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TFP SHOCKS AND ENDOGENOUS INNOVATION ABILITY IN MANUFACTURING INDUSTRY: FROM THE PERSPECTIVE OF STRUCTURAL STICKINESS

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Abstract. This paper identifies the systemic shocks of total factor productivity (TFP) at the macro level and industry level, and then evaluates the structural stickiness of TFP shocks by using information entropy and industry correlation degree through counterfactual structural simulation based on China's manufacturing companies. We find that: in the face of TFP systemic shocks, the industries with less structural stickiness include computer communication and other electronic equipment manufacturing, special equipment manufacturing and general equipment manufacturing, indicating that these industries have a strong internal innovation power. The TFP distribution of electrical machinery and equipment manufacturing industry and ferrous metal smelting and rolling industry showed structural differentiation, and the lower tail enterprises are not sensitive to TFP shocks. The industries with strong structural stickiness are non-ferrous metal processing industry and non-metallic mineral products industry, etc., which have weak internal innovation power and need exogenous innovation incentives. In addition, there is a significant positive correlation between industry correlation and information entropy, which emphasizes the radiation effect role of industries with high industry correlation degree. The research provides a new method to evaluate the innovation ability of the industry and a basis for the differentiation of innovation incentive policies in the industry.

Keywords: total factor productivity shocks, manufacturing industry, structural viscosity, endogenous innovation.

JEL Classification: C51, L6, O35.

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1. Introduction and literature review

Since the global financial crisis in 2008, the external uncertainty of China's economy, especially the manufacturing industry, has intensified. In the meantime, the shocks of COVID-19 make the upgrading of the manufacturing industry and the high-quality operation of the macro economy face many challenges in the "post-epidemic" period (Feng et al., 2024). Total factor productivity (TFP) is a combination of technological progress, technological efficiency improvement and industrial structural transformation (Buccirossi et al., 2013; Syverson, 2011), and it is also a significant manifestation of endogenous innovation capability. Acemoglu (2015) pointed out that China's economic miracle in recent decades is mainly due to resource reallocating rather than endogenous technological innovation, and Maćkowiak and Wiederholt (2015) pointed out that technology shocks can explain about 80% of China's economic fluctuations. The above facts show that the improvement of TFP plays a very important role in China's macro economy, and China's current level and structure of total factor productivity still have a lot of room for improvement and optimization (Lin et al., 2023). The manufacturing industry is the foundation of China and the foundation of a strong country (Hu et al., 2023; Li, 2013). Therefore, effectively identifying the dynamic evolution law of TFP systemic shocks and evaluating its specific impact on the distribution structure of manufacturing productivity could provide decision-making basis for accelerating the implementation of innovation-driven development strategy.

Deepening supply-side structural reform of China in recent years is to promote structural adjustment, reduce ineffective and low-end supply, enhance the adaptability and flexibility of the supply structure to changes in demand, and thus increase total factor productivity. Therefore, the assessment of the dynamic effects of TFP shocks should not only be concerned with the changes in the average value, but also pay attention to the changes in its distribution structure.

The purpose of this paper is to effectively identify the systematic shocks to TFP in China's manufacturing industry at the macro level and industry level and their dynamic evolution laws based on the micro performance of manufacturing firms. Further, at the meso-level, it systematically assesses the structural stickiness of each major industry in the manufacturing sector in the face of TFP systemic shocks (The driving force of TFP shocks on the structure of TFP distributions of manufacturing firms). If the structure of industry TFP distribution is sensitive to TFP shocks, the structural stickiness is small which show the industry's intrinsic innovation drive is relatively strong, and the government only needs to give a small amount of support to these industries to generate efficient economic consequences. On the contrary, if the structure of the industry TFP distribution is sticky, then the industry's intrinsic incentive to innovate is weaker, and powerful exogenous incentives to innovate are necessary. Differences in the sticky structure of industry TFP distribution are in fact differences in the intrinsic innovation dynamics of different industries, which could provide a policy basis for differentiated innovation incentives.

Existing methods to measure industrial innovation capability focus on input and output of innovation (Kaplinsky & Readman, 2005), such as TOPSIS (Li et al., 2022) and DEA (Lin et al., 2023). However, the selection of indicators changes with the changes of the industry. Patents are generally used as indicators to measure the innovation capability of high-tech manufacturing. For example, Grindley and Teece (1997) uses patents and other intellectual property rights to measure the innovation ability of high-tech industries; Tseng and Wu (2007) used five patent-related indicators, including the number of patents and the rate of patent citations, to evaluate the innovation quality of the automotive industry; Orlando et al. (2020) used the number of enterprises applying for patents as the innovation capability of the medical industry; Yu et al. (2020) takes the elasticity of invention patent output as an indicator of innovation ability in high-tech industries. However, for some light industries, most studies measure industry innovation ability based on new product development and service creation. For example, Kaplinsky and Readman (2005) uses product unit price and market share to measure the innovation ability of furniture industry. It can be found that it is difficult to use a unified index to quantify the innovation ability of an industry (Malewicki & Sivakumar, 2004; Moser, 2012). Although patent data are widely used, there is no single linear relationship between patent and innovation output (Crepon & Duguet, 1997), and patent data in different patent databases vary widely (Kim & Lee, 2015). In addition, there is a problem of time lag in the disclosure of patent data (Fisch et al., 2017).

In fact, the growth rate of TFP is also an important characteristic of innovation capability (Antonelli & Scellato, 2011; Cameron et al., 2005), which is more generally applicable to most industries. The higher the growth rate of TFP, the stronger the innovation ability of the industry, indicating that the TFP of this industry is more sensitive to a series of factors. Currently, although there is a large body of literature studying the effects of various shocks on TFP, there are relatively few literatures analyzing the impact of systemic shocks on the distribution structure of TFP in manufacturing. The existing literatures mainly focused on the effect of influencing factors on the average level of TFP, rather than the change of distribution structure. Some of them measured the quantitative relationship between technological progress, capital input, manufacturing agglomeration and total factor productivity of enterprises by means of mean regression. Examples include Griliches (1980), Griliches and Mairesse (1981) and Harhoff (1998). Other literatures analyzed the specific contribution of technology shocks to TFP based on the decomposition of TFP, such as León-Ledesma et al. (2010, 2015), Klump et al. (2012) and Zhen et al. (2021).

Obviously, revealing the effect of systemic shocks on the distribution structure of TFP in major manufacturing industries could provide more comprehensive and targeted structural information for the formulation and implementation of industrial policies from the perspective of the transformation and upgrading of the manufacturing industry.

In view of the above, this paper studies the specific impact of systemic shocks on the distribution structure of TFP in major manufacturing industries and the internal structure of macroeconomic operation based on the micro-data of manufacturing enterprises. Compared with the existing literatures, the innovations of this paper are mainly reflected as follows:

First, we construct TFP multiple shocks model and identifying TFP systemic shock factors at both macro and industry levels, which provides a new perspective for measuring economic shocks at multiple levels. Second, based on panel quantile regression, we determine the distribution structure of TFP in the manufacturing industry with and without systemic shocks, and the structural stickiness of systematic shocks to TFP in each major manufacturing industry was comprehensively evaluated from the perspectives of information entropy and industry correlation degree, which clearly demonstrates the heterogeneity of the innovation capabilities of firms at different levels and provides a benchmark for targeted and differentiated industry innovation policies. Third, unlike traditional studies that use patent aggregation to quantify the innovation capacity (Bena et al., 2022; Li et al., 2019; Yuan & Wen, 2018), we quantify industry innovation ability from the perspective of structural stickiness of TFP to overcome the problem of not reflecting structural changes, industry changes and the disclosure time lag problem that cannot be reflected by patents (Fisch et al., 2017).

The remaining contents of this paper are arranged as follows. The second section describes the identification of systemic shocks of TFP and the measurement method of the viscosity of the distribution structure of TFP in manufacturing industry. The third section presents the sample data description and statistical description, including the measurement method of enterprise TFP. The fourth section reports the evaluation results and analysis of TFP on structural viscosity of systemic shocks in manufacturing industry. The fifth section further analyzes the structural stickiness and industry correlation degree of manufacturing industry. The sixth section is the conclusion of this paper.

2. Methods: identification of systematic shocks in TFP and measurement of structural stickiness

The change of TFP of enterprise is not only affected by individual factors, such as R&D investment, technology accumulation, organizational structure and incentive mechanism, but also affected or restricted by external environmental factors, such as macro environmental factors and industry cycle factors. Different from individual factors, the shocks of macro factors are the same for all enterprises, and the industry factors are the same for all enterprises in the industry. Therefore, the shocks of macro factors and industry factors on enterprise TFP are systemic common shocks.

In this section, we identify macro shocks and industry shocks to TFP in manufacturing firms effectively first. Further, the sensitivity of the TFP distribution structure of each major industry in the manufacturing sector to systemic shocks is analysed, that is, the stickiness of the TFP distribution structure to systemic shocks is assessed.

2.1. Identification of systematic shocks in TFP

The current literatures on the identification and estimation of TFP shocks can be roughly divided into four categories. The first method is constructing indicators to measure TFP shock, such as Glick and Rogoff (1995), Decressin and Disyatat (2008), Bussière et al. (2010) and El-Shagi (2023). They take the deviation of individual TFP from the weighted average TFP of the whole population as the TFP shocks of the individual. The second method of identification of TFP shocks is by processing TFP time series. For example, King et al. (1987) identified the persistent impulse of TFP based on the neoclassical stochastic growth model; DeJong et al. (2000) used seasonal time series decomposition to obtain TFP shocks. The second method of identification of TFP shocks is by panel data model. For example, Salgado et al. (2019) established a dynamic panel model with TFP as the explained variable, and took the residual as the proxy variable of TFP shock after eliminating time and individual fixed effects. The fourth is to decompose TFP directly. For example, Schulze (2007) used Shift-Share Analysis to isolate technology shocks from TFP; Zhen et al. (2021) and Chen et al. (2022) used stochastic frontier analysis (SFA) or other decomposition methods to estimate TFP and decompose technical progress and technical efficiency.

The essence of above methods is numerical transformation or decomposition of individual TFP of enterprises. However, these methods cannot identify the common shocks at the macro and industry level which are the systemic shocks.

Systemic shocks come from the economic environment and policy changes. Among them, changes in domestic and foreign economic environment are mainly manifested as systemic macro shocks (Yang & Yang, 2023b) (such as the international financial crisis in 2008), while policy changes are not only manifested as systemic macro shocks, but also reflected in systemic industry shocks (such as China's supply-side reform in 2015). Because China's industrial policies are very targeted and highly interventionist, the impact on enterprises in different industries is significantly different. These shocks are difficult to quantify, so we choose a TFP multiple shocks model to identify macro TFP shocks and industry TFP shocks from the disturbance terms.

Given firms' TFP, this paper identifies macro-level and industry-level systematic shocks through a two-level factor interaction effects panel model. The model is shown as follow:

$$TFP_{it,\tau}^{s} = X_{it}^{s}\beta + u_i + \varepsilon_{it}^{s}; \tag{1}$$

$$\varepsilon_{it}^{s} = \gamma_s^{'} g_t + \lambda_i^{s'} f_t^s + v_{it}^{s}, \tag{2}$$

$$s = 1,2,\ldots S;\, i = 1,2,\ldots,N_s;\, t = 1,2,\ldots,T; N = \sum_s N_s,$$

where $TFP_{it,\tau}^{s}$ is the TFP of firm i in industry s in period t. X_{it}^{s} is the control variable that can be quantified. u_i is the individual fixed effect. ε_{it}^{s} and v_{it}^{s} are both perturbation terms. g_t is the macro shock that all firms face in common, and γ_s is the loading of g_t, reflecting the sensitivity of the response of industry s to the macro systematic shocks. f_t^s is the common shock faced by industry s, and λ_i^s is its loading, reflecting the responsiveness of firm i within industry s to industry shocks.

Referring to Bai and Wang (2015), We apply the following constraints to ensure that macro shock factors and industry shock factors are identifiable:

$$Cov\left(g_t, f_t^s\right) = 0. \tag{3}$$

The consistent estimation of Eq. (1) ~ Eq. (2) can be achieved, and the estimates of macro factors, industry factors and their loads can be obtained by referring to Bai (2009) and Yang and Yang (2023a, 2023b) and the iterative algorithms based on LSDV and principal component analysis (PCA)[1].

2.2. Measurement of structural stickiness

In order to clarify the effect of systematic shocks of TFP on the distribution structure of TFP in manufacturing industry, the distribution of TFP in each major industry with and without systematic shock is constructed. Then, the structural stickiness of TFP distribution to systemic shocks is revealed by their distribution curves and information entropy.

This analysis is essentially a counterfactual analysis. In other words, we assess the sensitivity of TFP distribution structure to systemic shocks by simulating the counterfactual distribution of TFP in the absence of systemic shocks.

2.2.1. Distribution fitting of TFP with and without shocks

Mean regression fits the distribution of the conditional expectations of the explanatory variables rather than the distribution of the variables themselves, so we need quantile regression to fit the empirical distribution of TFP. The equation fitted to the distribution of TFP in the context of a systematic shocks is as follow.

$$TFP_{it,\tau}^{s} = X_{it}^{s}\beta_\tau + \gamma_{s\tau}' \hat{g}_t + \lambda_{i\tau}^{s'} \hat{f}_t^s + \varepsilon_{it,\tau}. \tag{4}$$

[1] Detailed steps of the iterative algorithm are shown in Appendix.

Among them, τ is the partial site. $\hat{g}_t$ and $\hat{f}_t^s$ are the macro shock factors and industry shock factors estimated in Eq. (1) ~ Eq. (2). Accordingly, if there are no systematic shocks, that is, if only individual random shocks are assumed, then the fitting equation for the counterfactual distribution of TFP is as follow:

$$TFP_{it,\tau}^{s,u} = X_{it}^s \beta_\tau + u_{it,\tau}. \tag{5}$$

The above two regression equations can be uniformly estimated by panel quantile regression estimator (Powell, 2020, 2022). Based on the estimated results, the fitting quantiles of TFP under the two scenarios are:

$$\hat{Q}_{TFP_{it,\tau}^s | X_{it}, \hat{g}_t, \hat{f}_t^s} = X_{it}^s \hat{\beta}_\tau + \gamma'_{s\tau} \hat{g}_t + \lambda_{i\tau}^{s'} \hat{f}_t^s; \tag{6}$$

$$\hat{Q}_{TFP_{it,\tau}^{s,u} | X_{it}} = X_{it}^s \hat{\beta}_\tau. \tag{7}$$

$\hat{Q}_{TFP_{it,\tau}^s | X_{it}^s, \hat{g}_t, \hat{f}_t^s}$ and $\hat{Q}_{TFP_{it,\tau}^{s,u} | X_{it}^s}$ fit numerical distributions that are respectively actual and counterfactual distributions of the TFP[2], which are distributions with and without the systematic shocks.

Referring to Adrian et al. (2019), the numerical distribution of TFP in both scenarios is fitted via skewness t-distribution to obtain smooth distribution curves and corresponding distribution parameters. The probability density function of the skewness t-distribution is:

$$h\left(TFP;\mu,\sigma,\alpha,\upsilon\right) = \frac{2}{\sigma} t\left(\frac{TFP-\mu}{\sigma};\ \upsilon\right) T\left(\alpha \frac{TFP-\mu}{\sigma} \sqrt{\frac{\nu+1}{\upsilon+\left(\frac{TFP-\mu}{\sigma}\right)^2}};\ \upsilon+1\right), \tag{8}$$

where μ, σ, α, υ are mean, standard deviation, skewness and degrees of freedom parameters, respectively. *t*(.) and *T*(.) represent the probability density function (pdf) and the cumulative distribution function (cdf) of the standard t-distribution respectively. The skewness t-distribution is to adjust the skew effect of probability density function by adding the skewness t-distribution α on the basis of traditional t-distribution. When α = 0, the distribution is a t-distribution with mean μ, standard deviation σ and υ degrees of freedom.

$H(\tau;\ \mu,\ \sigma,\ \alpha,\ \upsilon)$ represents the cumulative distribution function of the skewness t-distribution at the subsite τ. $H^{-1}(\tau;\ \mu,\ \sigma,\ \alpha,\ \upsilon)$ is its inverse function, that is, the quantile of the skewness t- distribution at the component site τ. We minimize the distance between the numerical distribution of TFP and the skewness t-distribution to estimate the distribution parameters of the skewed t-distribution. The estimation model is as follows.

$$\left\{\hat{\mu},\hat{\sigma},\hat{\alpha},\hat{\upsilon}\right\} = \underset{\mu,\sigma,\alpha,\upsilon}{\arg\min} \sum_\tau (\hat{Q}_{TFP_{it,\tau}^s | X_{it}, \hat{g}_t, \hat{f}_t^s} - H^{-1}(\tau;\mu,\sigma,\alpha,\upsilon))^2; \tag{9}$$

$$\left\{\hat{\mu}^u,\hat{\sigma}^u,\hat{\alpha}^u,\hat{\upsilon}^u\right\} = \underset{\mu,\sigma,\alpha,\upsilon}{\arg\min} \sum_\tau (\hat{Q}_{TFP_{it,\tau}^{s,u} | X_{it}} - H^{-1}(\tau;\mu,\sigma,\alpha,\upsilon))^2. \tag{10}$$

Therefore, we can obtain the distribution fitting results $h\left(TFP^s;\hat{\mu},\hat{\sigma},\hat{\alpha},\hat{\upsilon}\right)$ and $h\left(TFP^{s,u};\hat{\mu}^u,\hat{\sigma}^u,\hat{\alpha}^u,\hat{\upsilon}^u\right)$ under the condition of shock and no shock respectively. For each manufacturing industry, two smooth distribution fitting curves can be plotted.

[2] The mean of all individual fitting results is taken to obtain the TFP value distribution on each quantile τ.

The relative deviation between the two distribution curves under shock and no shock conditions can intuitively depict the sensitivity of the TFP distribution in the industry to systemic shocks, that is, the structural viscosity. The greater the degree of deviation between the two is, the more sensitive the industry is to the systemic shocks of TFP, and the smaller the structural viscosity is. On the contrary, the smaller the degree of deviation between the two is, the greater the structural viscosity is.

The TFP shocks in this paper are endogenous shocks, so the industry with weaker structural viscosity has stronger intrinsic innovation impetus. The more viscous the structure of the industry is, the weaker the internal innovation drive is, indicating that these industries need powerful external innovation incentives.

The stickiness assessment based on the distribution structure has a very important advantage that it can clarify and compare the stickiness difference between the enterprises with TFP on the upper side and the enterprises on the lower side so as to intuitively show the performance difference between backward production capacity and advanced production capacity under the effect of systemic shocks, which could provide more specific and targeted decision-making information for optimization and upgrading of industrial structure.

2.2.2. Quantification of structural viscosity

The comparative assessment of the viscosity of manufacturing to systemic shocks based on distribution curves has the advantage of being intuitive, but the disadvantage is that we are unable to obtain specific quantitative evaluation results.

Referring to Adrian et al. (2019), the difference between the two distributions can be specifically quantified by information entropy. Define $L_s^{D\tau}$ as the information entropy of the lower quantile τ, $L_s^{U\tau}$ as the information entropy of the upper quantile τ, and L_s as the overall information entropy.

$$L_s^{D\tau} = \int_{-\infty}^{H^{-1}(\tau)} \left[\log h\left(y;\hat{\mu},\hat{\sigma},\hat{\alpha},\hat{\upsilon}\right) - \log h\left(y;\hat{\mu}^u,\hat{\sigma}^u,\hat{\alpha}^u,\hat{\upsilon}^u\right)\right] h\left(y;\hat{\mu},\hat{\sigma},\hat{\alpha},\hat{\upsilon}\right) dy; \tag{11}$$

$$L_s^{U\tau} = \int_{H^{-1}(1-\tau)}^{\infty} \left[\log h\left(y;\hat{\mu},\hat{\sigma},\hat{\alpha},\hat{\upsilon}\right) - \log h\left(y;\hat{\mu}^u,\hat{\sigma}^u,\hat{\alpha}^u,\hat{\upsilon}^u\right)\right] h\left(y;\hat{\mu},\hat{\sigma},\hat{\alpha},\hat{\upsilon}\right) dy; \tag{12}$$

$$L_s = L_s^{D\tau} + L_s^{U\tau}. \tag{13}$$

Among them, $h\left(\hat{\mu},\hat{\sigma},\hat{\alpha},\hat{\upsilon}\right)$ represents the probability density function fitting the distribution under shocks, while $h\left(\hat{\mu}^u,\hat{\sigma}^u,\hat{\alpha}^u,\hat{\upsilon}^u\right)$ represents the probability density function fitting the distribution without shocks. $H^{-1}\left(\tau\right)$ is under the condition of shocks fitting distribution in quantile τ.

Based on the measurement results of information entropy, we can quantitatively evaluate and compare the structural stickiness of the systematic shocks of TFP in the major manufacturing industries. The value of information entropy (absolute value) reflects the sensitivity of TFP to systemic shocks of the upper and lower tail enterprises. The greater the value is, the weaker the viscosity is. The symbol of the value reflects the increase or decrease of the number of enterprises in the tail interval. The positive sign indicates that the TFP system shocks lead to an increase in the number of enterprises at the tail side, and vice versa, the number decreases.

The advantage of the distribution curve is intuitive, and the advantage of information entropy is quantitative. The combination of the fitted distribution curve and information entropy index can well reveal the structural viscosity of the systematic shocks of the manufacturing industry on TFP.

3. Description of variables and data

The sample data selected in this paper is the annual manufacturing data of China's A-share listed companies from 2000 to 2021. Enterprise micro variable data are derived from CSMAR database. When selecting enterprises, the listed companies that have experienced ST, *ST, S*ST and PT during the sample period are excluded. Listed companies are usually large-scale enterprises in various industries with good operating conditions. Although they cannot completely represent the overall situation of the industry, such enterprises belong to the forefront of the industry innovation, and their innovation ability may be strongly representative of the technological progress and development trend of the industry. On the contrary, small enterprises generally acquire new technologies through imitation (König et al., 2022), so it is not meaningful to discuss the innovation capability of such enterprises.

The selected manufacturing industries and number of companies are: special equipment manufacturing (396), non-ferrous metal smelting and rolling (98), automobile industry (184), manufacture of electrical machinery and equipment (355), computer communications and other electronic equipment manufacturing (587), general machinery manufacturing (230), railway, ship, aerospace and other transport equipment manufacturing (99), manufacture of non-metallic mineral products (151), smelting and pressing of ferrous metals (47).

When extracting common factors, listed companies with missing and changing industries in the sample period were further excluded, and enterprises with balanced data were obtained. Among them, there are 14 special equipment manufacturers, 8 non-ferrous metal smelting and rolling industries, 13 automobile manufacturers, 7 electrical machinery and equipment manufacturers, 18 computer communication and other electronic equipment manufacturers, 8 general equipment manufacturers, 5 railway, ship, aerospace and other transportation equipment manufacturers, and 11 non-metallic mineral products industries, 10 ferrous metal smelting and rolling industries.

3.1. Quantification of structural viscosity

We measure TFP through Cobb-Douglas production function(C-D) of manufacturing enterprises based on Syverson (2011).

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta}. \tag{14}$$

It can be obtained by logarithmic linearization as follow:

$$\ln Y_{it} = \alpha \ln K_{it} + \beta \ln L_{it} + u_{it}. \tag{15}$$

Referring to Salgado et al. (2019), $\hat{u}_{it}$ is the estimated TFP value of enterprise i at time t by OP method (Olley & Pakes, 1996). Where, Y which is denote by company's main business income is the output. K is capital input, and we use net fixed assets of the company as a proxy variable for it. L is the labor input, and we use the company shall pay salaries to its employees as a proxy variable for it. The company's main business income and salaries payable to employees are deflated by the GDP deflator, and the company's net fixed assets are deflated by the fixed assets investment price index, both of which are based on the year 2000. Both GDP deflator and fixed assets deflator are derived from *China Statistical Yearbook* (2001–2022)[3] (National Bureau of Statistics of China, 2022). In addition, we also use LP method to measure enterprises TFP (Levinsohn & Petrin, 2003)[4].

The estimated parameter value and standard error of Eq. (15) are respectively: $\alpha = 0.703$ (0.0265), $\beta = 0.278$ (0.0135). This result shows that the returns to scale of China's manufacturing industry are approximately constant.

Table 1 shows the basic statistical parameters of TFP for sample enterprises, and Figure 1 and Figure 2 report the distribution histograms and density curve of TFP for various industries and the whole sample.

Table 1. Descriptive statistics of TFP of enterprises by industry

Industry	N	Mean	SD	Min	Max	Skewness	Kurtosis
Special equipment manufacturing industry	2,627	4.944	0.695	1.221	13.11	0.676	11.14
Smelting and pressing of non-ferrous metals	981	5.464	0.817	2.009	8.760	0.161	3.575
Automobile industry	1,536	5.118	0.717	1.814	7.585	0.276	3.471
Manufacture of electrical machinery and equipment	2,706	5.215	0.689	2.743	8.446	0.218	3.712
Computer communications and other electronic equipment manufacturing	4,291	5.063	0.827	0.689	10.47	0.569	5.099
General machinery manufacturing	1,716	4.867	0.639	2.322	7.699	0.133	3.957
Railway, ship, aerospace and other transportation equipment manufacturing	734	5.210	0.736	2.926	7.185	–0.240	2.755
Manufacture of non-metallic mineral products	1,404	4.702	0.604	0.943	8.503	0.247	7.158
Smelting and pressing of ferrous metals	636	5.756	0.598	2.885	11.08	–0.563	13.880
Total	16,631	5.080	0.759	0.689	13.11	0.415	5.191

Notes: Numbers 1 to 9 in the figure represent special equipment manufacturing, nonferrous metal smelting and rolling processing industry, automobile manufacturing industry, electrical machinery and equipment manufacturing industry, computer communication and other electronic equipment manufacturing industry, general equipment manufacturing industry, railway, ship, aerospace and other transportation equipment manufacturing industry, non-metallic mineral products industry, ferrous metal smelting and rolling processing industry in turn.

[3] The actual statistical years are 2000–2001.

[4] The results of LP method are presented in Figure 9 of Appendix.

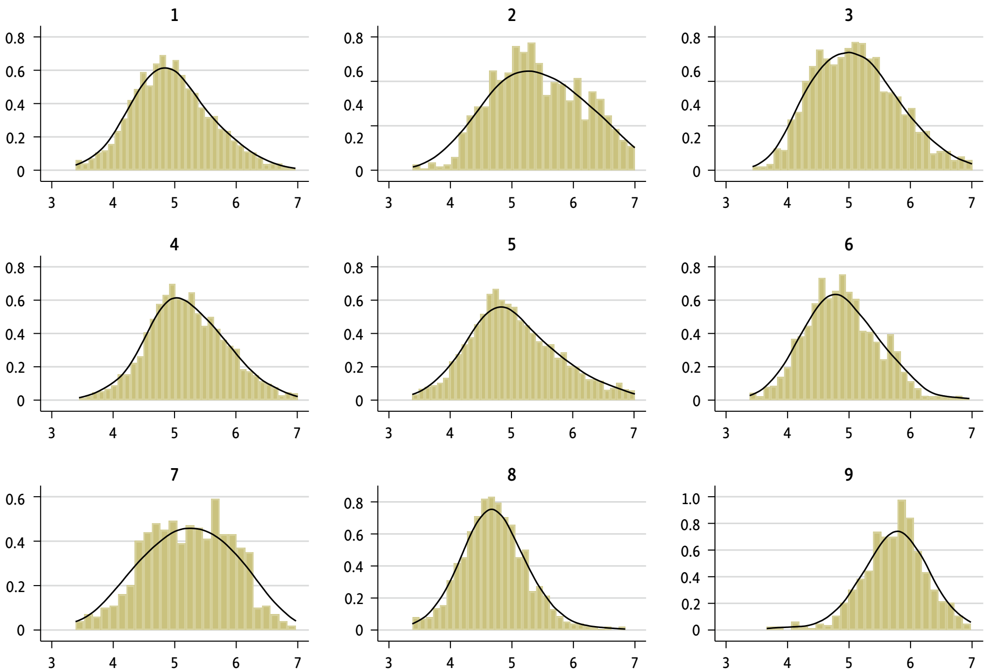


Figure 1. TFP distribution by industry

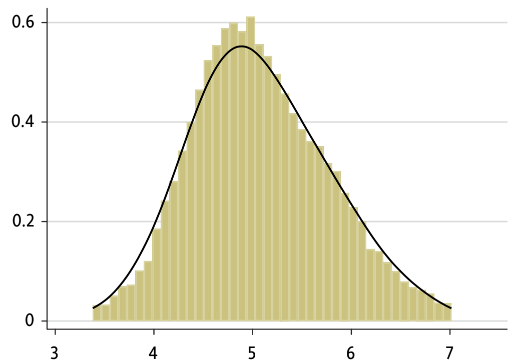


Figure 2. TFP distribution of the whole sample

The results of Figure 1 show that the standard deviation of TFP in computer communication and other electronic equipment manufacturing industry is the largest (0.827), which indicates that the productivity of enterprises in this industry varies greatly, which may be because the structure of this industry is more diversified and the industrial chain is relatively long. The standard deviation of TFP in ferrous metal smelting and rolling processing industry is the smallest (0.598), and the kurtosis is the largest (13.880), which may be because the ferrous metal industry is a basic industry, with earlier development, more mature technology, and relatively high degree of product homogenization.

3.2. Other variables

When estimating the systemic impact of TFP, we select company age, asset-liability ratio, nature of enterprise ownership, capital intensity, ROE, cash flow and GDP as control variables after considering the completeness and availability of data referring to Song et al. (2022), Ma et al. (2023), Cheng et al. (2023). If the company is established and listed less than one year, it is calculated as one year. The descriptive statistics of each variable are shown in Table 2.

Table 2. Descriptive statistics of other variables

variable	Implication	N	Mean	SD	Min	Max
Revenue	Log (revenue)	16,631	20.73	1.477	13.51	26.88
Asset	Log (net fixed assets)	16,631	20.06	1.576	4.615	26.16
Wage	Log (wage)	16,631	16.87	1.683	4.783	23.18
Age	Corporate age	16,631	15.21	6.434	1	41
Lev	Debt to asset ratio	16,631	0.425	0.199	0.00912	3.625
Nature	State owned = 1, Nonstate owned = 0	16,631	0.375	0.484	0	1
Intensity	Capital intensity	16,631	2.395	11.35	0.131	1039
Roe	Net profit/Net assets	16,631	0.0563	0.533	–60.15	2.379
Cf	(Cash flow) Current net cash flow/Current total assets	16,631	0.0419	0.0744	–1.938	0.523
GDP	Log (GDP)	16,631	8.577	1.268	0.0677	10.67

4. Evaluation results and analysis of structural stickiness in manufacturing industry

4.1. TFP shock factors

Figure 3 and Figure 4 are macro shock and industry factors of TFP identified based on Eq. (1) and Eq. (2).

It should be noted that the systematic impact factors are standardized in the identification algorithm. What is identified here is the dynamic trend of the shocks, and the impact effect size is reflected by its load coefficient. Therefore, the value of the shock factors has no economic significance[5].

In general, during the sample period, the dynamic evolution of TFP macro shocks in China's manufacturing industry can be divided into three stages: the macro shocks continued to rise from 2000 to 2008; the macro shocks showed a downward trend from 2008 to 2016; the macro shocks began to stabilize after 2016, and there is a significant recovery in 2021.

Specifically speaking, first of all, the dividends of China's reform and opening up continued to be released, and the process of international economic globalization continued to accelerate, which made the internal and external markets of China's manufacturing industry develop rapidly, and the macro systemic shocks of TFP showed a continuous upward trend before 2008. Some studies attributed the driving force of TFP growth in China at this stage

[5] The specific values of TFP shock factors are shown in Table 9 and Table 10 of Appendix.

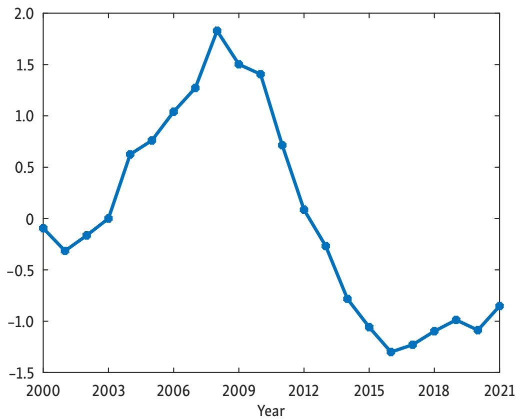
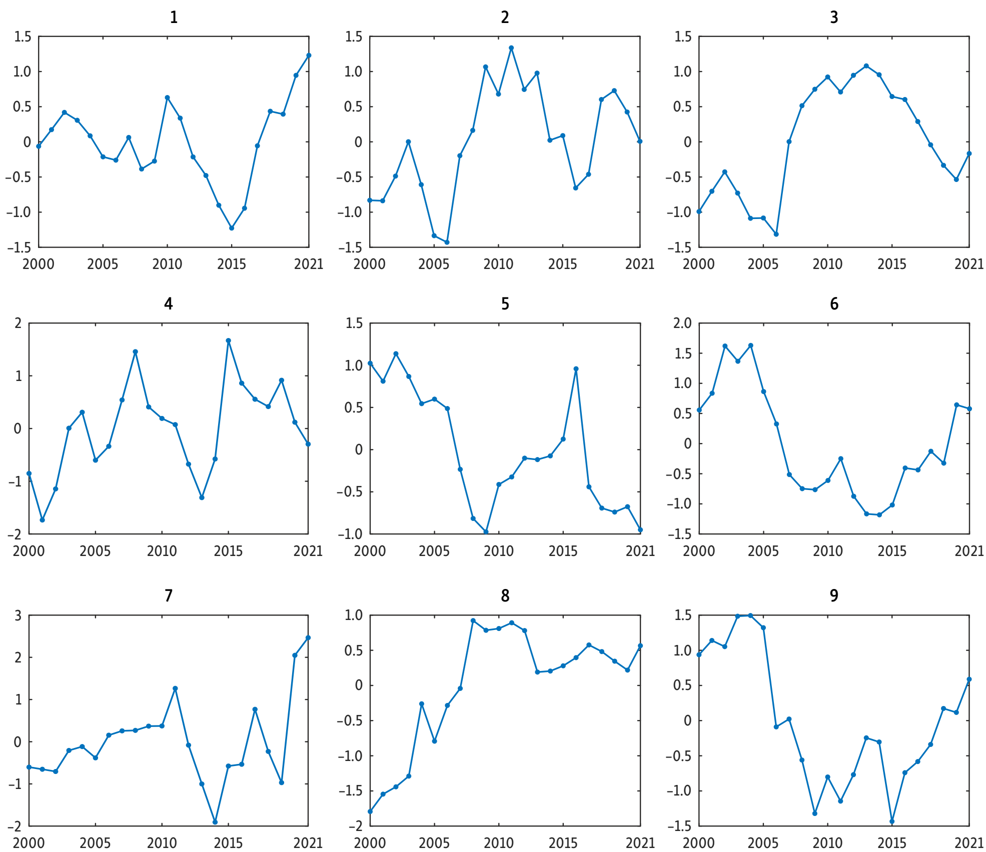


Figure 3. Macro shocks factors of TFP



Notes: Numbers 1 to 9 in the figure represent special equipment manufacturing, general equipment manufacturing, computer, communication and other electronic equipment manufacturing, electrical machinery and equipment manufacturing, railway, ship, aerospace and other transportation equipment manufacturing, automobile manufacturing, non-ferrous metal smelting and rolling processing industry, non-metallic mineral products industry and ferrous metal smelting and rolling processing industry in turn.

Figure 4. Estimates of industry TFP shock factors

to several aspects: first, the demographic dividend formed by the increase of labor population and the transfer of rural surplus labor; second, the deepening of capital brought about by urbanization and industrialization; third, the increasingly prominent role of the market in resource allocation. These factors have formed a sustained positive shock on TFP in China's manufacturing industry.

The systematic shocks of TFP in China's manufacturing industry showed a continuous downward trend from 2008 to 2016, because the global financial crisis in 2008 was a watershed for economic globalization. Since then, the international trade protectionism continues to heat up, and the external uncertainty of China's economy continues to intensify, thus forming a systematic negative shock on China's manufacturing TFP.

The supply-side structural reform aimed at improving the quality and efficiency of the supply system began to advance and continue to deepen after 2016, which optimized and upgraded the structure of China's manufacturing industry. Meanwhile, the macro systemic shocks of TFP in the manufacturing industry began to stabilize. In addition, the policy of "Build a new development pattern of 'double cycle'" and "Enhance the autonomous and controllable ability of the industrial chain and supply chain to solve a number of 'stuck neck' problems" has had an obvious positive impact on manufacturing TFP since 2020.

Given the macro shock factors, the industry factor mainly reflects the cyclical characteristics of the industry. Overall, the dynamic trend of TFP shocks in various industries are quite different. The estimated results are shown as follows.

In comparison, the impact volatility of the electrical machinery and equipment manufacturing industry is strong, and the volatility of the non-ferrous metal smelting and rolling processing industry is relatively weak. Non-metallic mineral products industry shows a relatively stable upward trend. The trend of automobile manufacturing industry is similar to that of railway, ferrous metal smelting and rolling processing industry, which has experienced the process of first rising, then falling, and then rising. The computer communications and other electronic equipment manufacturing industry has similar trend characteristics as the general equipment manufacturing industry. This similarity between industries may be related to the proximity of the industry's location nodes in the industrial chain and supply chain.

4.2. Evaluation of structural viscosity

4.2.1. Changes in the TFP distribution curve

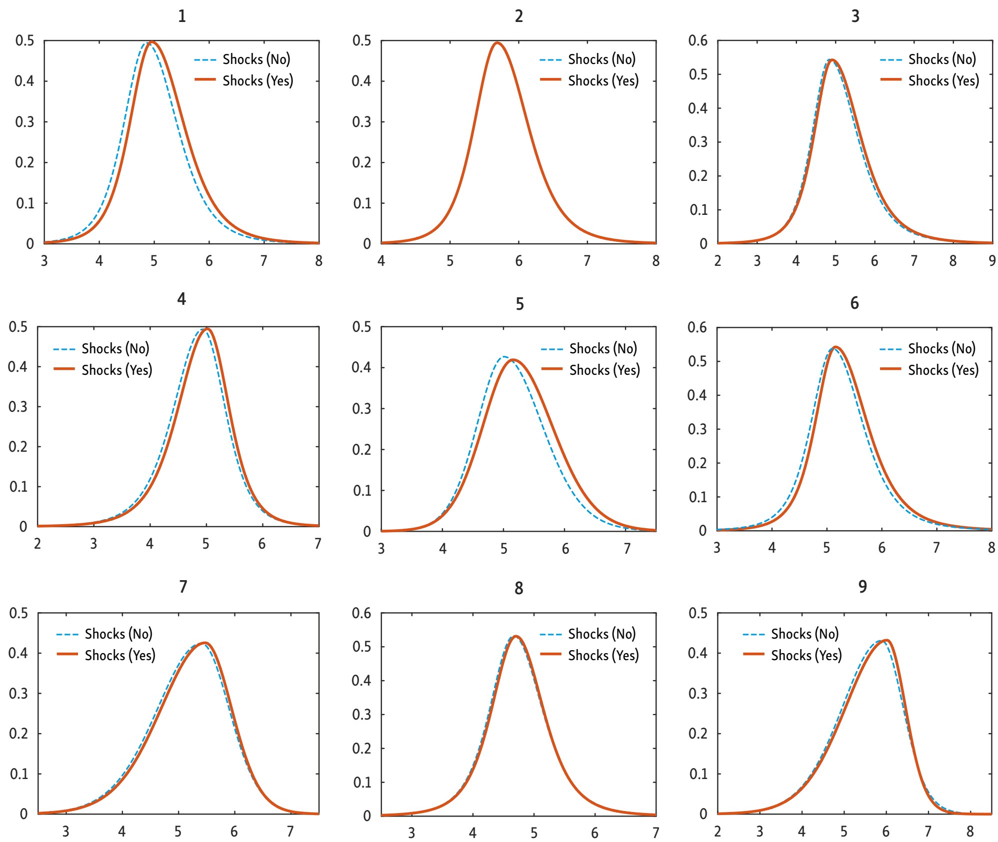
In order to visually present the changes of TFP distribution structure in various industries, Figure 5 depicts the probability density curve of TFP distribution with and without shocks in various industries based on the fitting of Eq. (9) and Eq. (10)[6].

In comparison, there are obvious differences in the sensitivity of TFP distribution structure to systemic shocks in different industries. First of all, the industries that are more sensitive to the systemic shocks of TFP are computer communication and other electronic equipment manufacturing, special equipment manufacturing, and general equipment manufacturing. Moreover, these industries have a common feature that the systemic impact of TFP pushes

[6] The results of panel quantile regression by industry are shown in Tables 11–19 of Appendix. The fitting results of skewness t-distribution parameters of TFP in various industries are shown in Table 20 of Appendix.

the industry distribution curve to the right as a whole, significantly improving the overall TFP level of the industry, indicating that these industries have a strong internal impetus for innovation. This result is quite consistent with the actual background. On the one hand, during the sample period, the technology update of the computer communication industry is significantly faster than that of other industries. On the other hand, both special equipment manufacturing and general equipment manufacturing are typically technology-intensive industries and are indeed more vulnerable to systemic shocks from TFP.

Besides, the electrical machinery and equipment manufacturing industry and the ferrous metal smelting and rolling industry are also more sensitive to the systemic shocks of TFP, indicating that these industries also have a certain inherent impetus for innovation. Moreover, the performance of the two is similar: both the upper and lower tail firms are less sensitive to TFP systemic shocks, and the affected firms are mainly near the median. This structural



Notes: Numbers 1 to 9 in the figure represent special equipment manufacturing, nonferrous metal smelting and rolling processing industry, automobile manufacturing industry, electrical machinery and equipment manufacturing industry, computer communication and other electronic equipment manufacturing industry, general equipment manufacturing industry, railway, ship, aerospace and other transportation equipment manufacturing industry, non-metallic mineral products industry, ferrous metal smelting and rolling processing industry in turn.

Figure 5. Probability density curve of TFP distribution by industry

differentiation shows that the two industries are not performing well in the adjustment of backward production capacity. Compared with the above industries, non-ferrous metal smelting and pressing processing industry and non-metallic mineral products industry all show strong structural viscosity to the systemic shocks of TFP. Obviously, these industries have weak internal innovation motivation and need external innovation incentives.

4.2.2. Quantification of structural viscosity

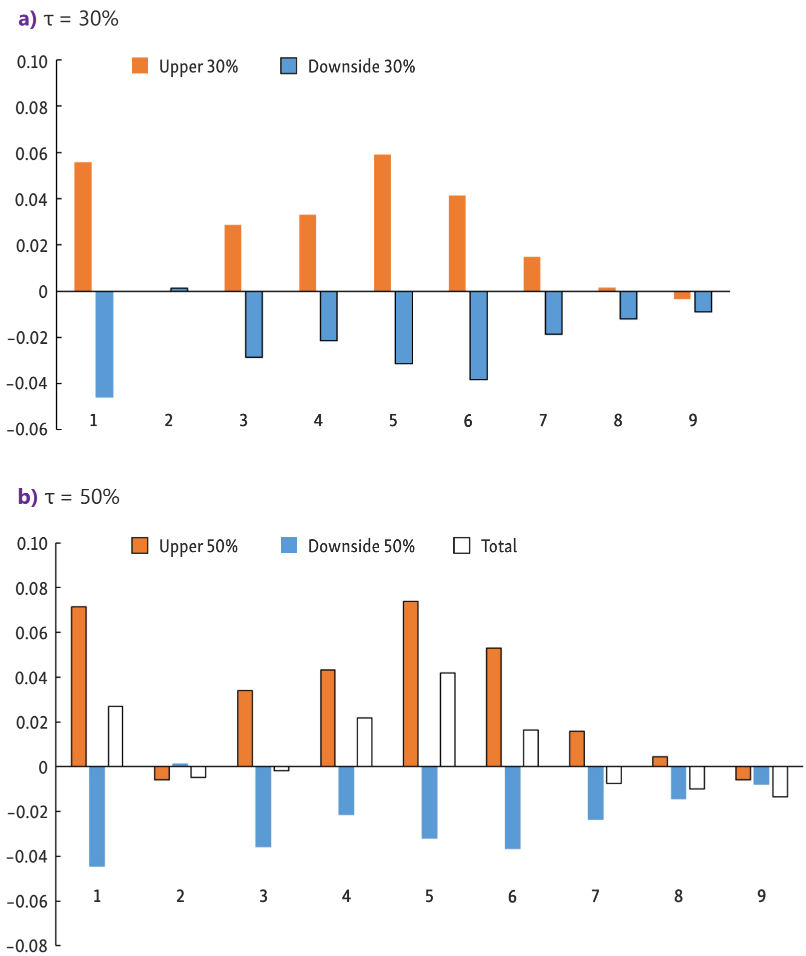
Although the change of the probability density curve of TFP distribution can intuitively show its sensitivity to systemic shocks, there is no index of specific quantitative evaluation. Referring to Adrian et al. (2019), this paper further quantifies the difference between TFP distributions under shock and non-shock conditions by means of information entropy. Table 3 reports the quantification results of information entropy of various industries calculated based on Eqs (11)–(13).

Table 3. Information entropy by industry

Number	Upper 50%	Lower 50%	Total	Upper 30%	Lower 30%
1	0.0714	–0.0444	0.0270	0.0557	–0.0458
2	–0.0059	0.0011	–0.0048	–0.0003	0.0013
3	0.0339	–0.0357	–0.0018	0.0286	–0.0286
4	0.0433	–0.0214	0.0219	0.0331	–0.0215
5	0.0737	–0.0318	0.0419	0.0591	–0.0314
6	0.0530	–0.0366	0.0164	0.0415	–0.0384
7	0.0159	–0.0235	–0.0076	0.0147	–0.0187
8	0.0044	–0.0144	–0.0100	0.0015	–0.0120
9	–0.0059	–0.0077	–0.0136	–0.0034	–0.0089

Notes: Numbers 1 to 9 in the table represent special equipment manufacturing, nonferrous metal smelting and rolling processing industry, automobile manufacturing industry, electrical machinery and equipment manufacturing industry, computer communication and other electronic equipment manufacturing industry, general equipment manufacturing industry, railway, ship, aerospace and other transportation equipment manufacturing industry, non-metallic mineral products industry, ferrous metal smelting and rolling processing industry in turn.

Figure 6a and Figure 6b are the corresponding bar chart about Table 3. From the perspective of industrial optimization and upgrading and elimination of backward production capacity, it is hoped that the proportion of efficient enterprises will increase and the proportion of inefficient enterprises will decrease in the structural change of TFP distribution in the industry. This goal is reflected in information entropy that the upper side tends to be positive and the lower side tends to be negative. The changes in the distribution structure of TFP in the computer communication and other electronic equipment manufacturing industry fully conform to this feature obviously, indicating that the industry presents typical characteristics of structural optimization and upgrading under the systematic shocks of TFP. On the contrary, the non-ferrous metal smelting and rolling processing industry is very insensitive to the systemic shocks of TFP, and the optimization and upgrading of the industry level is facing strong constraints.



Notes: τ is the quantile which is defined in Eqs (11)–(13).

Figure 6. Information entropy

Basically consistent with the results of the distribution probability density curve, both the upper and lower 50% and the upper and lower 30% information entropy results show that the information entropy (absolute value) value of computer communication and other electronic equipment manufacturing and professional equipment manufacturing is large, that is, its TFP distribution structure is sensitive to systemic impact and its viscosity is weak. Other industries with high information entropy (absolute value) are: general equipment manufacturing, electrical machinery and equipment manufacturing, etc. However, the information entropy (absolute value) of non-ferrous metal processing industry and non-metallic mineral products industry is small, indicating that the TFP structure of these industries is not sensitive to systemic shocks, and the viscosity is the strongest.

It should be noted that the sensitivity of the ferrous metal smelting and rolling industry to the systemic impact of TFP is greater than that of the automobile manufacturing industry from the point of view of the distribution curve. However, the value of ferrous metal smelting and rolling processing industry is significantly smaller than that of automobile manufacturing industry from the point of view of information entropy, because the distribution curve of ferrous metal smelting and rolling industry with and without impact shows a cross shape on the upper side. Specifically, in the region near the middle point, the probability density value of impact is greater than that of no shock; on the contrary, in the region near the upper tail, the probability density value of no shock is greater than that of shock. Thus, when calculating the information entropy, the two will cancel each other and obtain the information entropy with a smaller absolute value.

This problem shows that information entropy also has its disadvantages although it has the advantage of quantitative evaluation. When the distribution curves with and without shocks cross in the examined interval, the information entropy is difficult to accurately reflect the real structural viscosity, which is precisely the reason why the two methods of distribution curve and information entropy are integrated in this paper.

4.3. Factor loadings of macro shocks

The size of factor loadings of macro shocks can also reflect the sensitivity of industry TFP to macro systemic shocks. However, the loadings of macro factor reflect the average impact of macro shocks on industry TFP different from the above distribution curve and information entropy, rather than the change of distribution structure. The greater the factor loadings are, the more sensitive the TFP of the industry is on average to macro systemic shocks, and vice versa, the more viscous it is. Table 4 reports estimates of loadings of macro TFP shock factors by industry.

Obviously, the industries with large factor loads (the average viscosity is weak) are: nonferrous metal smelting and rolling industry, special equipment manufacturing, computer communications and other electronic equipment manufacturing. In other words, these sectors are less sticky to macro systemic shocks on average. It can be seen from the distribution curve that the structural viscosity of these shocks on TFP by industry is also relatively small.

Table 4. Loadings of TFP macro shock factors in different industries

Number	Industry	Loadings of macro TFP shock factors
1	special equipment manufacturing	0.118
2	nonferrous metal smelting and rolling processing industry	0.162
3	automobile manufacturing industry	0.076
4	electrical machinery and equipment manufacturing industry	0.041
5	computer communication and other electronic equipment manufacturing industry	0.114
6	general equipment manufacturing industry	0.039
7	railway, ship, aerospace and other transportation equipment manufacturing industry	0.075
8	non-metallic mineral products industry	0.034
9	ferrous metal smelting and rolling processing industry	0.014

However, the order of size between structural viscosity and average viscosity is not exactly the same. The weakest structural stickiness is in the computer communications and other electronic equipment manufacturing industry, while the weakest average stickiness is in the ferrous metal smelting and rolling processing industry.

In order to directly reflect the relationship between structural viscosity and average viscosity, the scatterplots between the absolute value of 30% and 50% information entropy on the upper and lower sides and the loadings of macroscopic shocks factors are drawn in Figure 7[7]. The dashed line is the fitted straight line without considering smelting and pressing of non-ferrous metals. Combined with the OLS regression results in Table 5 and Table 6, it is obvious that if smelting and pressing of non-ferrous metals are not considered, there is a significant positive correlation between the average viscosity (factor loadings) and structural viscosity (information entropy) (Table 5). However, considering all industries comprehensively, the value of R^2 (goodness of fit) between Factor load and information entropy is low, and the estimated coefficient of Factor loading is not significant (Table 6), indicating that the correlation between the two is not obvious.

In summary, the factor load can only reflect the average viscosity of the industry, but not really reflect the structural viscosity of the industry. Therefore, it is necessary to fully reveal the evolution law of the industry TFP distribution structure under the systematic shocks based on the distribution curve and information entropy.

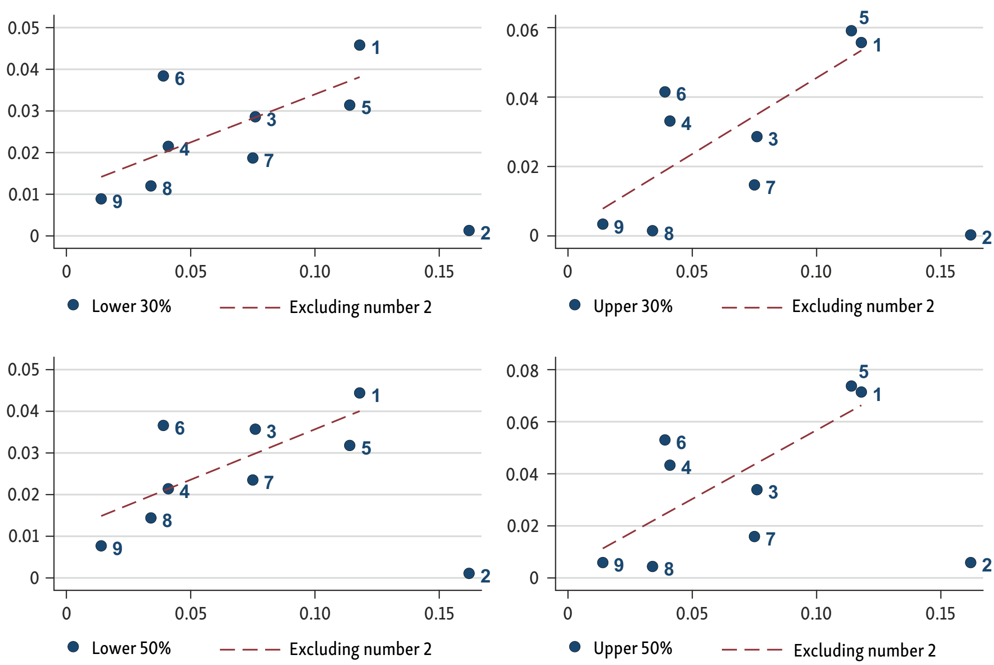


Figure 7. Scatterplots of factor loadings of TFP shocks and information entropy

[7] The serial number next to the scatter in the figure indicates the industry number, and the corresponding industry name is detailed in Table 4.

Table 5. Regression results of factor loadings of TFP shocks and information entropy (excluding smelting and pressing of non-ferrous metals (number = 2))

	Lower 30%	Upper 30%	Lower 50%	Upper 50%
Factor loading	0.2304**	0.4381***	0.5288***	0.2420**
	(0.0867)	(0.1056)	(0.1347)	(0.0800)
R^2	0.4755	0.5770	0.5393	0.5612

Notes: Values in brackets are robust standard errors. *, ** and *** indicate that the statistic is statistically significant at the significance level of 10%, 5% and 1%, respectively.

Table 6. Regression results of factor loadings of TFP shocks and information entropy (Total)

	Lower 30%	Upper 30%	Lower 50%	Upper 50%
Factor loading	0.0124	0.1021	0.1404	0.0119
	(0.1493)	(0.2265)	(0.2659)	(0.1534)
R^2	0.0017	0.0470	0.0597	0.0016

Notes: Values in brackets are robust standard errors. *, ** and *** indicate that the statistic is statistically significant at the significance level of 10%, 5% and 1%, respectively.

5. Further analysis: structural stickiness and industry correlation

Industries with similar positions in the supply chain of the industrial chain show similar structural stickiness to a certain extent (Leontief, 1936) in the face of the systemic shocks of TFP. So, is the structural stickiness of industry TFP to systemic shocks related to its industry status? A reasonable assumption is that the more connected an industry is to other industries, the more likely it is to be affected by shocks from other industries, and the less sticky it will be. In order to test this hypothesis, the correlation between industry structure stickiness and industry correlation degree is further analyzed.

5.1. Industry correlation degree

According to Baqaee and Farhi (2019), the correlation degree between industry i and industry j can be expressed as:

$$cov_{ij} = Cov_{\Omega^{(k)}}\left(\Psi_{(i)}\Psi_{(j)}\right) = \sum_{l=1}^{N+F}\Omega_{kl}\Psi_{li}\Psi_{lj} - \left(\sum_{l=1}^{N+F}\Omega_{kl}\Psi_{li}\right)\left(\sum_{l=1}^{N+F}\Omega_{kl}\Psi_{lj}\right), \tag{16}$$

where Ω denotes the matrix of direct consumption coefficients in the input-output table for the national economic sector. Specifically, $\Omega_{ij} = \frac{p_j x_{ij}}{p_i y_j}$. ψ is the Leontief inverse matrix of the input-output table $\Psi = \left(I - \Omega\right)^{-1}$.

Suppose there are S industries, and the industry relevance matrix is a symmetric square matrix of $S \times S$:

$$\begin{matrix} 1 & \cdots & cov_{1S} \\ \vdots & \ddots & \vdots \\ cov_{S1} & \cdots & 1 \end{matrix}. \tag{17}$$

The comprehensive industry correlation degree between industry i and all other industries is:

$$COV_i = \sum_{k \neq i} cov_{ik}\,. \tag{18}$$

The input-output table used to calculate the industry correlation index is from the National Bureau of Statistics of the People's Republic of China (2020), and the specific results are shown in Table 7. It can be found that the industries with a greater degree of correlation with other industries in order are: special equipment manufacturing, general equipment manufacturing, computer communications and other electronic equipment manufacturing. The least relevant industries are the ferrous metal smelting and rolling processing industry and the non-ferrous metal smelting and rolling processing industry.

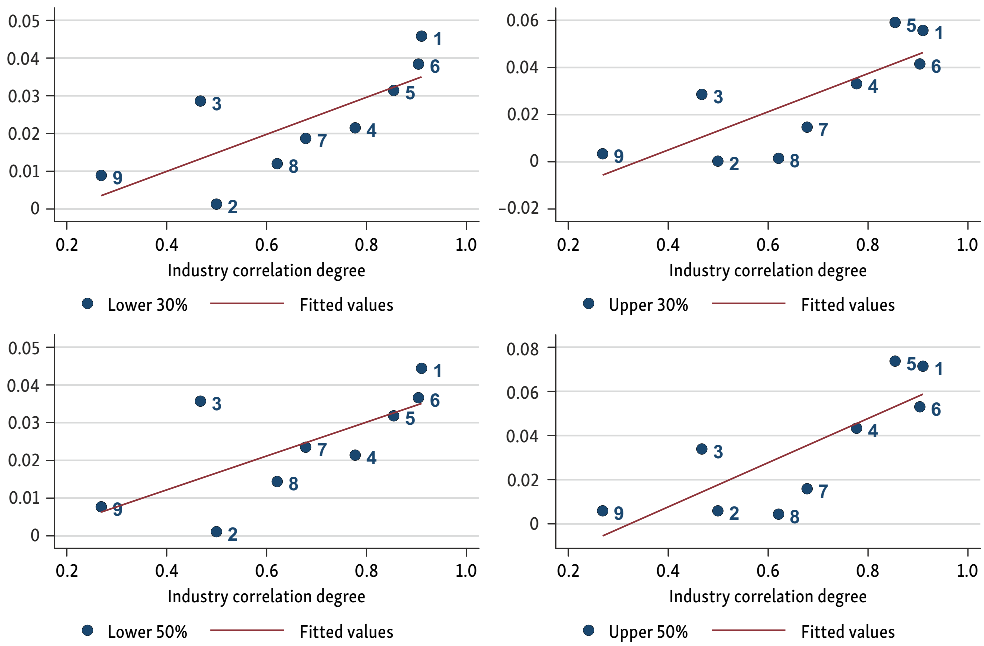
Table 7. Results of industry correlation degree

Number	Industry	industry correlation degree
1	special equipment manufacturing	0.9100
2	nonferrous metal smelting and rolling processing industry	0.4995
3	automobile manufacturing industry	0.4674
4	electrical machinery and equipment manufacturing industry	0.7771
5	computer communication and other electronic equipment manufacturing industry	0.8542
6	general equipment manufacturing industry	0.9038
7	railway, ship, aerospace and other transportation equipment manufacturing industry	0.6781
8	non-metallic mineral products industry	0.6210
9	ferrous metal smelting and rolling processing industry	0.2689

5.2. Industry correlation degree and structural stickiness

Figure 8a and Figure 8b plot the scatter plot of the industry correlation degree and the absolute value of 30% and 50% information entropy on the upper and lower sides to directly reflect the correlation between the two. Table 8 shows the OLS regression results of industry correlation degree and information entropy. We can find that, although the ranking of industry correlation degree is not the same as that of information entropy, both scatter plot and OLS regression results show that industry correlation degree has a very significant positive correlation with information entropy, which indicates that industries with stronger correlation with other industries are more likely to be affected by the impact of other industries (the weaker the structural stickiness), thus verifying our hypothesis. The above results not only show that industry correlation is another important indicator reflecting the stickiness of industry structure, but also highlight an important economic significance: industries with high industry correlation can exert radiation power, and then drive other industries to coordinate innovation and development.

a) Structural stickiness in different quartile and Industry correlation degree



b) Structural stickiness in total and Industry correlation degree

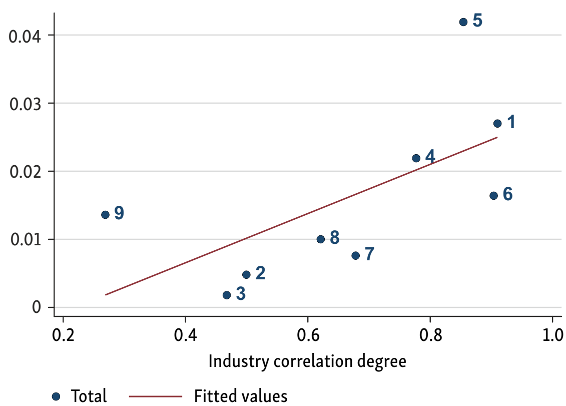


Figure 8. Scatterplots of industry correlation degree and information entropy

Table 8. Regression results of industry correlation degree and information entropy

	Lower 30%	Upper 30%	Lower 50%	Upper 50%	Total
Industry correlation degree	0.0491**	0.0810***	0.1001***	0.0449**	0.0361*
	(0.0151)	(0.0201)	(0.0236)	(0.0158)	(0.0187)
R^2	0.5636	0.6146	0.6310	0.4737	0.4027

Notes: Values in brackets are robust standard errors. *, ** and *** indicate that the statistic is statistically significant at the significance level of 10%, 5% and 1%, respectively.

6. Conclusions and discussion

A systematic analysis of the response of TFP distribution structure and the internal structure of macroeconomic equilibrium path to the systematic impact of productivity and its evolution law can provide decision-making reference for the implementation of innovation-driven strategy.

This paper effectively identifies and decomposes the systemic impact of manufacturing TFP at the macro level and industry level based on the micro data of China's manufacturing listed companies. Then, the structural stickiness of TFP systemic impact of major manufacturing industries is evaluated based on the distribution curve, information entropy and industry correlation degree of TFP under the condition of shock and no shock.

The research results are mainly reflected in the following three points.

First, the results of estimation of TFP macro shock factors show that the supply-side structural reform in 2016 effectively reversed the downward trend of TFP shock in China's manufacturing industry.

Second, the evaluation results of the structural stickiness of the manufacturing industry show that: (1) the industries that are more sensitive to the systemic shocks of TFP are computer communication and other electronic equipment manufacturing, special equipment manufacturing, and general equipment manufacturing. These industries have a strong internal impetus for innovation, and the systemic shocks of TFP has significantly improved the overall TFP level of the industry. (2) The electrical machinery and equipment manufacturing industry and the ferrous metal smelting and rolling industry also have a certain inherent innovation power, but they show structural differentiation, and the lower tail enterprises are not sensitive to the systemic shocks of TFP. (3) Non-ferrous metal smelting and pressing processing industry and non-metallic mineral products industry all show strong structural viscosity to the systematic shocks of TFP, and their internal innovation power is weak, requiring external innovation incentives.

Third, there is a significant positive relationship between industry correlation degree and information entropy, indicating that industry correlation degree is another important index reflecting the viscosity of industry structure. In addition, the industry with a higher degree of industry correlation can give play to its industrial chain supply chain position advantages and drive the innovation and coordinated development of other related industries. For example, the government only needs to give a small amount of policy support to the special equipment manufacturing industry, general equipment manufacturing industry, computer communications and other electronic equipment manufacturing industry, which is related to the weak structural stickiness of the industry, and the small amount of policy support can effectively promote the development of other industries, and play the effect of half the effort. For industries with very strong structural stickiness (such as the non-ferrous metal processing industry and the non-metallic mineral products industry), targeted and strong exogenous incentive policies should be given. In a word, this differentiated industry innovation incentive policy is different from the traditional extensive scientific and technological innovation capital investment policy, which avoids the waste of resources and the low efficiency of the policy.

Finally, the research of this paper provides a new method to evaluate the innovation ability of the industry, and reveals the significant differences in the inherent innovation motivation of different industries in China's manufacturing industry, so as to provide a targeted basis for the differentiation of industry innovation incentives.

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APPENDIX

1. Detailed steps of iterative algorithm

Step 1: Ignoring macro shock factors and industry shock factors, LSDV method or GLS method are used to estimate Eq. (1) to obtain the initial value $\widehat{\beta_j}$ of β_j and the initial residual value of $\widehat{\varepsilon_{it}^s}$.

Step 2: Let $\widehat{\varepsilon_{it}^s} = \gamma_s^{'} g_t + \epsilon_{it}^s$, ignoring the industry impact factor and use principal component analysis (PCA) to obtained $\widehat{g_t}$, $\widehat{\gamma_i^{'}}$ and $\widehat{\epsilon_{it}^s}$.

Step 3: Let $\widehat{\epsilon_{it}^s} = \lambda_i^{s'} f_t^s + \varepsilon_{it}^s$, principal component analysis is performed for each industry s to obtain $\widehat{f_t^s}$, then we get orthogonalized equation $\widehat{f_t^s} = \left(I_T - \widehat{g_t}\widehat{g_t^{'}} / T\right)\widehat{f_t^s}$ based on the Eq. (3), and we get $\widehat{\lambda_i^{s'}}$ and $\widehat{\varepsilon_{it}^s}$ further.

Step 4: $\widetilde{\varepsilon_{it}^s} = \widehat{\varepsilon_{it}^s} - \widehat{\lambda_i^{s'}}\widehat{f_t^s}$, and replace $\widehat{\varepsilon_{it}^s}$ with $\widetilde{\varepsilon_{it}^s}$, and iterative operations for Step 2 and Step 3;

Step 5: Let $\widetilde{TFP^s{}_{it}} = TFP^s{}_{it} - \widehat{\gamma_s^{'}}\widehat{g_t} + \widehat{\lambda_i^{s'}}\widehat{f_t^s}$.

Step 6: Repeat Step 2 to Step 5 until the estimated parameter results converge. In this case, the results of all parameter estimates are consistent.

Finally, we can obtain the macroscopic system technical shock factor estimates $\widehat{g_t}$ and the industrial technical shock factor estimates $\widehat{f_t^s}$ and their loadings $\widehat{\gamma_s^{'}}$, $\widehat{\lambda_i^{s'}}$.

2. Specific estimates of TFP shock factors

Table 9. TFP macro shock factors

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Shock	–0.094	–0.315	–0.164	0.001	0.625	0.761	1.040	1.272	1.829	1.503	1.406
Year	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Shock	0.714	0.086	–0.268	–0.782	–1.058	–1.300	–1.229	–1.097	–0.988	–1.087	–0.853

Table 10. Factors of TFP industry shock

Number	1	2	3	4	5	6	7	8	9
2000	–0.063	–0.602	0.557	–0.851	–0.992	–0.831	1.024	–1.793	0.937
2001	0.174	–0.653	0.836	–1.735	–0.703	–0.838	0.811	–1.545	1.140
2002	0.419	–0.706	1.620	–1.145	–0.427	–0.487	1.137	–1.442	1.052
2003	0.307	–0.207	1.366	0.007	–0.729	0.002	0.867	–1.289	1.485
2004	0.086	–0.115	1.629	0.309	–1.088	–0.609	0.545	–0.261	1.495
2005	–0.213	–0.383	0.864	–0.601	–1.083	–1.335	0.599	–0.793	1.322
2006	–0.260	0.155	0.326	–0.337	–1.314	–1.429	0.487	–0.284	–0.089
2007	0.063	0.257	–0.514	0.542	0.003	–0.197	–0.234	–0.042	0.023
2008	–0.386	0.268	–0.748	1.458	0.514	0.163	–0.816	0.923	–0.561
2009	–0.274	0.369	–0.764	0.410	0.748	1.066	–0.975	0.785	–1.321
2010	0.630	0.373	–0.611	0.192	0.923	0.679	–0.413	0.810	–0.801
2011	0.337	1.265	–0.250	0.075	0.709	1.337	–0.324	0.892	–1.145
2012	–0.214	–0.082	–0.874	–0.676	0.946	0.745	–0.101	0.781	–0.769
2013	–0.479	–1.001	–1.166	–1.310	1.080	0.978	–0.118	0.190	–0.245
2014	–0.902	–1.908	–1.182	–0.578	0.954	0.023	–0.074	0.205	–0.304
2015	–1.227	–0.576	–1.018	1.669	0.644	0.089	0.125	0.280	–1.434
2016	–0.944	–0.535	–0.405	0.860	0.602	–0.656	0.959	0.396	–0.741
2017	–0.056	0.768	–0.436	0.556	0.289	–0.462	–0.441	0.576	–0.582
2018	0.435	–0.231	–0.127	0.416	–0.042	0.602	–0.693	0.482	–0.339
2019	0.394	–0.970	–0.324	0.916	–0.334	0.728	–0.740	0.345	0.173
2020	0.946	2.048	0.643	0.120	–0.536	0.424	–0.676	0.219	0.117
2021	1.230	2.466	0.578	–0.296	–0.166	0.007	–0.950	0.566	0.589

Notes: Numbers 1 to 9 in the table represent special equipment manufacturing, nonferrous metal smelting and rolling processing industry, automobile manufacturing industry, electrical machinery and equipment manufacturing industry, computer communication and other electronic equipment manufacturing industry, general equipment manufacturing industry, railway, ship, aerospace and other transportation equipment manufacturing industry, non-metallic mineral products industry, ferrous metal smelting and rolling processing industry in turn.

3. Significant results of quantile regression for each industry in the presence of shocks

Due to space constraints, only the regression results for 5%, 25%, 50%, 75% and 95% of the significant quantiles for each industry are given here.

Table 11. Special equipment manufacturing industry

Quantile	5%	25%	50%	75%	95%
Age	–0.0004	–0.0004	–0.0019	–0.0029	0.0021
	(0.0023)	(0.0023)	(0.0021)	(0.0031)	(0.0039)
Lev	0.4816***	0.4816***	0.5703***	0.7362***	0.5337***
	(0.0636)	(0.0636)	(0.0724)	(0.0937)	(0.1591)

End of Table 11

Quantile	5%	25%	50%	75%	95%
Nature	0.1543***	0.1543***	0.1663***	0.2099***	0.3012***
	(0.0274)	(0.0274)	(0.0269)	(0.0413)	(0.0629)
Intensity	–0.1966***	–0.1966***	–0.1650***	–0.1217***	–0.0341
	(0.0096)	(0.0096)	(0.0152)	(0.0218)	(0.0350)
Roe	0.8038***	0.8038***	1.0283***	1.0713***	0.3649
	(0.0258)	(0.0258)	(0.0833)	(0.1828)	(0.3195)
Cf	–0.7802***	–0.7802***	–0.7135***	–0.6353***	–0.3053
	(0.1586)	(0.1586)	(0.1780)	(0.2267)	(0.4463)
GDP	–0.0298***	–0.0298***	–0.0357***	–0.0381**	0.0253
	(0.0107)	(0.0107)	(0.0113)	(0.0157)	(0.0234)
Factor of TFP macro shock	0.1500***	0.1500***	0.1313***	0.1642***	0.2197***
	(0.0209)	(0.0209)	(0.0226)	(0.0291)	(0.0416)
Factor of TFP industry shock	–0.0379***	–0.0379***	–0.0164	0.0072	–0.0255
	(0.0146)	(0.0146)	(0.0146)	(0.0200)	(0.0325)
N	2627	2627	2627	2627	2627

Notes: Values in brackets are robust standard errors. *, ** and *** indicate that the statistic is statistically significant at the significance level of 10%, 5% and 1%, respectively.

Table 12. General machinery manufacturing

Quantile	5%	25%	50%	75%	95%
Age	0.0041	0.0041	0.0048	0.0002	0.0150*
	(0.0028)	(0.0028)	(0.0038)	(0.0066)	(0.0091)
Lev	0.4672***	0.4672***	0.3618***	0.2698	0.4759
	(0.0772)	(0.0772)	(0.1157)	(0.1888)	(0.3340)
Nature	–0.0501	–0.0501	–0.0782*	–0.0786	–0.3439***
	(0.0332)	(0.0332)	(0.0438)	(0.0696)	(0.1109)
Intensity	–0.4891***	–0.4891***	–0.4970***	–0.4309***	–0.2006**
	(0.0247)	(0.0247)	(0.0302)	(0.0741)	(0.0853)
Roe	0.3909**	0.3909**	0.1035	–0.1282	–0.0143
	(0.1671)	(0.1671)	(0.0898)	(0.2207)	(0.1080)
Cf	–0.5087**	–0.5087**	–1.0965***	–0.5705	–0.8096
	(0.1988)	(0.1988)	(0.2592)	(0.3523)	(0.6592)
GDP	–0.0526***	–0.0526***	–0.0867***	–0.0427	0.0108
	(0.0114)	(0.0114)	(0.0188)	(0.0272)	(0.0566)
Factor of TFP macro shock	0.0503**	0.0503**	0.0228	0.0171	0.1031*
	(0.0244)	(0.0244)	(0.0233)	(0.0364)	(0.0574)
Factor of TFP industry shock	0.0068	0.0068	0.0034	–0.0421	0.0167
	(0.0177)	(0.0177)	(0.0253)	(0.0378)	(0.0719)
N	981	981	981	981	981

Notes: Values in brackets are robust standard errors. *, ** and *** indicate that the statistic is statistically significant at the significance level of 10%, 5% and 1%, respectively.

Table 13. Computer, communications and other electronic equipment manufacturing

Quantile	5%	25%	50%	75%	95%
Age	–0.0025	–0.0025	–0.0023	–0.0051	0.0009
	(0.0022)	(0.0022)	(0.0030)	(0.0035)	(0.0064)
Lev	1.0015***	1.0015***	1.4830***	1.3854***	1.7523***
	(0.0860)	(0.0860)	(0.1096)	(0.1074)	(0.2039)
Nature	0.4274***	0.4274***	0.4127***	0.3532***	0.5754***
	(0.0298)	(0.0298)	(0.0364)	(0.0391)	(0.0866)
Intensity	–0.2166***	–0.2166***	–0.0888**	–0.0802***	–0.0598***
	(0.0250)	(0.0250)	(0.0401)	(0.0259)	(0.0034)
Roe	1.0591***	1.0591***	1.0352***	1.1852***	1.2572***
	(0.0844)	(0.0844)	(0.1434)	(0.1362)	(0.1888)
Cf	–0.1303	–0.1303	0.2570	–0.0063	–1.2476**
	(0.1892)	(0.1892)	(0.2567)	(0.2578)	(0.5436)
GDP	0.0136	0.0136	0.0234	–0.0054	–0.0290
	(0.0117)	(0.0117)	(0.0164)	(0.0177)	(0.0342)
Factor of TFP macro shock	0.0708***	0.0708***	0.1667***	0.1828***	0.2051***
	(0.0214)	(0.0214)	(0.0280)	(0.0247)	(0.0580)
Factor of TFP industry shock	0.0748**	0.0748**	0.0250	0.0362	0.1513*
	(0.0342)	(0.0342)	(0.0407)	(0.0408)	(0.0888)
N	1536	1536	1536	1536	1536

Notes: Values in brackets are robust standard errors. *, ** and *** indicate that the statistic is statistically significant at the significance level of 10%, 5% and 1%, respectively.

Table 14. Manufacture of electrical machinery and equipment

Quantile	5%	25%	50%	75%	95%
Age	–0.0001	–0.0001	0.0039*	0.0077***	–0.0035
	(0.0021)	(0.0021)	(0.0022)	(0.0028)	(0.0061)
Lev	0.8330***	0.8330***	0.8109***	0.8095***	0.7121**
	(0.1150)	(0.1150)	(0.0753)	(0.1231)	(0.3003)
Nature	0.1509***	0.1509***	0.1949***	0.2470***	0.4294***
	(0.0335)	(0.0335)	(0.0301)	(0.0399)	(0.0829)
Intensity	–0.2660***	–0.2660***	–0.2312***	–0.2031***	–0.1881***
	(0.0127)	(0.0127)	(0.0143)	(0.0139)	(0.0426)
Roe	0.2353	0.2353	0.1351	0.0304	0.0370
	(0.4610)	(0.4610)	(0.2281)	(0.1723)	(0.9028)
Cf	–0.5962**	–0.5962**	–0.4789**	–0.1356	–0.3342
	(0.2674)	(0.2674)	(0.1862)	(0.2357)	(0.6701)
GDP	0.0274**	0.0274**	0.0303**	0.0394***	0.0268
	(0.0123)	(0.0123)	(0.0118)	(0.0150)	(0.0286)
Factor of TFP macro shock	0.0957***	0.0957***	0.1010***	0.1378***	0.2329***
	(0.0187)	(0.0187)	(0.0186)	(0.0240)	(0.0593)
Factor of TFP industry shock	–0.0693***	–0.0693***	–0.1037***	–0.1090***	–0.0129
	(0.0177)	(0.0177)	(0.0164)	(0.0203)	(0.0481)
N	2706	2706	2706	2706	2706

Notes: Values in brackets are robust standard errors. *, ** and *** indicate that the statistic is statistically significant at the significance level of 10%, 5% and 1%, respectively.

Table 15. Railway, Marine, aerospace and other transportation equipment manufacturing

Quantile	5%	25%	50%	75%	95%
Age	–0.0014	–0.0014	–0.0026	–0.0027	–0.0123**
	(0.0014)	(0.0014)	(0.0020)	(0.0027)	(0.0051)
Lev	0.7894***	0.7894***	1.1403***	1.3629***	1.3671***
	(0.0496)	(0.0496)	(0.0733)	(0.0915)	(0.1809)
Nature	0.2344***	0.2344***	0.2975***	0.3374***	0.3168***
	(0.0216)	(0.0216)	(0.0272)	(0.0403)	(0.0657)
Intensity	–0.1920***	–0.1920***	–0.1361***	–0.1141***	–0.0599***
	(0.0100)	(0.0100)	(0.0127)	(0.0103)	(0.0214)
Roe	0.7592***	0.7592***	0.7538***	0.5157***	0.3980
	(0.1015)	(0.1015)	(0.0829)	(0.0891)	(0.2441)
Cf	–1.3664***	–1.3664***	–1.5015***	–1.3574***	–1.1623***
	(0.1302)	(0.1302)	(0.1605)	(0.2079)	(0.4398)
GDP	0.0489***	0.0489***	0.0830***	0.0903***	0.0403
	(0.0058)	(0.0058)	(0.0110)	(0.0169)	(0.0293)
Factor of TFP macro shock	0.0704***	0.0704***	0.1086***	0.1389***	0.1067**
	(0.0122)	(0.0122)	(0.0171)	(0.0197)	(0.0436)
Factor of TFP industry shock	–0.0142	–0.0142	–0.0260**	–0.0384**	0.0240
	(0.0091)	(0.0091)	(0.0124)	(0.0166)	(0.0319)
N	4291	4291	4291	4291	4291

Notes: Values in brackets are robust standard errors. *, ** and *** indicate that the statistic is statistically significant at the significance level of 10%, 5% and 1%, respectively.

Table 16. Automobile industry

Quantile	5%	25%	50%	75%	95%
Age	0.0024	0.0024	–0.0025	–0.0118*	–0.0253**
	(0.0027)	(0.0027)	(0.0039)	(0.0070)	(0.0112)
Lev	0.9107***	0.9107***	1.3377***	1.3097***	0.9427***
	(0.1231)	(0.1231)	(0.0819)	(0.1774)	(0.1589)
Nature	0.2200***	0.2200***	0.1581***	0.1905**	0.1390
	(0.0311)	(0.0311)	(0.0515)	(0.0797)	(0.1989)
Intensity	–0.0372	–0.0372	–0.0029	–0.0032	–0.0035
	(0.1203)	(0.1203)	(0.1916)	(0.2805)	(0.4563)
Roe	1.7826***	1.7826***	1.5255***	1.2274	1.2328
	(0.3989)	(0.3989)	(0.3522)	(1.1059)	(1.1664)
Cf	–0.4287*	–0.4287*	–0.0904	–0.7081	–1.6619**
	(0.2280)	(0.2280)	(0.3811)	(0.6482)	(0.7858)
GDP	0.0534***	0.0534***	0.0263	0.0579***	0.0900**
	(0.0151)	(0.0151)	(0.0352)	(0.0166)	(0.0455)
Factor of TFP macro shock	0.0343	0.0343	0.0965**	0.0895*	0.0776
	(0.0284)	(0.0284)	(0.0392)	(0.0479)	(0.0994)
Factor of TFP industry shock	–0.0333***	–0.0333***	–0.0025	0.0089	0.0504*
	(0.0129)	(0.0129)	(0.0114)	(0.0223)	(0.0263)
N	1716	1716	1716	1716	1716

Notes: Values in brackets are robust standard errors. *, ** and *** indicate that the statistic is statistically significant at the significance level of 10%, 5% and 1%, respectively.

Table 17. Smelting and pressing of non-ferrous metals

Quantile	5%	25%	50%	75%	95%
Age	0.0070*	0.0070*	–0.0032	–0.0017	0.0182**
	(0.0038)	(0.0038)	(0.0045)	(0.0037)	(0.0083)
Lev	0.3477***	0.3477***	0.5764***	0.3597***	–0.0541
	(0.1278)	(0.1278)	(0.1497)	(0.1246)	(0.2271)
Nature	0.2911***	0.2911***	0.2510***	0.1600***	0.1359
	(0.0534)	(0.0534)	(0.0565)	(0.0619)	(0.0855)
Intensity	–0.2806***	–0.2806***	–0.2997***	–0.2456***	–0.1876***
	(0.0152)	(0.0152)	(0.0233)	(0.0245)	(0.0349)
Roe	0.3816*	0.3816*	0.2504**	0.2771***	0.2897
	(0.2153)	(0.2153)	(0.1091)	(0.0889)	(0.4092)
Cf	–0.6469*	–0.6469*	0.0435	0.4551	0.0347
	(0.3863)	(0.3863)	(0.4044)	(0.2966)	(0.6345)
GDP	0.0375	0.0375	0.0472**	0.0491**	0.0242
	(0.0236)	(0.0236)	(0.0225)	(0.0223)	(0.0203)
Factor of TFP macro shock	0.0392	0.0392	0.0341	0.0328	0.1151**
	(0.0351)	(0.0351)	(0.0379)	(0.0348)	(0.0580)
Factor of TFP industry shock	–0.0264	–0.0264	–0.0169	0.0166	–0.0542
	(0.0295)	(0.0295)	(0.0335)	(0.0278)	(0.0590)
N	734	734	734	734	734

Notes: Values in brackets are robust standard errors. *, ** and *** indicate that the statistic is statistically significant at the significance level of 10%, 5% and 1%, respectively.

Table 18. Manufacture of non-metallic mineral products

Quantile	5%	25%	50%	75%	95%
Age	–0.0054	–0.0054	–0.0050**	–0.0063*	0.0014
	(0.0048)	(0.0048)	(0.0025)	(0.0036)	(0.0085)
Lev	0.5322***	0.5322***	0.6423***	0.7364***	0.5081
	(0.1689)	(0.1689)	(0.0883)	(0.1427)	(0.3281)
Nature	0.0168	0.0168	0.0792**	0.1220***	0.1812*
	(0.0354)	(0.0354)	(0.0333)	(0.0376)	(0.1014)
Intensity	–0.0214	–0.0214	–0.0041	–0.0042	–0.0044
	(0.0234)	(0.0234)	(0.0121)	(0.0198)	(0.0644)
Roe	1.2080***	1.2080***	1.1579***	0.7315***	0.4054
	(0.1561)	(0.1561)	(0.0764)	(0.2189)	(0.5481)
Cf	0.6086	0.6086	0.1098	–0.1910	–0.6851
	(0.4770)	(0.4770)	(0.1991)	(0.4510)	(0.9966)
GDP	–0.0011	–0.0011	0.0179	0.0603***	0.0862**
	(0.0213)	(0.0213)	(0.0115)	(0.0169)	(0.0364)
Factor of TFP macro shock	0.0441*	0.0441*	0.0182	0.0109	0.1347*
	(0.0245)	(0.0245)	(0.0204)	(0.0270)	(0.0704)
Factor of TFP industry shock	–0.0077	–0.0077	0.0123	0.0012	–0.0015
	(0.0239)	(0.0239)	(0.0217)	(0.0245)	(0.0516)
N	1404	1404	1404	1404	1404

Notes: Values in brackets are robust standard errors. *, ** and *** indicate that the statistic is statistically significant at the significance level of 10%, 5% and 1%, respectively.

Table 19. Smelting and pressing of ferrous metals

Quantile	5%	25%	50%	75%	95%
Age	–0.0117***	–0.0117***	–0.0097***	–0.0189***	–0.0054
	(0.0036)	(0.0036)	(0.0030)	(0.0053)	(0.0063)
Lev	–0.0966	–0.0966	–0.0129	0.3173**	–0.5454***
	(0.1396)	(0.1396)	(0.0830)	(0.1476)	(0.1485)
Nature	0.1925***	0.1925***	0.2516***	0.3163***	0.0783
	(0.0625)	(0.0625)	(0.0262)	(0.0493)	(0.1739)
Intensity	–0.3316***	–0.3316***	–0.3409***	–0.2975***	–0.1786**
	(0.0608)	(0.0608)	(0.0176)	(0.0666)	(0.0743)
Roe	0.1253	0.1253	0.0941	0.1412	–0.0002
	(0.1846)	(0.1846)	(0.0645)	(0.1211)	(0.1802)
Cf	0.1973	0.1973	0.0653	0.2062	0.2510
	(0.2673)	(0.2673)	(0.1913)	(0.3746)	(0.5194)
GDP	0.0339**	0.0339**	0.0117	–0.0316	–0.0614***
	(0.0139)	(0.0139)	(0.0083)	(0.0208)	(0.0202)
Factor of TFP macro shock	0.0944***	0.0944***	0.0793***	0.0194	0.2057***
	(0.0230)	(0.0230)	(0.0157)	(0.0381)	(0.0324)
Factor of TFP industry shock	–0.0271	–0.0271	0.0134	–0.0255	0.0198
	(0.0296)	(0.0296)	(0.0148)	(0.0181)	(0.1827)
N	636	636	636	636	636

Notes: Values in brackets are robust standard errors. *, ** and *** indicate that the statistic is statistically significant at the significance level of 10%, 5% and 1%, respectively.

4. Estimation results of skew t-distribution parameters of TFP in various industries

Table 20. Estimation results of skew t-distribution parameters of TFP μ, σ, α, υ

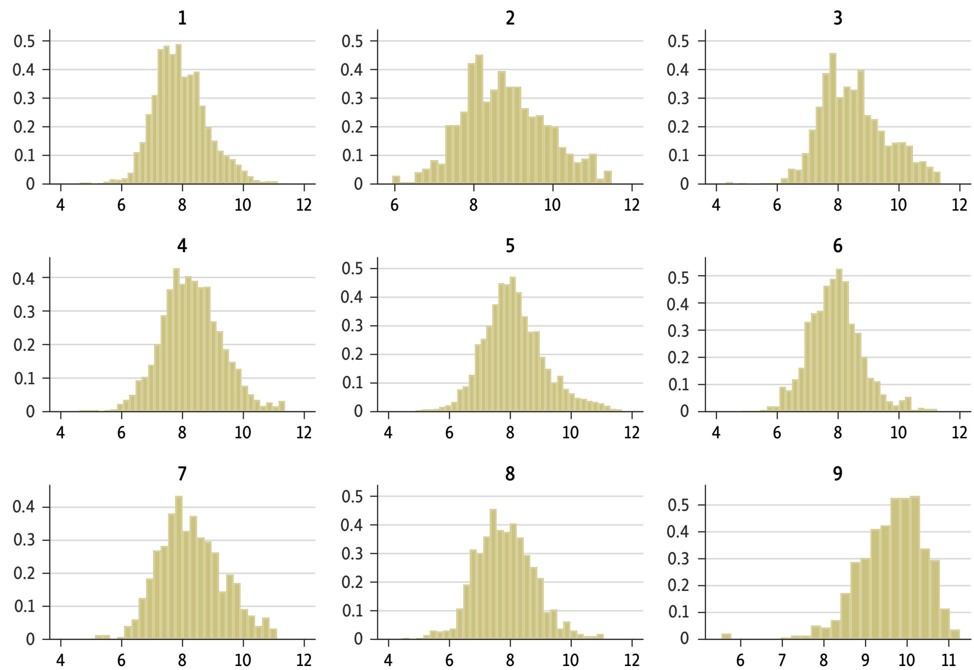
Industry	shock	μ (Mean)	σ (SD)	α (Skewness)	υ (degree of freedom)
Special equipment manufacturing industry	Yes	5.1289	0.6612	0.1812	5
	No	4.9967	0.6498	0.1443	5
Smelting and pressing of non-ferrous metals	Yes	5.7972	0.5231	0.1471	5
	No	5.8002	0.5222	0.1551	5
Automobile industry	Yes	5.1737	0.8844	0.2166	4
	No	5.1140	0.8659	0.2265	4
Manufacture of electrical machinery and equipment	Yes	4.8831	0.6117	–0.1512	5
	No	4.8165	0.6186	–0.1319	5
Computer, communications and other electronic equipment manufacturing	Yes	5.2813	0.6228	0.1272	18
	No	5.1664	0.5941	0.1705	14
General machinery manufacturing	Yes	5.3664	0.7030	0.2167	4
	No	5.2622	0.6961	0.1632	4
Railway, Marine, aerospace and other transportation equipment manufacturing	Yes	5.2011	0.7011	–0.2531	17
	No	5.1587	0.7103	–0.2250	17

End of Table 20

Industry	shock	μ (Mean)	σ (SD)	α (Skewness)	υ (degree of freedom)
Manufacture of non-metallic mineral products	Yes	4.7524	0.6241	0.0533	4
	No	4.7432	0.6348	0.0829	4
Smelting and pressing of ferrous metals	Yes	5.5504	0.8012	–0.3839	19
	No	5.5242	0.8185	–0.2902	15

5. The enterprise TFP results of LP method

a) TFP distribution of the whole sample



b) TFP distribution by industry

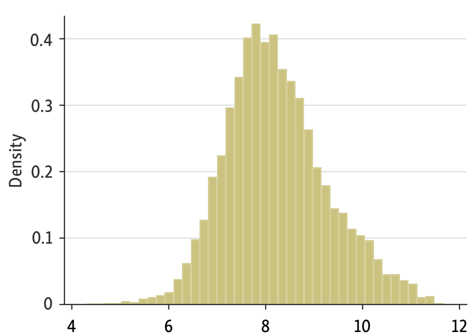


Figure 9. TFP distribution by industry (LP method)