0.010)	(0.044)	(0.013)	(0.038)
𝟙(t=0) × Shock × AI	**0.096**	**0.015**	**-0.181**	**0.295**	**-0.046**	**0.299**	**-0.015**	**-0.176**
	(0.106)	**(0.072)**	**(0.232)**	**(0.258)**	**(0.044)**	**(0.227)**	**(0.035)**	**(0.197)**
During-disaster window								
𝟙(t=1)	0.090	0.112	-0.075	0.212*	-0.006	0.108	-0.028	-0.054
	(0.110)	(0.179)	(0.112)	(0.116)	(0.049)	(0.101)	(0.056)	(0.117)
𝟙(t=1) × Shock	3.444	-1.432**	-1.274**	-0.911***	-0.284*	-1.146***	-0.379	-0.931
	(2.398)	(0.565)	(0.558)	(0.316)	(0.149)	(0.398)	(0.260)	(0.670)
𝟙(t=1) × AI	0.084*	0.053	0.051	0.006	0.002	-0.022	-0.000	0.038
	(0.042)	(0.040)	(0.046)	(0.046)	(0.009)	(0.044)	(0.022)	(0.042)
𝟙(t=1) × Shock × AI	**-0.709***	**0.236****	**-0.149**	**-0.173**	**0.238****	**0.223**	**0.236*****	**0.651****
	(0.356)	**(0.100)**	**(0.466)**	**(0.322)**	**(0.091)**	**(0.215)**	**(0.080)**	**(0.257)**
After-disaster window								
𝟙(t=2)	0.080	-0.017	-0.066	0.101	-0.015	0.091	-0.028	-0.089
	(0.084)	(0.128)	(0.068)	(0.117)	(0.048)	(0.102)	(0.056)	(0.110)
𝟙(t=2) × Shock	0.067	-0.632	-0.444*	-0.634**	-0.108	-0.756**	-0.420**	-0.318
	(0.602)	(0.448)	(0.259)	(0.253)	(0.125)	(0.321)	(0.186)	(0.474)
𝟙(t=2) × AI	0.021	0.030	0.078*	-0.022	-0.008	0.012	-0.006	0.024
	(0.027)	(0.018)	(0.041)	(0.029)	(0.007)	(0.031)	(0.010)	(0.031)
𝟙(t=2) × Shock × AI	**-0.045**	**0.003**	**0.063**	**-0.129**	**0.140****	**0.069**	**0.219*****	**-0.002**
	(0.128)	**(0.085)**	**(0.165)**	**(0.179)**	**(0.062)**	**(0.164)**	**(0.056)**	**(0.241)**
Obs	1381	26062	22655	6188	272683	26422	40153	22353
R^2	0.12	0.41	0.19	0.50	0.46	0.33	0.14	0.47
Control: HighTech	Y	Y	Y	Y	Y	Y	Y	Y
Control: Time-varying basics	Y	Y	Y	Y	Y	Y	Y	Y
FE: Firm + Disaster	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The table shows results from the pooled event study at each NAICS2 group. The dependent variable is the stock return. NAICS 2-digit code corresponds to agriculture, forestry, fishing and hunting (11), mining (21), utilities (22), construction (23), manufacturing (31-33), wholesale trade (42), retail trade (44-45), transportation and warehousing (48-49). Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Production function regressions across industry groups

	Log value added							
NAICS 2-digit =	11	21	22	23	31-33	42	44-45	48-49
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Labor input								
Log labor	0.685	0.841***	0.260	0.685***	0.480***	0.363***	0.907***	0.260***
	(1.401)	(0.124)	(0.177)	(0.225)	(0.033)	(0.083)	(0.093)	(0.083)
Shock × log labor	0.647	-0.107	-0.160	-0.331	0.026	-0.204***	-0.106**	-0.073
	(0.699)	(0.096)	(0.105)	(0.267)	(0.024)	(0.067)	(0.054)	(0.050)
AI × log labor	-0.250	-0.072	-0.040	-0.497***	-0.007	0.060	0.028	-0.045
	(0.756)	(0.064)	(0.057)	(0.191)	(0.008)	(0.055)	(0.025)	(0.045)
Shock × AI × log labor	**-2.599***	**0.136**	**0.360***	**1.771****	**0.080****	**-0.059**	**0.095****	**0.228****
	(1.440)	**(0.113)**	**(0.198)**	**(0.854)**	**(0.041)**	**(0.157)**	**(0.043)**	**(0.099)**
Capital input								
Log capital	0.272***	0.143***	0.023	0.062	0.182***	0.225***	0.108***	-0.003
	(0.091)	(0.024)	(0.020)	(0.058)	(0.011)	(0.030)	(0.024)	(0.022)
Shock × log capital	-0.646*	-0.177***	-0.162***	-0.106	-0.218***	-0.132***	-0.191***	-0.206***
	(0.357)	(0.030)	(0.042)	(0.100)	(0.009)	(0.023)	(0.028)	(0.026)
AI × log capital	0.214	0.009	-0.003	0.200***	0.005	-0.027*	-0.012	0.011
	(0.314)	(0.015)	(0.024)	(0.071)	(0.003)	(0.016)	(0.011)	(0.017)
Shock × AI × log capital	**1.153***	**0.103*****	**0.045**	**-0.570**	**0.131*****	**0.191*****	**0.098*****	**0.067**
	(0.596)	**(0.034)**	**(0.086)**	**(0.353)**	**(0.015)**	**(0.054)**	**(0.015)**	**(0.056)**
Const.	0.281	1.834***	3.379***	0.852**	1.167***	0.980***	0.291	3.247***
	(2.054)	(0.169)	(0.275)	(0.418)	(0.075)	(0.192)	(0.264)	(0.172)
Obs	230	3225	2316	827	34692	3053	4109	2552
R^2	0.83	0.76	0.79	0.71	0.85	0.80	0.80	0.83
Control: HighTech	Y	Y	Y	Y	Y	Y	Y	Y
FE: naics2*year*quarter	Y	Y	Y	Y	Y	Y	Y	Y
FE: firm	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The table shows results from the production function regression at each NAICS2 group. The dependent variable is the log-transformed value added. NAICS 2-digit code corresponds to agriculture, forestry, fishing and hunting (11), mining (21), utilities (22), construction (23), manufacturing (31-33), wholesale trade (42), retail trade (44-45), transportation and warehousing (48-49). Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

J Validity Check with an Instrumental Variable

A concern remains that our results from IV regressions could be driven by unobservables that simultaneously affect aggregate ability-AI score and firm performance along the dimension of certain preexisting ability-based firm structures. Hence, we check the validity of our IV by testing if firm fixed effects (considering both observed and unobserved firm-specific factors) could predict the instrumented AI intensity. We first regress various measurements of firm performance on generic control variables such as firm size as well as fixed effects at the firm level (columns 1, 3, 5, 7, 9, 11 in Table A10). Then, we retrieve the fitted value of firm fixed effects from above and use it as an explanatory factor for the estimated AI intensity. The non-significance of firm fixed effects (coefficients of term $Firm\_fixed\_effect$) supports no sign of the omitted variable problem.

Table A10: IV validity test

	I		II		III		IV		V		VI	
DV	Log income	IV	Log sales	IV	Log costs	IV	Log expense	IV	Log ROA	IV	Log margin	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log asset	0.668***	0.044	0.544***	0.041	0.390***	0.041	0.453***	0.043	0.065***	0.037	0.061***	0.038*
	(0.027)	(0.016)	(0.008)	(0.034)	(0.007)	(0.079)	(0.004)	(0.064)	(0.003)	(0.665)	(0.005)	(0.506)
Log employee	0.079	0.000	0.411***	0.012	0.506***	0.013	0.476***	0.011	-0.057***	0.006	-0.049***	0.005
	(0.048)	(0.010)	(0.016)	(0.008)	(0.014)	(0.010)	(0.009)	(0.008)	(0.006)	(0.011)	(0.009)	(0.011)
Log leverage	-0.622***	0.169	0.506***	0.108	0.418***	0.109	0.319***	0.513	-0.268***	0.099	-0.076***	0.108
	(0.099)	(0.251)	(0.024)	(0.089)	(0.020)	(0.096)	(0.013)	(0.040)	(0.009)	(0.095)	(0.015)	(0.093)
Book to market	-0.890***	-0.036	-0.145***	-0.008	-0.076***	-0.005	-0.078***	-0.007	-0.039***	-0.007	-0.027***	-0.005
	(0.034)	(0.026)	(0.009)	(0.019)	(0.008)	(0.018)	(0.005)	(0.021)	(0.003)	(0.018)	(0.005)	(0.017)
R&D to sales	0.008***	-0.000	-0.000***	-0.000	0.000*	-0.000	-0.000**	-0.000	-0.000*	-0.000	0.000	0.000
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Master intensity	-0.001	-0.002	0.001	-0.001	0.000	-0.001	0.001***	-0.001	0.000	-0.001	0.000	-0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Firm fixed effect		-0.007		0.004		-0.001		-0.011		0.038		0.030
		(0.007)		(0.007)		(0.007)		(0.013)		(0.025)		(0.015)
Cons.	-1.000***	-0.191**	0.738***	-0.152**	1.182***	-0.154**	1.343***	-0.162***	-0.247***	-0.158**	0.039	-0.173**
	(0.152)	(0.045)	(0.044)	(0.032)	(0.038)	(0.032)	(0.024)	(0.027)	(0.017)	(0.033)	(0.025)	(0.036)
Obs	17166	14687	25422	20716	25398	20693	25394	20690	25146	20486	23583	19527
R^2	0.10	0.18	0.37	0.21	0.35	0.21	0.61	0.21	0.07	0.21	0.01	0.20

Notes: The table shows validity check for the instrumental variable. Odd columns present regressions of various measurements of firm performance on generic control variables including time-varying indices and time-invariant firm fixed effects. Even columns present regressions of the instrumental variable on a set of explanatory variables plus the fitted values of firm fixed effects retrieved from the corresponding previous regression. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

K Exogenous Change of Ability-AI Scores

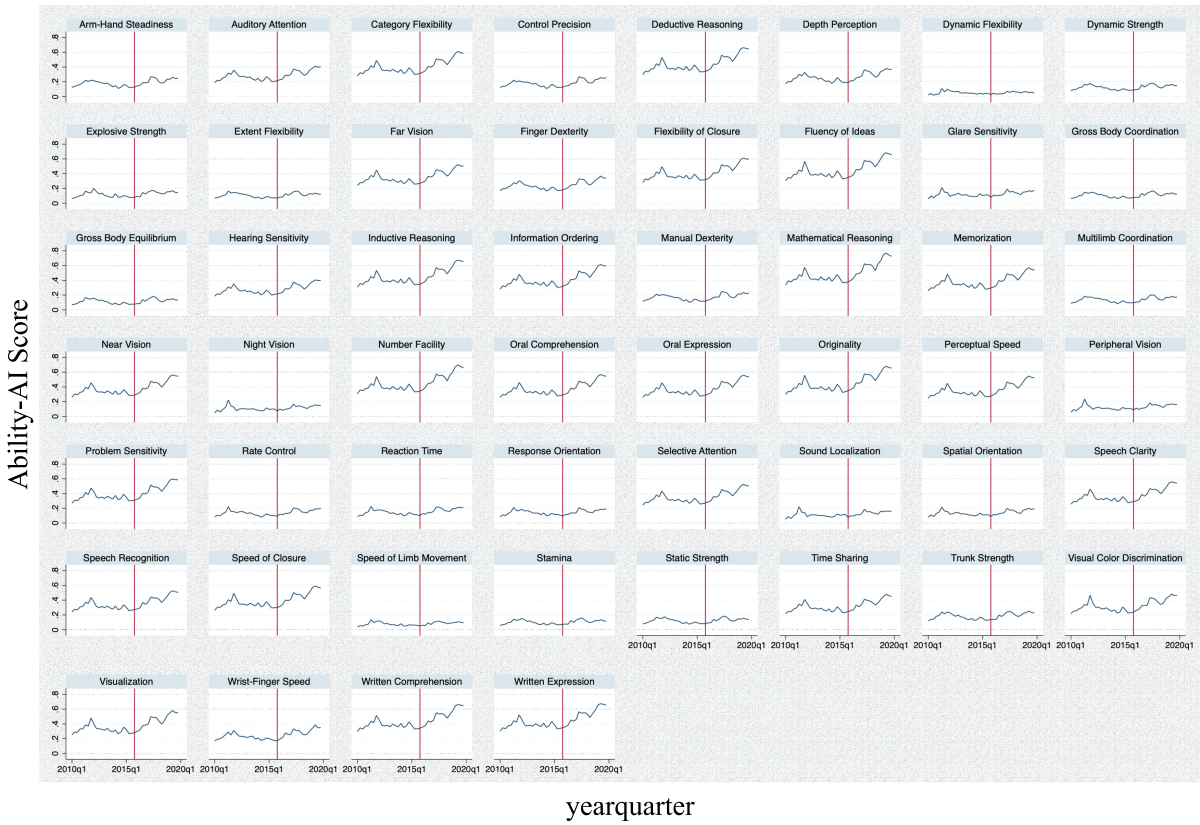
As mentioned in the main text, our instrumental variable potentially suffers from two alternative concerns: 1) if ability-AI scores seldom vary across time, then the variation in our instrument could be dominated by firm baseline structure, thus accounting for little changes in AI investment;[A.2] 2) if the ability-AI scores indeed vary, but managers somewhat foresee the suitability dynamics, firms might alter their hiring strategy to embrace the changes in advance. Therefore, we run another set of specifications in which we replace the time-series ability-AI scores with the abrupt changes in ability-AI scores before and after exogenous shocks. The essential idea is that we are trying to find an exogenous shock that alters the variation in our instrument variable (i.e., averaged ability-AI score), and investigate if such variation leads to corresponding changes in the estimated effect of our interest (i.e., AI mitigating disrupted production elasticity). This practice enables us to address the above-mentioned two concerns that our instrumental variable 1) has little variation across time (thus regressing to a weak instrument), and 2) is endogenously expected and manipulated by firm managers (thus violating the exclusion condition). Ideally, we look for an event that is exogenous and unexpected and induces different variations in the AI scores among abilities. As execution, we reference Rock (2019) and exploit the sudden releases of the first major open-source machine learning platform, TensorFlow, that significantly facilitates AI-related tasks, reduces AI-related skill training costs, and boosts the AI-related skill supply. Because the release of TensorFlow is totally unexpected by the market and purely due to Google's strategic consideration, concern 2 is inherently taken care of.

Figure A3 depicts the time-series AI scores for each ability, with red vertical lines indicating the time of TensorFlow release (i.e., quarter 4 in the year 2015). We observe significantly different trajectories of AI-score among abilities after TensorFlow release; in specific, some abilities become more compatible with AI whereas others remain still. This suggests the validity of using this event as an effective source to induce useful variations in ability-AI scores, hence addressing concern 1. TensorFlow brings material changes because the AI index of each work activity is affected by the feasibility of various tools being invented and released. AI programming has been extremely technical-demanding, beyond the reach of all but the best-trained university graduates who majored in computer science. The advent of machine learning platforms on which libraries of off-the-shelf codes are available on-demand made AI programming more approachable by generally trained labor. The open and free release further reduces the cost of firms exploiting such

[A.2] If firms with certain abilities in the very base year remain higher level of resilience throughout the following years, and these certain abilities happen to be more compatible with AI, then the concern of little variation in ability-AI scores across time series could be magnified, since now the time-series changes contribute little to the overall instrument construction.

platforms. Consequently, taking together the larger supply of AI-capable labor and the expanding demands of AI-affordable tasks, the development of AI shall be fueled significantly along the ability dimensions that better absorb relevant knowledge. The observation from Acemoglu et al. (2022) that AI vacancy postings notably accelerated around 2015-2016 echoes our argument.

Figure A3: AI score among 52 abilities



Notes: The figure depicts the time-series AI scores (i.e., compatibility of using AI) for each ability, with red vertical lines indicating the time of TensorFlow release (i.e., quarter 4 in the year 2015). We observe significant differences among abilities in terms of the level of AI compatibility, and the trajectories of AI compatibility changes after TensorFlow release. In specific, some abilities become more compatible with AI whereas others remain at a lower level.

To exploit the changes in ability-AI scores induced by TensorFlow release, we construct a weighted AI growth rate, i.e., the changes of ability-AI scores at year-quarter q compared to the pre-TensorFlow year-quarter q_0 weighted by the baseline share of abilities, as defined below:

$$AI\_Growth_{i,q} = \sum_{a \in A} BaseShare_{i,a,q_0} \times \frac{AI\_Score_{-i,a,q} - AI\_Score_{-i,a,q_0}}{AI\_Score_{-i,a,q_0}} \tag{14}$$

With this variable of changes, our research question transforms from whether the *level* of AI affects the *level* of factor elasticity to whether the *changes* of AI affect the *changes* of factor elasticity. To empirically test the latter question, an ideal estimation procedure would be to first calculate the factor elasticity within each firm-by-year-by-quarter cell, then regress the differences of factor elasticity across time on the differences of AI intensity (i.e., AI growth rate) and shock severity. However, due to the widely-documented challenge in estimating firm-specific factor elasticity (Bryniolfsson and Hitt 1995), we omit the first step and estimate with one single equation that is directly derived from equation (7). After organizing together the identical terms, we obtain the following equation:

$$\begin{aligned}
lnVA_q - lnVA_0 =& \alpha_0(lnK_q - lnK_0) + \\
& \alpha_1(Shock_q \times lnK_q - Shock_0 \times lnK_0) + \\
& \alpha_2(lnK_q \times (1 + AI_Growth_q) - lnK_0) \times AI_0 + \\
& \alpha_3(Shock_q \times lnK_q \times (1 + AI_Growth_q) - Shock_0 \times lnK_0) \times AI_0 + \\
& \beta_0(lnL_q - lnL_0) + \\
& \beta_1(Shock_q \times lnL_q - Shock_0 \times lnL_0) + \\
& \beta_2(lnL_q \times (1 + AI_Growth_q) - lnL_0) \times AI_0 + \\
& \beta_3(Shock_q \times lnL_q \times (1 + AI_Growth_q) - Shock_0 \times lnL_0) \times AI_0
\end{aligned} \tag{15}$$

where for simplicity, we omit the subscript i indicating firms. Essentially, the regression answers: how does the change in AI (i.e., before and after TensorFlow release) affect the change in the outcome variable (i.e. value added) especially when there is an exogenous change in the uncertainty level (i.e., $Shock_q \neq Shock_0$). α_0 estimates the effect of labor input changes on value-added changes (shorthanded as the elasticity effect) at the baseline level. α_1 estimates the elasticity effect when there are accompanying changes in the uncertainty level. α_2 estimates the elasticity effect when there are accompanying changes in the AI intensity. α_3 estimates the elasticity effect when there are both accompanying changes in the uncertainty level and in the AI intensity. β coefficients follow the same logic but for capital input. Our coefficients of interest, α_3 and β_3 corroborate our tests for AI mitigating the disruptive elasticity of input during uncertain periods.

A caveat is that, for the estimation of α_2 and α_3 (same for β_2 and β_3), the impact of any change in AI (i.e., AI_Growth_q) depends on the pre-TensorFlow level (i.e., AI_0).[A.3]. Hence, as a robustness check, we consider pre-TensorFlow level of AI at different time points in Table A11. We consider AI_0 at one quarter (Columns 1, 4), one year (Columns 2, 5), and three years (Columns 3, 6) before TensorFlow release. We run regressions with either raw (Columns 1-3) or instrumented (Columns 4-6) index of AI intensity.

Consistent with our earlier findings, Table A11 shows positive elasticity effects at the baseline

[A.3] Note that different from a standard Bartik-style shift-share regression where only the variable of changes (i.e., AI_Growth_q) is included (Borusyak et al. 2022), we need to also include the variable at pre-TensorFlow level (i.e., AI_0) due to the constraint from the formally-structured production function.

Table A11: Regressions with Bartik IV

	Difference in log valued added					
	(1)	(2)	(3)	(4)	(5)	(6)
alpha0	0.677***	0.403***	0.429***	0.744***	0.570***	0.582***
	(0.049)	(0.057)	(0.061)	(0.088)	(0.090)	(0.092)
alpha1	-0.132***	-0.085***	-0.078**	-0.229**	-0.181*	-0.096
	(0.026)	(0.026)	(0.031)	(0.112)	(0.107)	(0.118)
alpha2	-0.347	-0.088*	-0.082	0.015	0.015	0.018
	(0.546)	(0.050)	(0.054)	(0.031)	(0.033)	(0.034)
alpha3	0.071***	0.108***	0.067**	0.030	0.030	-0.027
	(0.022)	(0.024)	(0.028)	(0.042)	(0.041)	(0.045)
beta0	0.094***	0.059***	0.099***	0.200***	0.163***	0.187***
	(0.014)	(0.015)	(0.015)	(0.032)	(0.034)	(0.036)
beta1	-0.169***	-0.176***	-0.214***	-0.298***	-0.318***	-0.328***
	(0.010)	(0.011)	(0.012)	(0.041)	(0.040)	(0.043)
beta2	-0.026*	0.002	-0.024	-0.004	-0.001	-0.004
	(0.014)	(0.024)	(0.024)	(0.012)	(0.013)	(0.014)
beta3	0.033***	0.070***	0.069***	0.056***	0.067***	0.077***
	(0.009)	(0.011)	(0.010)	(0.016)	(0.016)	(0.017)
Cons.	-0.040***	0.083***	0.030**	0.145***	0.047***	-0.022
	(0.013)	(0.012)	(0.012)	(0.014)	(0.016)	(0.014)
Obs	12486	12448	12199	11930	12357	12486
R^2	0.32	0.32	0.32	0.32	0.35	0.31
FE	Y	Y	Y	Y	Y	Y

Notes: The table shows results from the Bartik-style regressions. The dependent variable is the difference in log-transformed value added before and after the TensorFlow release. The pre-TensorFlow level of AI is considered at different time points: one quarter (Columns 1, 4), one year (Columns 2, 5), and three years (Columns 3, 6) before TensorFlow release. Columns 1-3 use raw AI intensity; columns 4-6 use instrumented AI intensity.

line (as suggested by significantly positive estimates of α_0 and β_0), weaken elasticity effect considering any changes in uncertainty level (as suggested by significantly negative estimates of α_1 and β_1), non-impacted elasticity effect considering any changes in AI but no changes in uncertainty level (as suggested by insignificant estimates of α_2 and β_2), while positively mitigated elasticity effect considering changes in both uncertainty level and in AI (as suggested by largely positive estimates of α_3 and β_3).

L Discussion on Multiple Treatment Periods and Continuous Dosage Issues

In our pooled event study setting (Section 4), there are two treatments. Clearly, natural disasters serve as the baseline treatment. As for AI investment, although we consider it as an interaction term in the regression, our augmentation with the instrumental variable adds causal explainability to the interpretation. Thus, we tend to recognize both natural disasters and AI investment as treatments. We illustrate the two concerns (i.e., multiple treatment periods and continuous dosage) for both treatments as follows.

The problem of multiple treatment periods lies in heterogeneous treatment effects over time. We were not be able to find an appropriate estimator to rigorously resolve this issue in our setting because of the following reasons: (a) most available estimators focus on an absorbing treatment such that the treatment status over time is a non-decreasing sequence of zeros and then ones, while our treatments take values that switch between zeros and ones; (b) most available estimators deal with binary or discrete treatments, while our treatments are continuous (which are related to the continuous dosage issue in the next paragraph); (c) most available estimators consider one treatment, while we have two sets of independent treatments (shocks from disaster and AI intensity) at the same time.[A.4] To probe into the severity of this concern, instead, we look into the possible across-disaster heterogeneity in our results. For treatment effects at different periods, we refer to Baker et al. (2022) and plot the distribution of coefficient estimates from each event (i.e., every single disaster) in Figure A4. The approximately normal distributions have *narrow* dispersion, meaning less heterogeneity among coefficients estimated at different time points. Therefore, the multiple treatment periods issue in our context is not a severe concern.

The problem of continuous treatment centers around the heterogeneous causal responses to an additional treatment unit when conditional on different levels of existing treatment (Callaway et al. 2021). We follow the canonical literature (Flores et al. 2012) and estimate the dose-response function with a partial mean estimator.[A.5] The process is as follows. First, we discretize the continuous treatment variable into ten bins (i.e., analogous to ten dosages in canonical examples). Second, we run the regressions of interest respectively among samples from different bins (i.e., analogous to different levels of dosage in canonical examples). Note that in these sub-sample regressions, the treatment variable is a dummy and the control group consists of matched firms

[A.4] Although we could combine two treatments into one by separately discretizing and then multiplying together to get all possible treatment pairs, it is hard to interpret the estimated results to disentangle what variation dominates the effect and in what ways.

[A.5] This procedure is the same as the dose-response function we use in the Section 4.

with zero treatment (i.e., with zero AI investment, analogous to zero dosage in canonical examples). Finally, we calculate the estimated average treatment effect across levels (i.e., the average effect of being treated with a particular number of doses) by averaging all other independent values within the corresponding sub-sample.

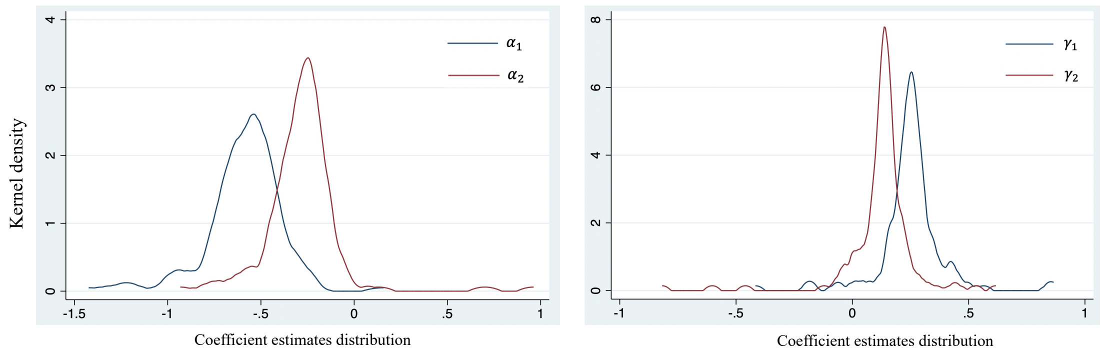
To illustrate clearly, we demonstrate the procedure where AI is considered as the varying treatment of interest. First, we rank all the firm-by-disaster observations with $AI_{i,e} > 0$ by their $AI_{i,e}$ and divide them into 10 groups by the decile, denoted as group $\Pi_{j,AI_{i,e}>0}$ where $j \in [1,10]$. For one observation unit (i,e) (firm-by-disaster), if its value $AI_{i,e}$ is in the j_{th} decile of the rank, we say this observation belongs to the j_{th} group, $(i,e) \in \Pi_{j,AI_{i,e}>0}$. We then match the observations in each group $\Pi_{j,AI_{i,e}>0}$ with observation units of similar observed characteristics but $AI_{i,e} = 0$. These matched observations form the control groups $\Pi_{j,AI_{i,e}=0}$. The group $\Pi_j = \Pi_{j,AI_{i,e}>0} \cup \Pi_{j,AI_{i,e}=0}$. Now, we obtain ten groups of observations, each group Π_j consisting of both AI units ($AI_{i,e} > 0$) and non-AI units ($AI_{i,e} = 0$). For each group Π_j, we run the following regression with all the observations $(i,e) \in \Pi_j$:

$$Return_{i,e,t} = \sum_{T=0,1,2} I\{t = T\}(\alpha_t Shock_{i,e} + \beta_t \mathbf{1}_{i,e} + \gamma_t Shock_{i,e} \times \mathbf{1}_{i,e}) + X_{i,e}\phi + \varepsilon_{i,e,t} \tag{16}$$

Note that $\mathbf{1}_{i,e}$ is a dummy variable that equals one if the focal observation (i,e) has $AI_{i,e} > 0$, and zero if $AI_{i,e} = 0$. Finally, the average treatment effect for each group Π_j is calculated by $\alpha_t \overline{Shock_{i,e}} + \beta_t \overline{\mathbf{1}_{i,e}} + \gamma_t \overline{Shock_{i,e}} \times \overline{\mathbf{1}_{i,e}} + \overline{X_{i,e}}\phi$, where $\overline{\cdots}$ denotes the average of values for all observations $(i,e) \in \Pi_j$.

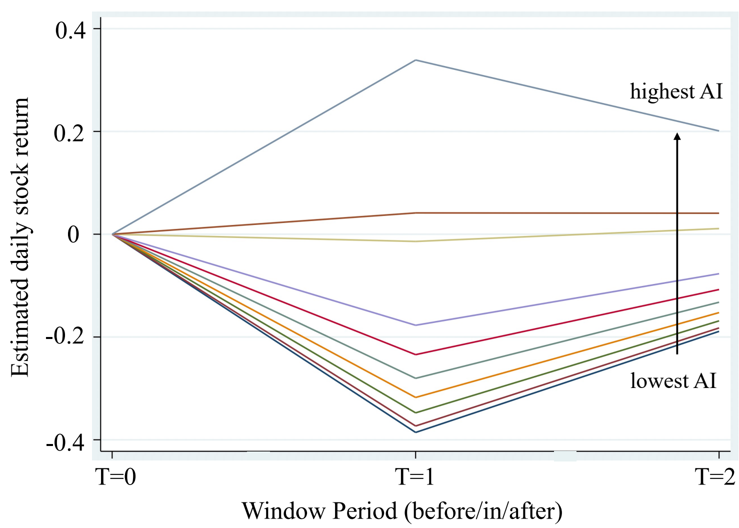
We plot the estimates from the dose-response calculation in Figure A5 (considering AI as a varying treatment) and Figure A6 (considering shock as a varying treatment). We find approximately linear dosage effects for both variables, AI and uncertainty shock, alleviating the concern about large heterogeneity across levels. Nevertheless, we do observe a slightly increasing dosage response as the shock reaches the severest or the AI reaches the highest. Therefore, the results from models with a continuous treatment variable could potentially be biased and should be interpreted with caution.

Figure A4: Distribution of coefficient estimates from event studies.



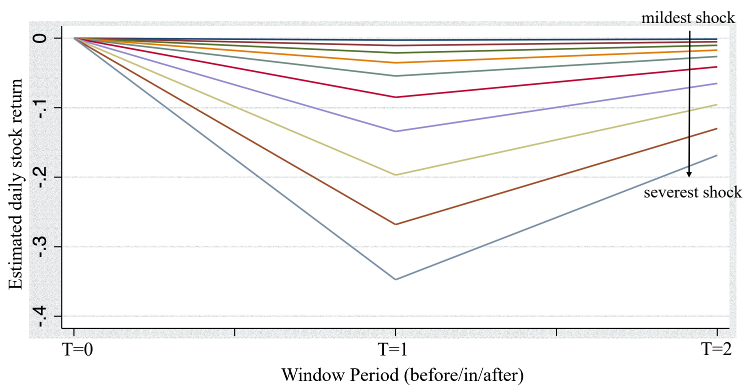
Notes: These plots show the kernel density distribution of the coefficient estimates from regressions with each event study. α and γ are the estimates in Equation (4) in the paper.

Figure A5: Heterogeneous treatment effects by different levels of AI intensity



Notes: The vertical axis shows the estimated daily stock return (i.e., estimated treatment effect at T=1/2 compared to T=0). The horizontal axis shows the three window periods: before, in and after the disaster event. Colors mark different levels of AI intensity (i.e., the continuous AI intensity variable discretized into decile).

Figure A6: Heterogeneous treatment effects by different levels of uncertainty shocks



Notes: The vertical axis shows the estimated daily stock return (i.e., estimated treatment effect at T=1/2 compared to T=0). The horizontal axis shows the three window periods: before, in and after the disaster event. Colors mark different levels of uncertainty shock (i.e., the continuous shock variable discretized into decile).