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Does Corporate Expansion Create Better Jobs?

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ABSTRACT: Whether employment growth is converted into better jobs is central to understanding how capital markets serve the real economy and how high-quality employment policies should be evaluated. Using a panel dataset of employees and wages among Chinese listed firms compiled from CSMAR, this study constructs a firm-level sample covering 5,329 listed firms and 56,589 firm-year observations from 2000 to 2022. It examines the dynamic tension between employment absorption and pay quality from five perspectives: aggregate expansion, industry and regional differentiation, wage distribution, job flows, and within-firm adjustment. The results show that the number of sample firms increased from 1,010 to 5,106, total employment rose from 2.75 million to 29.49 million, and total employee compensation payable expanded by approximately 108.8 times. In the log growth of total compensation, employment expansion and the increase in employment-weighted average wages contributed 50.6% and 49.4%, respectively. After controlling for firm fixed effects and year fixed effects, the elasticity of average wages with respect to employment is -0.326 and remains statistically significant after winsorisation, in a balanced panel, after excluding the financial sector, among normally listed firms, and in a first-difference model. The importance of this study lies in moving the employment debate from the quantity-oriented question of stabilising jobs to the distributional question of whether employment expansion improves pay quality. It addresses the limitations of prior research, which has tended to focus on employment counts, single-year cross-sections, or employer data from advanced economies, while paying less attention to the long-run co-evolution of wages and employment among Chinese listed firms.

KEYWORDS: listed firms; firm employment; pay quality; wage distribution; fixed effects; labour reallocation

1. RESEARCH BACKGROUND AND PROBLEM STATEMENT

Employment is the most direct link between macroeconomic stability, household income, and the sustainable operation of firms. Compared with aggregate labour statistics, employee and wage data disclosed by listed firms are continuous, traceable at the firm level, and decomposable by industry and region. They allow the question of whether employment has increased to be further unpacked into which industries absorb jobs, which regions carry employment, and whether average pay improves when the same firm expands its workforce. This question matters because capital-market entities not only create profits but also shape worker welfare through jobs, wages, and career development. Evidence from Chinese university graduates further shows that employer brand attractiveness strengthens private-enterprise employment intentions through person-organisation fit and career decision-making self-efficacy (Cao and Gan, 2026). If employment growth is not converted into higher average pay, evaluating corporate social value solely by the number of jobs created will overstate the quality of employment expansion. International labour economics has repeatedly shown that firms are not neutral containers of wage formation. Firm size, productivity, governance structure, job organisation, and employer-employee matching all affect wage distribution and labour compensation (Abowd et al., 1999; Brown and Medoff, 1989; Oi and Idson, 1999; Lazear and Shaw, 2007).

Existing research has three main limitations. First, much of the firm-employment literature emphasises job counts, technological shocks, or policy constraints, but it rarely examines employment expansion and changes in firm-level average pay within the same statistical framework. Second, classic evidence on firm wage dispersion mostly comes from European and US employer-employee matched datasets, leaving the dynamics of pay quality in long-run panels of Chinese listed firms underexplored. Third, many studies rely on a single cross-section or a specific policy shock,

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making it difficult to display aggregate expansion, distributional change, industry and regional differentiation, and within-firm adjustment at the same time. The research design of this paper directly addresses these gaps. It uses a 2000-2022 long panel to characterise the joint evolution of employment and wages among Chinese listed firms, applies growth decomposition to identify the sources of total compensation expansion, uses Gini coefficients and job-flow rates to describe reallocation across firms, and estimates two-way fixed effects models to identify the elasticity of average pay when the same firm expands.

The marginal contributions are threefold. First, in terms of research object, this study advances the analysis of listed-firm employment from whether firms create more jobs to whether employment expansion is accompanied by higher pay quality, thereby placing employment stabilisation and high-quality employment in a unified empirical framework. Second, in terms of evidence, it uses a long firm panel to provide a cross-cycle, cross-industry, and cross-regional picture of labour compensation, avoiding judgements based only on a single-year cross-section. Third, in terms of method, it combines visual facts, formal derivations of key indicators, fixed effects estimation, job-flow rates, and growth decomposition, while drawing on the literatures on job creation and destruction, firm heterogeneity, and cluster-robust inference (Davis and Haltiwanger, 1992; Haltiwanger et al., 2013; Petersen, 2009; Cameron et al., 2011). The conclusions are therefore supported by both visual evidence and reproducible econometric results.

2. LITERATURE BASE AND RESEARCH PERSPECTIVE

The first relevant strand examines firm wage differentials and labour-market inequality. The AKM framework shows that wage differences can be decomposed into worker effects, firm effects, and match effects, and that firm-side heterogeneity is itself an important source of wage inequality (Abowd et al., 1999). Subsequent studies find that the sorting of high-ability workers into high-wage firms, differences in firm wage policies, and rising between-firm wage premia can increase overall wage inequality (Card et al., 2013; Card et al., 2018; Song et al., 2019). Evidence at the level of US firms and establishments further shows that the rise in earnings dispersion increasingly occurs between employers rather than solely within the same employer (Barth et al., 2016). These studies imply that understanding wage quality among listed firms requires more than observing average pay levels; it also requires attention to dynamics across firms and within the same firm over time.

The second strand emphasises firm heterogeneity, productivity, and employment reallocation. Since Melitz (2003), theories of heterogeneous firms in trade have shown that the expansion of high-productivity firms changes resource allocation within industries. Bernard et al. (2007, 2012) further embed firm heterogeneity in empirical studies of international trade, while Hsieh and Klenow (2009) and Syverson (2011) show that productivity differences and resource misallocation have substantial implications for aggregate efficiency. Research on job flows demonstrates that aggregate employment change consists of extensive firm-level job creation and job destruction, and that young firms, expanding firms, and contracting firms play different roles in employment dynamics (Davis and Haltiwanger, 1992; Haltiwanger et al., 2013). Employment expansion among listed firms should therefore be understood as the joint outcome of between-firm reallocation and within-firm expansion.

The third strand focuses on how technology, governance, corporate culture, and pay incentives affect labour demand and wage structure. Task-biased technological change, automation, and robot adoption alter job structures and skill premia (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2020). A recent systematic review further indicates that AI and robotics can substitute codifiable routine tasks, intensify wage polarisation, and place particular pressure on low-skilled workers, while augmentation-oriented adoption and institutional responses can moderate these effects (Gan et al., 2026a). Trade openness and global value-chain restructuring influence wage distribution through firm selection, wage premia, and job substitution (Amiti and Davis, 2012; Helpman et al., 2010; Helpman et al., 2017). Corporate governance, performance pay, employee satisfaction, corporate culture, and CSR also affect labour compensation, organisational efficiency, and firm value (Bertrand and Mullainathan, 2003; Lazear, 2000; Edmans, 2011, 2012; Guiso et al., 2015; Flammer, 2015). On this basis, this study develops a joint quantity-quality evaluation framework. If total compensation and employment grow proportionally, average pay remains unchanged; if total compensation grows faster than employment, average pay improves; if total compensation grows more slowly than employment, employment expansion is accompanied by pay dilution.

3. DATA SOURCES, VARIABLE CONSTRUCTION, AND RESEARCH DESIGN

This study uses the dataset entitled Employees and Wages of Listed Companies (2000-2022), whose source is identified as the CSMAR database. The raw data contain 60,399 records and include year, stock code, stock name, industry name, industry code, province, city, county or district, first listing year, listing status, number of employees, employee compensation payable, and average employee compensation. The cleaning procedure removes observations with missing year or firm identifiers, excludes observations in which employment, total compensation, or average compensation is missing, zero, or negative, and retains firm-year records for which logarithmic variables can be computed. The final sample covers 5,329 listed firms and 56,589 valid observations from 2000 to 2022. Industry heterogeneity is constructed by compressing the first letter of the industry code into broad national-economy sectors, while regional heterogeneity is based on provinces classified into eastern, central, western, northeastern, Hong Kong-Macao-Taiwan, and overseas regions.

The core variables are the natural logarithm of employment, the natural logarithm of average employee compensation, and the natural logarithm of total employee compensation payable. Average employee compensation is measured in 10,000 yuan per person, and total compensation is measured in 10,000 yuan. Because the data are nominal, all interpretations of compensation changes refer to nominal wages and are not adjusted for regional price levels or inflation. The baseline model controls for firm fixed effects and year fixed effects. Firm fixed effects absorb time-invariant firm characteristics, while year fixed effects absorb common macroeconomic shocks, price changes, and capital-market cycles.

It is important to stress that the current dataset does not contain sales revenue, profit, assets, R&D investment, capital intensity, financing constraints, or employee composition. The fixed effects estimates should therefore not be interpreted as strict causal effects, but as strong associations and panel facts. This boundary does not weaken the value of the study, because the joint evolution of employment quantity and pay quality is itself a fundamental fact for understanding the social value of listed firms, the distribution of labour compensation, and the quality of information disclosure.

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3.2 Formulae and Derivations for Key Indicators

To avoid misreading changes in employment quantity as improvements in employment quality, this study first defines all core indicators from the firm-level accounting identity. Let E_{it} denote the number of employees of firm i in year t, P_{it} denote total employee compensation payable, and W_{it} denote average employee compensation. Firm-level average pay is not an exogenously given variable; it is obtained by dividing total compensation by employment. Conversely, total compensation can be decomposed into the product of employment and average pay. This identity is the starting point for the subsequent growth decomposition and fixed effects estimation.

$$W_{it} = P_{it} / E_{it}$$

$$P_{it} = E_{it} \times W_{it}$$

At the annual level, total employment in the listed-firm sector, E_t, equals the sum of employees across all sample firms in a given year, while total compensation, P_t, equals the sum of employee compensation payable across all sample firms. The employment-weighted average wage is not a simple firm average. It uses each firm's employment share, s_{it}, as the weight and is therefore equal to annual total compensation divided by annual total employment. This definition incorporates the influence of large employers on the wage distribution actually faced by workers.

$$E_t = \Sigma_i E_{it}$$

$$P_t = \Sigma_i P_{it}$$

$$s_{it} = E_{it} / E_t$$

$$\bar{W}_t = P_t / E_t = \Sigma_i s_{it} W_{it}$$

From $P_t = E_t \times \bar{W}_t$, the log growth of total compensation can be decomposed exactly into employment growth and growth in employment-weighted average pay. The contribution rates reported in this paper are the shares of each component in $\Delta \ln P_t$. A high employment contribution indicates that total compensation expansion mainly comes from an increase in the number of jobs, whereas a high average-pay contribution indicates a stronger increase in labour compensation per worker.

$$\Delta \ln P_t = \Delta \ln E_t + \Delta \ln \bar{W}_t$$

$$\text{Employment contribution} = \Delta \ln E_t / \Delta \ln P_t$$

$$\text{Pay contribution} = \Delta \ln \bar{W}_t / \Delta \ln P_t$$

Between-firm pay dispersion is measured using the Gini coefficient. Let a_{it} denote the weight of firm i and μ_t the corresponding weighted mean wage. The Gini coefficient equals the weighted average of all pairwise differences in firms' average pay divided by twice the mean. When $a_{it} = 1/N_t$, the result is an equal-weighted firm Gini; when $a_{it} = s_{it}$, the result is an employment-weighted Gini. The former describes the dispersion across firms, while the latter describes the between-firm wage dispersion faced by the actual distribution of workers.

$$\mu_t = \Sigma_i a_{it} W_{it}$$

$$\text{Gini}_t = [\Sigma_i \Sigma_j a_{it} a_{jt} |W_{it} - W_{jt}|] / [2\mu_t]$$

$$a_{it} = 1/N_t \text{ or } a_{it} = s_{it}$$

Job-flow rates are calculated only for the set C_t of firms that appear in two adjacent years, so that sample entry and exit are not mistaken for within-firm hiring or downsizing. The job creation rate sums positive employment changes, and the job destruction rate sums the absolute values of negative employment changes. The denominator is average employment across the two adjacent years. The net employment growth rate equals the creation rate minus the destruction rate and is used to identify whether employment expansion comes from broad-based hiring or between-firm reallocation.

$$M_t = 0.5 \times [\Sigma_{i \in C_t} E_{it} + \Sigma_{i \in C_t} E_{i,t-1}]$$

$$JCR_t = \Sigma_{i \in C_t} \max(E_{it} - E_{i,t-1}, 0) / M_t$$

$$JDR_t = \Sigma_{i \in C_t} \max(E_{i,t-1} - E_{it}, 0) / M_t$$

$$NET_t = JCR_t - JDR_t$$

The fixed effects model compares how average pay changes when the same firm expands or contracts in different years. The term μ_i controls for time-invariant firm characteristics, λ_t controls for common year shocks, and ε_{it} is the error term. Because $\ln P_{it} = \ln E_{it} + \ln W_{it}$, an employment elasticity below one in the total payroll model is equivalent to a negative average-wage elasticity. This study also estimates a first-difference model to test whether adjacent-year changes provide evidence in the same direction.

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$$\ln W_{it} = \beta \ln E_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

$$\ln P_{it} = \theta \ln E_{it} + \mu_i + \lambda_t + u_{it}$$

$$\ln P_{it} = \ln E_{it} + \ln W_{it}, \text{ therefore } \theta = 1 + \beta$$

$$\Delta \ln W_{it} = \rho \Delta \ln E_{it} + \lambda_t + \eta_{it}$$

In the robustness tests, the winsorised variables are treated at the 1st and 99th percentiles. Let x_{it} denote the log variable to be processed, and let $Q_{0.01}$ and $Q_{0.99}$ denote the 1st and 99th percentiles of the sample. The winsorised variable x_{it}^{w} retains the original values in the middle interval and compresses the two tails to the corresponding percentile values. This checks whether the baseline conclusion is driven by extreme firms.

$$x_{it}^{w} = \min[\max(x_{it}, Q_{0.01}), Q_{0.99}]$$

Table 1: Sample Cleaning and Valid Observations

Step	Obs.	Description
Raw observations	60,399	All firm-year records in the data file
Valid firm-year identifiers	60,397	Year and firm identifiers define the panel baseline
Positive employment, total compensation, and average pay	56,589	Ensures that logarithmic variables and growth rates can be computed
Final regression sample	56,589	5,329 listed firms, 2000-2022

Note: Obs. = observations.

Table 2: Variable Definitions and Construction

Variable	Measure	Meaning
Employment	Number of employees disclosed in annual reports, measured in persons	Scale of employment absorption
Employee compensation payable	Employee compensation payable, measured in 10,000 yuan	Total labour compensation paid by the firm
Average employee compensation	Employee compensation payable divided by employment	Firm-level proxy for pay quality
lnEmployment	Natural logarithm of employment	Core explanatory variable in the fixed effects model
lnWage	Natural logarithm of average employee compensation	Dependent variable in the baseline model
lnPayroll	Natural logarithm of employee compensation payable	Dependent variable in the total payroll elasticity model
Region	Provinces classified into eastern, central, western, northeastern and related regions	Regional heterogeneity
Broad industry	Mapped from the first letter of the industry code to broad industry categories	Industry heterogeneity

Note: Variables beginning with ln are natural logarithms; monetary variables are measured in 10,000 yuan unless otherwise stated.

Table 3: Descriptive Statistics for the Main Variables

Variable	N	Mean	SD	Min	P25	Med.	P75	Max
Employment (persons)	56,589	5,732.730	22,716.616	1.000	788	1,764	4,124	570,060
Employee compensation Payable (10,000 yuan)	56,589	19,515.525	152,016.5	0.012	733.727	2,140.199	6,147.1	7,146,900
Average employee compensation (10,000 yuan)	56,589	2.912	16.266	0.000	0.594	1.336	2.633	2,727.172
Listing age (years)	55,884	9.327	7.272	0.000	3	8	14	32
Log employment	56,589	7.508	1.377	0.000	6.669	7.475	8.325	13.253
Log average pay	56,589	0.169	1.339	-11.41	-0.521	0.290	0.968	7.911

Note: SD = standard deviation; Med. = median; P25 and P75 denote the 25th and 75th percentiles.

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4. DESCRIPTIVE FACTS AND DATA VISUALISATION

Figure 1 shows that the listed-firm sector experienced marked expansion in both employment and compensation from 2000 to 2022. The number of sample firms rose from 1,010 to 5,106, a 5.1-fold increase; total employment increased from 2.75 million to 29.49 million, a 10.7-fold increase; and total employee compensation payable increased from RMB 14.285 billion to RMB 1,554.877 billion, a 108.8-fold increase. From 2000 to 2022, the log growth of total compensation was 4.690, of which total employment growth contributed 2.371 and employment-weighted average wage growth contributed 2.319. Their respective contribution shares were approximately 50.6% and 49.4%. This indicates that the expansion of aggregate labour compensation among listed firms came from both job quantity and unit pay, rather than from a single source.

Figure 2 shows that the distribution of firm-level average pay shifted to the right overall, while the right tail remained visible. This is consistent with the literature on firm wage dispersion and employer effects: rising average wages do not imply the disappearance of wage differences across firms (Card et al., 2013; Barth et al., 2016; Song et al., 2019). Figures 3 and 4 reveal industry and regional concentration. In 2022, the industries with the largest employment scale included computer, communications and electronic equipment manufacturing, civil engineering construction, electrical machinery, and automobile manufacturing, as well as high-paying finance and information technology services. At the regional level, Beijing, Guangdong, Zhejiang, Shanghai, and Jiangsu were important employment bases for listed firms. Figure 5 further shows that between-firm average wage dispersion and job creation and destruction coexisted over the long term. Employment expansion among listed firms was therefore not a synchronised increase across all firms, but was accompanied by reallocation across firms.

These descriptive facts show that aggregate expansion, distributional change, and structural differentiation must be interpreted jointly. If one observes only total employment, the listed-firm sector appears to have continuously absorbed labour. If one observes the wage distribution, differences across firms remain pronounced. If one observes job flows, firm expansion and contraction coexist. This pattern is consistent with the mechanisms emphasised in the literatures on firm heterogeneity, resource reallocation, and superstar firms (Melitz, 2003; Bernard et al., 2007; Bernard et al., 2012; Autor et al., 2020). The fixed effects estimates below are therefore not a rejection of aggregate growth; rather, they further decompose the within-firm pay adjustment mechanism behind aggregate growth.

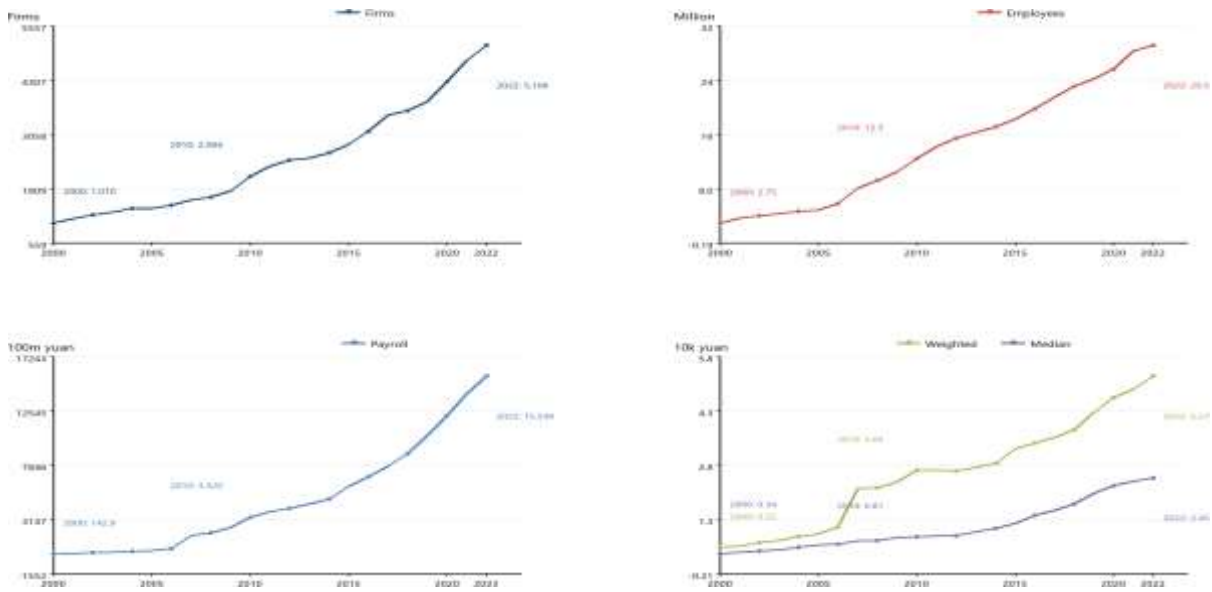


Figure 1: Long-Term Expansion of Employment and Compensation among Listed Firms, 2000-2022

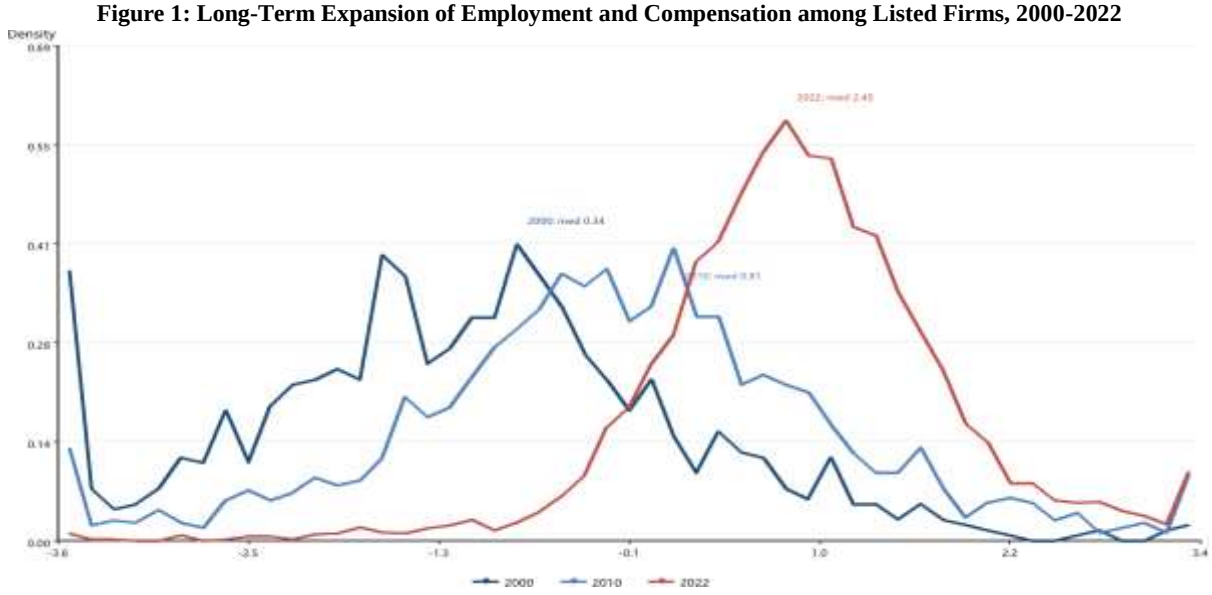


Figure 2: Changes in the Distribution of Average Pay per Employee

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Table 4: Comparison of Key Sample Indicators in 2000 and 2022

Indicator	2000	2022	Cum. growth	Ann. growth
Number of firms	1,010	5,106	405.5%	
Total employment (persons)	2,752,621	29,487,893	971.3%	11.4%
Total employee compensation payable (10,000 yuan)	1,428,518.0	155,487,715.7	10784.5%	23.8%
Employment-weighted average pay (10,000 yuan/person)	0.519	5.273	916.0%	11.1%
Median average pay (10,000 yuan/person)	0.337	2.445	626.3%	

Note: Cum. = cumulative; Ann. = average annual; pay variables are measured in 10,000 yuan per person.

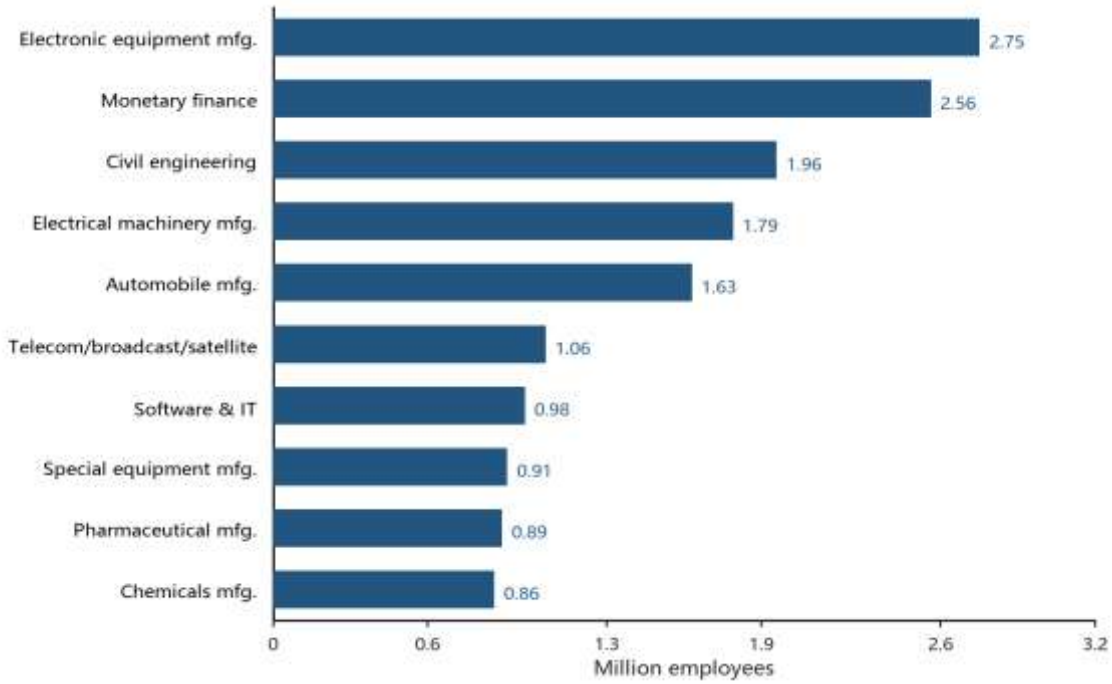


Figure 3: Ten Listed-Firm Industries with the Largest Employment Absorption in 2022

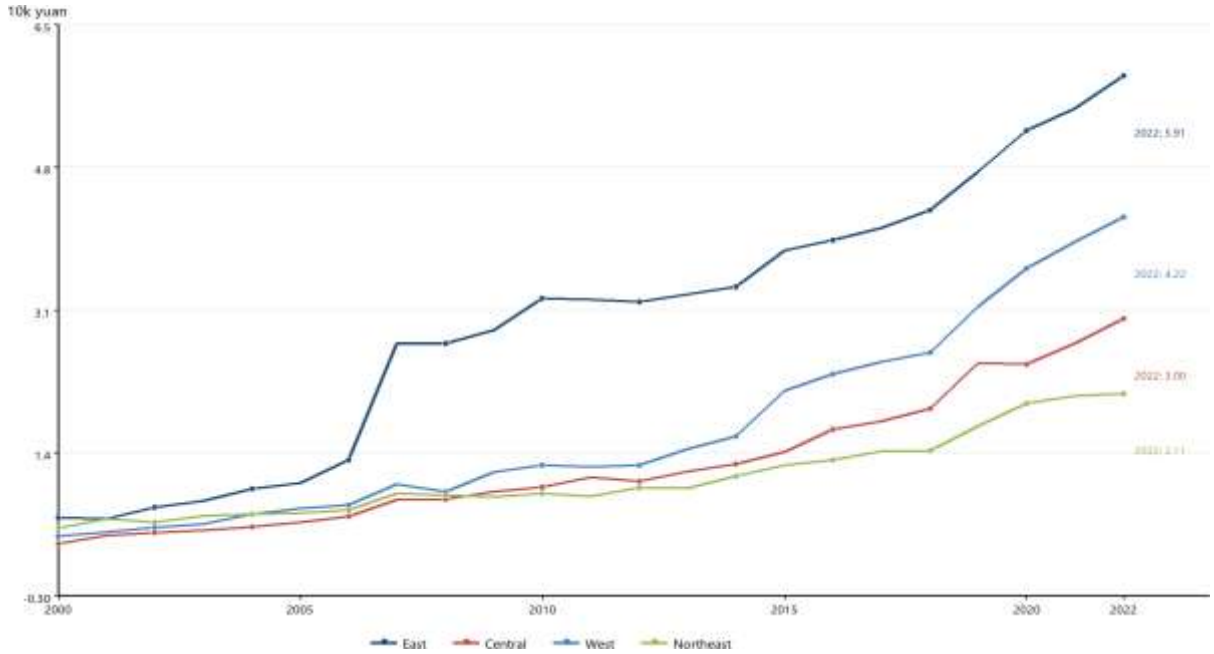


Figure 4: Dynamics of Employment-Weighted Average Pay across Four Major Regions

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Table 5: Top Ten Industries by Employment Scale in 2022

Industry	Firms	Emp.	Comp.	Pay med.
Computer, communications and other electronic equipment manufacturing	576	2,748,642	8,723,755.8	2.455
Monetary and financial services	43	2,562,314	47,280,305.2	18.826
Civil engineering construction	73	1,956,429	5,635,570.2	2.615
Electrical machinery and equipment manufacturing	321	1,790,319	5,925,151.3	2.148
Automobile manufacturing	172	1,625,441	6,482,252.9	1.887
Telecommunications, broadcasting, television and satellite transmission services	19	1,061,759	3,577,485.3	3.931
Software and information technology services	336	977,567	2,862,223.4	2.979
Special-purpose equipment manufacturing	365	908,129	3,176,657.1	2.685
Pharmaceutical manufacturing	315	893,997	3,010,821.5	2.599
Chemical raw materials and chemical products manufacturing	337	861,219	2,609,077.6	2.448

Note: Emp. = employment; Comp. = total employee compensation payable; Pay med. = median average pay; monetary variables are measured in 10,000 yuan.

Table 6: Top Ten Provinces by Employment Scale in 2022

Province	Firms	Emp.	Pay med.
Beijing	456	7,379,778	3.331
Guangdong	839	5,963,215	2.336
Zhejiang	666	2,172,547	2.348
Shanghai	420	1,913,037	3.513
Jiangsu	640	1,777,687	2.351
Shandong	295	1,335,551	2.375
Fujian	170	922,613	2.344
Anhui	165	828,489	2.128
Henan	106	668,513	1.794
Hunan	138	626,479	2.383

Note: Emp. = employment; Pay med. = median average pay, measured in 10,000 yuan.

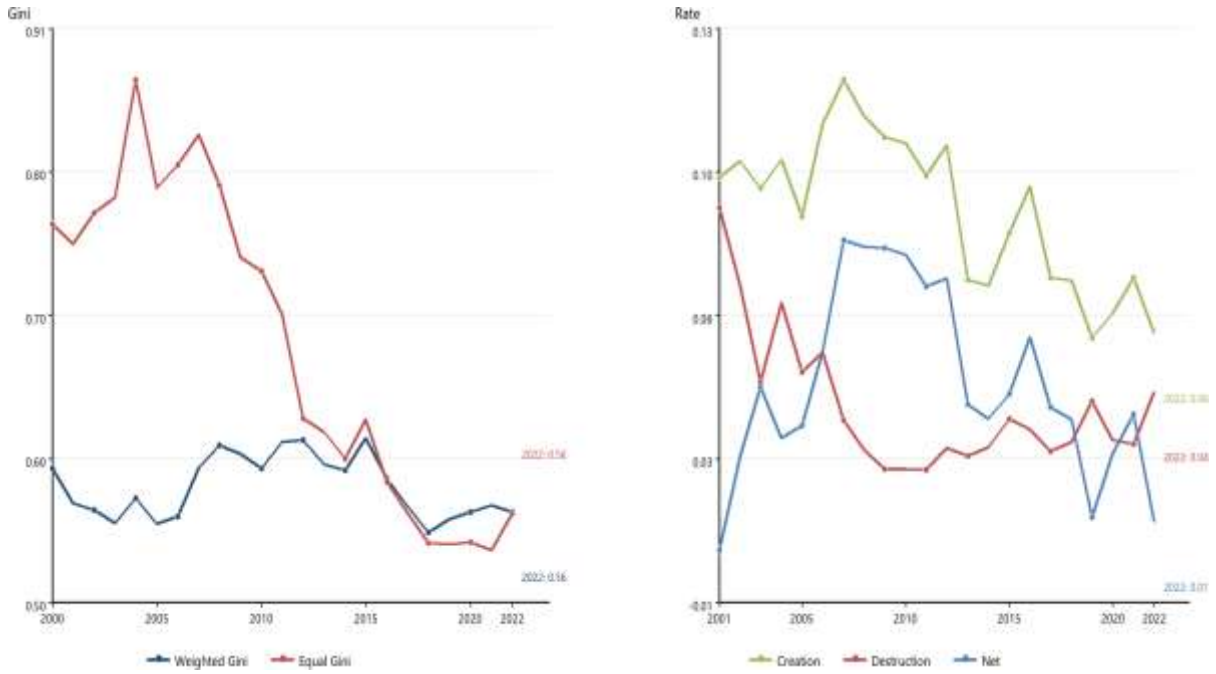


Figure 5: Wage Dispersion and Employment Reallocation

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5. PANEL FIXED EFFECTS ESTIMATION RESULTS

Table 7 reports the baseline regression results. When only year fixed effects are controlled for, the elasticity of average pay with respect to employment is -0.099. After additionally controlling for firm fixed effects, the elasticity becomes -0.326 and is statistically significant. This result implies that, within the same listed firm, a 1% increase in employment is associated with an average decline of about 0.326% in average pay. It does not mean that compensation among listed firms declined overall, because Figure 1 has already shown a long-term increase in nominal average pay. Rather, it indicates that when within-firm employment expands faster than total payroll, average pay is diluted. This finding sits in productive tension with the literatures on the firm-size wage effect, changes in job composition, and firm wage premia, and therefore has empirical value (Brown and Medoff, 1989; Oi and Idson, 1999; Card et al., 2018).

The total payroll elasticity model further confirms this interpretation. The two-way fixed effects coefficient of lnPayroll on lnEmployment is 0.674, significantly below one. Since total compensation equals employment multiplied by average pay, this coefficient is equivalent to one plus the average-pay elasticity. In other words, firm-level employment expansion raises total payroll, but total payroll does not grow proportionally with employment. The first-difference model, which uses adjacent-year changes, produces an estimate of -0.515. This suggests that in short-run expansion periods, firms are more likely to increase employment through marginal jobs, front-line jobs, or labour-intensive segments than to immediately raise compensation per worker.

A negative elasticity does not necessarily mean that firms reduce the wages of incumbent employees. Because the data observe only firm-level average employee compensation, the coefficient may also reflect changes in workforce composition. When firms add more front-line workers, production workers, or lower-paid regional positions, average firm-level pay can fall even if incumbent employees' wages do not decline. Technological change, task reorganisation, performance pay, and corporate culture may all change the skill content and pay structure of new jobs (Autor et al., 2003; Acemoglu and Autor, 2011; Lazear, 2000; Edmans, 2011; Guiso et al., 2015). The effect identified in this study should therefore be understood as a structural effect on firm-level average pay, not as evidence of individual wage cuts.

Table 7: Baseline Fixed Effects Regression Results

Variable	(1)	(2)	(3)	(4)
ln(employment)	-0.099***	-0.326***	0.674***	-0.515***
	(0.014)	(0.019)	(0.019)	(0.021)
Firm FE	No	Yes	Yes	FD
Year FE	Yes	Yes	Yes	Yes
DV	ln(avg pay)	ln(avg pay)	ln(payroll)	Delta ln(avg pay)
Obs.	56,589	56,589	56,589	51,079
Firms	5,329	5,329	5,329	4,916
R^2	0.013	0.070	0.244	0.099

Note: FE = fixed effects; DV = dependent variable; Obs. = observations; FD = first difference. Robust SEs clustered at the firm level are reported in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Column (4) uses Delta ln(employment) as the core explanatory variable.

6: ROBUSTNESS TESTS AND HETEROGENEITY ANALYSIS

Table 8 reports the robustness tests. First, after the logarithms of employment and average pay are winsorised at 1%, the coefficient remains significantly negative, indicating that the conclusion is not driven by extreme firms or abnormal wage values. Second, when the sample is restricted to firms continuously observed from 2000 to 2022, the coefficient remains significant, suggesting that sample entry and exit are not the sole explanation. Third, after excluding the financial sector, the result is almost unchanged, indicating that high-pay financial firms do not dominate the baseline conclusion. Finally, restricting the sample to normally listed firms and using a first-difference model both yield estimates in the same direction. These checks are consistent with the basic requirements of cluster-robust inference for panel data and reduce concerns that the results are driven by sample structure or extreme values (Petersen, 2009; Cameron et al., 2011).

Figure 6 and Table 9 show regional heterogeneity. The fixed effects elasticities are negative in all four major regions, indicating that pay dilution is not confined to a single region. At the industry level, the coefficients differ in magnitude across manufacturing, construction, information technology services, wholesale and retail, transportation, and finance, reflecting differences in job structure, technological intensity, and business model. The literatures on trade, technology, and firm heterogeneity suggest that firm expansion is not always accompanied by an increase in homogeneous jobs; it is often accompanied by changes in task bundles, skill demand, and the distribution of productivity (Amiti and Davis, 2012; Helpman et al., 2010; Helpman et al., 2017; Acemoglu and Restrepo, 2020). The heterogeneity results in this paper are consistent with this mechanism.

The listing-age grouping further shows that the corporate life cycle is related to employment and pay structure. Younger listed firms have a smaller median workforce, while firms with a longer listing history are larger in organisational scale. However, median average pay does not increase monotonically with listing age. This indicates that corporate maturity does not necessarily imply a continuous rise in pay per worker; industry position, region, governance capability, and job structure jointly determine pay quality. The literatures on corporate governance, competitive pressure, CSR, and employee satisfaction also suggest that human-capital outcomes depend not only on firm size but also on internal governance and organisational practices (Nickell, 1996; Bertrand and Mullainathan, 2003; Edmans, 2012; Flammer, 2015).

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Table 8: Robustness Tests

Test	Coef.	SE	Obs.	Firms	R^2
1% winsorisation	-0.311***	(0.017)	56,589	5,329	0.070
Balanced panel	-0.382***	(0.027)	18,009	783	0.105
Excluding finance	-0.325***	(0.018)	54,764	5,271	0.069
Normally listed firms only	-0.319***	(0.021)	51,475	4,978	0.062
First difference	-0.515***	(0.021)	51,079	4,916	0.099

Note: Coef. = coefficient; SE = standard error; Obs. = observations; FE structure follows the baseline firm and year fixed effects specification unless otherwise stated.

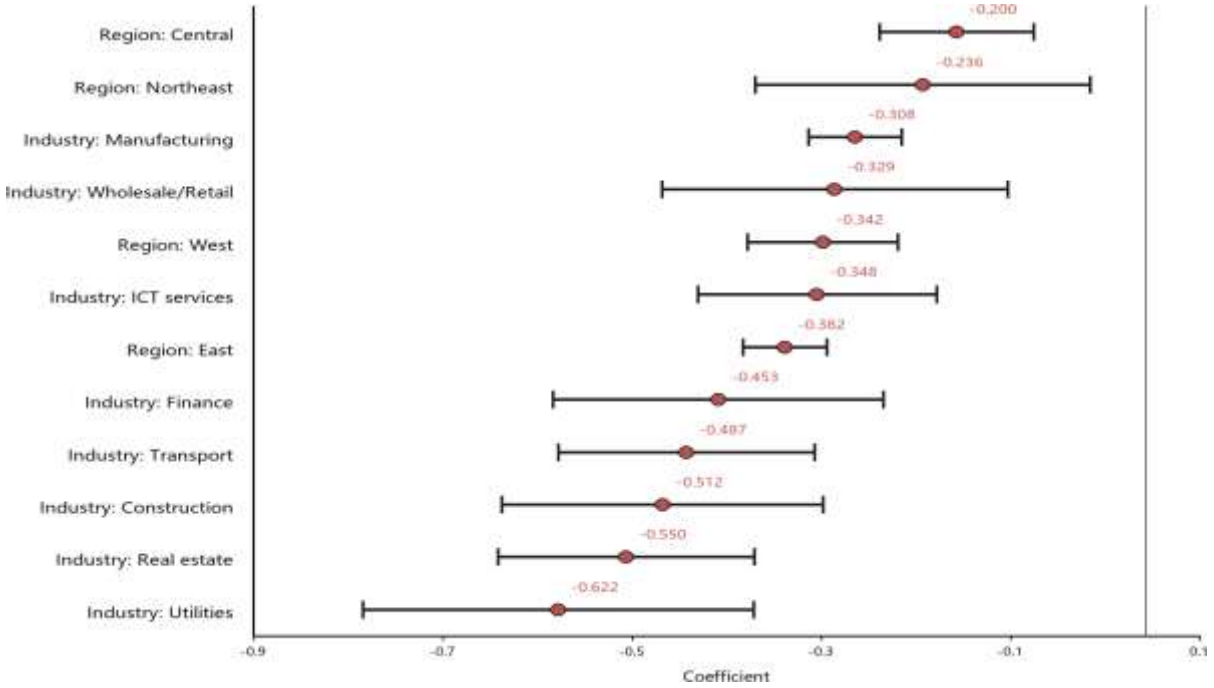


Figure 6: Fixed Effects Elasticity of Average Pay with Respect to Employment Expansion: Regional and Industry Heterogeneity

Table 9: Regional Heterogeneity Regression Results

Region	Coef.	SE	Obs.	Firms	R^2
Northeastern region	-0.236***	(0.091)	3,021	226	0.026
Eastern region	-0.382***	(0.023)	37,062	3,843	0.098
Central region	-0.200***	(0.042)	8,036	721	0.022
Western region	-0.342***	(0.041)	8,441	669	0.080

Note: Coef. = coefficient; SE = standard error; Obs. = observations; all specifications include firm and year FE within the corresponding regional subsample.

Table 10: Employment and Pay Medians by Listing Age

Listing age	Firms	Obs.	Med. emp.	Pay med.
0-2 years since listing	4,431	11,481	1,064	1.280
3-5 years since listing	3,553	9,814	1,598	1.126
6-10 years since listing	3,157	13,328	1,972	1.168
11-20 years since listing	2,357	15,689	2,481	1.402
More than 20 years since listing	1,080	5,572	2,528	2.271

Note: Obs. = observations; Med. emp. = median employment; Pay med. = median average pay, measured in 10,000 yuan.

7. CONCLUSIONS AND POLICY IMPLICATIONS

Using employee and wage data for Chinese listed firms from 2000 to 2022, this study systematically characterises the joint evolution of employment absorption and pay quality in the listed-firm sector. The evidence shows that both total employment and total compensation increased substantially, indicating that capital-market entities have developed an increasingly strong capacity to absorb labour, organise jobs, and pay labour

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compensation. Total compensation growth was jointly driven by employment expansion and increases in employment-weighted average pay, so quantity expansion and quality improvement together form the basic coordinates for understanding changes in labour compensation. The within-firm fixed effects evidence further shows a significant negative association between employment expansion and average pay, with total payroll elasticity below one, suggesting that employment expansion may be accompanied by changes in job structure and dilution of average pay. This conclusion does not deny the contribution of listed firms to employment stabilisation. Rather, it indicates that in the stage of high-quality development, evaluations of firms should include both more jobs and better jobs.

From a policy perspective, the constructive implication of this study is that employment policy, industrial policy, and capital-market regulation can form a more refined coordination framework around stabilising quantity, improving quality, and optimising structure. When local governments encourage listed firms to expand employment, they should move beyond counting jobs alone and also examine total compensation, average pay, skills training, job stability, and career-growth opportunities. Consistent evidence from Chinese graduates shows that perceived job security, management compliance, and humanistic care strengthen organisational attractiveness and private-enterprise employment intentions (Gan et al., 2026b). It is especially important to distinguish labour-intensive absorption, skill-upgrading absorption, and capital-intensive expansion, so that rapid increases in low-paid jobs are not mistaken for improvements in high-quality employment. At the firm level, human-resource strategy should be embedded in long-term competitiveness. During expansion, firms should plan payroll budgets, job hierarchies, training investment, and internal promotion channels in parallel, so that new jobs not only expand employment capacity but also accumulate organisational capability, improve employee stability, and strengthen sustainable productivity. Capital markets and ESG disclosure can also refine their labour dimension by encouraging listed firms to disclose employment counts, total compensation, average pay, workforce composition, training investment, and labour turnover more transparently. This would allow investors, regulators, and the public to evaluate more accurately the real labour value created by firms.

In terms of future research, this study maintains necessary boundary awareness. The current data are measured in nominal compensation, without adjustment for regional price levels or inflation. They also lack information on employee education, job hierarchy, age, gender, working hours, and firm-level operating variables such as profit, assets, sales revenue, capital expenditure, financing constraints, and ESG ratings. The fixed effects coefficients should therefore be interpreted as strong firm-level associations and structural facts rather than strict causal effects. Future research can proceed in two directions. First, employee wage data can be matched with financial performance, technological innovation, robot adoption, digital transformation, and regional labour-market data to identify which firms truly achieve simultaneous improvements in employment quantity and pay quality. Second, labour information disclosure by listed firms should move from headcount disclosure to quality disclosure, providing a stronger data foundation for policy coordination across employment stabilisation, income growth, skills upgrading, and firm competitiveness.

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