

Article

Industry Volatility and Employment Extreme Risk Transmission: Evidence from China

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Abstract: China's socio-economic growth path aims to achieve full and sustainable employment, which requires an in-depth understanding of the linkages between employment and different industrial sectors within the economic system. The objective of this study is to examine the heterogeneous transmission effects of industry fluctuations on the distribution of employment, with special attention to the transmission effects of industry fluctuations on employment under extreme conditions. The research methodology of this paper is to systematically examine the risk spillover effects between industry sectors and employment distribution using the quantile risk spillover model. The results show that industry volatility significantly affects employment volatility in China. The impact of industry volatility is stronger under extreme conditions, both more adverse and favorable than that of under normative conditions. Among labor-intensive industries, the employment impact of skilled labor-intensive and integrated labor-intensive industries is relatively small compared to that of the relatively large impact of manual labor-intensive industries. The results suggest that traditional indicators of the spillover effect, such as the mean-based indicator, cannot accurately capture the source and real effect of risk transmission, leading to unemployment fluctuations, underscoring the need to focus on the heterogeneity of the distribution of employment fluctuations. The findings also present the evolution of the risk transmission structure of employment in China, which provides implications for policymaking on full and sustainable employment.

Keywords: full and sustainable employment; industry stock price volatility; employment extreme risk; quantile VAR; risk spillover



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1. Introduction

This paper investigates the heterogeneous transmission effects of volatility in China's industry sectors on their employment risk under extreme risk conditions. China's socio-economic growth path aims to achieve full and sustainable employment, which requires an in-depth understanding of the linkages between employment and different industrial sectors within the economic system. Many economic factors, including monetary policy, foreign trade, FDI, production efficiency, and significant occurrences in the field of public health, may have an impact on employment rates. However, these factors mostly affect employment through industry sectors. Meanwhile, employment changes directly caused by economic factors will also be fed back to the industry sector. The mutual transmission between the two parties will spread to all facets of the entire economic system, causing more profound effects. At the same time, there are differences in the impact of economic shocks on different industry sectors, not only from the difference in factor density in different industry

sectors but also from the types of labor skills in different industry sectors. Therefore, examining the heterogeneous transmission effect of different types of industry sectors on employment fluctuations is the cornerstone of understanding the internal mechanism of economic shocks affecting employment fluctuations, which is also the contribution of this study.

Due to factors such as labor market stickiness and fixed costs in business operations, the existing literature found that the decision-making behavior of enterprises to expand or shrink the scale of operation (thereby expanding or reducing the scale of employment) is usually made when the economic condition is good enough or bad enough (Cooper et al., 1999; Cooper and Haltiwanger, 2006; Stokey, 2009) [1–3], which means that employment risks are likely to occur in environments when the economy is in extreme situations. The outbreak of extreme risk events such as the financial crisis from 2007 to 2009 and the spread of COVID-19 in 2020–2023 caused the continuous turbulence of the labor market, the sharp decrease in labor demand, and also showed that the impact of extreme events on employment is huge (Lai and Cai, 1999; Arthi and Parman, 2021; Zou and Meng) [4–6]. However, there are methodological challenges to scientifically examine the transmission effect of industry fluctuations on extreme employment risks. The mean-based risk spillover model is typically used in the existing literature (Diebold and Yilmaz, 2009, 2012, 2014) [7–9] to statistically evaluate the relationship between economic variables, but this model is unable to account for the effect of the heterogeneity effect in the spillover distribution. According to recent studies (Ando et al., 2018; Chatziantoniou et al., 2021; Bouri et al., 2022) [10–12], extreme events have a greater impact on the connections among different sectors of the economic system. The spillover effect based on the mean value only reflects the extreme risk spillover effect indirectly. Therefore, this paper adopts the quantile risk spillover effect model to accurately capture the dynamic distribution relationship between employment volatility and industry volatility and explore the employment risk transmission pathway under high-risk conditions.

In this study, we first use the mean-based risk spillover model proposed by Diebold and Yilmaz (2009, 2012, 2014) [7–9] to examine the transmission effect of five types of industry sector fluctuations on employment level to serve as a benchmark for the results of the extreme risk spillover model used thereafter. Then, we examine the effect of fluctuations in the five types of industry sectors on changes in employment distribution using the quantile-based risk spillover effects model proposed by Ando et al. (2018) [10] and Chatziantoniou et al. (2021) [11]. We focus in particular on the extremely good scenario (the unemployment rate quantile is in the range of 0.05–0.15) and the extremely bad case (the unemployment rate quantile is in the range of 0.85–0.95). After comparing with mean-based risk spillover model, we find that industry volatility has the strongest impact on employment levels in the extremely good and extremely bad cases but weaker on employment levels in the normal scenario. We then examine the impact of industry volatility on employment by different types of labor skills and find significant heterogeneous transmission effects.

In the existing research literature, there are few discussions on the impact of macroeconomic aggregate shock on employment extreme risk and almost no reference to industry sector heterogeneity. Although there are many empirical research literatures on the impact of industry fluctuations on employment level, they rarely pay attention to the extreme risk of employment. Through the innovative use of the quantile risk spillover model and empirical tests with data from China, this paper confirms that the impacts of economic shocks on employment levels are mainly reflected in the extreme risk scenarios, revealing the essence of risk in the labor market, and are an academic contribution to the study of labor and employment. If the employment risk is mainly reflected in the employment changes in extremely scenarios, mitigation of the employment fluctuations in the economic downturn phase by reducing the frictional factors in the labor market, lowering the cost of business adjustments and increasing the resilience of the industry's economy to withstand the risks, has become a theme that the relevant governmental authorities need to consider. From

this perspective, the study in this paper not only fills the gap in the existing employment research literature but also provides valuable references to the relevant authorities.

The main structure of this paper is as follows: Section 2 contains the literature review and research hypotheses; Section 3 contains models and indicators; Section 4 contains instructions for processing sample data; Section 5 contains mean-based industry and employment risk spillover effects; Section 6 contains distribution-based employment risk spillover effects; and Section 7 contains conclusions.

2. Literature Review and Research Hypothesis

2.1. Literature Review

This paper relates to the study of the link between industry and employment in China. China's social and economic structure has changed dramatically over the past 20 years and, as a result, has impacted the employment level and employment structure. Yuan and Li (2008) [13] noted a strong correlation between the level of capital deepening and the employment trend in China's manufacturing sector from 1996 to 2005. The manufacturing sector's ability to absorb new jobs gradually decreased as capital investment grew deeper. Ma et al. (2013) [14] investigated the manufacturing sector's employment issue using data from industrial firms between 1998 and 2007 and discovered that traditional manufacturing industries experienced a loss in employment, whereas the consumer goods sector added the most jobs. Yuan and Gao (2015) [15] estimated the effect of the increase in manufacturing employment on employment in the service sector using urban data from 2003 to 2012. The findings of the empirical test indicated that an increase in manufacturing employment of 1% can result in an increase in service employment of 0.476% in the same city. To examine the relationship between China's domestic and international demand and China's employment level from 1995 to 2009, Ge and Xie (2019) [16] built a worldwide multi-regional input–output model comprising 35 subsectors. They discovered that the primary element influencing China's employment is domestic demand. In particular, the drop in agricultural demand reduces employment by 12.35 million people per year, the rise in manufacturing demand adds 900,000 jobs annually, and the rise in service industry demand adds 3.23 million jobs annually. By creating the new factor kinetic energy index of economic growth, Liu and Lu (2022) [17] thoroughly investigated the effects of the development of new factor kinetic energy on the employment structure against the backdrop of the digital economy. They found that the trend in China's overall employment structure has become more polarized as a result. The growth of the service sector will lead to the formation of new economic growth factors, which will enhance the employment of low-skilled and high-skilled labor while further decreasing the employment of junior and senior high school graduates. The data of publicly traded service businesses from 2009 to 2019 were used by Luo et al. (2023) [18] to experimentally discover that the digital transformation of the service industry will increase employment through corporate innovation, lower corporate costs, and higher corporate demand. According to some research, China's industry employment level fluctuations are caused by the employed group's inability to adjust their skill level and skill structure to shifts in industry demand. According to Qu (2014) [19], China's industrial sector is at overcapacity, with 27 million redundant workers as a result. This group of people is at a low level of education and labor skills, making them susceptible to changes in employment. Yao et al. (2014) [20] investigated the employment pressure faced by college students and discovered that the employment challenges faced by college students were primarily caused by a mismatch between the structure of talent demand after industrial transformation and the supply structure of college students' professional education, rather than an increase in university enrollment. The economic impacts of outside shocks that are communicated to employment groups through industry sectors are also examined in other studies. In the manufacturing sector, labor-intensive businesses will see an increase in employment as the RMB depreciates, whereas capital- and technology-intensive businesses will see an increase in employment as the RMB appreciates [21]. Tong and Liu (2018) [22] investigated how the manufacturing, employment, and home-building industries' employment structures had

changed. They conducted empirical tests utilizing urban data from 2004 to 2013 and discovered that rising housing costs led to an increase in labor employment in the construction industry but decreased manufacturing employment. Shen et al. (2021) [23] examined the effect of COVID-19 on employment levels using the urban unemployment survey data of 31 major cities from October 2018 to September 2020 and discovered that COVID-19 had a substantial adverse effect on urban employment. From March to November 2020, Cai et al. (2021) [24] gathered survey information from more than 5600 practitioners across a range of industries. They discovered that the manufacturing and wholesale and retail sectors, which have been particularly badly impacted by the epidemic, are where the majority of the unemployed are located. During the normalization of epidemic prevention and control in China, Chen et al. (2022) [25] used online recruiting and mobile Internet positioning data to analyze the variations and causes of the employment market in various cities. According to the study, there was a clear differential in the urban job market throughout the era of economic recovery due to the exogenous influence of the COVID-19 epidemic, and the urban size significantly contributed to the recovery of employment.

There are still two issues with the economic relationship between industry and employment, despite much discussion and testing in the existing literature. First, there is little examination of the overall interplay between industry variations and employment changes during the previous ten years in the research mentioned above, which mostly focuses on local issues and the effects of specific industries on employment. Second, most of the literature in existence uses mean-based regression analysis, which is unable to accurately describe how the economic link between industries and employment changes in a variety of contexts (especially in the most extreme ones). Therefore, this paper tries to make up both of these gaps.

This study is closely related to the literature on employment risk. According to the New Keynesian macroeconomic theory, employment risk comes from economic aggregate shocks, such as monetary policy shocks, productivity shocks, consumption and investment demand shocks, wage and price shocks, etc. (Gali, 1999; Christiano et al., 2005) [26,27]. Empirical studies have shown that when the economy is in a situation of higher inflation, higher credit growth, looser bond financing, and lower unemployment in the past, the likelihood of unemployment rises more sharply in subsequent periods, and the effects of the changes in inflation, credit, and the labor market on the risk of employment are asymmetric: they have a greater effect on the increase in unemployment than on the decrease in unemployment. (Kiley, 2018; Cook and Doh, 2019) [28,29]. Some studies have found that the impact of aggregate shocks on employment risk is heterogeneous across industries and regions. Neumann and Topel (1991) [30] argued that differences in the regional distribution of unemployment were due to differences in the distribution of industrial labor demand, and the greater the diversity of labor demand in an industry the lower the overall level of unemployment if the labor force is free to move. Mian and Sufi (2012) [31] examined the causes of the rise in unemployment in the United States between 2007 and 2009 and pointed out that the rise in unemployment was mainly due to the decline in aggregate demand, and the level of unemployment in the non-tradables sector was significantly greater than in the tradables sector. On the other hand, Simon (2014) [32] investigated the influencing factors of the rising unemployment in the UK during the same period (2007 to 2009) and found that the employment changes in industrial sectors were the main source of influence. Watson and Deller (2017) [33] found that the greater the diversity of regional industries the lower the unemployment level in the region during economic recession. They believed that it was mainly because of differences in the impact of economic shocks across industries, and thus the distribution of diverse industries acts as a buffer against employment risk. Since 2020, much of the literature has focused on the impact of the COVID-19 shock on the entire economy, including the employment risks. It is generally believed that the COVID-19 shock caused inter-sectoral supply chain disruption and aggregate demand decline, which led to increased unemployment levels (Guerrieri et al., 2022; Baqaee and Farhi, 2022) [34,35]. Barrot et al. (2021) [36] found that policies of

social distancing to guard against the spread of the neo-creeping virus led to a fall in labor supply, which spread through the production networks of industry sectors, resulting in a decline in overall economic output. Kaplan et al. (2020) [37] compared the social and economic costs caused by blockade and non-blockade, pointing out that the employment and income status of middle-income households will be most affected no matter blockade or not.

From the employment risk literature above, it is clear that industry sector fluctuations have an important impact on employment. The existing literature has made a more in-depth discussion on the total shock that leads to industry sector volatility. However, the factors that cause industry sector volatility are not only aggregate shocks but also include enterprise heterogeneity shocks. Therefore, it is necessary to comprehensively analyze the transmission effect between industry volatility and employment risk from the industry level by combining the characteristics of total shock and firm heterogeneity shock. At the same time, the above studies rarely discuss the extreme risk of employment, mainly focusing on the impact of macro factors on the extreme risk of employment, lacking the role of industry factors. This study is expected to make up for the shortcomings of existing literature in this respect.

This paper, which is a marginal contribution compared to earlier studies, investigates the risk spillover effects between large-scale industry fluctuations and employment fluctuations from 2010 to 2022, with a particular emphasis on the industry and employment risk spillover effects of labor skill heterogeneity. The industry and employment volatility distribution spillover effect index, which can completely and accurately explore the distribution heterogeneity relationship between the two and has methodological contributions to the existing research field, is constructed in this paper using the quantile risk spillover effect model.

2.2. Research Hypothesis

The employment change in the economic system is mainly affected by the heterogeneity shock at the firm level and the aggregate shock at the macro level. Firm heterogeneity shocks include changes in firms' technological research and development or financing conditions, which may affect the scale of firms' production and entrepreneurial decision-making behaviors, with regard to expansion or contraction, and thus affect firm employment. The aggregate shock at the macro level includes economic cyclical changes, external aggregate demand changes, and supply-side factor changes. When there is a negative shock to the economy (such as a reduction in aggregate demand), firms are likely to cut back on external hiring or even lay off employees in order to ride out the hard times. The heterogeneous shocks of enterprises that can have a relatively evident effect on the overall employment level usually have the characteristics of industry similarity, i.e., enterprises in the same industry usually face similar technology shocks or financing condition shocks, but the technology shocks or financing condition shocks of different industries are quite different. Aggregate shocks have different impacts on different industries; for instance, in the recessionary phase, the consumer durables industry (e.g., the automobile industry) is more negatively impacted, whereas the consumer goods industry is less negatively impacted (Mian and Sufi, 2012) [31]. Therefore, both firm heterogeneity shocks and aggregate shocks can ultimately be reflected in different degrees of industry shocks. At the same time, the unemployment risk faced by workers with different skills is different, with higher-skilled workers having a lower risk of unemployment and lower- and medium-skilled workers having a higher risk of unemployment (Autor and Dorn, 2013) [38]. Thus, industry fluctuations with different degrees of labor skill heterogeneity in more labor-intensive industry sectors are bound to have heterogeneous effects on employment fluctuations.

Based on the following two factors, we believe that industry shocks have a smaller impact on employment in the normal scenario and a greater impact on employment in the extreme case:

The first is the frictional factors of the labor market. In the labor market, firms and workers need to sign a labor contract for a certain period of time in order to formally establish an employment relationship, and the labor contract usually stipulates the number of years of service, wages, benefits, payment of social insurance premiums, conditions for termination of the contract, and so on. Considering the costs of dismissal and hiring, it is difficult for firms to adjust the scale of employment in response to industry shocks. Therefore, when the economic environment is in the general situation (the business situation of the enterprise is also in the general situation), only in relatively extreme circumstances (such as the economic situation is very good or very bad, and the corresponding business situation is good or poor), the benefits of adjusting the scale of employment will outweigh the costs.

The second is the fixed cost factor in enterprise operation. When an enterprise expands or shrinks its business scale, it needs to pay a considerable amount of fixed costs, such as liquidation costs and disposal costs of related assets when the enterprise closes down, and the cost of new management expenses and depreciation of fixed assets when the enterprise expands (Cooper et al., 1999; Cooper and Haltiwanger, 2006; Stokey, 2009) [1–3].

Based on the above, we have the following testable research hypotheses:

Industry sector fluctuations affect employment fluctuations, with the strongest industry risk spillover effects on employment in the extremely bad and extremely good cases and relatively weak industry risk spillover effects on employment in the general cases. Among labor-intensive industries, the impact on employment is relatively weak in skilled and comprehensive labor-intensive sectors and relatively strong in manual labor-intensive sectors.

3. Risk Spillover Effect Model and Indicators

The mean-based risk spillover effect model between economic variables was put forth by Diebold and Yilmaz (2009, 2012, 2014) [7–9]. The goal is to first estimate the vector autoregressive model containing the relevant economic variables, after which the H-step forecast error of variable j to variable i is decomposed (FEVD), and the resulting variance decomposition index represents the variance of variable j to variable i . Risk output shock is a measure of how closely two variables are connected and their indicator value. The same method is used to determine the risk output index value for variables i and j . To calculate the net effect value of risk spillover, the risk output value of economic variable i to other economic variables is deducted from the risk output value of other economic variables to i . The variable i is known as the risk taker if the value is negative and the risk creator if the value is positive. Similarly, the relationship between risk input and output for two variables is assessed based on the net risk spillover impact between the two variables.

The risk spillover effect model based on the distribution, created by Ando et al. (2018) [10] and Chatziantoniou et al. (2021) [11], will be used in this paper since the risk spillover scenario can be difficult to characterize using the risk spillover effect model based on the mean in extreme circumstances. This study first chooses employment factors and significant industry variables to build the quantile vector autoregressive (QVAR) model shown below.

$$y_t = \Psi_0(q) + \Psi_1(q)y_{t-1} + \Psi_2(q)y_{t-2} + \cdots + \Psi_p(q)y_{t-p} + \varepsilon_t(q) \quad (1)$$

In Equation (1), y_t is a vector of employment variables and industry volatility, and $\Psi_i(q)$ is a constant item vector in the q -quantile regression. $i = 1, \dots, p$ is a coefficient matrix, $\varepsilon_t(q)$ is a disturbance item vector, and its covariance matrix is $\Sigma(q)$. Like the general VAR model, the QVAR model can be expressed as a moving average of the disturbance term for all periods in the present and past:

$$y_t = \bar{A}_t(q) + A_1(q)\varepsilon_{t-1}(q) + A_2(q)\varepsilon_{t-2}(q) + \cdots + A_t(q)\varepsilon_1(q) + \varepsilon_t(q) \quad (2)$$

In Equation (2), $\bar{A}_t(q)$ is a matrix of constant items, and $A_j(q)$ $j = 1, \dots, t - 1$ is a matrix of disturbance items. The impulse response function of the VAR model is typically

calculated using the Cholesky decomposition method, but the outcome of the impulse response function depends on the order of the variables and is constrained by the researcher's subjective cognition, making it challenging to make an accurate determination in many situations. As a result, the expanded Pesaran and Shin (1998) [39] method is used in this study to estimate the variance decomposition of the QVAR model's prediction error. Specifically, in the sum of squared forecast errors of the q quantile of variable i in the future H period, the proportion of shocks from variable j is:

$$\theta_{ij}^q(H) = \frac{\sigma_{jj}^{-1}(q) \sum_{h=0}^{H-1} (e' A_h(q) \Sigma(q) e_j)^2}{\sum_{h=0}^{H-1} (e' A_h(q) \Sigma(q) A_h'(q) e_i)} \quad (3)$$

This indicator reflects the connection between the q quantile of the variable i and the variable j . To make the sum of the row vector of 1, the following standardized processing is performed:

$$\bar{\theta}_{ij}^q(H) = \frac{\theta_{ij}^q(H)}{\sum_{j=1}^N \theta_{ij}^q(H)} \quad (4)$$

We then define the positive risk spillover effect indicator that the shock of variable i affects other variable q quantiles as:

$$S_{i \cdot}^q(H) = \frac{\sum_{j=1, j \neq i}^N \bar{\theta}_{ji}^q(H)}{N} \times 100 \quad (5)$$

Similarly, the negative risk spillover effect index defining the q quantile of variable i affected by shocks of all other variables is:

$$S_{i \cdot}^q(H) = \frac{\sum_{j=1, j \neq i}^N \bar{\theta}_{ij}^q(H)}{\sum_{i,j=1}^N \bar{\theta}_{ij}^q(H)} \times 100 = \frac{\sum_{j=1, j \neq i}^N \bar{\theta}_{ij}^q(H)}{N} \times 100 \quad (6)$$

The net effect index of risk spillover can be obtained from the above equation, namely:

$$S_i^q(H) = S_{i \cdot}^q(H) - S_{\cdot i}^q(H) \quad (7)$$

Similarly, the net effect index of risk spillover between two variables is:

$$S_{ij}^q(H) = \left(\frac{\bar{\theta}_{ji}^q(H) - \bar{\theta}_{ij}^q(H)}{N} \right) \times 100 \quad (8)$$

Using the risk spillover net effect index, we evaluate the risk output and input direction of variables. Therefore, in the next portions of this paper's study, we use the risk spillover net effect index to look at how industry variations are translated into high employment risks.

4. Sample Data Processing

This paper chooses the year-on-year change rate of urban unemployment from the first quarter of 2004 to the second quarter of 2022 (hereinafter referred to as the urban unemployment rate or unemployment rate) and the period from January 2004 to June 2022 to measure the relationship between employment and industry dynamics over a longer period. The industry's volatility data are a mixed frequency sample data set that includes monthly and quarterly data. The quarterly urban unemployment rate data in this paper comes from the database on the website of the National Bureau of Statistics of China (<https://data.stats.gov.cn/>, accessed on 5 February 2022), which is the employment

data sample with the longest time horizon to date, and the stock return data required for calculating sectoral fluctuations comes from China Stock Market & Accounting Research Database (<https://cn.gtadata.com/>, accessed on 5 February 2022). Schorfheide and Song (2015) [40] recommended that we treat the unobservable monthly urban unemployment rate as a state variable, build a state space equation, and estimate the urban unemployment rate at the monthly level using the Bayesian approach. For 31 large cities, the National Bureau of Statistics also provides monthly urban unemployment rate survey statistics, but the data are relatively recent (the records only go back to 2018). The graph of the urban unemployment rate in 31 major cities is shown in Figure 1 below, along with the original and mixed-frequency estimated urban unemployment rates. We can see that the three measures' fundamental trends are consistent, particularly following COVID-19's impact in January 2020, when the three unemployment variables all revealed the same ups and downs.

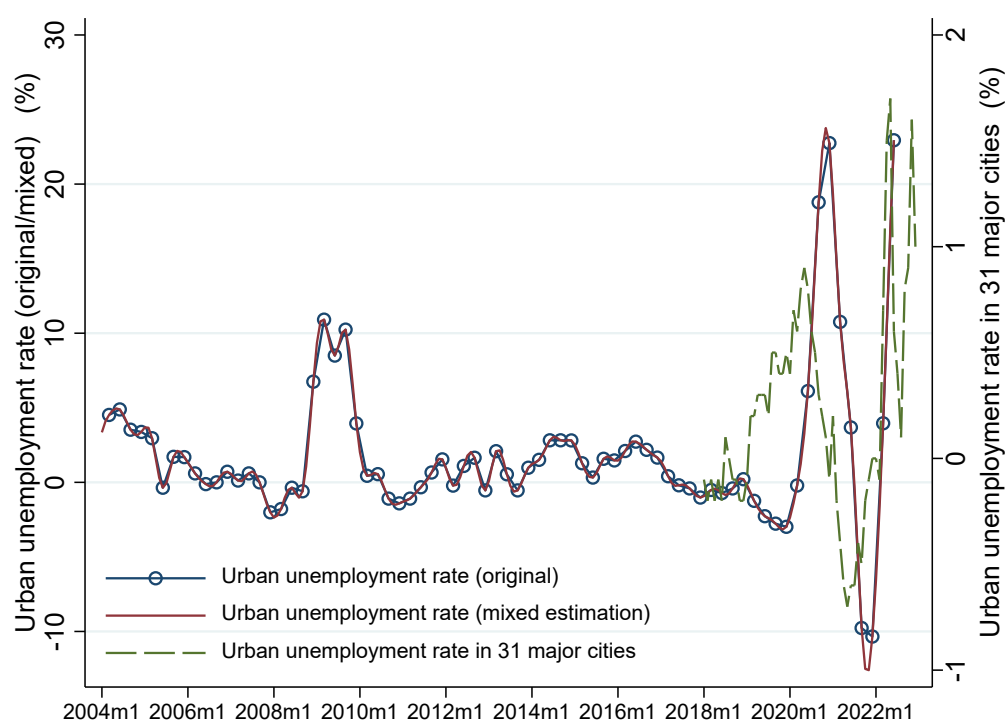


Figure 1. 2004–2022 Urban Unemployment Rate in China.

This study divides China's A-share listed firms into three main categories, including technology-intensive, capital-intensive, and labor-intensive industries, based on the concentration of production components. The latter qualifier further categorizes listed corporations in labor-intensive industries based on the number of worker skills. Technical labor-intensive, comprehensive labor-intensive, and manual labor-intensive are the three different sorts of industries [41]. We choose a sample of daily stock returns from January 2004 to June 2022, calculate the monthly standard deviation (SD) of daily returns, and then apply the equation from Diebold and Yilmaz (2012) [8] to convert to annualized standard deviation of returns to match the unemployment period.

$$\tilde{\sigma}_{it} = 100 \times \sqrt{365 \times 0.361 \times SD^2} \quad (9)$$

Then, we determine the industry volatility by calculating the standard deviation of the average annualized rate of return of the industry weighted by the circulating market. Next, we create the QVAR equation using the monthly industry volatility data and the derived monthly unemployment rate. We next use the elastic network technique to estimate

the equation's parameters, and, based on this calculation, we determine the value of the relevant risk spillover index.

The descriptive statistics and associated statistical tests for the variables used in this study are shown in Table 1 below, including the Jarque–Bera (JB) test, which measures normality. The test results for the unemployment rate and the volatility of the five industries in Table 1 all contradict the null hypothesis of a normal distribution, demonstrating the need for QVAR and that the distribution of the sample data are skewed. The unit root is the null hypothesis in the stationarity test known as the ERS. The ERS test results reveal that every variable has rejected the unit root null hypothesis, proving the stability of the variables used in the QVAR model. The Q test is a test used to determine whether the time series under consideration exhibits serial correlation. If the time series exhibits the clustering phenomena, there is a significant serial correlation. The Q test results in Table 1 disproved the null hypothesis that there is no serial connection, indicating that exceptional events are probably clustering the distribution of variable sequences.

Table 1. Descriptive statistics and tests.

	Unemployment Rate	Industry Volatility				
		Technology Intensive	Capital Intensive	Skilled Labor Intensive	Comprehensive Labor Intensive	Manual Labor Intensive
Mean	1.843	55.82	46.13	54.50	52.91	51.37
Variance	24.97	295.07	347.00	314.61	301.03	354.51
Skewness	1.838	1.678	1.285	1.391	1.434	1.500
kurtosis	6.297	4.101	1.326	2.221	2.142	2.426
JB test	491.71 ***	259.67 ***	77.39 ***	117.21 ***	118.46 ***	137.76 ***
ERS test	−5.350 ***	−3.220 ***	−2.407 ***	−3.006 ***	−2.715 ***	−2.790 ***
Q test	501.338 ***	369.38 ***	614.53 ***	423.14 ***	521.20 ***	532.46 ***

Note: *** indicate significance at the 1% statistical level.

5. Mean-Based Employment and Industry Risk Spillovers

To compare the findings of the sub-number risk overflow effects in the following section, this section first gives the findings of the dynamic risk overflow based on the mean. Our scrolling estimated average risk overflow effect model was used to determine the dynamic risk overflow impact following Diebold and Yilmaz's (2012) [8] methodology. Due to the low frequency and low monthly sample volume, we picked a rolling estimation window of 72 months (6 years). So, starting in January 2010, the value of the dynamic risk overflow is determined. Due to the monthly sample period's limited characteristics, the average VAR model is set to 3 periods, with Phase 1 as the projected period.

The unemployment rate as determined using Equation (7) and the dynamic risk overflow of the five industries are shown as a net effect in Figure 2 below. Industry risks have an impact on unemployment rates, whereas hazards have an impact on labor- and technology-intensive industries. As a result, the output of industry risk and the tolerance for employment risk are directly related. The capital-intensive industry's level of risk overflow is relatively modest, and most of the periods have negative spillover effects, suggesting that the industry is unlikely to have an impact on the unemployment rate. The average risk of the unemployment rate having negative net consequences was approximately −13.33% when measured in terms of quantity. Quantitatively, the capital-dense sectors were around −3.29%, the technology-intensive industries were about 6.56%, and the average risk of the unemployment rate surpassing net impacts was about −13.33%. An average risk correlation of 10.06% was seen among the three labor-intensive industries.

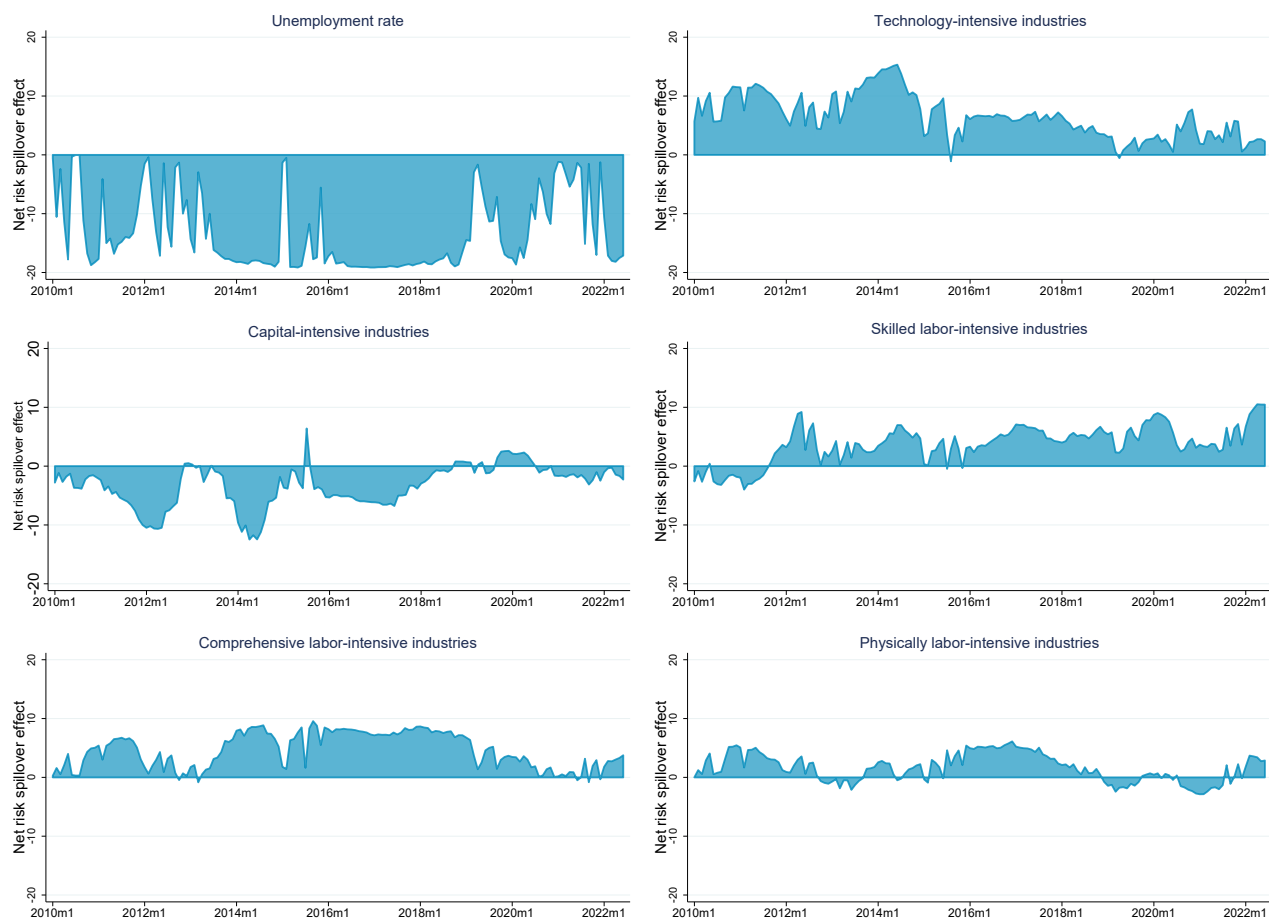


Figure 2. The net effect of unemployment rate and industry risk overflow (%).

Figure 2 does not identify the specific industries at risk; it just depicts the detrimental impact of employment on the risk of external shocks to all industries. We rolled evaluated the dynamic risk spillover impact between pairings in accordance with Equation (8) to precisely grasp the risk transmission effect of industrial categories on the unemployment rate. The results are shown in Figure 3 below.

We further categorized labor-intensive businesses into skilled labor, comprehensive labor, and manual labor-intensive industries since they employed more listed companies and were the subject of this paper. Figure 3 demonstrates that the five industrial types all transmitted risk to the unemployment rate, with the capital-intensive industry having a weaker risk spillover effect than the other four categories. Additionally, the employment risk grew when the level of physical work elements rose. Compared to the distribution-based estimates below, the average risk spillover effect of a single industry on the unemployment rate, as measured quantitatively, was only about 0.6%. We could also see that the net spillover effect of various industry changes on employment levels dramatically decreased in the time following the start of the epidemic. Given this circumstance, the epidemic's spread may first directly disrupt the employment group, affecting the industry, and reducing the overall impact of risk spillovers.



Figure 3. Mean Risk Transmission Between Unemployment Level and Industries (%).

6. Distribution-Based Employment and Industry Risk Spillovers

6.1. Overall Distribution of Employment and Industry Volatility Risk Spillovers

We first look at the overall distribution of employment and industry volatility's net risk spillover effect or how all external risks, as determined by the Equation (7), affect the quantiles of employment and industry volatility. The net impact of distributional risk spillovers is assessed using the same parameters as the mean risk spillover model in Section 5. The net impact of distributional risk spillovers is calculated on a rolling basis for each month using the same settings as the mean risk spillover model in Section 4. The quantile (q) in Figure 4 below indicates the net risk spillover effect of external risk shocks on the unemployment rate distribution. When the employment level is in an extremely good state (the unemployment rate quantile is in the range of 0.05–0.15) or when the employment level is in an extremely bad state (the unemployment rate quantile is in the range of 0.85–0.95), which is when external risk shocks are most deeply felt, we can see that the employment group has always been a risk bearer. The influence of external threats is minimal when the employment level is in a normal state, i.e., when the quantile of the unemployment rate lies between the two extreme ranges. External shocks have the least impact when the unemployment rate is at its 0.55 quantile. Quantitatively, compared to the mean-based risk spillover impact (13.33%), the average risk spillover effect on the unemployment rate in the extreme range is 24.17%. The average risk spillover impact that is experienced under typical conditions is 9.11%, which is less than the risk spillover effect calculated using the average value. The severe risk is 2.65 times greater than the average risk, which has significant economic implications. Additionally, we can see that the external

extreme risk spillover effect of the unemployment rate before the COVID-19 (2010–2019) is distributed evenly across each year, showing that China's labor market has a relatively high-risk exposure and is susceptible to external risk shocks during the sample period (2019–2022). After the outbreak of COVID-19 (2020–2022), the spillover effect of external extreme risks to the unemployment rate has weakened, which may be due to three reasons: first, the lockdown and social distancing policies adopted to prevent the spread of COVID-19 may weaken the effective transmission channels of unemployment in other sectors; second, the hedging policies adopted by the Chinese government to withstand the impact of the epidemic have mitigated the negative effects of industry shocks on employment to a certain extent; third, some industries (such as healthcare and consumer goods) experienced significant increases in demand during the pandemic, which offset the unemployment effects in other sectors.



Figure 4. Net Risk Spillover Effect of Unemployment Rate Distribution (%).

The net spillover effect of volatility distribution in capital- and technology-intensive businesses from 2010 to 2022 is depicted in Figure 5 below. Most of the time, capital- and technology-intensive industries are risk-outputting sectors and only sometimes engage in risk-taking. The volatility risk spillovers of the two main industry sectors both display an extreme value distribution pattern, which is similar to the pattern shown in Figure 4. The net effect of risk spillover over time is greatest at the lowest and highest quantiles, but it is very small in the medium quantile range. The extreme spillover effect is 1.9 times greater than the general spillover effect and has significant economic implications for technology-intensive industries, with net spillover effects in the two extreme quantile ranges of 0.05–0.15 and 0.85–0.95 being, on average, about 5.76% and 3%, respectively. The extreme spillover effect for capital-intensive businesses is twice as great as the general spillover effect, and

its economic impact is also significant. In relative terms, the extreme spillover effects of capital-intensive industries are weaker than those of technology-intensive industries, which indicates that the direct and indirect employment-absorbing effects of capital-intensive industries are weaker than those of technology-intensive industries. From the perspective of the time-series change in the risk spillover effect of extreme cases, the change in the risk spillover effect of technology-intensive industries is relatively stable, whereas the risk spillover effect of capital-intensive industries changes more in extreme bad scenarios, reflecting the stronger economic cycle sensitivity of capital-intensive industries. There are evident disparities in the distribution spillover effects of the subdivision industry categories, as shown in Figures 6–8 below, which indicate the net effect of fluctuation distribution spillovers of the three labor subdivision industries. Figure 6 shows that risk acceptance is typically dominant in skilled labor-intensive businesses. Combining the data in Figures 9–11, we can conclude that the risk input for skilled labor-intensive industries that require a high level of labor is caused by fluctuations in other industries rather than spillovers from the risk of unemployment. Figure 6 further demonstrates that industries that depend heavily on skilled labor are less influenced by extreme events than they are by general ones, demonstrating that the risk of extreme employment for skilled labor is relatively low and that they belong to a stable employment group. Comprehensive and manual labor-intensive industries are primarily based on risk output, and, as the level of labor skills declines, the depth to which their risk spillover effects are affected by extreme events is deeper. This finding suggests that low-skilled physical strength labor-intensive industries are more vulnerable, and, as the level of labor skills declines, the extreme risk of employment of workers rises. The above analyses are consistent with the theoretical logic and testable research hypotheses of this paper.

6.2. Distributed Risk Transmission between Employment and Industry Fluctuations

This section especially looks at the Equation (8)-derived pairwise distribution transmission relationship between employment fluctuations and industry variations. The net impact of risk spillovers at employment and industry volatility quantiles of 0.05 and 0.95 is depicted in Figure 9 below, where quantile 0.05 denotes an extremely unfavorable scenario, and quantile 0.95 denotes an extraordinarily favorable situation. We may observe that changes in five industries have a large impact on employment in severe circumstances. The average net effect of individual industry risk spillovers is roughly 4.9%, with a high of 8.4%. The risk spillover impact based on the average, in comparison, is only 0.6% on average, demonstrating that it is unable to accurately reflect the employment risk. Figure 9 demonstrates that the distribution of the extreme risk of the unemployment rate is symmetrical, i.e., the influence of industry variations on unemployment rate risk transmission is essentially the same in both extremely favorable and extremely bad circumstances. At the same time, we can also discover that capital-intensive industries and labor-intensive technology-intensive businesses both, in extreme circumstances, have a substantial risk of transmission to the unemployment rate in contrast to the above findings. From the perspective of time-series changes in extreme risk spillovers, after the outbreak of COVID-19 and among the three labor-intensive industries, the technology-intensive industry has the smallest extreme risk spillover effect on unemployment rate fluctuations, followed by the comprehensive labor-intensive industry, and the manual labor-intensive industry has the largest extreme risk spillover effect on unemployment rate, which is consistent with the research hypothesis of this paper. Autor and Dorn (2013) [38] argue that there is polarization in the labor market, i.e., high-skilled and low-skilled workers have a lower risk of unemployment, whereas medium-skilled workers have a higher risk of unemployment. However, their study does not provide a comparison of the unemployment risk of different skilled workers in extreme cases, whereas the results of this paper show that low-skilled workers have a greater risk of unemployment (in the form of higher extreme unemployment risk spillover effects in manual labor-intensive industries) in extreme bad cases, which is a useful supplement to existing research.

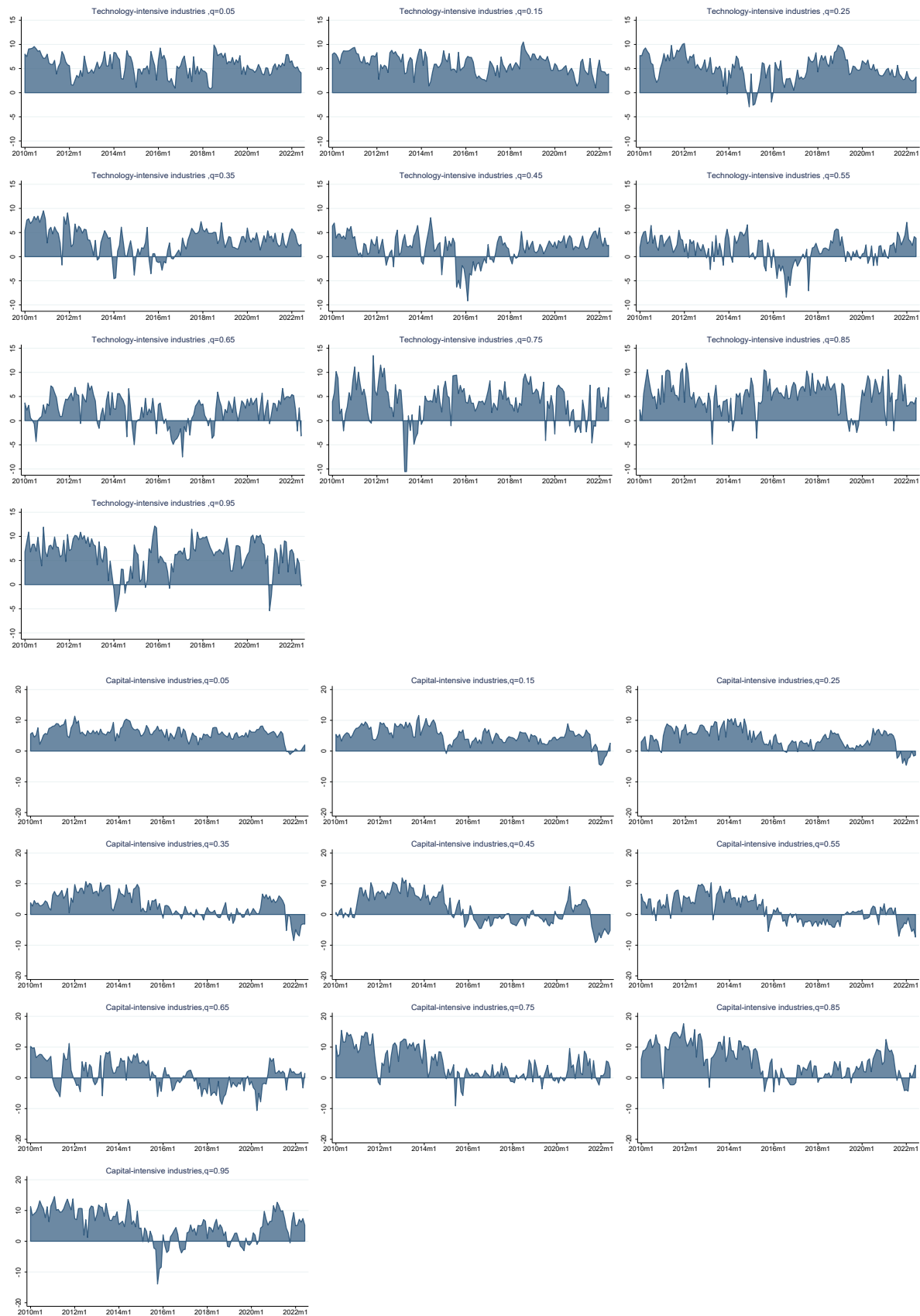


Figure 5. The net effect of risk spillovers on the volatility distribution of technology–intensive and capital-intensive industries (%).



Figure 6. The net effect of risk spillovers on the volatility distribution of skilled labor-intensive industries (%).

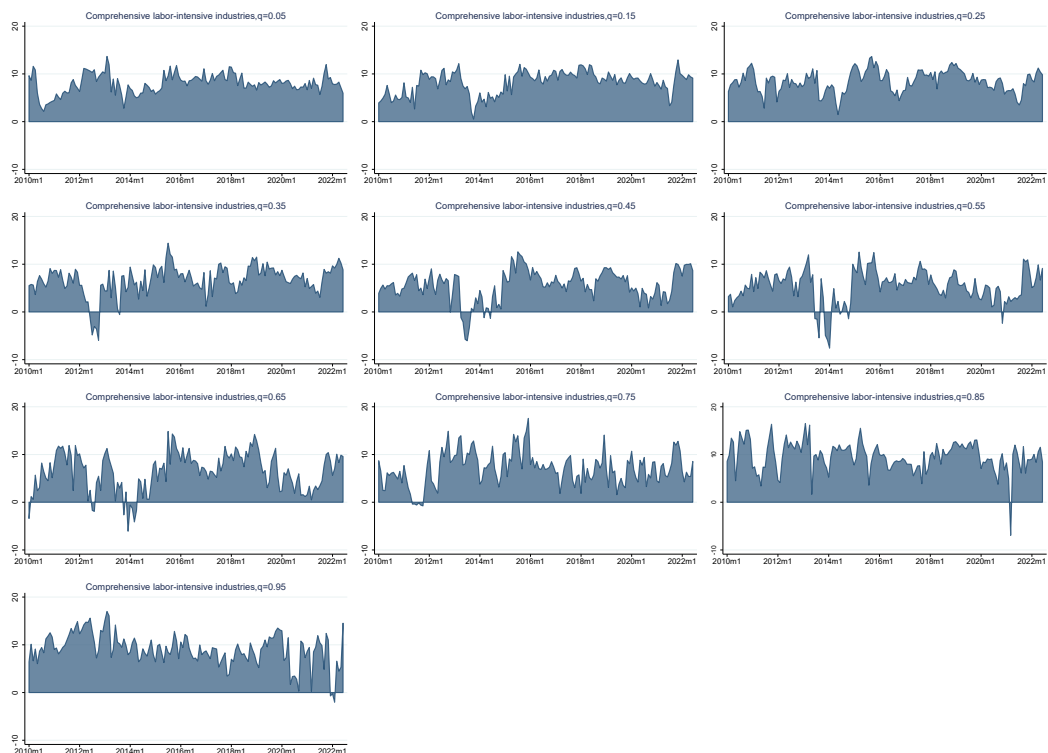


Figure 7. The net effect of risk spillovers on the volatility distribution of comprehensive labor-intensive industries (%).



Figure 8. The net effect of risk spillovers on the volatility distribution of manual labor-intensive industries (%).

The impacts of industry fluctuations with quantiles between 0.35 and 0.65 on the unemployment rate are depicted in Figures 10 and 11, respectively. Figures 10 and 11 demonstrate that the effects of the five industries' risk spillover on the unemployment rate are substantially less severe compared to the extreme situation. The average risk spillover net effect is only 1%, and, for quantiles nearer the median, the unemployment rate's risk is negative. The distributional spillover pattern we discovered in the preceding section is consistent with the lesser spillover. Figures 10 and 11 also demonstrates that, even under normal conditions since the epidemic's outbreak, the impact of industry risk on the unemployment rate has generally increased, with low-skilled labor-intensive industries having a stronger impact than higher-skilled labor-intensive industries. This finding is similar to the one in the previous section.

In summary, by using the distribution-based model of extreme risk spillovers to measure the net effect of risk spillovers between each industry and the unemployment rate, the conclusions we obtain in this section are consistent with the results of the measurement of overall industry risk spillovers in the previous section and are also in line with the research hypotheses of this paper.

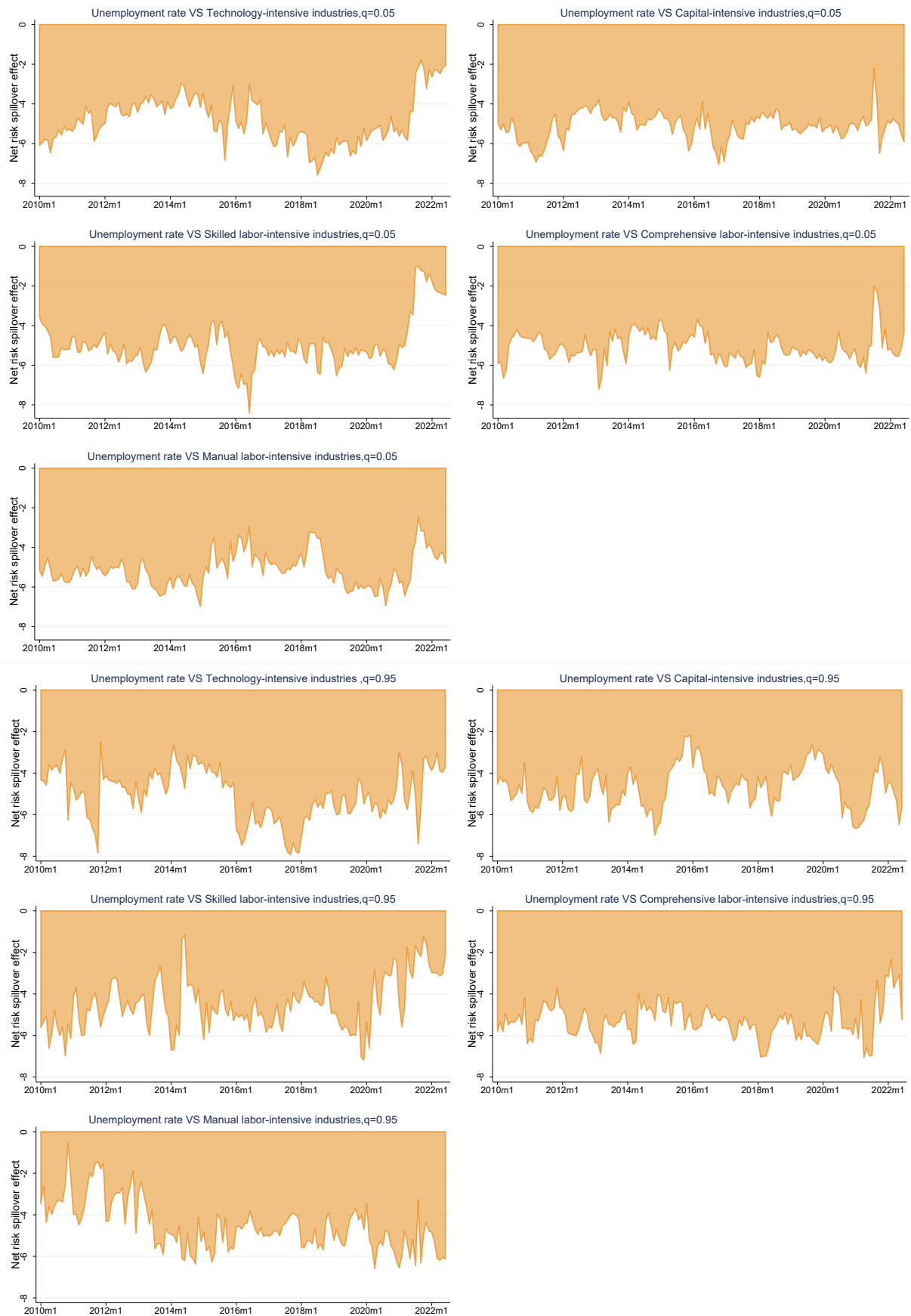


Figure 9. Extreme Risk Spillover Effects of Industry Volatility Affecting Employment (%).

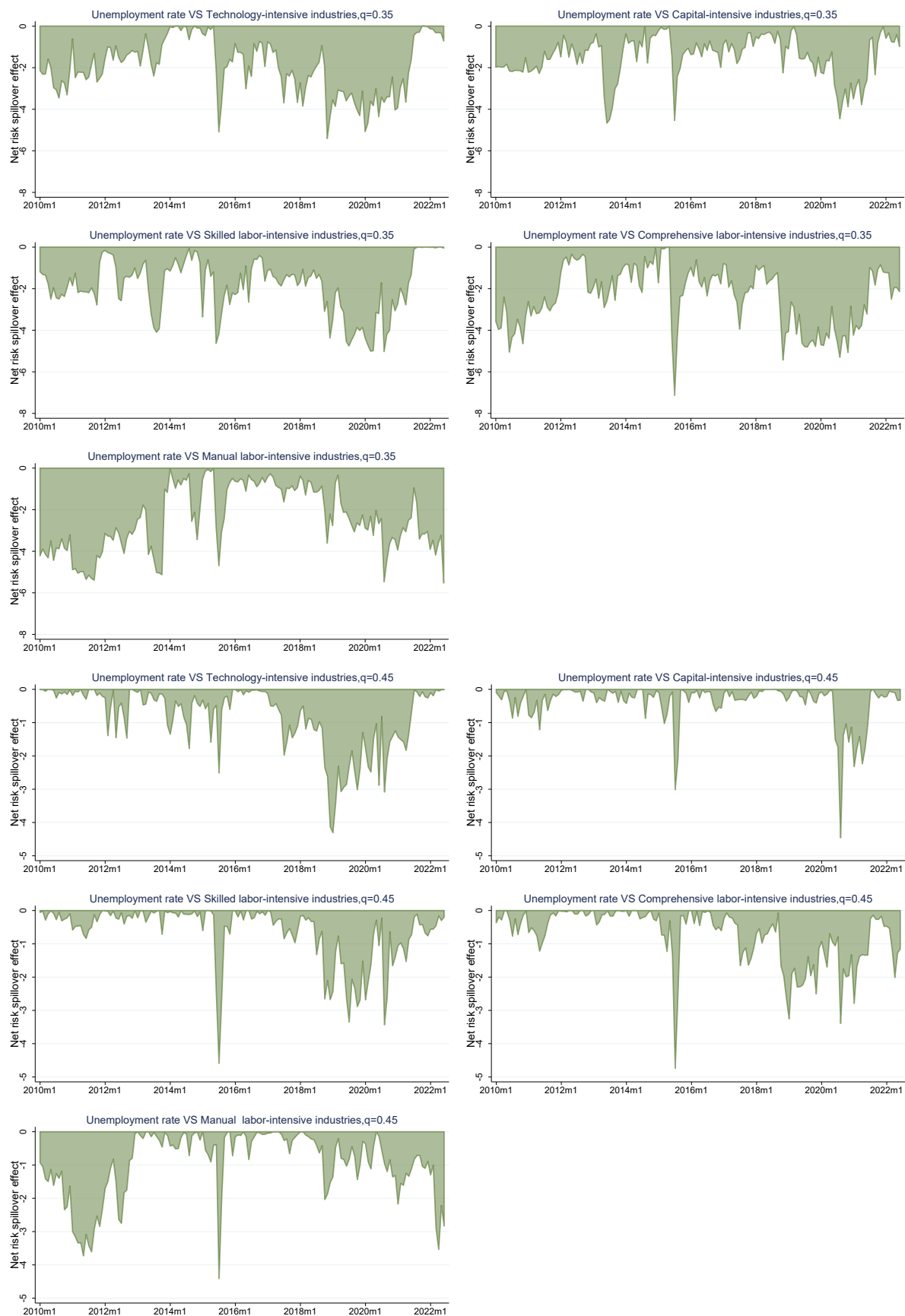


Figure 10. General Risk (the unemployment rate quantile is in the range of 0.35–0.45) Spillover Effects of Industry Volatility on Employment (%).

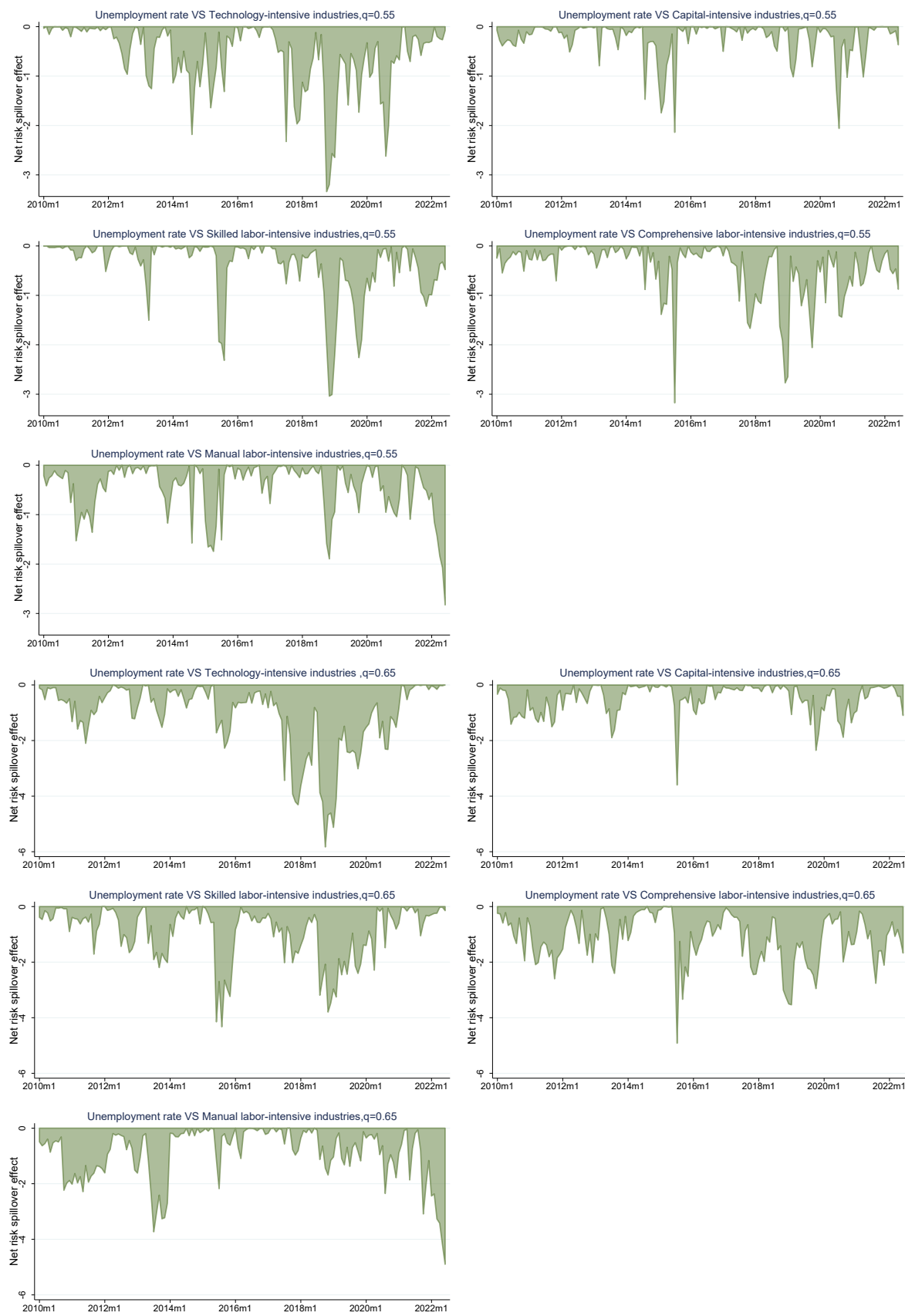


Figure 11. General Risk (the unemployment rate quantile is in the range of 0.55–0.65) Spillover Effects of Industry Volatility on Employment (%).

7. Conclusions

In this paper, using a cutting-edge dynamic quantile risk spillover model, we analyze the volatility relationship between industry sectors and employment under times of severe risk. The new findings from this research are as follows.

First, as industry sector changes have a major impact on China's employment fluctuations, a risk spillover model based on the mean is unable to account for extremely high employment risks. The average sum of the risk spillover from industry variations to the unemployment rate is 13.33%, and the average risk spillover from a single industry to the unemployment rate is 0.6%, according to the risk spillover model based on the mean value. The unemployment rate's average risk spillover from all industries combined is 24.17%, and the unemployment rate's average risk spillover from just one industry is 4.9%. Therefore, the extreme employment risk in China differs greatly from the risk impact under normal circumstances, and the risk spillover model based on the mean cannot accurately capture this extreme risk.

Second, under both extremely poor and extremely good conditions, the industry has the biggest risk of spillover effect on employment; but, under typical conditions, this effect is quite weak. According to the calculations, the risk spillover effect of all industries on employment in severe situations is 2.65 times greater than it would be in normal situations, and the risk spillover effect of each industry individually on employment is 4.9 times greater than it would be in normal situations. As a result, the major source of employment risk in China is the high risk brought on by extraordinary events.

Third, among labor-intensive industries, manual labor-intensive sectors have a relatively strong impact on employment while technical labor-intensive sectors, and comprehensive labor-intensive sectors have a relatively weak impact, making groups with weaker labor skills more susceptible to severe risks.

The analysis in this study demonstrates that the mean-based risk spillover effect indicator cannot accurately reflect the source of risk transmission, and the real transmission effects that cause variations in unemployment and that greater emphasis should be paid to the distribution heterogeneity of employment fluctuations. The existing literature on the influence of industry sector fluctuation on employment level has basically ignored the employment fluctuation in extreme cases, especially the extreme fluctuation effect caused by fluctuations in industries with different types of labor skills. Although there is a small amount of empirical literature focusing on the macro-economic factors affecting the extreme risk of employment, such literature has largely ignored the role of industry heterogeneity. Therefore, the extreme risk transmission effect of industry volatility on employment revealed in this paper is a relatively novel empirical test result. The research conclusions of this paper are consistent with the theoretical logic based on frictional factors in the labor market and fixed costs of business operation (Cooper et al., 1999; Cooper and Haltiwanger, 2006; Stokey, 2009) [1–3]. On this ground, in order to reduce the negative economic consequences of a sharp decline in employment under extreme circumstances, it is necessary to take effective measures to increase the liquidity of the labor market, reduce the cost of adjusting the labor contract, and provide a certain degree of financial subsidies for the expansion of investment by firms in the stage of recession in order to promote employment in a more targeted manner.

This study also had some limitations. Although we provided a clear theoretical description of the sources of industry shocks, due to the lack of relevant literature and methodological guidelines, we have not identified and decomposed different sources of industry shocks in our empirical tests, so as to more effectively reveal the channels through which different types of economic shocks at the industry level lead to employment fluctuations. We will find effective identification and disaggregation methods in our subsequent studies and continue to promote the in-depth expansion of relevant research.

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