

Digital Transformation and the Restructuring of Employment: Evidence from Chinese Listed Firms

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Abstract

This paper examines how digital transformation reshapes employment structures within Chinese listed firms, focusing on occupational functions and task intensity. Drawing on recruitment data classified under ISCO-08 and the Chinese Standard Occupational Classification 2022, we categorize jobs into five functional groups: management, professional, technical, auxiliary, and manual. Using a task-based framework, we construct routine, abstract, and manual task intensity indices through keyword analysis of job descriptions. We find that digitalization is associated with increased hiring in managerial, professional, and technical roles, and reduced demand for auxiliary and manual labor. At the task level, abstract task demand rises, while routine and manual tasks decline. Moderation analyses link these shifts to improvements in managerial efficiency and executive compensation. Our findings highlight how emerging technologies, including large language models (LLMs), are reshaping skill demands and labor dynamics in China's corporate sector.

Keywords: Digital transformation; Employment structure; Task intensity; Large language models (LLMs); Recruitment; Corporate governance

1 Introduction

The rapid proliferation of artificial intelligence, automation, big data analytics, and digital platforms is fundamentally reshaping the nature of work across the globe. In both developed and emerging economies, digital transformation is altering not only the aggregate level of employment, but also its functional structure across occupations, skill intensities, and task domains. While a growing literature has documented the macro-level effects of automation on labor demand, considerably less is known about how digital technologies reshape within-firm hiring structures—particularly in the context of large developing economies undergoing simultaneous industrial upgrading and digital leapfrogging.

This paper studies the impact of digital transformation on firm-level employment composition, focusing on Chinese listed firms between 2016 and 2023. These firms are a critical segment of the economy: they account for a disproportionate share of innovation, productivity growth, and formal employment, and are at the forefront of adopting digital technologies. To measure the extent of digital transformation, we construct a novel firm-level digitalization index using natural language processing (NLP) techniques inspired by large language models (LLMs) to analyze corporate annual reports. This approach captures both the breadth and depth of technology integration across strategic narratives and operational disclosures.

We then link this measure to detailed recruitment data—classified under a refined mapping of the ISCO-08 and the Chinese Standard Occupational Classification (2022)—to analyze how digitalization affects hiring patterns across five occupational functions: manual, auxiliary, technical, professional, and managerial roles. The use of LLM-based text embeddings further enhances our ability to categorize job descriptions into abstract, routine, and manual task intensities, enabling a more granular analysis of evolving skill demands.

The Chinese setting offers an ideal empirical environment for this inquiry. Between 2014 and 2023, the share of digital economy value added in GDP rose from approximately 26% to over 40% (Figure 1), reflecting the deepening penetration of digital tools into business

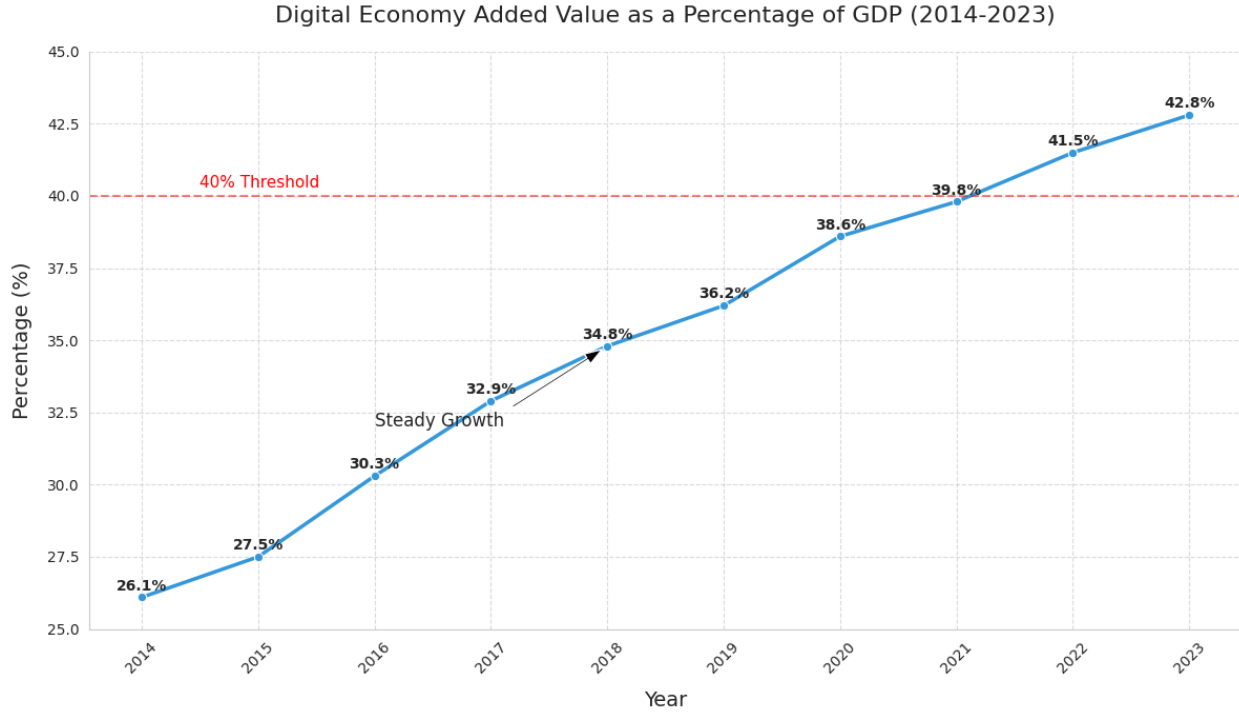


Figure 1: Digital Economy Added Value as a Percentage of GDP (2014–2023)

Data source: China Academy of Information and Communications Technology (CAICT)

operations. At the same time, the labor market has undergone significant compositional shifts: recruitment for data science, AI, and cybersecurity positions has surged, while hiring for routine manual and clerical roles has contracted sharply.

To investigate how digital transformation restructures employment, we adopt a multi-step research approach. First, we develop a theoretical framework grounded in the task-based model of labor demand, which allows us to predict how firms reallocate tasks between labor and digital capital as digital capabilities increase. Second, we construct comprehensive measures of occupational hiring by leveraging granular job posting data from major online recruitment platforms in China. Third, we estimate the effects of digitalization using panel regressions with firm fixed effects, controlling for firm size, profitability, governance structure, and regional and industry heterogeneity. Fourth, we employ instrumental variable strategies to address potential endogeneity concerns and conduct mechanism analyses by estimating structural equation models that incorporate agency costs, executive compensation, and firm

valuation as mediating variables. Finally, we explore heterogeneity in firm responses across ownership types, development stages, and digital infrastructure environments.

Our analysis yields four main findings. First, digital transformation is associated with a modest decline in total hiring, driven by reductions in occupations intensive in routine and manual tasks. Second, digitalization is strongly correlated with a shift in recruitment structure: the relative share of managerial, professional, and technical hires increases, while auxiliary and manual roles shrink. Third, this restructuring is most pronounced in manufacturing and IT-intensive sectors, and in regions with stronger digital infrastructure and human capital endowments. Fourth, we document heterogeneity in firm response consistent with task-based theory: firms reallocate tasks from low-skill functions toward either digital execution or high-skill human capital, in line with a skill-biased, task-reallocation mechanism.

These findings contribute to several strands of literature. We add to the body of work on labor market effects of digital technologies by providing firm-level evidence from an emerging economy undergoing rapid technological upgrading. Our results complement macro and sector-level analyses by uncovering within-firm mechanisms behind observed employment polarization. Moreover, we advance the task-based framework by empirically validating theoretical predictions regarding endogenous recruitment shifts under digitalization.

Policy implications are immediate. As firms increasingly substitute low-skill functions with digital capital and reorient toward abstract-task intensive roles, the need for targeted reskilling, adaptive workforce planning, and investment in regional digital infrastructure becomes urgent. Our findings underscore that digital transformation is not a neutral productivity shock; it is a reallocation force that restructures the nature of work within firms and amplifies pre-existing regional and occupational inequalities. Understanding its micro-level effects is therefore critical to designing inclusive responses to technological change.

2 Literature Review and Theoretical Framework

The rapid advancement and widespread adoption of digital technologies, including artificial intelligence (AI), big data analytics, and automation, are profoundly reshaping labor markets globally. This technological wave, often termed the Fourth Industrial Revolution, necessitates a re-evaluation of how work is organized, what skills are valued, and how employment structures evolve (Brynjolfsson and McAfee, 2011; Manyika et al., 2017). This section reviews the pertinent literature, establishing the theoretical underpinnings and empirical context for examining how digital transformation influences employment structures within firms, with a particular focus on the Chinese context. We delve into the evolving discourse on technology's labor market impacts, the specific challenges and opportunities presented by AI, the nuances of these transformations in developing economies like China, and finally, the critical role of firm-level analysis in understanding these complex dynamics.

2.1 The Evolving Discourse on Technological Change and Labor Markets

The impact of technological change on employment has been a central and often contentious theme in economic discourse for centuries, from the Luddites to contemporary debates about AI (Autor, 2015). Early theories often grappled with the dual nature of technology as both a substitute for and a complement to human labor. A foundational perspective that has gained significant traction is the task-based framework (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018). This framework posits that technological advancements, particularly automation, do not uniformly affect entire occupations but rather specific tasks within them. Technologies tend to replace labor in routine or codifiable tasks (both manual and cognitive), while potentially increasing demand for labor in tasks requiring complex problem-solving, creativity, critical thinking, and interpersonal skills (Acemoglu and Restrepo, 2018). The core insight is that the impact of technology is contingent on the task content of occupations and how technology alters the comparative advantage of capital and labor in performing

those tasks ([Gathmann and Schönberg, 2007](#)).

Building on this, the concept of Skill-Biased Technological Change (SBTC) emerged, arguing that technological advancements in the late 20th century disproportionately favored skilled labor, increasing its relative demand and wages compared to unskilled labor ([Autor, 2014](#); [Card and Dinardo, 2002](#); [Griliches, 1969](#)). However, more recent evidence from the 1990s onwards, particularly in developed economies, pointed to a more nuanced pattern known as job polarization. This phenomenon describes a scenario where employment grows in high-skill, high-wage occupations (often intensive in abstract, non-routine cognitive tasks) and in low-skill, low-wage service occupations (often intensive in manual, non-routine tasks), while employment and wage growth stagnate or decline for middle-skill, middle-wage occupations (typically intensive in routine tasks) ([Autor and Dorn, 2009](#); [Goos et al., 2014, 2009](#); [Senftleben and Wielandt, 2012](#)). The automation of routine tasks, facilitated by advancements in information and communication technologies (ICT), is widely considered a primary driver of job polarization ([Autor and Salomons, 2018](#)). Offshoring of routine tasks has also been identified as a contributing factor, often intertwined with technological advancements ([Goos et al., 2014](#)).

2.2 Artificial Intelligence and the New Wave of Automation

The recent surge in Artificial Intelligence (AI) capabilities, particularly in machine learning, natural language processing, and computer vision, has introduced new dimensions and intensified the debate on automation's labor market impact ([Brynjolfsson et al., 2018](#); [West, 2015](#)). Unlike earlier waves of automation that primarily targeted routine manual and cognitive tasks, modern AI exhibits the potential to perform a broader spectrum of tasks, including those previously considered non-routine and requiring sophisticated cognitive abilities ([Felten et al., 2018, 2019](#)). This has led to concerns about potentially more widespread labor displacement across a wider range of occupations and skill levels ([Frey and Osborne, 2017](#); [Arntz et al., 2017](#)).

However, the impact of AI is complex and not necessarily unidirectional. [Marguerit \(2025\)](#) distinguish between "automation AI" (which substitutes for labor) and "augmentation AI" (which enhances human capabilities and productivity), suggesting differing consequences for employment and wages. The overall effect of AI on labor demand hinges on the interplay of several forces ([Acemoglu and Restrepo, 2018, 2019](#)):

- **Displacement Effect:** AI takes over tasks previously performed by human labor, directly reducing demand for those workers.
- **Productivity Effect:** AI adoption can lower production costs and increase firm productivity, potentially leading to lower prices, increased product demand, and consequently, higher demand for labor in complementary or non-automated tasks within the same industry or in other industries.
- **Reinstatement Effect:** Technological progress, including AI, can lead to the creation of new tasks, new products, or even new industries where labor has a comparative advantage, thereby creating new employment opportunities.

Empirical evidence on AI's current aggregate labor market impact is still developing. Some studies, using detailed occupational data and measures of AI exposure (e.g., based on patent text analysis or AI capabilities mapped to job tasks), find that while AI is reshaping task content within occupations, its net effect on overall employment and wages at the aggregate level may still be limited or heterogeneous across different worker groups and contexts ([Acemoglu and Restrepo, 2020](#); [Felten et al., 2019](#); [Webb, 2019](#)). For instance, [Gulati et al. \(2025\)](#) find that GenAI adoption is associated with higher requirements for cognitive and social skills. The need for more granular, especially firm-level, data to understand these dynamics is widely acknowledged ([Seamans and Raj, 2018](#)).

2.3 Digital Transformation in Developing Economies: The Chinese Context

While much of the seminal research on automation and labor has focused on developed economies, the implications of digital transformation for large, rapidly industrializing, and digitizing developing countries like China are of paramount importance and present distinct characteristics (Mishra and Deichmann, 2016). China's unique trajectory characterized by unprecedented economic growth, its role as a global manufacturing hub, significant state influence in economic development and technology promotion, and an exceptionally rapid adoption and diffusion of digital technologies (e.g., e-commerce, mobile payments, AI applications) provides a critical context for studying these phenomena (Huo et al., 2024; Lv et al., 2025; Wu et al., 2023).

A growing body of literature is examining the impact of digitalization on China's labor market. Studies using macro, regional, or industry-level data suggest that the development of China's digital economy significantly influences both the scale and structure of employment. For example, Wu et al. (2023) find that digital economic development improves the employment scale of listed companies and favors high-skilled labor. Similarly, Zhang (2025) show that digital technologies increase demand for high-skilled labor while reducing the proportion of medium- to low-skilled jobs, alongside driving industrial upgrading. Sun (2024) also finds a positive contribution of the digital economy to overall labor demand, promoting high-tech employment while suppressing low-tech employment.

Regarding AI specifically, research in the Chinese manufacturing sector by Huo et al. (2024) suggests a U-shaped relationship between AI development and total employment, with short-term substitution effects and long-term creation effects, and a clear bias towards replacing low-skilled labor. Wang (2024) also highlights AI's dual impact in Chinese manufacturing, correlating with reduced employment numbers but enhanced wage rates. Furthermore, the digital economy has been linked to employment polarization trends in China, echoing patterns in Western countries, although these trends may be shaped by China's specific institutional context, industrial structure, and technological innovation pathways

(Zhang et al., 2022). Liang et al. (2025) explore how technological innovation mediates AI's impact on different skill groups in China. The interplay between AI adoption and firm innovativeness, considering labor structure, is also an emerging area of research (Wu et al., 2025).

2.4 The Firm-Level Perspective and Identified Research Gaps

While aggregate, sectoral, and regional studies offer valuable broad-stroke insights, a deeper and more nuanced understanding of labor market restructuring necessitates analysis at the firm level. Firms are the primary decision-making units regarding technology adoption, investment in new processes, and the subsequent adjustments to their workforce composition and skill demands (Benzell et al., 2019). Firm-level data can reveal heterogeneity in responses to digitalization that are often masked in more aggregated analyses. For instance, Bartel et al. (2005) show how IT adoption in valve manufacturing plants altered business strategies, improved process efficiency, and increased skill requirements.

Despite the burgeoning literature, significant research gaps persist, particularly concerning the micro-level impacts of digital transformation in the Chinese context.

1. **Granularity of Firm-Level Evidence:** While some studies, like Wu et al. (2023), examine listed companies, there is a continued need for more granular evidence that systematically links robust, multi-dimensional measures of firm-level digital transformation to detailed changes in occupational hiring patterns and, crucially, task intensity. Many existing studies rely on broader regional or industry-level data, or use less direct proxies for digitalization.
2. **Understanding Mechanisms within Chinese Firms:** The precise mechanisms through which digitalization reshapes employment structures within Chinese firms such as changes in managerial efficiency, specific skill-set demands (beyond broad educational categories), organizational restructuring, internal labor market adjustments, and the adoption of new work practices are not yet fully elucidated.

3. **Task-Content Dynamics in China:** While the task-based approach is well-established, its empirical application to the Chinese firm landscape, particularly linking digital transformation to shifts in demand for abstract, routine, and manual tasks at the hiring margin, requires further investigation.

This paper aims to address these gaps by leveraging a unique and comprehensive dataset of Chinese listed firms. By constructing firm-level digitalization indices based on textual analysis of annual reports and combining them with detailed online recruitment data classified according to both internationally comparable occupational functions (ISCO-08, mapped to the Chinese Standard Occupational Classification 2022) and a task-based framework (routine, abstract, manual task intensities derived from job descriptions) this study provides a nuanced analysis of how digital transformation is restructuring employment within a critical segment of the Chinese economy. The dual focus on occupational functions and task intensities allows for a richer understanding that moves beyond simple skill dichotomies (e.g., high-skill vs. low-skill based on education alone) and contributes to a more comprehensive picture of labor market dynamics in the digital era in China. This approach allows us to directly observe shifts in firms' revealed preferences for different types of labor as they navigate the digital transition, offering insights into the micro-foundations of the displacement, productivity, and reinstatement effects of technology.

3 Theoretical Framework: Digital Transformation and Endogenous Task Assignment

We develop a task-based model of firm-level labor demand to examine how digital transformation reshapes recruitment structure. Building on ?, the model features a continuum of tasks and heterogeneous occupational capabilities along three skill dimensions, allowing for endogenous assignment between labor and digital capital.

3.1 Tasks, Skills, and Production Technology

The firm must execute a continuum of tasks indexed by $z \in [0, 1]$, where higher values of z correspond to greater cognitive complexity and abstraction. Each task is associated with a skill composition vector:

$$s(z) = (m(z), r(z), a(z)),$$

where:

- $m(z)$: manual intensity,
- $r(z)$: routine intensity,
- $a(z)$: abstract intensity,

subject to the normalization constraint $m(z) + r(z) + a(z) = 1$. We adopt the following functional forms:

$$\begin{aligned} m(z) &= 1 - z, \\ r(z) &= 4z(1 - z), \\ a(z) &= z. \end{aligned}$$

These ensure that low- z tasks are predominantly manual or routine, while high- z tasks emphasize abstraction.

Tasks can be assigned to either digital capital (D) or one of five occupation types $k \in \mathcal{K} = \{\text{phys, aux, tech, prof, mgmt}\}$, each with varying comparative advantages in skill execution.

3.2 Occupational Capabilities and Task Costs

Each occupation $k \in \mathcal{K}$ is characterized by a capability vector $\Lambda_k = (\lambda_k^m, \lambda_k^r, \lambda_k^a)$, measuring efficiency in manual, routine, and abstract tasks, respectively. The effective productivity at

task z is:

$$\lambda_k(z) = \lambda_k^m m(z) + \lambda_k^r r(z) + \lambda_k^a a(z),$$

leading to a unit cost of:

$$c_k(z) = \frac{w_k}{\lambda_k(z)},$$

where w_k denotes the wage of occupation k .

Digital capital has task-specific productivity $\kappa(z; \theta)$, increasing in z and parameterized by digital capability $\theta > 0$:

$$\kappa(z; \theta) = \bar{\kappa} + \theta z^\gamma, \quad \gamma > 1,$$

with associated cost:

$$c_D(z; \theta) = \frac{r}{\kappa(z; \theta)} = \frac{r}{\bar{\kappa} + \theta z^\gamma},$$

where r is the rental price of digital capital.

3.3 Task Assignment and Labor Demand

Each task z is assigned to the lowest-cost executor:

$$\chi_j(z; \theta) = \mathbb{I} \left[j = \arg \min_{i \in \mathcal{K} \cup \{D\}} c_i(z; \theta) \right].$$

The recruitment demand for occupation k is the mass of tasks optimally assigned to it:

$$L_k(\theta) = \int_0^1 \chi_k(z; \theta) dz.$$

3.4 Cutoff Tasks and Reallocation

Suppose both $\lambda_k(z)$ and $\kappa(z; \theta)$ are strictly increasing in z . Define the cutoff $z_k^*(\theta)$ such that:

$$c_k(z_k^*, \theta) = c_D(z_k^*, \theta),$$

or explicitly:

$$\frac{w_k}{\lambda_k(z_k^*)} = \frac{r}{\bar{\kappa} + \theta(z_k^*)^\gamma}.$$

Solving yields the implicit equation:

$$z_k^*(\theta) = \left(\frac{r}{w_k} \lambda_k(z_k^*) - \bar{\kappa} \right)^{1/\gamma} \theta^{-1/\gamma}.$$

Proposition 1 (Digital Capability and Task Assignment). *Under regularity conditions, the task cutoff $z_k^*(\theta)$ is strictly decreasing in θ . That is, increases in digital capability expand the set of tasks performed by digital capital, thereby crowding out human labor especially in low-skill occupations.*

Proof. Recall that the task cutoff $z_k^*(\theta)$ satisfies the implicit equation:

$$\frac{w_k}{\lambda_k(z_k^*)} = \frac{r}{\bar{\kappa} + \theta(z_k^*)^\gamma}$$

Differentiating both sides with respect to θ and applying the implicit function theorem, we obtain:

$$\frac{dz_k^*}{d\theta} = - \frac{\partial c_D(z_k^*, \theta) / \partial \theta}{\partial (w_k / \lambda_k(z_k^*)) / \partial z_k^* - \partial c_D(z_k^*, \theta) / \partial z_k^*}$$

Compute each term:

- Digital capital cost:

$$c_D(z; \theta) = \frac{r}{\bar{\kappa} + \theta z^\gamma} \Rightarrow \frac{\partial c_D}{\partial \theta} = -\frac{r z^\gamma}{(\bar{\kappa} + \theta z^\gamma)^2} < 0 \quad \text{and} \quad \frac{\partial c_D}{\partial z} = -\frac{r \theta \gamma z^{\gamma-1}}{(\bar{\kappa} + \theta z^\gamma)^2} < 0$$

- Labor cost derivative:

$$\lambda_k(z) = \lambda_k^m m(z) + \lambda_k^r r(z) + \lambda_k^a a(z) \Rightarrow \frac{d}{dz} \left(\frac{w_k}{\lambda_k(z)} \right) = -\frac{w_k \lambda_k'(z)}{\lambda_k(z)^2}$$

Thus,

$$\frac{dz_k^*}{d\theta} = - \left[\frac{-\frac{r z_k^{*\gamma}}{(\bar{\kappa} + \theta z_k^{*\gamma})^2}}{-\frac{w_k \lambda_k'(z_k^*)}{\lambda_k(z_k^*)^2} - \frac{r \theta \gamma z_k^{*\gamma-1}}{(\bar{\kappa} + \theta z_k^{*\gamma})^2}} \right]$$

Since all terms in the numerator and denominator are positive under the assumptions $r, \theta, z_k^*, \gamma > 0$, and assuming $\lambda_k'(z_k^*) > 0$ (i.e., task productivity rises with task complexity), it follows that:

$$\frac{dz_k^*}{d\theta} < 0$$

Economic intuition: Higher digital capability θ raises the productivity of digital capital disproportionately for high- z (complex) tasks. This makes it optimal for the firm to reassign increasingly complex tasks away from human labor (especially occupations with low λ_k^a) to digital capital, leading to a declining cutoff $z_k^*(\theta)$. \square

3.5 Empirical Implications

The model delivers several testable predictions:

- Digitalization reallocates tasks away from occupations with high manual or routine advantage (λ_k^m, λ_k^r), such as physical and auxiliary roles.
- The hiring share of low-skill occupations declines with increasing θ .
- Occupations with stronger abstract task capabilities (e.g., professionals, managers) gain importance when digital capital exhibits increasing returns to task complexity.

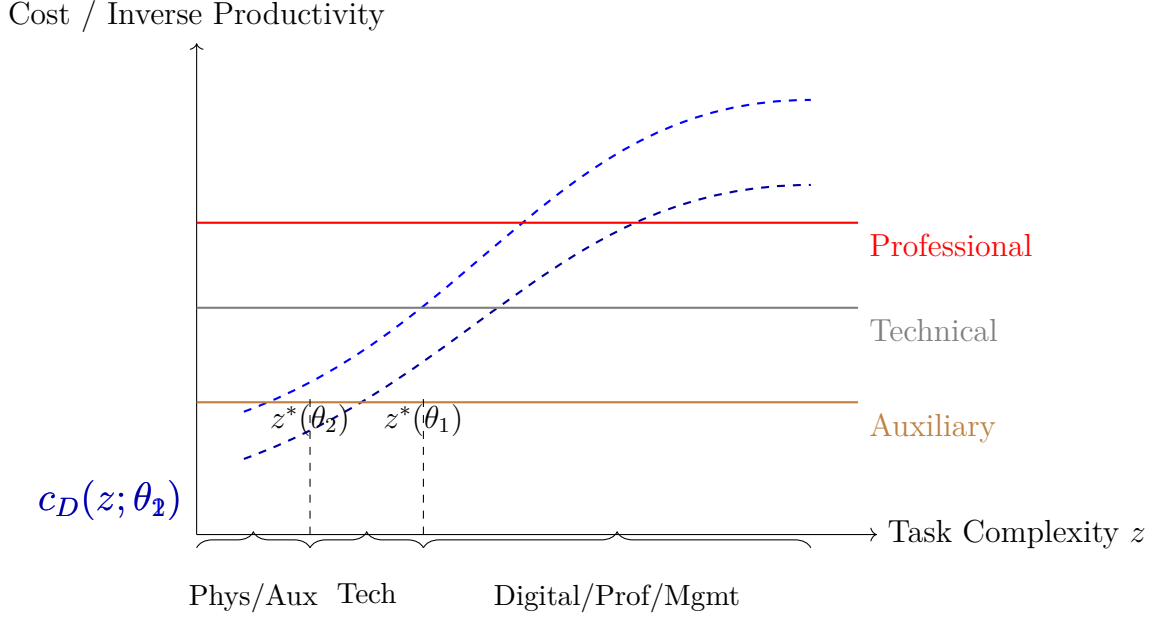


Figure 2: Reallocation of Tasks with Increasing Digital Capability

Figure 2 visualizes the decline in the cutoff $z_k^*(\theta)$ as digital capability rises, shifting task execution from low-complexity occupations toward digital capital and high-skill roles. This mechanism provides a theoretical foundation for our empirical results on occupational polarization and demand reallocation.

4 Data and Measurement

4.1 Data Description

To examine how digital transformation reshapes employment structures, we compile a comprehensive dataset of job postings from major Chinese online recruitment platforms, including 51job, BOSS Zhipin, Zhaopin, Liepin, Lagou, and Kanzhun, covering the period from 2016 to 2023. These platforms collectively account for the vast majority of online recruitment activity in China and provide granular, real-time information on firms hiring behaviors across various industries and regions.

We focus our analysis on listed firms and their affiliated entities comprising parent compa-

nies, subsidiaries, joint ventures, and associate companies to construct firm-level recruitment data at the corporate group level. This approach allows us to align recruitment patterns with firms' financial and strategic characteristics. To ensure data quality and consistency in our empirical analysis, we exclude firms that are classified as ST or *ST (special treatment stocks), which are typically associated with financial distress or regulatory scrutiny. Additionally, we remove all firms operating in the financial sector due to their distinct labor demand patterns and regulatory environment, which may confound our analysis of digital transformation's impact on general employment structures.

Using a custom-built web scraping framework, we collect structured data on each job posting, including job titles, required skills, occupational categories, industry affiliations, and hiring firm identities.

4.2 Variable Construction

Our empirical analysis leverages a rich, multi-source dataset that integrates firm-level financial, operational, and recruitment information drawn from both commercial and official repositories.

The core independent variable, digital transformation intensity, is obtained from the China Stock Market & Accounting Research (CSMAR) database. This measure is constructed using natural language processing (NLP) techniques that quantify the frequency and prominence of digitization-related keywords in firms' annual reports and public disclosures. It serves as a proxy for the strategic prioritization of digital technologies within the firm.

To characterize firm-level attributes and performance, we draw on a range of accounting and market indicators such as total assets, sales revenue, return on equity (ROE), and the market-to-book ratio from the Wind Financial Terminal. Corporate governance variables, including ownership structure, board composition, and executive compensation, are extracted from Wind and cross-validated against filings submitted to the China Securities Regulatory Commission (CSRC).

Innovation activity is measured using patent application records sourced from Qichacha and Tianyancha, covering invention, utility model, and design patents. Data on legal disputes and litigation histories further complement our understanding of firm-level risk exposure.

Control variables including firm size, leverage, profitability, human capital intensity, and ownership type are primarily sourced from CSMAR and Wind. These variables are meticulously matched to recruitment data using consistent firm identifiers and reporting periods. Macroeconomic and industry-level indicators are derived from the annual statistical yearbooks published by the National Bureau of Statistics of China.

This integrated data architecture enhances the depth and credibility of our empirical framework, ensuring that estimates of digital transformation effects are both statistically robust and economically meaningful.

4.3 Occupational Classification: The First Dimension

To systematically examine patterns in labor demand, we develop an occupation-based classification framework that utilizes job responsibilities as the primary dimension of differentiation. Our approach draws conceptual inspiration from the International Standard Classification of Occupations (ISCO-08), which emphasizes the nature of work performed rather than industry affiliation or educational credentials.

We classify all identified job titles into five functionally distinct categories namely, **Mgmtfunc** (Management Function), **Proffunc** (Professional Function), **Techfunc** (Technical Function), **Auxfunc** (Auxiliary Function), and **Physfunc** (Physical Function) based on their core responsibilities. Each category reflects a unique constellation of task structures and skill requirements, enabling us to trace how firms allocate human capital across different organizational roles.

Unlike traditional manual coding approaches which are time-consuming, costly, and subject to coder heterogeneity we employ the *Qwen2.5-14B-Instruct* large language model (LLM), accessed via the SiliconCloud API, to automate the classification process. This state-of-the-

art model, developed by Tongyi Lab, features 14 billion parameters and demonstrates strong performance in natural language understanding and reasoning tasks, making it particularly suitable for semantic classification of job titles.

The classification pipeline begins with a structured prompting strategy that explicitly defines each category and provides illustrative examples, ensuring consistent interpretation by the LLM across all job titles. Specifically, we construct a system-level prompt that guides the model to output only numeric codes corresponding to the five occupational groups thereby eliminating ambiguity and reducing decoding variability. The full prompt reads as follows:

1 Management Function: Involves leadership, coordination, and strategic decision-making (e.g., CEO, Manager, Director)

2 Professional Function: Requires formal education and professional expertise (e.g., Doctor, Lawyer, Accountant, Engineer)

3 Technical Function: Involves technical operations, maintenance, or development (e.g., Programmer, Technician, Developer)

4 Auxiliary Function: Provides support and administrative services (e.g., Assistant, Clerk, Secretary, Receptionist)

5 Physical Function: Relies primarily on physical labor (e.g., Cleaner, Laborer, Driver) *Please classify the following job titles into one of the five categories below. For each title, respond only with the corresponding number (1-5), separated by spaces, without any additional text or explanation:*

1 Management Function: Involves leadership, coordination, and strategic decision-making (e.g., CEO, Manager, Director)

2 Professional Function: Requires formal education and professional expertise (e.g., Doctor, Lawyer, Accountant, Engineer)

3 Technical Function: Involves technical operations, maintenance, or development (e.g., Programmer, Technician, Developer)

4 Auxiliary Function: Provides support and administrative services (e.g., Assistant, Clerk, Secretary, Receptionist)

5 Physical Function: Relies primarily on physical labor (e.g., Cleaner, Laborer, Driver)

Each batch of job titles is submitted to the SiliconCloud API endpoint, where the *Qwen2.5-14B-Instruct* model processes the input and returns predicted classifications in a standardized format. To improve efficiency and scalability, we implement parallel processing using multi-threaded execution, grouping job titles into batches of 30 entries and distributing requests across multiple concurrent threads. This strategy not only reduces overall processing time but also ensures robust handling of large-scale datasets.

In cases where the model fails to return a valid classification or generates ambiguous responses, we activate a rule-based keyword matching mechanism as a fallback. This secondary classifier relies on domain-specific lexicons associated with each occupational group (e.g., manager, engineer, assistant) to ensure high coverage even when LLM confidence is low. The combination of automated LLM inference and deterministic keyword rules significantly enhances the reliability and completeness of our classification framework.

Table 1 provides a detailed mapping between our functional categories and corresponding ISCO-08 occupations, ensuring theoretical coherence and facilitating cross-study comparability.

Figure 3 illustrates our classification pipeline, which integrates structured prompting with automated categorization and rule-based refinement.

This responsibility-oriented typology provides a granular view of internal labor allocation and facilitates nuanced analysis of how firms adjust workforce composition in response to strategic initiatives such as digital transformation and organizational restructuring.

Table 1: Mapping of Functional Categories to ISCO-08 Classifications

Functional Code	ISCO-08 Category	Example Occupations
Management Function (Mgmtfunc)	1 Managers	Corporate Manager, Project Manager, HR Director
Professional Function (Proffunc)	2 Professionals	Doctor, Software Engineer, University Lecturer
Technical Function (Techfunc)	3 Technicians and Associate Professionals	Lab Technician, Web Designer, Legal Assistant
Auxiliary Function (Auxfunc)	4 Clerical Support Workers	Administrative Assistant, Data Entry Clerk, Receptionist
Physical Function (Physfunc)	7 Craft and Related Trades Workers 8 Plant and Machine Operators and Assemblers 9 Elementary Occupations	Electrician, Truck Driver, Cleaner, Warehouse Worker

Table 2: Accuracy Assessment of Occupational Classification: Results from Manual Validation

Classification Method	Sample Size	Correct Labels	Accuracy Rate (%)	Ambiguous
LLM-based (Qwen2.5-14B-Instruct)	500	463	92.6%	12
Keyword-based Fallback	37	29	78.4%	
Overall Accuracy	500	492	98.4%	

Note. LLM classification was performed first; keyword-based fallback was applied only to unresolved cases ($n = 37$). Final accuracy combines both methods.

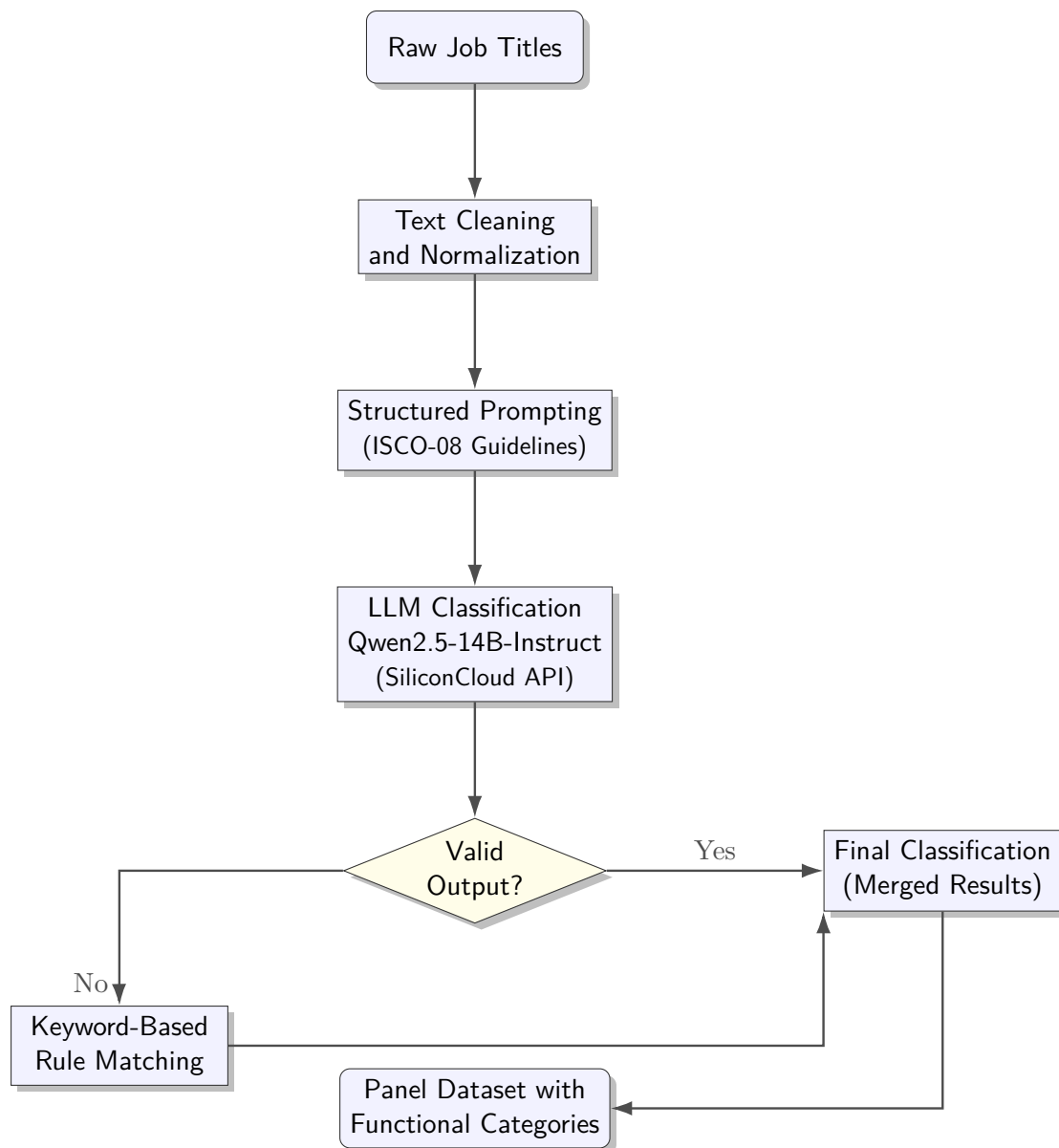


Figure 3: Multi-Stage Occupational Classification Pipeline Using Large Language Model and Rule-Based Enhancement

To ensure the reliability and validity of our classification methodology, we conducted a manual validation exercise on a random sample of 500 job titles (see Table 2). The results demonstrate that our hybrid approach combining large language model inference with rule-based keyword fallback achieves an overall accuracy rate of 98.4%. Specifically, the LLM-based classifier achieved a high precision of 92.6%, while the keyword-based fallback mechanism resolved most ambiguous cases with an accuracy of 78.4%. This dual-stage design not only improves robustness but also ensures consistency across large-scale categorical data processing.

In subsequent sections, we enrich the analytical framework by introducing additional classification dimensions including skill intensity and sectoral affiliation to further dissect the structure and dynamics of labor demand.

4.4 Occupational Ability and Task Intensity: The Second Dimension

Building on the task-based framework introduced by Autor et al. (2003) and further refined in Autor (2013), we classify occupations according to their underlying ability requirements specifically, the intensity of *routine*, *abstract*, and *manual* tasks performed on the job. This classification captures how different types of labor interact with technological change, particularly automation and digitization.

Following a similar LLM-driven approach as described in Section 4.3, we use the *Qwen2.5-14B-Instruct* model via the SiliconCloud API to assess each job title’s alignment with these three task dimensions. A keyword-based fallback mechanism ensures robustness in edge cases where the model fails to provide confident classifications.

This second dimension complements our functional classification and enables a more nuanced analysis of how workforce composition responds to technological advancements and organizational transformations.

As shown in Table 3, we assign each functional job category a qualitative score along these three dimensions. For example, managers and professionals exhibit high levels of abstract

task intensity and low exposure to routine tasks, whereas machine operators and assemblers face high demands for both routine and manual abilities. These patterns reflect broader trends in labor market polarization and offshorability documented in the literature. Using

Table 3: Occupational Task Intensity by Ability Type

Occupation Group	Routine	Abstract	Manual
Managers, Professionals, Technicians, Finance, Public Safety	–	+	–
Production, Craft Workers	+	+	–
Transportation, Construction, Mechanics, Mining, Farming	–	–	+
Machine Operators and Assemblers	+	–	+
Clerical and Retail Sales Workers	+	–	–
Service Occupations	–	–	+

Note: This table assigns task intensity scores to major occupational groups based on ability requirements. Routine tasks are defined as repetitive cognitive or manual activities; abstract tasks involve problem-solving and creativity; manual tasks require physical dexterity and strength.

this mapping, we compute firm-level task intensity indices by aggregating job posting counts across categories, weighted by their respective task scores. Specifically, for each firm-year observation, the total score for a given task type is calculated as:

$$\text{Task Score}_{i,t} = \log \left(1 + \sum_j (\text{Task Weight}_j \times \text{Job Count}_{i,t,j}) \right)$$

where i indexes firms, t indexes years, and j indexes occupation groups. The logarithmic transformation ensures that the measure remains interpretable and bounded even for large-scale employers.

This ability-driven dimension complements our earlier responsibility-based classification and provides a richer understanding of how firms restructure labor demand in response to digital transformation and other strategic shifts.

4.5 Control Variables and Summary Statistics

To account for potential confounding factors, we incorporate a comprehensive set of firm-level control variables that jointly influence both digital transformation and employment

structures. These controls capture multiple dimensions of firm characteristics, including size, performance, governance, and operational efficiency.

Our primary outcome variable is *total_hire*, which denotes the total number of job postings made by a firm in a given year. To better understand the internal composition of labor demand, we compute the functional distribution of hires across five occupational categories. Specifically, *share_mgmtfunc* captures the proportion of managerial positions, while *share_proffunc* reflects the share of professional roles, such as legal, finance, and research-related jobs. *share_techfunc* represents technical and associate professional positions (e.g., software development, engineering), *share_auxfunc* includes clerical and administrative support roles, and *share_physfunc* measures the share of physical and manual labor (e.g., logistics and manufacturing).

To describe the nature of job tasks, we include three task intensity indicators derived from a keyword-based classification of job descriptions. *Abstract*, *Routine*, and *Manual* quantify the degree of cognitive abstraction, procedural repetition, and physical intensity, respectively, following a task-based framework inspired by Autor, Levy, and Murnane (2003).

The key explanatory variable, *digital*, is a firm-level digitalization index constructed from textual analysis of annual reports provided by CSMAR. It reflects the strategic emphasis on digital technologies in corporate disclosures and serves as a proxy for the extent of digital transformation.

We further control for a set of standard financial and organizational variables. *Size*, measured as the natural logarithm of total assets, captures firm scale. *ROA* (return on assets) and *Cashflow* (operating cash flow scaled by total assets) proxy for profitability and liquidity, respectively. *ATO* (asset turnover ratio) reflects the efficiency of asset utilization. *Board*, defined as the log of board size, indicates the intensity of corporate governance. *TobinQ*, the ratio of market value to book value, is included to account for investment and growth opportunities.

All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the

influence of outliers. Table 4 presents summary statistics for the full sample, which comprises 30,661 firm-year observations from Chinese listed companies over the period 2016–2023.

Table 4: Summary Statistics

Variable	Mean	SD	Min	Max
Total hires	411.197	1330.846	1.000	81007.000
Share of management func.	0.154	0.176	0.000	1.000
Share of professional func.	0.225	0.222	0.000	1.000
Share of technical func.	0.146	0.174	0.000	1.000
Share of auxiliary func.	0.101	0.142	0.000	1.000
Share of physical func.	0.374	0.260	0.000	1.000
Abstract task intensity	4.060	2.164	0.000	12.932
Routine task intensity	4.206	2.024	0.000	14.456
Manual task intensity	4.072	2.063	0.000	14.433
Digital index	3.672	0.998	2.125	6.873
Firm size (log)	22.256	1.240	18.538	27.774
ROA	0.040	0.060	-0.794	0.547
Cashflow	0.049	0.060	-0.447	0.516
ATO	0.605	0.380	0.012	4.353
Board size (log)	2.096	0.184	1.386	2.708
Tobin's Q	1.887	1.047	0.742	58.592
Observations	30,661	30,661	30,661	30,661

Note: All continuous variables are winsorized at the 1st and 99th percentiles. Functional shares refer to the proportion of hires in each category.

5 Baseline Regression Results

5.1 Effects on Occupational Hiring Patterns

We estimate the impact of digital transformation on hiring demand across five occupational categories by regressing firm-level job posting shares in each category on a digital transformation index, controlling for firm size, profitability, governance structure, and operational efficiency. The baseline regression model is specified as follows:

$$\text{Share}_{i,t}^j = \alpha + \beta_1 \text{Digital}_{i,t} + \gamma X_{i,t} + \lambda_t + \mu_p + \delta_s + \epsilon_{i,t}, \quad (1)$$

where $\text{Share}_{i,t}^j$ denotes the share of job postings in occupational function j (management, professional, technical, auxiliary, or manual) within firm i in year t . $\text{Digital}_{i,t}$ represents the firm's digital transformation intensity, and $X_{i,t}$ includes a set of control variables: firm size (log total assets), board size, return on assets (ROA), operating cash flow over total assets, fixed asset ratio, Tobins Q, and asset turnover ratio. The model also controls for year fixed effects (λ_t), province fixed effects (μ_p), and industry fixed effects (δ_s) to account for time-specific, region-specific, and sector-specific unobserved heterogeneity.

Table 5 reports the estimated coefficients on the digital transformation index across the five occupational functions. Consistent with the hypothesis that digitalization favors high-skill labor, we find that firms undergoing greater digital transformation significantly increase hiring in professional ($\hat{\beta} = 0.019, p < 0.001$) and technical roles ($\hat{\beta} = 0.004, p < 0.05$). In contrast, the coefficient on management function hiring is positive but statistically insignificant.

Concurrently, we observe a significant reduction in demand for auxiliary ($\hat{\beta} = -0.005, p < 0.001$) and manual labor positions ($\hat{\beta} = -0.019, p < 0.001$), suggesting that digital technologies substitute for routine-based and low-skill occupations. These findings align with the task-based framework of Autor, Levy, and Murnane (2003), which posits that automation disproportionately affects jobs involving repetitive tasks.

The control variables also reveal meaningful patterns. Larger firms exhibit lower shares of managerial and professional hires, potentially reflecting economies of scale in administrative staffing. Higher profitability (ROA) is associated with increased demand for skilled labor and reduced reliance on manual work, consistent with capital- and skill-biased technological change. Asset turnover ratios are positively correlated with manual labor hiring, possibly indicating greater production intensity among digitally active firms.

Overall, these results provide robust evidence that digital transformation reshapes em-

ployment structures by increasing demand for high-skill, non-routine-intensive roles while reducing reliance on support and physical labor.

Table 5: Baseline Regression Results: Digital Transformation and Occupational Hiring Patterns

	(1) Management	(2) Professional	(3) Technical	(4) Auxiliary	(5) Manual
Digital	0.001 (0.002)	0.019*** (0.002)	0.004* (0.002)	-0.005*** (0.001)	-0.019*** (0.003)
Size	-0.005** (0.001)	-0.008*** (0.002)	-0.003* (0.001)	-0.004*** (0.001)	0.020*** (0.002)
Board	-0.009 (0.008)	0.020* (0.010)	-0.005 (0.008)	-0.003 (0.006)	-0.003 (0.011)
ROA	-0.086*** (0.020)	0.143*** (0.023)	0.088*** (0.017)	-0.046** (0.015)	-0.099*** (0.028)
Cashflow	0.027 (0.021)	-0.079** (0.025)	-0.085*** (0.019)	0.021 (0.017)	0.116*** (0.030)
Fixed	-0.080*** (0.014)	-0.099*** (0.015)	0.040** (0.013)	-0.000 (0.011)	0.140*** (0.020)
TobinQ	0.001 (0.001)	0.001 (0.001)	-0.002 (0.001)	-0.003*** (0.001)	0.002 (0.002)
Ato	-0.015*** (0.005)	-0.029*** (0.004)	-0.000 (0.003)	-0.000 (0.003)	0.045*** (0.006)
Constant	0.299*** (0.033)	0.332*** (0.038)	0.202*** (0.030)	0.226*** (0.022)	-0.059 (0.046)
Observations	26009	26009	26009	26009	26009
Adj. R-squared	0.063	0.145	0.027	0.068	0.091
Year FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2 Effects on Task Intensity Dimensions

To further investigate how digital transformation reshapes the skill content of jobs, we examine its impact on three task intensity dimensions—abstract, routine, and manual—following the task-based framework of Autor, Levy, and Murnane (2003). For each firm-year observation, we construct a normalized task score as:

$$\text{Task Score}_{i,t} = \log \left(1 + \sum_j (\text{Task Weight}_j \times \text{Job Count}_{i,t,j}) \right), \quad (2)$$

where j indexes individual job postings within a firm-year, and Task Weight_j is an occupation-specific loading derived from ISCO-08 classifications and textual analysis of job descriptions. We then estimate separate regressions for abstract, routine, and manual task intensities using the following specification:

$$\text{Task Score}_{i,t}^k = \alpha + \beta_1 \text{Digital}_{i,t} + \gamma X_{i,t} + \lambda_t + \mu_p + \delta_s + \epsilon_{i,t} \quad (3)$$

for each task dimension $k \in \{\text{abstract}, \text{routine}, \text{manual}\}$, with controls $X_{i,t}$ identical to those used in Section 5.1.

Table 6 presents the results. Digital transformation exhibits statistically significant positive associations with all three task dimensions. However, the magnitude of the coefficient is notably larger for abstract tasks ($\hat{\beta} = 0.446, p < 0.001$) compared to both routine tasks ($\hat{\beta} = 0.248, p < 0.001$) and manual tasks ($\hat{\beta} = 0.333, p < 0.001$).

This pattern suggests that digital technologies disproportionately increase demand for cognitive flexibility, problem-solving, and non-routine analytical capabilities—skills typically associated with high-value-added roles. In contrast, while digitalization still raises the overall intensity of routine and manual work, these effects are relatively smaller in magnitude, consistent with substitution effects being partially offset by complementarities in production workflows.

The control variables largely reinforce this interpretation. Larger firms exhibit higher

scores across all task dimensions, potentially reflecting greater complexity in organizational structure. Higher fixed asset intensity is associated with lower task scores, possibly indicating rigidities in adapting to new technological paradigms. Positive and significant coefficients on Tobins Q suggest that growth-oriented firms prioritize hiring workers with digitally compatible skills.

Taken together, these findings provide robust evidence that digital transformation not only reallocates employment across occupations but also fundamentally alters the nature of work by elevating the importance of abstract reasoning and reducing reliance on repetitive or physical labor.

6 Further Analysis

To ensure the robustness of our findings and to provide a focused examination of the mechanisms through which digital transformation affects labor demand, we analyze a representative set of outcomes that capture skill- and task-biased effects. We focus on four key labor market indicators: *Professional Function Hiring* (ProfFunc), *Physical Function Hiring* (PhysFunc), *Abstract Task Intensity*, and *Manual Task Intensity*. These variables allow us to distinguish between roles likely complemented by digital technologies (professional and abstract tasks) and those subject to substitution (physical and manual tasks).

6.1 Addressing Endogeneity

A key concern in estimating the impact of digital transformation on hiring structure is potential endogeneity arising from omitted variable bias or reverse causality. Specifically, unobserved firm characteristics may simultaneously influence both digital adoption and labor composition, leading to biased estimates.

To address this issue, we employ two instrumental variable (IV) strategies. First, we construct an instrument based on the city-level average of digital transformation, excluding the focal firm itself:

Table 6: Baseline Regression Results: Digital Transformation and Task Intensity

	(1) Abstract Tasks	(2) Routine Tasks	(3) Manual Tasks
Digital	0.446*** (0.022)	0.248*** (0.021)	0.333*** (0.021)
Size	0.599*** (0.019)	0.660*** (0.019)	0.656*** (0.019)
Board	-0.262** (0.093)	-0.306*** (0.089)	-0.353*** (0.089)
ROA	0.919*** (0.208)	0.017 (0.191)	0.358 (0.199)
Cashflow	-0.364 (0.220)	0.189 (0.215)	-0.247 (0.215)
Fixed	-1.978*** (0.160)	-1.101*** (0.153)	-0.713*** (0.157)
TobinQ	0.065*** (0.013)	0.066*** (0.013)	0.046*** (0.013)
Ato	-0.086 (0.045)	0.173*** (0.045)	0.201*** (0.051)
Constant	-10.172*** (0.412)	-10.882*** (0.403)	-11.184*** (0.399)
Observations	26009	26009	26009
Adj. R-squared	0.329	0.319	0.327
Year FE	✓	✓	✓
Industry FE	✓	✓	✓
Province FE	✓	✓	✓

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

$$Z_{it} = \frac{1}{N_{ct} - 1} \sum_{j \neq i} D_{jt}$$

where Z_{it} denotes the instrument for firm i in year t , and D_{jt} represents the digital transformation index of other firms located in the same city c . This approach leverages cross-firm variation within cities under the assumption that local industry trends affect digital adoption but are otherwise orthogonal to firm-specific hiring decisions.

Second, we use lagged values of the digital transformation index ($L.digital$, $L^2.digital$) as instruments. These lags help isolate exogenous variation in digitalization from contemporaneous shocks.

Tables 7 and 8 report the results from our IV regressions using the two identification strategies. Standard errors are clustered at the firm level, and high-dimensional fixed effects for year, industry, and province are included.

The first-stage F-statistics (not shown) indicate strong instruments, and overidentification tests do not reject the validity of the exclusion restrictions. Overall, the IV estimates remain consistent with our baseline findings, suggesting that the observed relationships are unlikely to be driven by simple reverse causality or common trends.

Table 7: IV Results: Digitalization and Hiring Structure

	(1) Share Prof	(2) Share Phys	(3) Abstract	(4) Manual
Digital	0.079** (0.035)	-0.056 (0.043)	1.935*** (0.469)	1.511*** (0.435)
Observations	26009	26009	26009	26009

Standard errors in parentheses

Instrument: City Mean (excluding self)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Lagged IV Results: Digitalization and Hiring Structure

	(1)	(2)	(3)	(4)
	Share Prof	Share Phys	Abstract	Manual
Digital	0.025*** (0.003)	-0.023*** (0.004)	0.480*** (0.028)	0.357*** (0.026)
Observations	16724	16724	16724	16724

Standard errors in parentheses

Instrument: Lagged Digitalization

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.2 Mechanism Analysis

To uncover the underlying channels through which digital transformation shapes the hiring structure, we estimate a structural equation model (SEM) incorporating three mediators: agency costs (`agc1_1`), executive compensation (`pay`), and firm valuation (`tobinq`). The full model results are summarized in Table 9, and the path diagram is shown in Figure 4.

First, digitalization significantly increases agency costs, which are positively associated with professional function hiring. This supports the classical agency theory of [Jensen and Meckling \(1976\)](#), which emphasizes how information asymmetries shape organizational behavior, and is consistent with recent evidence from [Li and Zhang \(2018\)](#), who show that digital technologies in China have mixed effects on governance efficiency.

Second, we find that digital adoption is linked to higher executive compensation, which in turn significantly predicts abstract task hiring. This pattern echoes the findings of [Bloom and Van Reenen \(2007\)](#) and [Murphy \(1999\)](#), suggesting that technological transformation modifies incentive schemes in favor of strategic and cognitively demanding roles.

Third, digital transformation is positively associated with Tobins Q, indicating enhanced firm valuation. In line with the arguments by [Autor and A.Salomons \(2020\)](#), higher valuations may reflect digital-led investments in skill-biased assets, leading to increased demand for both professional and abstract labor inputs.

Overall, these results highlight that digital transformation affects employment structures

not only through direct technological impacts but also via shifts in corporate governance, managerial incentives, and market expectations. These multi-channel mechanisms provide novel insights into the labor-market consequences of technological progress.

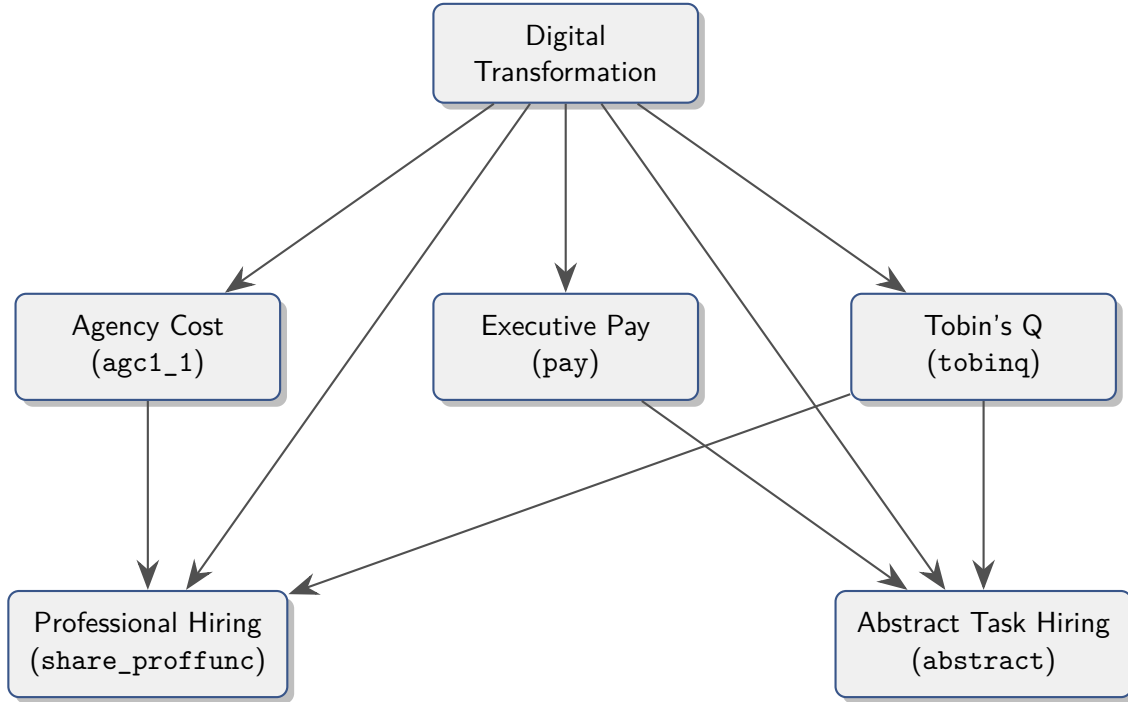


Figure 4: Structural Equation Model: Digitalization and Hiring Structure

6.3 Heterogeneity Analysis

We examine how the labor market effects of digital transformation vary across firm characteristics, focusing on size group, development status, and ownership type. Analyses are conducted separately for four key outcomes: the share of professional function recruitment (`share_prof`), the share of physical function recruitment (`share_phys`), abstract task intensity, and manual task intensity.

Table 10 presents the results for professional function hiring shares. The coefficient on the interaction term between `Digital` and `Size Group` indicates that the positive effect of digitalization on the share of professional hiring is significantly stronger among large firms compared to small firms ($p < 0.01$). Additionally, state-owned enterprises (SOEs) exhibit

Table 9: Structural Equation Model Estimates

	Agc1	Pay	TobinQ	Share_proffunc	Abstract
Digital	0.003*** (0.000)	0.091*** (0.004)	0.051*** (0.008)	0.041*** (0.001)	0.666*** (0.012)
Agc1_1				0.058 (.)	
TobinQ				0.005*** (0.001)	-0.004 (0.009)
Pay					0.682*** (0.003)
Observations	25,972				
Log Likelihood	-134,936.3				
AIC	269,910.7				
BIC	270,065.8				

Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

a relatively stronger response, as evidenced by the statistically significant SOE-by-digital interaction at $p < 0.05$. In contrast, no meaningful differences are observed across firms at different stages of development.

For physical function hiring shares (Table 11), we find a similar pattern in terms of firm size: larger firms show a more pronounced decline in the share of physical function hiring associated with digitalization. However, unlike the results for professional functions, the reduction in physical hiring shares is less severe among SOEs, suggesting potential institutional or operational rigidities that moderate substitution effects.

Tables 12 and 13 report the heterogeneity in the effects of digitalization on abstract and manual task intensities. While larger firms still respond more strongly in absolute terms, the differences across firm types are generally smaller and less statistically robust compared to the occupational-level outcomes.

Overall, these findings suggest that the impacts of digital transformation are not uniform across firms but rather depend on structural and contextual factors such as firm size and ownership type. Digitalization appears to amplify skill-biased employment trends particularly

among larger and state-controlled firms.

6.4 Robustness Checks

As a first robustness check, we substitute the main digital transformation index with an alternative measure based on CSMAR’s *Technology Leadership* sub-index, which captures firms investment in and adoption of advanced digital technologies. Columns (1)–(4) of Table 14 report estimates from models using this narrower but conceptually aligned indicator. The results remain qualitatively consistent with our baseline findings: digitalization is positively associated with professional function hiring and abstract task intensity, and negatively correlated with physical function hiring.

Second, we adopt two-way clustering at the firm-year level for standard errors, following best practices in panel data estimation. This adjustment does not alter the significance or direction of our estimates, confirming the robustness of our results to different error dependence assumptions.

Together, these checks support the reliability of our baseline findings across both skill-biased and task-based specifications. Additional analyses including alternative variable definitions and subsample restrictions are reported in Appendix Tables 14 and 15.

7 Conclusion

This study provides robust empirical evidence on how digital transformation is reshaping employment structures within Chinese listed firms, offering nuanced insights into both occupational reallocation and task intensity shifts. By leveraging a comprehensive dataset of job postings and firm-level digital transformation indices, we document a dual-edged impact: while overall employment exhibits a modest decline primarily due to reductions in clerical and manual roles there is a significant reallocation toward high-skill occupations, particularly managerial, professional, and technical functions.

Our findings align with the theoretical framework of skill-biased technological change and

Table 10: Heterogeneity Analysis: share_prof

	(1) Size Group	(2) Development Status	(3) Ownership Type
Digital	0.022*** (0.003)	0.018*** (0.003)	0.020*** (0.003)
0.size_group	0.000 (.)		
1.size_group	0.020 (0.014)		
0.size_group×c.Digital	0.000 (.)		
1.size_group×c.Digital	-0.005 (0.003)		
1.dev_dum		0.000 (.)	
2.dev_dum		0.000 (.)	
1.dev_dum×c.Digital		0.000 (.)	
2.dev_dum×c.Digital		0.006 (0.004)	
0.SOE			0.000 (.)
1.SOE			0.016 (0.016)
0.SOE×c.Digital			0.000 (.)
1.SOE×c.Digital			-0.001 (0.004)
_cons	0.322*** (0.049)	0.332*** (0.038)	0.359*** (0.039)
Observations	26009	25993	26009
adj. R^2	0.145	0.145	0.145

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Heterogeneity Analysis: share_phys

	(1) Size Group	(2) Development Status	(3) Ownership Type
Digital	-0.028*** (0.003)	-0.020*** (0.003)	-0.020*** (0.003)
0.size_group	0.000 (.)		
1.size_group	-0.048*** (0.017)		
0.size_group×c.Digital	0.000 (.)		
1.size_group×c.Digital	0.015***		
1.dev_dum		0.000 (.)	
2.dev_dum		0.000 (.)	
1.dev_dum×c.Digital		0.000 (.)	
2.dev_dum×c.Digital		0.005 (0.005)	
0.SOE			0.000 (.)
1.SOE			-0.015 (0.019)
0.SOE×c.Digital			0.000 (.)
1.SOE×c.Digital			0.004 (0.005)
_cons	0.033 (0.060)	-0.059 (0.046)	-0.054 (0.049)
Observations	26009	25993	26009
adj. R^2	0.092	0.091	0.091

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Heterogeneity Analysis: Abstract Task Intensity

	(1) Size Group	(2) Development Status	(3) Ownership Type
Digital	0.398*** (0.027)	0.450*** (0.024)	0.414*** (0.024)
0.size_group	0.000 (.)		
1.size_group	-0.368*** (0.131)		
0.size_group×Digital	0.000 (.)		
1.size_group×Digital	0.088*** (0.031)		
1.dev_dum		0.000 (.)	
2.dev_dum		0.000 (.)	
1.dev_dum×Digital		0.000 (.)	
2.dev_dum×Digital		-0.016 (0.040)	
0.SOE			0.000 (.)
1.SOE			-0.912*** (0.159)
0.SOE×Digital			0.000 (.)
1.SOE×Digital			0.101*** (0.039)
_cons	-10.213*** (0.565)	-10.163*** (0.412)	-11.281*** (0.418)
Observations	26009	25993	26009
adj. R^2	0.329	0.328	0.339

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Heterogeneity Analysis: Manual Task Intensity

	(1) Size Group	(2) Development Status	(3) Ownership Type
Digital	0.258*** (0.025)	0.337*** (0.023)	0.300*** (0.022)
0.size_group	0.000 (.)		
1.size_group	-0.508*** (0.127)		
0.size_group×Digital	0.000 (.)		
1.size_group×Digital	0.136*** (0.030)		
1.dev_dum		0.000 (.)	
2.dev_dum		0.000 (.)	
1.dev_dum×Digital		0.000 (.)	
2.dev_dum×Digital		-0.016 (0.039)	
0.SOE			0.000 (.)
1.SOE			-0.912*** (0.150)
0.SOE×Digital			0.000 (.)
1.SOE×Digital			0.104*** (0.037)
_cons	-10.865*** (0.549)	-11.177*** (0.400)	-12.269*** (0.404)
Observations	26009	25993	26009
adj. R^2	0.328	0.326	0.338

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Robustness Analysis Using Technology Leadership Index

	(1) Prof-Tech	(2) Phys-Tech	(3) Abstract-Tech	(4) Manual-Tech
Tech	0.011*** (0.001)	-0.013*** (0.002)	0.190*** (0.012)	0.148*** (0.012)
Observations	26,009	26,009	26,009	26,009
R^2	0.147	0.094	0.317	0.321

Robust standard errors clustered at the firm-year level are in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 15: Baseline Specification with Digital Transformation Index

	(1) Prof-Digital	(2) Phys-Digital	(3) Abstract-Digital	(4) Manual-Digital
Digital	0.019*** (0.003)	-0.019*** (0.003)	0.446*** (0.044)	0.333*** (0.041)
Observations	26,009	26,009	26,009	26,009
R^2	0.147	0.093	0.331	0.329

Robust standard errors clustered at the firm-year level are in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

support the broader literature on labor market polarization. However, this paper contributes novel micro-level evidence specific to China's rapidly evolving corporate sector, where digital adoption is not only driven by private-sector innovation but also accelerated by state-led infrastructure development.

The observed rise in demand for abstract-task-intensive roles underscores the growing importance of cognitive flexibility, creativity, and strategic decision-making in digitally transforming firms. Moreover, heterogeneity analyses reveal that these effects are most pronounced among large firms and state-owned enterprises, suggesting that institutional capacity and resource endowments play critical roles in mediating labor market outcomes under digitalization.

To further explore the structural implications of digital transformation, we examine the degree of concentration in hiring patterns using the Herfindahl-Hirschman Index (HHI), which measures the diversity of occupational hiring within firms. As shown in Table 16, digital transformation is associated with a reduction in HHI, indicating a more dispersed hiring structure across occupational categories. This implies that digital technologies may encourage greater specialization and diversification in workforce composition, rather than reinforcing centralized hiring practices.

From a policy perspective, our results highlight the urgency of investing in reskilling and upskilling programs, particularly for workers in routine-based and manual occupations who face displacement risks. Additionally, fostering regional digital infrastructure and improving labor mobility mechanisms may help mitigate spatial disparities and ensure more inclusive gains from technological progress.

While this study focuses on publicly listed firms which tend to be larger, more formalized, and technologically advanced than average, the implications extend beyond China. As emerging economies grapple with the dual challenges of rapid industrialization and digital disruption, understanding how technology reconfigures skill demands and organizational structures becomes increasingly vital.

Future research could explore longitudinal dynamics of individual worker transitions, examine wage and productivity linkages in greater depth, and investigate how digital transformation interacts with broader socio-institutional contexts such as labor regulations and social protection systems. Overall, this work underscores the complex interplay between digital technologies and labor markets, providing timely empirical grounding for both academic inquiry and policy formulation in the era of digital globalization.

Table 16: Hiring Structure Concentration Analysis

	(1) HHI Index
Digital	-0.0160*** (-7.49)
Control variables	✓
<i>N</i>	26009

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