Digital Technology Innovation and Corporate Labor Cost Stickiness

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Abstract. Using data on Chinese A-share listed firms from 2009 to 2022, this paper examines whether digital technology innovation affects labor cost stickiness. To do so, it constructs a firm-level measure of digital technology innovation based on patent applications matched to official digital-economy industry classifications. The results show that digital technology innovation significantly increases labor cost stickiness by amplifying the asymmetry of firms' labor-demand adjustment over expansions and contractions. This finding remains robust to instrumental-variable estimation and a wide range of robustness checks. Mechanism analyses indicate that the effect operates through stronger economies of scale and higher labor adjustment costs associated with skill upgrading and a larger skill premium. Further heterogeneity analyses show that the effect is more pronounced among labor-intensive firms, firms closer to the digital technological frontier, and firms operating in more competitive markets.

Keywords: Digital technology innovation; Labor cost stickiness; Skill premium; Economies of scale.

1 Introduction

With the rapid diffusion of frontier digital technologies such as artificial intelligence, big data, and cloud computing, digital innovation is reshaping firms' production organization and the broader economic structure. In China, digital technology invention patent applications increased sharply between 2009 and 2022, and the number of enterprises engaged in digital innovation also expanded substantially. Digital technology innovation has therefore become an important driver of high-quality economic development.

Existing studies show that the adoption of digital technologies - including artificial intelligence and the industrial internet - has important implications for firms' labor cost stickiness [1,2,3,4] . Yet much less is known about whether innovation at the technological frontier itself shapes the cyclical properties of labor demand. Labor cost stickiness refers to the asymmetric adjustment of labor costs to changes in revenue: labor costs fall less when revenue declines than they rise when revenue expands. This perspective offers a more refined way to understand firms' labor-demand decisions

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over the business cycle. Because labor cost stickiness reflects limited flexibility in labor adjustment, excessive stickiness may reduce productivity and operating performance. Prior research documents that labor cost stickiness is widespread among Chinese listed firms and identifies a range of institutional and organizational determinants. However, the role of frontier digital innovation in shaping labor cost stickiness remains underexplored.

Against this background, this paper uses data on Chinese A-share listed firms from 2009 to 2022 to construct a concordance linking the Classification of Core Industries of the Digital Economy, the National Economic Industry Classification, and IPC subgroups. Based on this concordance, the paper identifies firms' digital technology patent applications and uses them to measure digital technology innovation intensity. The empirical evidence shows that digital technology innovation strengthens the asymmetry of firms' labor-demand adjustment over output expansions and contractions. This result is robust to endogeneity tests and a battery of robustness checks. The paper further shows that the effect operates through stronger economies of scale and changes in labor adjustment costs, and that it is especially pronounced among labor-intensive firms, technologically leading firms, and firms operating in highly competitive industries.

2 Literature Review and Research Hypotheses

With respect to digital technology, Bresnahan et al. using U.S. firm-level data, show that information technology increases firms' demand for skilled technical and managerial workers [5]. Using European data, Falk and Biagi find that information technology raises the share of highly skilled workers in manufacturing firms [6]. More broadly, digital technology-induced changes in labor demand can widen the skill premium. For example, Ikeshita shows that digital technology innovation promotes economic growth while simultaneously increasing within-firm skill premia [7]. Acemoglu and Restrepo further document that the adoption of industrial robots reduces employment and wages, especially at the local labor-market level [8].

A large literature also examines the determinants and consequences of labor cost stickiness. In the Chinese context, high local government debt increases labor cost stickiness through a responsibility-shifting effect that constrains firms' ability to reduce employment during downturns [9]. State-owned enterprises tend to exhibit stronger labor cost stickiness, and a higher share of state-owned capital in private firms further amplifies this pattern [10]. Internal labor markets within business groups can mitigate labor cost stickiness [11], whereas sustained investment in high-skilled human capital tends to exacerbate it [12] At the firm level, labor cost stickiness has two distinct implications. On the one hand, it may reflect inefficient labor allocation and thus hinder productivity and profitability. On the other hand, when it is driven by persistent investment in human capital, it may support innovation and long-run transformation [13].

Labor cost stickiness is closely related to the costs and expected benefits associated with output fluctuations, especially labor adjustment costs and the expected returns to retaining employees [14,15]. Because labor is subject to employment protection, contractual rigidities, and partly irreversible investment in human capital, firms often treat labor as a quasi-fixed factor [16] and are therefore reluctant to cut labor costs immediately when output declines. At the same time, firms may continue to invest in human capital during downturns in order to preserve future competitive advantages and expected returns, thereby limiting the decline in labor costs [17]. As a result, labor costs typically respond less to decreases in output than to increases in output. Since total labor cost reflects both wages and the quantity of labor demanded, labor cost stickiness can be interpreted as asymmetry in overall labor demand: firms adjust labor demand less aggressively in downturns than in expansions.

Building on this framework, this paper argues that digital technology innovation intensifies this asymmetry in labor demand through two channels. First, because digital technologies are skill-biased, they increase firms' demand for high-skilled labor and raise the associated skill premium [18,19]. Owing to human capital specificity, incomplete contracting, and search frictions in the labor market, high-skilled workers and their wage premia are more costly to adjust. Firms therefore prefer to retain such workers during downturns rather than dismiss them [20,21]. Moreover, when firms continue to invest in human capital during downturns in anticipation of future gains, they are even less likely to compress the wage premium attached to high-skilled labor. A higher share of high-skilled employees therefore raises employment stickiness, while a larger skill premium increases wage stickiness; together, these forces strengthen overall labor cost stickiness.

Second, digital technology innovation may strengthen economies of scale. Economies of scale arise when average cost declines as output expands. When scale economies are stronger, labor demand tends to respond more strongly in booms, whereas in downturns firms may find it costly to cut labor quickly without undermining productive capacity or market share. Endogenous growth theory emphasizes that knowledge is a non-rival input and can therefore generate increasing returns to scale [22]. Consistent with this view, Bajari et al highlight the scalability of digital and data-driven methods [23]. If digital innovation shifts firms' technological frontier toward stronger scale economies, it may further intensify labor cost stickiness.

Accordingly, Hypothesis 1 is stated as follows: digital technology innovation increases corporate labor cost stickiness.

Hypothesis 2 states that digital technology innovation increases labor cost stickiness by raising the share of high-skilled labor within the firm and by increasing the skill premium. Hypothesis 3 states that digital technology innovation increases labor cost stickiness by strengthening firms' economies of scale.

3 Empirical Methodology and Results

3.1 Model Specification

Following Anderson et al, this paper estimates a specification with a triple interaction among digital technology innovation, sales changes, and a downturn indicator to capture labor cost stickiness [24]. The estimating equation is as follows:

$$\Delta\ LaborDemand_{i,t} = \beta_0 + \beta_1 + \beta_n\ Controls_{i,t} + (\gamma_0 + \gamma_1 + \gamma_n Controls_{i,t}) \times \Delta Sales_{i,t} + (\delta_0 + \delta_1 DigInno_{i,t} + \delta_n Controls) \times Dec_{it} \times \Delta Sales_{i,t} + \delta_i + \gamma_j + \mu_t + \varepsilon_{i,t} \quad (1)$$

All variables are defined as above. The coefficient on the triple interaction term, DigInno × Dec × ΔSales, captures the marginal effect of digital technology innovation on the cyclicality of corporate labor demand. A significantly negative coefficient indicates that digital technology innovation further reduces the elasticity of labor demand with respect to output during downturns, thereby intensifying labor cost stickiness. To mitigate omitted-variable bias, the baseline specification includes year, industry, and firm fixed effects, and standard errors are clustered at the firm level.

3.2 Data Source

The sample consists of Chinese A-share listed firms over the study period. The data are processed as follows: (1) firms in the financial sector are excluded; (2) firms designated ST, *ST, PT, or otherwise abnormal are excluded; (3) observations with missing values for key variables are removed; and (4) all continuous variables are winsorized at the 1% level in both tails to reduce the influence of outliers. The core explanatory variable—firm-level digital technology innovation—is constructed by matching each listed firm's annual patent applications, obtained from the China National Intellectual Property Administration (CNIPA), with the Statistical Classification of the Digital Economy and Its Core Industries. Control variables, robustness-test variables, and mechanism variables are collected from the Wind and CSMAR databases, as well as the China City Statistical Yearbook. After excluding missing observations and outliers, the final sample contains 17,138 firm-year observations.

3.3 Variable Construction

Digital Technology Innovation (DigInno). The main IPC classifications of each listed firm's annual patent applications are matched to the digital-economy industries defined in the Statistical Classification of the Digital Economy and Its Core Industries (2023) issued by the National Bureau of Statistics of China. This procedure identifies the annual number of digital-economy invention patents and utility-model patents held by each firm. DigInno is measured as the natural logarithm of one plus the sum of these patents.

Dependent variables. To examine how labor quantity and wages jointly generate labor cost stickiness, the paper uses three dependent variables: the annual growth rate of total labor cost (ΔLaborCost), the growth rate of employment (ΔEmployment), and the growth rate of average wages (ΔWage). Each variable is constructed as the first difference in the natural logarithm of the corresponding underlying measure. Total labor cost is proxied by employee compensation payable from the balance sheet; employment is measured by the year-end number of employees; and the average wage is measured as the ratio of total labor cost to the annual number of employees.

The control variables are grouped into three categories. The first captures firms' financial conditions, including firm age (FirmAge), revenue scale (Sale), leverage

(Leverage), Tobin's Q (TobinQ), cash flow ratio (CashFlow), liquidity ratio (Liquid), board size (Board), ownership type (SOE), R&D intensity (RDInput), and total annual patent applications (Patents). The second category contains variables commonly used to control for agency costs and external conditions in the estimation of labor cost stickiness, including asset intensity (AssetIntensity), a dummy for whether revenue also declined in the previous year (ConsecutiveDec), the average revenue growth of other firms in the same industry (GrowthRate), and the GDP growth rate of the prefecture-level city in which the firm is located (FirmLocationGDP). Descriptive statistics for the main variables are reported in Table 1 and their asymmetry is reported in Table 2.

Table 1. Descriptive statistics (Panel A).

Panel A.1 Total						
Variable	Observations	Mean	SD	Min	Median	Max
LaborCost	17138	19.7191	1.3323	15.7128	19.5641	25.8380
Δ *LaborCost*	17138	0.1617	0.2660	-2.8062	0.1323	6.1501
Employment	17138	7.9205	1.2410	3.4012	7.8053	13.2228
Δ *Employment*	16776	0.0752	0.3079	-2.3787	0.0331	6.9679
Wage	17138	11.7993	0.5210	8.2905	11.7795	17.2096
Δ *Wage*	16776	0.0844	0.2353	-5.9047	0.0865	3.2025
Panel A.2 Output Increase			Panel A.3 Output Decrease			Panel Difference
Variable	Observations	Mean	Variable	Observations	Mean	Absolute Difference
Δ *Employment*	12546	0.1126	Δ *Employment*	4230	-0.0358	0.1484
Δ *Wage*	12546	0.0934	Δ *Wage*	4230	0.0578	0.0356
Δ *LaborCost*	12847	0.2078	Δ *LaborCost*	4291	0.0234	0.1844

Table 2. Descriptive statistics (Panel B).

Variable	Observations	Mean	SD	Min	Median	Max
Sale	17138	21.7161	1.5164	16.9962	21.5306	28.7183
Δ *Sale*	17138	0.1372	0.3666	-3.2695	0.1182	22.3773
DigInno	17138	2.4649	1.4081	0.6931	2.1972	8.8670
FirmAge	17138	2.0851	0.8053	0.0000	2.1972	3.4657
RDInput	17138	0.0533	0.0622	0.0000	0.0396	2.5162
CashFlow	17138	0.0479	0.0666	-0.5562	0.0455	0.6641
Liquid	17138	0.5857	0.1841	0.0228	0.6006	0.9974
Size	17138	22.3561	1.3607	17.9544	22.1416	28.6365
Board	17138	8.5414	1.6981	0	9	18
Soe	17138	0.3455	0.4756	0	0	1
Patents	17138	3.7298	1.3311	0	3.6889	9.6105
Leverage	17138	0.4220	0.1999	0.0091	0.4168	3.6453
Tobin	17138	2.0686	1.5096	0.6413	1.6417	41.9711

4 Empirical Analysis

4.1 Baseline Regression Results

Table 3 reports the baseline regression results for the effect of digital technology innovation on labor cost stickiness. The coefficient of primary interest is that on DigInno × Dec × ΔSale. Columns (1) and (2) show that this coefficient is significantly negative, implying that digital technology innovation strengthens the asymmetry in employment adjustment over the cycle. Columns (3) and (4) indicate that digital technology innovation also increases wage stickiness. Columns (5) and (6) further show that overall labor cost stickiness becomes more pronounced as digital technology innovation intensifies. Taken together, the results suggest that digital technology innovation reinforces labor cost stickiness through both the quantity and price dimensions of labor demand, thereby supporting Hypothesis 1.

Table 3. Baseline regression results.

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Δ *Employment*		Δ *Wage*		Δ *LaborCost*	
DigInno	0.011***	-0.012**	-0.004*	0.006**	0.015***	0.018***
	(-2.73)	(-2.19)	(-1.65)	(-1.99)	(-3.05)	(-3.36)
DigInno ×Δ *Sale*	0.082***	0.088***	0.015	0.012	0.097***	0.099***
	(3.51)	(3.39)	(1.28)	(1.10)	(3.46)	(3.48)
DigInno×*Dec*×Δ *Sale*	0.101***	-0.087*	-0.031	0.047**	-0.132***	-0.133***
	(-2.69)	(-1.94)	(-1.24)	(-1.97)	(-3.41)	(-3.11)
Δ *Sale*	0.308***	0.293***	0.001	-0.006	0.314**	0.293**
	(3.38)	(3.09)	(0.02)	(-0.13)	(2.54)	(2.40)
Dec×Δ *Sale*	-0.128	-0.162	0.152*	0.145*	0.017	-0.023
	(-0.90)	(-1.08)	(1.83)	(1.84)	(0.09)	(-0.14)
Constant	0.015	-0.164**	0.092***	0.085*	0.107***	-0.077
	(0.92)	(-2.45)	(10.17)	(1.67)	(4.67)	(-1.50)
Observations	16,776	15,143	16,776	15,143	16,776	15,143
R-squared	0.304	0.341	0.009	0.041	0.501	0.544
Controls	NO	YES	NO	YES	NO	YES
Year FE	NO	YES	NO	YES	NO	YES
Industry_FE	NO	YES	NO	YES	NO	YES
Province_FE	NO	YES	NO	YES	NO	YES

4.2 Endogeneity Discussion

A potential endogeneity concern is that firms may increase digital innovation in response to labor adjustment frictions. For example, as firms expand and labor costs rise, managers may invest more in digital innovation to improve internal coordination and production efficiency. To address this concern, the paper adopts an instrumental-variable strategy. Because the empirical specification contains interaction terms involving the core explanatory variable, separate instruments are constructed for the relevant endogenous interaction terms.

Specifically, the instrument for firm-level digital technology innovation is based on the timing at which the integrated online government-service platform in the firm's province achieved province-city-county connectivity. The launch dates of these platforms are manually collected from provincial government documents and authoritative news reports. Most provinces completed this connectivity in 2017 or 2018, which broadly coincides with the acceleration of digital innovation among listed firms. The logic of the instrument is twofold. First, construction of integrated government-service platforms involves government procurement and may stimulate local firms' incentives to engage in digital innovation. Second, the timing of platform rollout is determined by provincial governments and should not directly affect firm-level labor-demand characteristics within the sample period, except through its effect on digital technology innovation. Based on this logic, a dummy variable, IV_GovPlat, is constructed that equals one if the firm's province had achieved three-level platform connectivity by year t, and zero otherwise. The results are reported in Table 4: columns (1)-(3) present the first-stage estimates, and column (4) presents the second-stage estimate.

Table 4. Endogeneity test.

Dependent Variable	(1)	(2)	(3)	(4)
	IV_GovPlat			
	DigInno	*DigInno×ΔSale*	*Dec×DigInno×ΔSale*	*ΔLaborCost*
IV_GovPlat	0.478***	-0.095	0.004	
	(24.71)	(0.072)	(0.008)	
IV_GovPlat×ΔSale	0.0586	1.651***	0.045***	
	(1.23)	(0.194)	(0.010)	
IV_GovPlat×Dec×ΔSale	-0.193	-0.707***	0.986***	
	(-1.67)	(0.243)	(0.109)	
DigInno×ΔSale				0.179***
				(6.03)
DigInno×Dec×ΔSale				-0.413**
				(-2.07)
Observation	17,637	17,637	17,637	17,637
Controls	YES	YES	YES	YES
Fixed_Effect	YES	YES	YES	YES
Anderson LM				51.132
C-D Wald F				17.008

4.3 Robustness Tests

Several additional tests are performed to assess the robustness of the baseline results. First, the paper directly estimates asymmetry in the elasticity of labor demand with respect to output. Assuming that firms have product-market power, and following De Loecker and Warzynski, it estimates a translog production function with labor, capital, and intermediate inputs to recover firm-level output elasticity with respect to labor [25]. This estimated elasticity is then regressed on digital technology innovation and the output-decline indicator. Second, the paper replaces the baseline measure of digital innovation with an alternative patent-based indicator constructed from the Key Digital Technology Patent Classification System (2023) issued by CNIPA. Third, because the essence of labor cost stickiness lies in asymmetry over output expansions and contractions, the sample is split into periods of sales growth and sales decline and the regressions are re-estimated separately. Fourth, to account for adjustment dynamics and reverse causality, the explanatory variable DigInno is lagged by one period. Overall, the results in Table 5 remain consistent with the baseline findings.

Table 5. Robustness tests.

Dependent Variable	*Estimating labor demand asymmetry*	*Alternative key variables*	*Grouped Regression(ΔSale >0)*	*Grouped Regressio(ΔSale >0)*	*Lagged DigInno*
	(1)	(2)	(3)	(4)	(5)
	Elasticity_Labor	*ΔLaborCost*	*ΔLaborCost*	*ΔLaborCost*	*ΔLaborCost*
DigInno_Tech		-0.003			
		(-1.25)			
DigInno_Tech×ΔSale		0.044***			
		(5.92)			
Dec×ΔSale×DigInno_Tech		-0.030*			
		(-1.71)			
ΔSale	0.290*	0.546***	0.285**	0.228***	-0.094
	(1.90)	(77.93)	(2.21)	(4.49)	(-0.33)
Dec×ΔSale	-0.015	-0.444***			0.523
	(-0.07)	(-29.89)			(1.03)
DigInno	-0.017***		-0.021***	-0.007	0.002
	(-2.61)		(-3.05)	(-1.44)	(0.55)
DigInno×ΔSale	0.106***		0.105***	0.001	-0.048**
	(2.89)		(3.46)	(0.03)	(-2.49)
Dec×ΔSale×.DigInno	-0.136**				0.088**
	(-2.42)				0.002
Constant	-0.075	0.066***	-0.068	-0.080	0.146
	(-0.35)	(29.95)	(-1.05)	(-0.94)	(1.42)
Observations	10,114	16,127	11,413	4,047	11,042
R-squared	0.546	0.430	0.543	0.234	0.564
Controls	YES	YES	YES	YES	YES
Fixed_Effect	YES	YES	YES	YES	YES

4.4 Heterogeneity Analysis

Factor intensity. Capital is another productive factor whose dynamic adjustment is closely linked to labor demand. Relative to labor, capital is often easier to adjust because it is less constrained by labor-market institutions and may involve lower replacement costs. It can therefore become the principal margin of adjustment for firms [26,27]. Accordingly, the paper expects the effect of digital technology innovation on labor cost stickiness to be weaker in firms with higher capital intensity. The capital-labor ratio (CLR) is calculated for each firm-year, and firms are divided at the median into capital-intensive and labor-intensive groups. Grouped regressions are then used to examine heterogeneity in the effect of digital technology innovation.

Technological leadership. For each industry-year, the paper calculates the average number of digital technology patents and the average R&D expenditure. A firm's ratio of digital technology patents to the industry average, together with its ratio of R&D expenditure to the industry average, is used to construct a measure of relative digital technological leadership (DCA). The sample is then split at the median DCA to examine whether the estimated effect is stronger among firms closer to the digital technological frontier.

Market competition. Firms' labor demand is a derived factor demand conditional on product demand. The price elasticity of demand for the firm's output therefore affects labor demand through both output-scale and factor-substitution channels. The paper expects the effect of digital technology innovation on labor cost stickiness to be stronger in more competitive industries, where product-demand elasticity is higher. To test this prediction, the sample is divided according to the industry-year Herfindahl-Hirschman Index (HHI), and grouped regressions are estimated accordingly.

Table 6. Heterogeneity analysis.

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)
	CLR <P50	*CLR >P50*	*DCA< P50*	*DCA>P50*	*HHI <P50*	*HHI >P50*
	Factor Intensity		Technological Leadership		Market Competition	
	Δ *LaborCost*					
DigInno	-0.015**	-0.011*	-0.003	-0.018**	-0.000	-0.016***
	(-2.36)	(-1.65)	(-0.41)	(-2.45)	(-0.03)	(-2.99)
DigInno×Δ *Sale*	0.076**	0.056	0.013	0.102***	0.003	0.090***
	(2.22)	(1.60)	(0.30)	(2.68)	(0.09)	(3.05)
DigInno×*Dec*×Δ *Sale*	-0.121**	-0.027	-0.022	-0.142**	0.033	-0.129**
	(-1.96)	(-0.51)	(-0.33)	(-2.22)	(0.66)	(-2.43)
Constant	0.200	0.021	0.193	0.222*	0.308***	0.007
	(1.44)	(0.18)	(1.46)	(1.74)	(2.58)	(0.07)
Observations	9,307	6,152	6,309	8,959	7,461	7,999
R-squared	0.619	0.566	0.632	0.582	0.600	0.611
Controls	YES	YES	YES	YES	YES	YES

Year FE	YES	YES	YES	YES	YES	YES
Industry_FE	YES	YES	YES	YES	YES	YES
Province_FE	YES	YES	YES	YES	YES	YES

Table 6 reports the regression results of the heterogeneity analysis. Column (1) shows that digital technology innovation has a stronger effect in intensifying labor cost stickiness among labor-intensive firms. Column (4) indicates that digital technology innovation with a leading position in the technology market is more likely to exacerbate firms' labor cost stickiness. Column (6) shows that, in more concentrated markets, the strengthening effect of digital technology innovation on cost stickiness is more pronounced. These findings are all consistent with the theoretical expectations.

4.5 Mechanism Analysis

Two channels may explain why digital technology innovation intensifies the cyclical asymmetry of labor demand: (1) stronger firm-level economies of scale; and (2) higher labor adjustment costs induced by skill upgrading and a larger skill premium.

Enhancement of Economies of Scale. As argued above, the scale properties of a firm's production technology fundamentally shape the cyclicality of labor demand. Stronger economies of scale are associated with greater asymmetry in labor demand over the cycle. If digital technology innovation enhances overall economies of scale, it should make labor demand more asymmetric and thus intensify labor cost stickiness. Because detailed firm-level production data are unavailable, the paper uses the change in the fixed-asset turnover ratio (FATOR) as a proxy for firm-level economies of scale [28]. It first uses FATOR as the dependent variable to test whether digital technology innovation strengthens economies of scale, and then conducts grouped regressions to examine whether labor cost stickiness is indeed more pronounced among firms with stronger scale economies.

Table 7. Mechanism analysis: economies of scale.

Dependent Variable	(1)	(2)	(3)
	FATOR	*FATOR<P_50*	*FATOR>P_50*
		Δ *LaborCost*	Δ *LaborCost*
DigInno	0.023*		
	(1.70)		
Δ *Sale*		0.664***	0.286***
		(17.52)	(7.40)
Dec×Δ *Sale*		-0.483	-0.169***
		(-7.68)	(-3.27)
Constant	2.395***	-0.090	-0.031
	(4.24)	(-1.20)	(-0.46)
Observations	8,161	6,985	6,926
R-squared	0.318	0.643	0.317
Controls	YES	YES	YES

Year FE	YES	YES	YES
Industry_FE	YES	YES	YES
Province_FE	*YES*	*YES*	*YES*

Table 7 reports the results for the economies-of-scale channel. In column (1), the coefficient on digital technology innovation is significantly positive, indicating that digital technology innovation enhances firm-level economies of scale. Columns (2) and (3) further show that labor demand asymmetry is significant only among firms with stronger scale economies. These results suggest that digital technology innovation changes the underlying cost structure by strengthening firm-level economies of scale, which in turn amplifies labor cost stickiness.

Upgrading in the Structure of Labor Demand. As discussed above, high-skilled labor is more costly to adjust than low-skilled labor. Firms are therefore less willing to reduce either the employment or the compensation of high-skilled workers when output falls, causing aggregate labor demand to deviate from a fully procyclical pattern. The contribution of this channel to overall labor cost stickiness depends on both the share of high-skilled labor and the relative wage paid to high-skilled workers. To test this mechanism, the paper constructs measures of within-firm skill upgrading and of the skill premium. Following Autor et al the workforce is classified into high- and low-skilled labor using both educational attainment and occupational categories [29].

Table 8. Mechanism analysis: adjustment costs.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable				*HighSkill<P50*	*HighSkill>P50*	*HighKnowledge<P50*	*HighKnowledge>P50*	*Skill_Pre<P50*	*Skill_Pre>P50*
	HighSkill	*HighKnowledge*	*Skill_Pre*	*Δ LaborCost*	*Δ LaborCost*	*Δ LaborCost*	*Δ LaborCost*	*Δ LaborCost*	*Δ LaborCost*
DigInno	0.020***	0.022***	0.054***						
	(4.67)	(5.29)	(3.66)						
Δ Sale				0.693***	0.691***	0.662***	0.701***	0.616***	0.504***
				(9.73)	(13.02)	(6.43)	(16.17)	(9.49)	(5.15)
Dec×Δ Sale				-0.497***	-0.607***	-0.336**	-0.611***	-0.458***	-0.291**
				(-5.08)	(-7.70)	(-2.26)	(-10.04)	(-5.20)	(-2.17)
Constant	0.210***	0.053*	1.562***	-0.107	-0.242**	-0.108	-0.204**	-0.223***	-0.035
	(7.79)	(1.88)	(15.71)	(-1.25)	(-2.29)	(-0.86)	(-2.54)	(-2.72)	(-0.52)
Observations	10,228	10,228	11,165	4,065	4,090	2,109	6,046	4,425	11,035
R-squared	0.528	0.535	0.089	0.586	0.576	0.599	0.578	0.582	0.505
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry_FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Province_FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

The paper uses two measures of within-firm skill upgrading: (1) the share of employees with a bachelor's degree or above (High_Knowledge), and (2) the share of employees in technical, managerial, financial, and sales positions (High_Skill). To measure the skill premium, recruitment data from 2016 to 2022 are collected from major Chinese online recruitment platforms, including 51job, BOSS Zhipin, and Zhaopin. These data are matched with the baseline sample to obtain firm-year recruitment information for listed firms. Each recruitment record includes the firm name, industry, job title, job description, salary, the number of positions advertised, posting duration, and posting status. After removing duplicate postings, each record is classified as high- or low-skilled labor according to the education and occupation criteria described above. The weighted average advertised wage is then computed separately for high-skilled and low-skilled labor, using the number of positions advertised as weights. The relative wage of high-skilled labor is defined as the skill premium, as illustrated in Figure 1.

$$Skill\_Premium_{i,t} = \frac{\sum_{j \in \boldsymbol{S}(\boldsymbol{H})} \frac{Num_{H\,i,j,t}}{TotalNum_{H\,i,t}} Wage^{Median}_{H\,i,j,t}}{\sum_{k \in \boldsymbol{S}(\boldsymbol{L})} \frac{Num_{L\,i,k,t}}{TotalNum_{L\,i,t}} Wage^{Median}_{L\,i,k,t}}$$

Fig. 1. Calculation of the skill premium

The results are reported in Table 8. Columns (1) and (2) show that digital technology innovation increases both the share of high-skilled labor and the share of high-knowledge labor. Column (3) further indicates that digital technology innovation raises the skill premium. Column (5) shows that labor cost stickiness is more pronounced among firms with a higher share of high-skilled labor, suggesting that the skill composition of employment is an important source of sticky labor adjustment. Columns (8) and (9) show that the asymmetry in labor demand is also stronger among firms with a higher skill premium, consistent with the wage-adjustment strategies of innovative firms.

5 Conclusion

Using data on Chinese A-share listed firms from 2009 to 2022, this paper identifies firms' digital technology patent applications and examines how digital technology innovation affects labor cost stickiness. The evidence shows that digital technology innovation amplifies the asymmetry of corporate labor demand over output expansions and contractions. This conclusion remains robust after addressing endogeneity concerns and conducting a battery of robustness checks. Mechanism analyses indicate that the effect operates through stronger economies of scale and higher labor adjustment costs associated with skill upgrading and a larger skill premium. Heterogeneity analyses further show that the effect is more pronounced for labor-intensive firms, technologically leading firms, and firms operating in more competitive markets.

This paper contributes to the literature in three respects. First, while existing studies mainly focus on the consequences of adopting already-mature digital technologies, digital transformation, or the broader development of the digital economy, this paper identifies the frontier stage of digital technology innovation itself by tracing digital product- and process-innovation patents of Chinese listed firms using official CNIPA classification documents. Second, prior studies primarily examine the direct effects of digital technologies on the level and structure of labor demand, wages, and total labor costs, while paying less attention to how digital technology affects the intrinsic cyclical properties of labor demand. This paper fills that gap by focusing on labor cost stickiness as a key manifestation of those cyclical properties. Third, unlike studies that emphasize managerial opportunism, adjustment costs, and other organizational rigidities, this paper highlights the scale-economy effects of digital technological progress and the accompanying upgrading of firms' labor skill structure and skill premium as mechanisms through which digital innovation intensifies labor cost stickiness.

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References

1. Hui, L., Xie, H., & Chen, X. (2024). Digital technology, the industrial internet, and cost stickiness. China Journal of Accounting Research, 17(1), 100339.
2. Wang, H., & Qiu, F. (2025). AI adoption and labor cost stickiness: Based on natural language and machine learning. Information Technology and Management, 26(2), 163–184.
3. Xiao, Z., Ren, R., Li, C., Gao, Y., & Chen, X. (2026). The impact of artificial intelligence adoption on labor cost stickiness: Firm-level evidence from China. Economic Analysis and Policy, 91, 47–73.
4. Xu, G., Qiu, Y., & Qi, J. (2024). Artificial intelligence and labor demand: An empirical analysis of Chinese small and micro enterprises. Heliyon, 10(13), e33893.
5. Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. Quarterly Journal of Economics, 117(1), 339–376.
6. Falk, M., & Biagi, F. (2017). Relative demand for highly skilled workers and use of different ICT technologies. Applied Economics, 49(9), 903–914.
7. Ikeshita, K. (2025). Effects of automation and human investment on skill premium. Innovation and Green Development, 4(2), 100220.
8. Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. Journal of Political Economy, 128(6), 2188–2244.
9. Chan, J., Lin, Q., & Zhang, G. (2023). Local government debt and corporate labor decisions: Evidence from China. SSRN Electronic Journal.
10. Xiao, Z., Niu, Q., Yun, F., & Ye, Y. (2024). The impact of state-owned capital on labor cost stickiness in private firms: Evidence from China. Economic Modelling, 141, 106906.
11. Xu, H., Chan, K. C., Na, C., & Fang, Q. (2023). The bright side of the internal labor market: Evidence from the labor cost stickiness of firms affiliated with privately owned business groups in China. Journal of Corporate Finance, 78, 102356.

12. Kong, D., Liu, S., & Shen, R. (2025). Labor cost stickiness and managerial decisions on human capital adjustment. Journal of Accounting Literature, 47(2), 325–350.
13. Cannon, J. N. (2014). Determinants of sticky costs: An analysis of cost behavior using United States air transportation industry data. Accounting Review, 89(5), 1645–1672.
14. Banker, R. D., & Byzalov, D. (2014). Asymmetric cost behavior. Journal of Management Accounting Research, 26(2), 43–79.
15. Banker, R. D., Byzalov, D., & Chen, L. (2013). Employment protection legislation, adjustment costs, and cross-country differences in cost behavior. Journal of Accounting and Economics, 55(1), 111–127.
16. Oi, W. Y. (1962). Labor as a quasi-fixed factor. Journal of Political Economy, 70(6), 538–555.
17. Chu, J., & Fang, J. (2020). Economic policy uncertainty and firms' labor investment decision. China Finance Review International, 11(1), 73–91.
18. Bloom, D. E., Prettner, K., Saadaoui, J., & Veruete, M. (2024). Artificial intelligence and the skill premium (Working Paper No. 32430). National Bureau of Economic Research.
19. Becker, G. S. (1962). Investment in human capital: A theoretical analysis. Journal of Political Economy, 70(5, Part 2), 9–49.
20. Neal, D. (1995). Industry-specific human capital: Evidence from displaced workers. Journal of Labor Economics, 13(4), 653–677.
21. Petrongolo, B., & Pissarides, C. A. (2001). Looking into the black box: A survey of the matching function. Journal of Economic Literature, 39(2), 390–431.
22. Romer, P. M. (1990). Endogenous technological change. Journal of Political Economy, 98(5, Part 2), S71–S102.
23. Bajari, P., Nekipelov, D., Ryan, S. P., & Yang, M. (2015). Machine learning methods for demand estimation. American Economic Review: Papers and Proceedings, 105(5), 481-485.
24. Anderson, M. C., Banker, R. D., & Janakiraman, S. N. (2003). Are selling, general, and administrative costs "sticky"? Journal of Accounting Research, 41(1), 47–63.
25. De Loecker, J., & Warzynski, F. (2012). Markups and firm-level export status. American Economic Review, 102(6), 2437–2471.
26. Caballero, R. J., & Hammour, M. L. (1998). Jobless growth: Appropriability, factor substitution, and unemployment. Carnegie-Rochester Conference Series on Public Policy, 48, 51–94.
27. Hamermesh, D. S. (1993). Labor demand. Princeton University Press.
28. Demsetz, H. (1973). Industry structure, market rivalry, and public policy. Journal of Law and Economics, 16(1), 1–9.
29. Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. Quarterly Journal of Economics, 135(2), 645–709.