AEA Papers and Proceedings 2025, 115: 35–39
https://doi.org/10.1257/pandp.20251002

Artificial Intelligence Makes Firm Operating Performance Less Volatile†

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The rise of artificial intelligence (AI)—and its growing commercial applications—is delivering multifaceted benefits for US firms. Firms that invest more in AI experience greater growth (Rock 2019; Babina et al. 2024b), productivity enhancements (Alderucci et al. 2020; Eloundou et al. 2023), and product quality improvements (Fedyk et al. 2022). AI is a prediction technology (Agrawal, Gans, and Goldfarb 2019), and AI-investing firms are able to harness its power to expand by innovating: These firms create new products, patents, and trademarks, capturing more upside as a result (Cockburn, Henderson, and Stern 2000; Babina et al. 2024b).

However, it is still an open question what effect, if any, AI is having on the second moment—the volatility of operating performance. On the one hand, as a prediction technology, AI can enable firms to make better forecasts and reduce overall risk. On the other hand, by spurring innovation and creating new products, AI can increase overall uncertainty.

In this paper, we offer the first evidence that investments in AI make firm operating performance *less* volatile in general. We directly examine how firm-level investments in AI relate to changes in the volatility of firms' sales, earnings, and cash flows. To do this, we leverage the measure of AI investments first introduced by Babina et al. (2024b) and subsequently used by Cao et al. (2024a, b) and others. This measure draws on detailed employer-employee matched data to identify AI-skilled workers from individual employees' resumes. Given the high reliance of AI implementation on human capital, AI-skilled workers at a firm offer a strong measure of the firm's AI investments.

To examine the volatility of firm operating performance, we focus on three aspects: sales, earnings, and cash flows. For sales, we consider the volatility of log sales; for earnings, we look at two measures—return on assets (ROA) and return on equity (ROE); and for cash flows, we examine cash flows over assets. We compute the volatility of each variable at the quarterly level over two nonoverlapping periods: 2008–2012 (five years around 2010) and 2016–2020 (five years around 2018). We then take the difference of each volatility measure at the beginning (2010) and the end (2018) of the sample period and tie these differences to firms' AI investments.

We find that a 1 standard deviation increase in firm-level AI investment translates into a 2.3 percent age point reduction in 5-year volatility of log sales, a 0.2 percent age point reduction in volatility of ROA, a 2.1 percent age point reduction in volatility of ROE, and a 0.7 percent age point reduction in volatility of cash flows over assets. These changes are statistically significant at the 5 percent level after accounting for numerous controls for all variables except sales.

All of the effects are economically sizable. The decline in the volatility of sales is 0.175 of the standard deviation of the dependent variable; the reduction in the volatility of ROA is 0.125 of the standard deviation; the effect on the volatility of ROE is 0.144 of the standard deviation; and the decline in the volatility of cash flows over assets is 0.194 of the standard deviation.

Overall, our empirical results show that so far, firms' investments in AI have been associated not only with increases in the first moment of firm operating performance but also with a reduction in the second moment. AI investments are associated with a decrease in the volatility of firm sales, earnings, and cash flows. At the same time, Babina et al. (2024a) examine the returns of AI-investing firms

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† Go to https://doi.org/10.1257/pandp.20251002 to visit the article page for additional materials and author disclosure statement(s).

and find that AI investments are associated with increases in firms' systematic risk (market beta). Together, our results suggest that AI reduces the volatility of firm operating performance but makes firms' returns more procyclical by increasing their growth opportunities.

I. Data and Measures

To measure firm-level investments in AI, we leverage the methodology introduced in Babina et al. (2024b). We use the intensity of firms' hiring of AI-skilled labor as a proxy for their use of AI, motivated by the heavy reliance of AI implementation on skilled human capital. The human-capital-based measure relies on employer-employee matched data containing 535 million individual employment profiles from Cognism, Inc.

A. *Employment Profiles*

Cognism obtains profiles from multiple sources, including publicly available online data, collaborations with recruiting agencies, and third-party resume aggregators.[1] The Cognism data are introduced and described in detail in Fedyk and Hodson (2023).

Importantly, Cognism data cover approximately 64 percent of the entire US workforce as of 2018, with a representative breakdown across industries and educational attainment (Fedyk and Hodson 2023). For each individual in the data, we observe the start and end dates, job title, company name, and job description of each listed job, as well as additional resume information such as patents, awards, and publications.

Cognism's AI research department uses techniques from machine learning and natural language processing to associate each public company employee with the corresponding firm in the Compustat dataset, identify the employee's seniority level and functional division within the firm, and disambiguate education records. This yields a sample of 101 million person-firm-years matched to US public firms between 2010 and 2018, including 19 million distinct individual employees.

B. *Firm-Level Measure of AI Investments*

We search individual resumes for the skill terms identified as the most AI related by Babina et al. (2024b). These 68 terms, identified from firms' job postings, include concepts such as "deep learning," "convolutional neural networks," and "Long Short-Term Memory (LSTM)."

We search for these terms in the employees' job titles, job descriptions, and any patents, publications, and awards produced on the job. If any of these fields include at least one of the highly AI-related terms, then that individual is considered to be an AI worker at that firm at that point in time. Otherwise, the individual is not considered to be an AI worker in that year. For example, if an individual's job title is "Computer Vision Scientist," that individual is considered an AI worker.

The firm-level measure of AI investments is computed by taking the difference between the fraction of employees who are classified as AI related at each firm in the starting year (2010) and the final year of our sample period (2018).[2] Babina et al. (2024b) provide extensive validation of this measure of individual firms' AI investments.

C. *Other Data*

We merge the AI investments measure constructed from Cognism data with quarterly and annual firm-level information on operating performance (net income, total assets, shareholders' equity, total employment, sales, cost of goods sold, R&D expenditures, cash, depreciation, capital expenditures, and working capital) from Compustat. For controls, we also collect commuting-zone-level wage and

[1] The processing of all profiles is compliant with the applicable GDPR and CCPA regulations.

[2] To ensure sufficient data coverage, we restrict the sample to firms with at least 20 US-based employees in both 2010 and 2018.

education data from the Census American Community Surveys (ACS) and industry-level wages from the Census Quarterly Workforce Indicators (QWI).

II. Results

We begin by examining the volatility of firms' overall sales, then look at earnings (specifically, ROA and return on shareholders' equity), and finally zoom in on cash flows. In all cases, AI investments are associated with a decrease in the volatility of firm operating performance.

A. *Sales*

Babina et al. (2024b) find that AI investments are associated with increases in the first moment of sales—AI-investing firms experience greater sales growth than non-AI-investing firms. In this paper, we look at the second moment: the volatility of quarterly sales. We calculate the standard deviation of each firm's log sales in each quarter over five-year periods surrounding 2010 and 2018.[3] We then compute $\Delta VolatilityLogSales$ as the difference between the 2010 and 2018 volatility measures and estimate the following long-differences specification:

$$(1)\quad \Delta VolatilityLogSales_{i,t} \;=\; b\,\Delta ShareAIWorkers_{i,[2010,2018]} + \mathbf{Controls}'_{i,2010}\gamma + SectorFE + \varepsilon_i,$$

where the main independent variable, $\Delta ShareAIWorkers_{i,[2010,2018]}$, is the change in the share of AI workers at firm *i* from 2010 to 2018 based on the Cognism resume data, standardized to have a mean of zero and a standard deviation of one. *SectorFE* are two-digit North American Industry Classification System (NAICS) industry fixed effects. In column 1, we include only industry fixed effects to examine the unconditional relationship between changes in AI investments and the volatility of firm sales. In column 2, we add a rich set of controls that are all measured at the start of the sample period in 2010: (i) initial firm-level characteristics that might relate to AI investments (log sales, cash/assets, R&D/sales, and log markups computed following De Loecker, Eeckhout, and Unger 2020) and the log of the firm's total Cognism employment; (ii) characteristics of the commuting zones (CZs) where the firms are located (the share of workers in IT-related occupations, the share of college-educated workers, log average wage, the share of foreign-born workers, the share of routine workers, the share of workers in finance and manufacturing industries, and the share of female workers); and (iii) the log industry-average wage. In all analyses, we exclude firms in tech sectors (NAICS industries 51 and 54) in order to focus on firm operations that *use* AI rather than produce AI tools for others.

Table 1 presents the results. A 1 standard deviation increase in firms' AI investments is associated with a 3.3 percent age point reduction in sales volatility when controlling for sector fixed effects and a 2.3 percent age point reduction when including all controls. The data are noisy (with large standard errors), so this result is statistically significant only without the full controls. However, the economic magnitudes are consistent across the specifications with and without extra controls and are large in both cases, corresponding to about 0.257 (0.175) of the standard deviation in the outcome variable (log sales volatility) without (with) full controls.

B. *Earnings*

We consider two measures of earnings: ROA, computed as the ratio of net income to lagged total assets, and ROE, measured as the ratio of net income to lagged shareholders' equity. For each measure, we calculate the volatility as the standard deviation of the corresponding quarterly measure across all quarters over a five-year period surrounding 2010 and 2018 and then take the difference. We reestimate Equation (1) for these two outcome variables: $\Delta VolatilityROA$ and $\Delta VolatilityROE$.

[3] The five-year period surrounding 2010 consists of quarters in 2008–2012, while the five-year period surrounding 2018 consists of quarters in 2016–2020. In untabulated analysis, we confirm that the results are similar if we compute the volatility of outcome variables over three-year windows instead of five-year windows.

Table 1—AI Investments and Sales Volatility

	ΔVol. log sales	
	(1)	(2)
ΔShare AI workers	−0.033	−0.023
	(0.018)	(0.017)
NAICS2 FE	Y	Y
Controls	N	Y
Coeff. norm. by SD	−0.257	−0.175
Coeff. norm. by IQR	−0.277	−0.189
Adj. R^2	0.149	0.199
Observations	913	913

Notes: This table reports estimates from long-differences regressions of changes in log sales volatility from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among US public firms. The measure of AI investments is standardized to mean zero and standard deviation of one. Regressions are weighted by the firm-level number of Cognism resumes as of 2010. All specifications control for industry sector fixed effects. Column 2 also controls for log employment, cash/assets, log sales, log industry wages, R&D/sales, log markups, and Cognism employment, as well as characteristics of the CZs where the firms are located and industry-average wages, all measured as of 2010. Standard errors are clustered at the five-digit NAICS industry level.

Table 2—AI Investments and Volatility of Earnings and Cash Flows

	ΔVolatility ROA		ΔVolatility ROE		ΔVolatility CFOA	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔShare AI workers	−0.001	−0.002	−0.009	−0.021	−0.004	−0.007
	(0.001)	(0.001)	(0.005)	(0.011)	(0.002)	(0.003)
NAICS2 FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y
Coeff. norm. by SD	−0.039	−0.125	−0.062	−0.144	−0.104	−0.194
Coeff. norm. by IQR	−0.049	−0.156	−0.183	−0.428	−0.130	−0.242
Adj. R^2	0.098	0.146	0.134	0.196	0.036	0.116
Observations	886	886	885	885	712	712

Notes: This table reports estimates from long-differences regressions of changes in volatility of ROA (net income over assets), ROE (net income over shareholders' equity), and CFOA (cash flows over assets) from 2010 to 2018 on the contemporaneous firm-level changes in AI investments among US public firms. The measure of AI investments is standardized to mean zero and standard deviation of one. Regressions are weighted by the firm-level number of Cognism resumes as of 2010. The controls are the same as in Table 1. Standard errors are clustered at the 5-digit NAICS industry level.

Table 2 reports the results in columns 1–4. The effects are negative and statistically significant, suggesting that AI investments are associated with a decline in the volatility of firm earnings. When all controls are included, a 1 standard deviation increase in the share of AI workers at a firm is associated with a 0.2 percent age point reduction (or 0.125 standard deviation decrease) in the volatility of the firm's ROA and a 2.1 percent (0.144 standard deviation) age point reduction in the volatility of the firm's ROE. Both effects are statistically significant at the 5 percent level. Overall, firms that invest in AI experience a decline in the volatility of their earnings, proxied by the ROA or ROE.

C. *Cash Flows*

The final outcome variable we consider is the volatility of firm cash flows, measured as net income plus depreciation minus capital expenditures and changes in net working capital scaled by lagged total assets (cash flows over assets or CFOA). As with the other outcome variables, we compute the standard deviation of the quarterly CFOA measured during the five years surrounding 2010 (2008–2012) and the five years surrounding 2018 (2016–2020) and then take the difference. Columns 5 and 6 of Table 2 show the results from estimating Equation (1) using the resulting firm-level measure, $\Delta VolatilityCFOA$, as the outcome variable.

The results reveal a strong negative relationship between firms' AI investments and the volatility of their cash flows over assets. For example, when all controls are included, a 1 standard deviation increase in our measure of AI investments translates into a 0.7 percent age point reduction in cash flow volatility, or 0.194 of the standard deviation of cash flow volatility. The effect is statistically significant at the 5 percent level. Thus, AI investments are associated with a decline in the volatility of not only sales and earnings but also cash flows.

III. Conclusion

This paper examines how AI investments are related to the second moment of firms' operating performance: the volatility of their sales, earnings, and cash flows. Previous work has found that AI benefits firms by increasing the first moment, driving higher sales, productivity, and market value (Rock 2019; Alderucci et al. 2020; Babina et al. 2024b).

Much less is known about how AI impacts firms' risk. In this paper, we present the first evidence that AI is associated with *reductions* in the volatility of firm operating performance, consistent with AI as a prediction technology being used to make better forecasts. However, that does not mean that all types of firm risk decline as firms invest more in AI: Babina et al. (2024a) study the relationship between firm AI investments and the market risk of firm equity and find that AI investments are associated with increased systematic risk, consistent with AI investments being used by firms to create growth options.

These findings invite further inquiry into how firms' risk profiles change with the advent of new technologies, including AI, and how the performance of individual firms adopting these technologies relates to broader market trends.

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