Financial risk and technology shifting: Firm-level evidence from the rise of AI

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Abstract

Does financial risk affect the firm decision to develop a new technology? We study this issue in the context of the take-off of Artificial Intelligence (AI). Using data on 28,000 Italian firms (2012–2019) matched with patent records, we find that companies handling higher cash-flow volatility are significantly more likely to innovate in AI. The role of financial risk is weaker for relatively more mature technologies, suggesting that firms more subject to financial uncertainty are more willing to undertake innovation in high-uncertainty, high-reward domains and drive frontier technological change.

JEL codes: O31; G32; L25; C23.

Keywords: Artificial Intelligence, Financial risk, Cash-flow volatility, Technological uncertainty.

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1. Introduction

During periods of technological breakthrough, firms decide whether to innovate by weighing expected returns against costs. Uncertainty plays a key role in this decision. While the costs of innovation are relatively well-defined, outcomes and future revenues are far more difficult to estimate in advance. As a result, firms that are better able to manage financial uncertainty are more likely to pursue and develop new technologies.

The decision to innovate is shaped by firm-specific characteristics, such as general financial conditions and technological capabilities, as well as contextual factors (e.g. spillovers and industry dynamics). While the literature on innovation determinants is extensive, the impact of risk exposure on technology development decisions remains largely under-explored. This gap is relevant in the context of Artificial Intelligence (IA). This technology is expected to bring substantial changes in firm production and organisation. Yet, returns to AI are highly uncertain, especially in the early stages of development and diffusion (Cockburn et al., 2018; Calvino & Fontanelli, 2023, 2024; Igna & Venturini, 2023; Babina et al., 2024; Bloom et al., 2025).

Internalizing AI production is a costly strategic choice. Since it relies on intangible assets with uncertain payback periods, it is difficult to use as collateral, making firms rely more on internal funds (Myers & Majluf, 1984; Hall & Lerner, 2010; Kerr & Nanda, 2015). However, while such financial frictions can hinder investment, high investment–cash flow sensitivity may also signal attractive opportunities rather than just binding constraints (Kaplan & Zingales, 1997). Consequently, developing AI represents both a technological and a financial decision, particularly for firms with high risk exposure. Financial uncertainty can either discourage innovation through precautionary motives that delay irreversible investment (Dixit & Pindyck, 1994; Calcagnini & Saltari, 2000; Bloom et al., 2007), or instead stimulate risk-taking behaviours if it exerts a *supporting effect* on innovation (Beladi et al., 2021). From this perspective, innovative investment acts as a growth option, allowing early movers to hedge against adverse future states and capture rents (Aghion et al., 2004, 2005; Baum et al., 2010; Keefe & Tate, 2013). Which of these forces prevails for AI remains an open empirical question.

This paper addresses this gap by examining how firm-level financial risk influences AI patenting, using a large sample of Italian firms from 2012 to 2019. We focus on this period as it precedes the rise of generative AI and is marked by significant uncertainty about AI's capabilities and returns—a setting well-suited to study how financial risk and technological uncertainty interact. By matching Moody's Orbis balance-sheet data with Google patent data, we apply a state-of-the-art AI classification (Gong et al., 2025).

Using probit models, we measure financial risk through cash-flow volatility, while controlling for technological uncertainty, volatility in real activity, and other key financial and technological characteristics. Our findings suggest that firms with higher cash-flow volatility are significantly more likely to patent in AI. Notably, this effect is specific to AI and is not driven by other forms of uncertainty or financial traits. By contrast, the impact of financial risk is weaker for innovations in ICT and Industry 4.0 domains, which represent more mature and less uncertain technologies. This pattern suggests that the *supporting effect* of uncertainty dominates for AI: rather than postponing investment, financially volatile firms turn to AI innovation as a strategic response to uncertainty. From this perspective, AI emerges as a high-risk, high-reward technology that firms pursue to achieve technological breakthroughs, secure higher rents, and signal long-run growth potential, distinguishing it from more established digital technologies.

The remainder of the paper describes the data and empirical strategy (Section 2), presents the main results and robustness checks (Section 3) and concludes (Section 4).

2. Data and empirical strategy

Our empirical analysis relies on a large sample of 28,020 Italian firms observed between 2012 and 2019. We collect information on firm characteristics using balance sheet data from Moody's Orbis. Patent data come from Google Patents Public Datasets. We restrict the analysis to firms that have filed at least one patent application since 1978. Using firm (assignee) names, we retrieve the corresponding patent publication numbers from the Google Patents Public Datasets. These publication numbers serve as matching keys to select AI-related patents using the publicly available list of AI patent applications developed by Gong et al. (2025).[1] This dataset flags AI-related patents within a comprehensive collection of 2,356,204 patents spanning 1960–2019, extracted from Espacenet. Using this procedure, we identify 153 firms with at least one AI-related patent during the sample period, representing 0.55% of the sample, most of which patent only once.

To analyze whether financial risk affects firms' propensity to develop AI technologies, we estimate pooled probit models of the probability that firm i patents in AI in year t:

$$Pr(AI_{it} = 1) = \alpha + \beta SD\_CF_{it} + \gamma SD\_PA_{it} + \delta SD\_VA_{it} + \lambda X_{it-1} + \mu_j + \tau_t + u_{it}, \tag{1}$$

where AI_{it} is a binary indicator equal to one if firm i files at least one AI-related patent in year t. The key explanatory variable is firm financial risk, measured as cash-flow volatility SD_CF_{it}, defined as the standard deviation of the cash-flow ratio over rolling three- or five-year backward-looking windows, depending on the specification (Keefe & Tate, 2013; Beladi et al., 2021). To disentangle financial risk from other sources of uncertainty, we include two additional volatility measures computed over the same rolling

[1] Gong et al. (2025) provide a large-scale, internationally dataset that classities patent applications into AI and non-AI categories. It applies a hierarchical methodology that combines keyword screening, large language models, and BERT-based classifiers, addressing the limitations of traditional keyword approaches (Pairolero et al., 2025).

windows: SD_PAT_{it}, the standard deviation of the firm's annual patent filings capturing technological uncertainty, and SD_VA_{it}, the standard deviation of firm-level value added capturing volatility in real activity. The vector X_{it} includes relevant controls for financial conditions (cash-flow ratio, leverage, and current ratio), technological characteristics (intangible ratio, firm patent stock, and ICT share), and firm demographics (size and age). Additionally, we account for the local innovative environment via regional patenting intensity. All controls are lagged by one year to mitigate simultaneity concerns. Industry and regional fixed effects μ_j, and year fixed effects τ_t account for sectoral and local shocks. Standard errors are clustered at the firm and year levels. Our empirical strategy also includes a comparative analysis across AI, Industry 4.0, and ICT domains—applying the baseline probit specification to these alternative technologies—alongside a DiD estimation designed to mitigate potential reverse causality concerns.[2]

Table 1 defines the main variables and Table 2 reports summary statistics by AI patenting status. Figure 1 illustrates the geographical distribution of AI patents across Italian provinces, highlighting a strong spatial concentration.

3. Main Results

3.1. Baseline estimates

Table 3 reports probit estimates for AI patenting, and progressively extends the empirical specification with the controls mentioned above. Column (1) includes our proxy for financial risk (cash-flow volatility), basic firm-level controls (size and age) and fixed effects. Column (2) adds two potential confounding factors capturing firms' exposure to other sources of

[2] Additional robustness checks are reported in the Appendix, where we consider alternative measures of financial risk and profitability, longer volatility windows (A.1), and tests for potential sample selection concerns (A.2).

uncertainty, namely the volatility of patenting activity and value added. Column (3) introduces controls for firms' financial conditions, including internal funds, balance-sheet structure, and liquidity. Column (4) represents our baseline model and further accounts for firms' technological capabilities, by including intangible intensity, patent stock, ICT specialization, and localised (spillover) effects of innovation activities.

Table 3 shows that firms facing more volatile internal funds, and which are therefore more capable to handle financial risk, are systematically more likely to invest in AI. A one-standard-deviation increase in cash-flow volatility raises the probability of AI patenting by about 0.28 percentage points.

Across all specifications, this effect remains positive and statistically significant and does not overlap with other sources of uncertainty. Our proxies for technological and market risk, captured by firms' patenting and VA volatility, are also positively related to AI patenting, although their magnitude is considerably smaller. These findings highlight financial volatility as a key driver of AI innovation, corroborating the view of a *supporting effect* of uncertainty: firms facing more volatile internal funds appear to pursue a strategic, high-risk/high-reward innovation posture, investing early in AI to secure future rents and market positions. There results are unlikely driven by idiosyncratic factors or sample composition. In the next subsections, we support this by showing that financial volatility plays a different role in firms' innovation decisions in less risky technological fields.

Control variables are also consistent with prior evidence. In particular, leverage has a negative and significant coefficient, suggesting that higher debt levels discourage risky innovation due to tighter financial constraints and higher default risk. Both liquidity measures are negatively correlated with AI patenting.[3] Intangible intensity and prior patent stock are both positively related to the probability of AI patenting, confirming that AI builds on pre-

[3]Importantly, all explanatory variables are lagged, which mitigates concerns that lower liquidity simply reflects contemporaneous resource absorption due to innovation activity.

existing knowledge assets (Igna & Venturini, 2023). Since we control for intangible intensity (which captures the constraints faced by low-liquidity firms), the negative link between liquidity and AI patenting likely reflects the high uncertainty surrounding innovation in this emerging field. Finally, younger and larger firms show a higher propensity to patent in AI.

3.2. Technology comparison

We next assess whether the effect of cash-flow uncertainty is specific to AI or reflects a broader propensity to innovate under financial risk. Table 4 compares the baseline AI specification (Column 1) with patenting in Industry 4.0 (Column 2) and ICT (Column 3).

ICT technologies emerged earlier and constitute the technological foundation of subsequent digital innovations, including Industry 4.0 and AI (Igna & Venturini, 2023). Industry 4.0 covers a broader set of digital technologies, including the Internet of Things and additive manufacturing. Many of these technologies are applied domains of AI and widely adopted in manufacturing (Venturini, 2022), implying lower uncertainty in returns.

The results reveal a sharp asymmetry across technological domains. While financial risk is positively and strongly associated with AI patenting, its effect is weaker for Industry 4.0 and not significant for ICT. This suggests that financial uncertainty selectively pushes firms toward more exploratory, high-risk domains. In contrast, innovation in ICT and, to a lesser extent, Industry 4.0 is primarily driven by existing capabilities, such as intangible intensity and prior experience, and follows more established, less exploratory trajectories. Overall, these findings reinforce the view that firms under financial pressure strategically adopt AI as a high-upside vehicle for breakthrough innovation and future rent generation, whereas more mature technologies appear relatively insensitive to financial risk.

3.3. Reverse causality

A potential concern that may affect our estimates is reverse causality: while financial risk may influence AI development, AI investment could also alter a firm's risk profile. Specifically, a firm introducing an AI patent in year t may experience higher cash-flow volatility from year $t + 1$ onward, potentially inflating our estimates. Addressing this ideally would require valid instruments, which are extremely difficult to identify given the highly idiosyncratic nature of firm-level uncertainty. We therefore adopt an alternative counterfactual approach designed to rule out feedback effects. We estimate a staggered Difference-in-Differences (DiD) panel model robust to intertemporal treatment effects (Chaisemartin & Haultfœuille, 2023), tracking the evolution of financial risk following AI adoption. Treatment is defined as an absorbing indicator equal to one from the year of first adoption. We include a one-year lead and lag to capture anticipation and delayed effects. To address selection bias, we control for the lagged dependent variable and implement propensity score matching, pairing each treated firm with its ten nearest neighbors based on a pre-treatment probit model (Marioni et al., 2024). Figure 2 reports the results. The top panel shows the change in firms' financial risk after the first AI patent filing, both in a baseline specification and including the full set of controls from the probit regression. The central panel replicates the same exercise for the introduction of Industry 4.0 and ICT patents. The bottom panel presents two additional exercises. First, we consider the release of Google TensorFlow in 2015, widely regarded as central to many AI applications (Chen & al., 2024), with treatment equal to one from 2015 onward for firms with at least one AI patent between 2012–2019. Second, we conduct a placebo test assigning a random treatment year to each AI-patenting firm. Overall, the figure shows no systematic evidence of feedback effects on firm financial risk across most specifications. The only exception is ICT patents, where financial risk rises by up to 2%, possibly reflecting the larger number of treated firms relative to AI.[4]

4. Conclusion

This paper explores how firm-level financial risk influences the development of frontier technologies, focusing on AI. Analyzing Italian firm-level data matched with patent records, we find that higher cash-flow volatility significantly increases the likelihood of AI innovation. This relationship is robust to alternative sources of uncertainty and a wide range of financial and technological controls.

Our results highlight a novel channel linking financial conditions and technological change: firms more accustomed to operating under financial volatility appear more inclined to invest in highly uncertain and exploratory domains like AI. This effect is significantly weaker for Industry 4.0 and non-existent for ICT, suggesting that financial risk selectively drives innovation toward more uncertain frontiers.

Overall, these findings indicate that financial risk tolerance is a key determinant of frontier innovation. Future research should examine the underlying mechanisms and long-term performance implications of these strategic choices across different institutional contexts.

[4] Appendix A.2 further shows that results are not driven by selection issues related to unobservable factors affecting patenting in AI and other technology fields.

Table 1: Variables definition

Variable	**Type**	**Definition**
AI patent	Dummy	Firm patenting an AI technology
4IR patent	Dummy	Firm patenting a 4IR technology
ICT patent	Dummy	Firm patenting an ICT technology
Cashflow ratio	Share	Cash flow / total assets
SD of cashflow (3y or 5y)	Continuous	St. deviation of the cashflow ratio over 3 or 5 years
Leverage	Share	Total financial debt / total assets
Current ratio	Share	Current assets / current liabilities
Intangible ratio	Share	Intangible assets / total assets
SD of patents (3y or 5y)	Continuous	St. deviation of firm patents over 3 or 5 years
SD of VA (3y or 5y)	Continuous	St. deviation of firm value added over 3 or 5 years (in million €)
Credit constraint	Dummy	=1 if firm shows positive value-added growth but cannot increase leverage
Patent stock (log)	Continuous	Firm patents portfolio
ICT share	Share	ICT patents / total patents
Patents per region (log)	Continuous	Cumulative patents per region (excluding the focal)
ROA	Share	Net income / total assets
Firm age (log)	Continuous	Years from firm establishment
Employees (log)	Continuous	Number of employees

Table 2: Summary Statistics (mean by groups)

	no AI	AI
SD of cashflow (3y or 5y)	0.05	0.06
SD of patents (3y or 5y)	0.55	0.98
SD of VA (3y or 5y, in mil.€)	0.28	0.29
Cashflow ratio	0.06	0.06
Leverage	0.67	0.63
Current ratio	2.18	1.91
Intangible ratio	0.18	0.38
Patent stock	0.39	59.13
ICT share	0.00	0.03
Patents per region	269.84	247.00

Figure 1: Geographical distribution

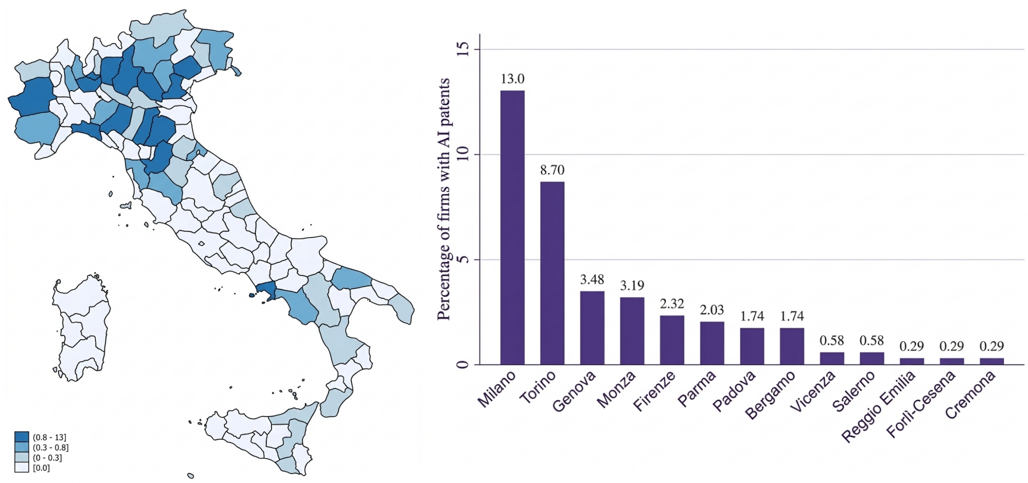


Table 3: Econometric results: Probit

	(1)	(2)	(3)	(4)
SD of cashflow (3y)	0.3282***	0.3285***	0.3830***	0.2816***
	(0.0979)	(0.0982)	(0.1111)	(0.1037)
SD of patents (3y)		0.000172***	0.000170***	0.000070**
		(0.000037)	(0.000036)	(0.000032)
SD of VA (3y)		0.000059**	0.000047*	0.000041*
		(0.000023)	(0.000024)	(0.000022)
Cashflow ratio			−0.2191***	−0.1686**
			(0.0732)	(0.0658)
Leverage			−0.1582***	−0.1135***
			(0.0428)	(0.0389)
Current ratio			−0.0147**	−0.0105**
			(0.0067)	(0.0050)
Intangible ratio				0.1084***
				(0.0247)
Patent stock				0.0973***
				(0.0096)
ICT share				−0.2077
				(0.1383)
Patents per region				−0.1332
				(0.0848)
Age	−0.0548***	−0.0511***	−0.0492***	−0.0324***
	(0.0073)	(0.0072)	(0.0074)	(0.0076)
Employees	0.0575***	0.0533***	0.0546***	0.0361***
	(0.0061)	(0.0059)	(0.0061)	(0.0049)
Observations	178,263	177,528	168,856	168,507
Pseudo R-squared	0.150	0.175	0.189	0.279

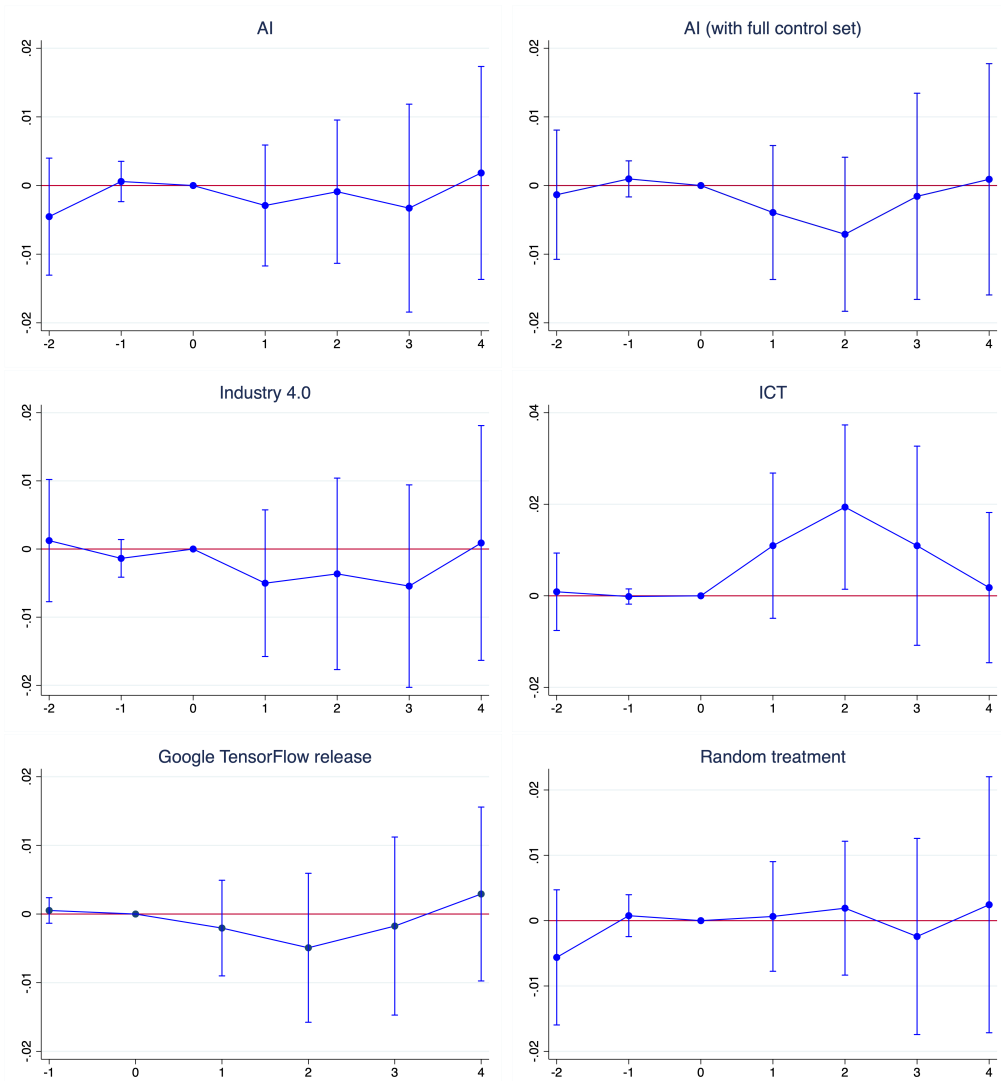
Notes: Dependent variable = 1 if the firm files ≥ 1 AI patent. MEs in percentage terms ($\times 100$) with robust SEs in parentheses, clustered at firm and year levels. Continuous variables (except SDs) in logs and lagged one year. Industry, region, and year FEs included in all specifications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Technology comparison

	(1) *AI*	(2) *4IR*	(3) *ICT*
SD of cashflow (3y)	0.2817***	0.2650*	0.0705
	(0.1037)	(0.1391)	(0.1046)
SD of patents (3y)	0.000070**	0.000185***	0.000078***
	(0.000032)	(0.000054)	(0.000030)
SD of VA (3y)	0.000041*	−0.000031	0.000055**
	(0.000022)	(0.000043)	(0.000021)
Cashflow ratio	−0.1686**	−0.0885	0.0004
	(0.0658)	(0.0962)	(0.0723)
Leverage	−0.1135***	−0.1504***	−0.0012
	(0.0389)	(0.0489)	(0.0209)
Current ratio	−0.0105**	−0.0063	0.0019
	(0.0050)	(0.0055)	(0.0021)
Intangible ratio	0.1084***	0.1956***	0.0448**
	(0.0247)	(0.0332)	(0.0216)
Patent stock	0.0973***	0.0910***	0.0427***
	(0.0096)	(0.0139)	(0.0104)
ICT share	−0.2077	0.1866	0.2845***
	(0.1383)	(0.1282)	(0.0558)
Observations	168,507	173,906	168,057
Pseudo R-squared	0.279	0.173	0.205

Notes: Dependent variable = 1 if the firm files ≥ 1 AI (1), 4IR (2), or ICT (3) patent. Marginal Effects (MEs) from probit regressions are expressed in percentage terms ($\times 100$). Standard errors in are in parentheses, clustered at firm and year levels. Continuous variables (except SDs) in logs and lagged one year. Firm age, employees, industry, region, and year FEs included in all specifications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 2: Response of firm financial risk to technlogy shocks: counter-factual analysis



Notes: DiD event-study results. The top panel shows the change in firms' financial risk following the first AI patent filing, in a baseline specification and with the full set of probit controls. The central panel replicates the exercise for Industry 4.0 and ICT patents. The bottom panel reports a specification exploiting the release of Google TensorFlow in 2015 as a treatment shock for AI-patenting firms, and a placebo test assigning a random treatment year to each AI-patenting firm. Bands indicate 95% confidence intervals.

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Web Appendix

A.1 Robustness cheks: Alternative measures of cash-flow volatility

Table A.1 shows that the positive association between cash-flow volatility and AI patenting is robust across a wide range of alternative specifications.

Column (1) restricts the computation of volatility to firms with at least three available years of data ($T \geq 3$), improving measurement precision at the cost of a smaller sample. Column (2) introduces an alternative identification of cash-flow uncertainty, based on a relative, industry-adjusted measure constructed following Beladi et al. (2021). Specifically, Δ of SD cash flow is defined as the time-difference between firm-level cash-flow uncertainty and the corresponding industry-level average computed over a rolling three-year window.[5] Column (3) computes cash-flow, patent, and value-added volatilities over a longer, five-year rolling window ($T \geq 2$), capturing more persistent financial risk. Column (4) employs lagged three-year cash-flow volatility, together with lagged measures of patent and value, added volatility—to further address simultaneity and reverse-causality concerns. Column (5) replaces cash-flow-based indicators with alternative profitability and risk measures based on ROA and ROA volatility, confirming that the main findings are not an artefact of the specific cash-flow definition.

Across all specifications, cash-flow volatility remains a strong and statistically significant predictor of AI patenting.[6]

[5] This specification captures deviations in firms' financial risk relative to their industry peers rather than absolute volatility levels.

[6] Including region–year fixed effects to absorb time-varying local shocks affecting both financial conditions and innovation leaves the results unchanged. Similarly, controlling for a revealed credit-constraint dummy—defined following Almeida et al. (2004) as equal to one when firms exhibit positive value-added growth without increasing leverage—does not affect the coefficient on cash-flow volatility, indicating that the baseline effect is not driven by limited access to external finance. Estimates available upon request.

Table A.1 - Robustness checks

	(1)	(2)	(3)	(4)	(5)
SD of cashflow (3y)	0.3143***				
	(0.1098)				
SD of cashflow lag.(3y)		0.2094*			
		(0.1188)			
SD of cashflow (5y)			0.2374**		
			(0.1136)		
Δ of SD cashflow (3y)				0.2790***	
				(0.1021)	
SD of ROA					0.1766**
					(0.0801)
SD of patents (3y)	0.000057			0.000070**	0.000076**
	(0.000037)			(0.000032)	(0.000031)
SD of patents lag.(3y)		−0.000133**			
		(0.000052)			
SD of patents (5y)			0.000077**		
			(0.000030)		
SD of VA (3y)	0.000045*			0.000043**	0.000040*
	(0.000024)			(0.000022)	(0.000022)
SD of VA lag. (3y)		0.000024			
		(0.000025)			
SD of VA (5y)			0.0000		
			(0.0000)		
Cashflow ratio	−0.1355*	−0.1279	−0.1752***	−0.1684**	
	(0.0704)	(0.0801)	(0.0653)	(0.0659)	
ROA					−0.1359***
					(0.0516)
Leverage	−0.1296***	−0.1225***	−0.1210***	−0.1137***	−0.1148***
	(0.0445)	(0.0462)	(0.0391)	(0.0389)	(0.0333)
Current ratio	−0.0092**	−0.0101**	−0.0101**	−0.0104**	−0.0084**
	(0.0046)	(0.0048)	(0.0048)	(0.0049)	(0.0039)
Technological controls	Yes	Yes	Yes	Yes	Yes
Observations	145,806	144,310	171,582	168,372	174,794
Pseudo R-squared	0.272	0.275	0.282	0.279	0.276

Notes: Dependent variable = 1 if the firm files ≥ 1 AI patent. MEs in percentage terms ($\times 100$) with robust SEs in parentheses, clustered at firm and year levels. Continuous variables (except SDs) in logs and lagged one year. Firm age, employees, industry, region, and year FEs included in all specifications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.2 Robustness checks: Selection and unobservable factors

Another potential concern is that our baseline estimates are obtained from a subsample of firms with at least one patent application since 1978, the first year for which patent records are available in Google Patents. While this restriction helps mitigate selection bias by focusing on firms with a demonstrated propensity to innovate, it does not fully rule out the possibility that unobservable factors jointly influence the decision to patent in AI, Industry 4.0, or ICT. The asymmetric effects documented in the main text—where financial risk primarily drives innovation in high-uncertainty domains—already suggest that our findings are not merely capturing a general propensity to patent. However, to formally account for the potential interdependence of these technological choices, we estimate a multivariate probit model using simulated maximum likelihood. This approach allows the error terms to be correlated across equations, capturing common unobserved determinants of innovation.

The results, reported in Columns (1)–(3) of Table A.2, are broadly consistent with the baseline estimates. Notably, the estimated correlations between the error terms are positive and statistically significant, confirming the presence of unobserved factors affecting firms' technological shifts and justifying the use of a joint estimation framework to validate the robustness of our results.

Table A.2 - Technology comparison: Multivariate probit estimates

	(1) *AI*	(2) *4IR*	(3) *ICT*
SD of cashflow (3y)	0.2894^{***}	0.1962	0.0012
	(0.1047)	(0.1382)	(0.1067)
SD of patents (3y)	0.000076^{**}	0.000175^{***}	0.000078^{***}
	(0.000033)	(0.000052)	(0.000027)
SD of VA (3y)	0.000039^{*}	-0.000044	0.000058^{**}
	(0.000022)	(0.000045)	(0.000021)
Cashflow ratio	-0.1648^{**}	-0.0886	-0.0049
	(0.0641)	(0.0946)	(0.0750)
Leverage	-0.1173^{***}	-0.1457^{***}	0.0122
	(0.0361)	(0.0475)	(0.0193)
Current ratio	-0.0107^{**}	-0.0069	0.0016
	(0.0046)	(0.0054)	(0.0020)
Intangible ratio	0.1048^{***}	0.1954^{***}	0.0439^{**}
	(0.0238)	(0.0317)	(0.0205)
Patent stock	0.0989^{***}	0.1015^{***}	0.0530^{***}
	(0.0069)	(0.0118)	(0.0085)
ICT share	-0.1692	0.2794^{**}	0.2849^{***}
	(0.1192)	(0.1020)	(0.0488)
Observations	184,119	184,119	184,119
Cross-eqs correlation	$\rho_{1,2}$	$\rho_{1,3}$	$\rho_{2,3}$
	0.3567^{***}	0.2820^{***}	0.5915^{***}
	(0.0274)	(0.0336)	(0.0304)

Notes: Dependent variable = 1 if the firm files $\geq$ 1 AI (1), 4IR (2), or ICT (3) patent. Marginal Effects (MEs) from multivariate probit regressions are expressed in percentage terms ($\times$100). Standard errors in are in parentheses, clustered at firm and year levels. Continuous variables (except SDs) in logs and lagged one year. Firm age, employees, industry, region, and year FEs included in all specifications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.