Measuring Innovation Efficiency Using Stochastic Frontier Analysis

Hao He
BA School of Business and Finance, University of Latvia, Riga, Latvia
hh25014@edu.lu.lv

Abstract: Innovation is widely regarded as a key driver of firm competitiveness, technological progress, and long-term economic growth. However, measuring innovation efficiency remains a challenging issue in both academic research and practical policy analysis. Many existing studies rely mainly on innovation input or output indicators, such as R&D expenditure, patent applications, or patent grants. Although these indicators provide useful information, they do not fully reflect how efficiently firms transform innovation resources into actual innovation outcomes. In addition, several commonly used measurement approaches, including simple ratio indicators and Data Envelopment Analysis (DEA), often assume that all deviations from the efficiency frontier are caused entirely by inefficiency. In reality, however, part of these deviations may result from external shocks, statistical noise, or measurement errors, which can lead to biased estimates of innovation efficiency. To address this issue, this paper proposes a more structured framework for measuring firm-level innovation efficiency using Stochastic Frontier Analysis (SFA). Compared with traditional non-parametric approaches, SFA provides the advantage of separating inefficiency effects from random disturbances, thereby offering a more realistic and reliable evaluation of innovation performance. The paper presents the basic theoretical logic of the SFA framework, including model specification, parameter estimation through maximum likelihood methods, and the calculation and interpretation of innovation efficiency scores. In addition, the study discusses the practical applicability of the framework in empirical research and highlights its advantages in handling firm-level panel data. To illustrate the proposed approach, an empirical example is conducted using panel data from Chinese A-share listed firms covering the period from 2012 to 2023, including more than 40,000 firm-year observations. The findings indicate that substantial differences in innovation efficiency exist across firms and industries. The results further suggest that the SFA-based approach is better able to identify these differences and provide more stable efficiency estimates than several conventional measurement methods. Overall, although the framework still has certain limitations, it offers a practical, transparent, and relatively flexible tool for evaluating innovation efficiency, and may provide useful implications for future academic research, enterprise management, and innovation policy design.

Keywords: Innovation Efficiency; Stochastic Frontier Analysis (SFA); Measurement Framework; Conventional Indicators

1. Introduction

New Ideas can help the company improve its competitiveness and promote the long-term economic development of the region. However, the amount of investment in innovation and the number of output units produced by the firms differ significantly, as well as the efficiency with which these innovation inputs are converted into outputs. Innovation efficiency refers to the amount of innovation output that can be achieved per unit of input resources; that is, the maximal increase in innovation output for a fixed set of inputs (Griliches, 1990; Dosi, 1988). Assess the actual effects of innovation accurately in the research and policy stage.

The Problem of innovation efficiency has not been addressed by a reliable measure yet. A typical type is a simple ratio-based index, such as the number of patents per unit of R&D investment (Griliches, 1990; Hall, Jaffe, & Trajtenberg, 2005). These are simple to compute, but they attribute all deviations from the best-observed performance solely to inefficiency and fail to consider random shocks, measurement errors, etc. Todorov and others (2024) have pointed out some problems of comparability and reliability in the analysis of the 23 innovation indicators. Data Envelopment Analysis (DEA) is another widely used method that constructs an efficiency frontier from the best practices in the data and does not assume a functional form (Charnes, Cooper, & Rhodes, 1978). DEA is also deterministic and therefore cannot differentiate between inefficiency and random noise. In the face of innovation, due to the uncertainty of the results and the noisiness of the data, there is a risk of biased efficiency estimates and incorrect rankings of the companies (Aigner, Lovell & Schmidt, 1977; Coelli et al., 2005).

Aigner and Meeusen and van den Broeck (1977) introduced Stochastic Frontier Analysis (SFA) to overcome the above problems by splitting the error term into a two-sided random noise component and a one-sided inefficiency component. Therefore, researchers can exclude random fluctuations in the inefficiency data. Although SFA has been used extensively in the study of productivity (Battese & Coelli, 1995; Kumbhakar & Lovell, 2000), it has not been applied to evaluate the efficiency of innovation and, thus far, has not been systematically compared with other indices.

Provide a practical SFA-based system for assessing the innovation efficiency at the firm level and empirically compare its results with those of traditional ratio indicators in this paper. Panel data of Chinese A-share listed companies from 2012 to 2023, with more than 40,000 firm-year observations, is used to estimate firm-level innovation efficiency based on a stochastic frontier innovation production function and compare the results with other indices.

The two reasons are as follows. First, construct an organised and reproducible SFA model for assessing innovation efficiency to provide researchers with an accessible tool in the presence of noisy innovation data. Second, we can establish a good evaluation system for the utility value function of the two SFA/traditional index groups and identify the different ranges of assessment that these indicators will cover for a company's innovation performance.

The remaining contents of this paper are as follows. Section 2 is a summary of related studies on the economy of innovation. Section 3 shows the SFA method. Section 4 shows the data and variables. Section 5 is the Empirical Results. Section 6 introduces the impact and shortcomings, and Section 7 concludes.

2. Literature Review

2.1 Measurement of Innovation Efficiency

Researchers have focused on how efficiently enterprises convert innovation resources into new products or services in empirical studies for a long time (Griliches, 1990). Todorov et al. (2024) have evaluated 23 innovation indicators and found that, while there are many such indicators to observe all faces of innovation, problems with comparison, time sensitivity and accuracy have arisen. The problem of reduced innovation efficiency is to identify and address shortcomings in the quality of the transformation process from raw materials to final products.

The most basic is a ratio, such as the number of patents per unit of R&D investment (Griliches, 1990; Hall et al., 2005). They are relatively simple to calculate, but they have a serious defect: they attribute all deviations from the best-performing model to inefficiency and ignore random shocks or measurement errors. Innovation has uncertain results and noisy patent data; therefore, the estimation will be biased. Ratio indicators only show one input-output relationship at a time and are thus inadequate for the multiple-input nature of innovation.

Therefore, the above deficiencies were no longer tolerable. Two broad classes have emerged: non-parametric approaches, notably DEA, and parametric approaches, notably SFA.

2.2 DEA and its Deficiencies

Charnes and his colleagues (1978) introduced the DEA model; it is a form that does not need to assume a functional form for the efficiency frontier and is suitable for multiple-input and multiple-output problems. Therefore, this has been widely used in studies of innovation efficiency.

However, as a deterministic method, DEA assigns all deviations from the frontier to inefficiency. Measurement errors in innovation data, random fluctuations in patent filings, or temporary external shocks may be wrongly identified as inefficiency. Due to the abundance of imperfections in the data for innovation, an overestimation of inefficiency and thus skewed firm rankings may occur (Aigner et al., 1977; Coelli et al., 2005). If there are problems of measurement error and random shocks in a specific situation, parametric stochastic methods can be used.

2.3 SFA as an Alternative

SFA addresses the first limitation of DEA by adding a stochastic error term that is split into two parts: a symmetric random noise term and a one-sided inefficiency term (Aigner et al., 1977; Meeusen & van den Broeck, 1977). Thus, the true inefficiency in SFA can be separated from the random noise to obtain a more stable estimate in the presence of measurement errors.

Battese and Coelli (1995) extended SFA to panel data and introduced time-varying efficiency estimation. Coelli et al. (2005) and Kumbhakar and Lovell (2000) have offered all-encompassing discussions of the SFA method. Innovation activities are naturally uncertain; R&D projects may fail, and the timing of patent applications is also unpredictable, so the SFA can be used to handle these random disturbances.

2.4 Innovation Efficiency in the Chinese Context

China's high-speed growth of R&D investment provides an appropriate background for the study of innovation efficiency. Zhou, Zhang, and Ruan (2023) use SFA to calculate the corporate innovation efficiency of Chinese listed companies and find that perceptions of economic policy uncertainty significantly affect this efficiency. Kong, Yang and Wang (2023) found that innovative efficiency promotes the market-to-book ratio of a company. Li and others (2023) have studied how artificial intelligence can be applied in boosting the speed of enterprise-level innovation. The above studies use innovation efficiency as the end-point and have not examined whether there are deficiencies in the measurement method.

2.5 Research Gaps

Methodological studies have shown that, to distinguish inefficiency from random fluctuations, SFA can be used and it is theoretically more advantageous than DEA and ratio indicators in noisy environments (Aigner et al., 1977; Coelli et al., 2005). Most empirical studies have used DEA without considering its deterministic nature, and SFA efficiency scores have not been systematically compared with simpler indicators. No one has investigated whether SFA-based indices can modify the performance indicators of innovation in companies to some extent by replacing traditional factors. Therefore, a reasonable SFA framework will be established and, at the same time, compared to traditional ratio-based indicators in this study.

3. Methodology

3.1 SFA Framework

SFA is used to study firm-level innovation efficiency in this paper. Aigner et al. (1977) and Meeusen and van den Broeck (1977) proposed a way to distinguish between two kinds of reasons for deviation from the frontier: real inefficiency and random statistical fluctuations. Therefore, SFA is relatively suitable for analysing innovation due to the uncertainty of the outcome and the uneven availability of data (Griliches, 1990; Coelli et al., 2005).

The key feature of SFA is the composed error structure. The error term is specified as the sum of a symmetric random disturbance and a one-sided inefficiency term. The general form is:

$$y_{it} = f(\mathrm{x}_{it};\beta) + v_{it} - u_{it}$$

Where y_{it} is output, x_{it} is a vector of inputs, β is a parameter vector, and $f(\cdot)$ is the deterministic production frontier. The error components are: v_{it}~N (0, σ_v^2), a two-sided random noise term capturing measurement errors and random shocks; and u_{it} ≥0, a one-sided inefficiency term. This separation distinguishes SFA from deterministic methods, which implicitly assume v_{it} = 0 for all observations.

3.2 Innovation Production Function

Based on the knowledge production function tradition (Griliches, 1990, 1994), we assume a Cobb-Douglas innovation production function where innovation output is a function of R&D expenditure, physical capital and labour:

$$\ln(1 + \mathrm{Patent}_{it}) = \beta_0 + \beta_1 \ln(\mathrm{RD}_{it}) + \beta_2 \ln(\mathrm{Capital}_{it}) + \beta_3 \ln(\mathrm{Labor}_{it}) + v_{it} - u_{it}$$

Patent counts are widely used as innovation output measures, capturing codified technological inventions systematically recorded over time (Griliches, 1990; Hall et al., 2005). We use *ln(1+Patent)* to accommodate zero patents. R&D expenditure represents deliberate knowledge creation investment (Griliches, 1990; Kumbhakar & Lovell, 2000). Capital and labor capture broader firm resources supporting innovation. The coefficients β_1 through β_3 represent output elasticities, with their sum indicating returns to scale.

3.3 Model Estimation

The Model is based on maximum likelihood estimation. Assuming that v_{it} follows a normal distribution and u_{it} follows a half-normal distribution, the likelihood function can be obtained and optimised numerically (Aigner et al., 1977; Coelli et al., 2005).

A Typical Characteristic is the variance ratio:

$$\gamma = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$$

where γ∈ [0,1]. When γ is close to 1, most of the variations in the composite error are caused by inefficiency, and SFA decomposition can be used. When γ is close to 0, random noise is relatively large. A likelihood-ratio (LR) test on *H_o: σ_u^2=0* has shown good statistical support for the stochastic frontier assumption.

3.4 Innovation Efficiency Scores

Firm-level innovation efficiency is defined as the ratio of actual output to the maximum achievable output:

$$TE_{it} = \frac{f(\mathrm{x}_{it};\beta)exp(v_{it}) - u_{it}}{f(\mathrm{x}_{it};\beta)exp(v_{it})} = exp(-u_{it})$$

Since u_{it} ≥0, TE_{it}∈ [0,1]. A value of 1 indicates that it is running at full speed of innovation. Values less than 1 are inefficient. They are relative measures that compare firms to the best-practice frontier constructed from the data (Coelli et al., 2005; Kumbhakar & Lovell, 2000).

3.5 Comparison with Conventional Indicators

We construct the following two representative ratio-based indicators for comparison:

$$Ratio_1 = \frac{Patent_{it}}{RD_{it}}; Ratio_2 = \frac{ln(1+Patent_{it})}{ln(RD_{it})}$$

The first are raw correlations of innovation output and R&D investment. They do not control for capital and labor inputs, and they are not random noise. We compare SFA efficiency scores with the above indicators using Spearman rank correlation coefficients. A relatively large positive correlation (greater than 0.90) indicates that SFA and the former indicators are positively correlated. A relatively strong correlation (0.50 - 0.80) would be expected for SFA and other dimensions of innovation efficiency. The two are used to verify whether SFA can better reflect the actual level of innovation efficiency by addressing random fluctuations.

4. Data and Variables

4.1 Data Source and Sample Construction

Panel data of Chinese A-share listed companies from 2012 to 2023 were used for the analysis. Financial variables such as R&D expenditure, total assets and employee count are available in the CSMAR database. Patent data are from the Chinese Patent Database. Exclude firms in the financial sector, remove observations with missing key variables, and winsorize continuous variables at the 1st and 99th percentiles. The final sample has 37,658 firm-year observations and 5,269 unique firms. China provides a suitable background for this study, and R&D investment has been expanding rapidly recently; moreover, enterprises in China are not uniform (Zhou et al., 2023; Kong et al., 2023).

4.2 Variable Definitions

Innovation output is measured by patent applications filed in a given year. Patents are the most widely used indicator of innovation output, capturing codified technological inventions that are systematically recorded and comparable across firms and over time (Griliches, 1990; Hall et al., 2005). We use ln(1+Patentit) to accommodate zero patent filings. While not all innovations are patented and patent value varies (Griliches, 1990; OECD/Eurostat, 2018), patent counts remain the most feasible output indicator for large-scale firm-level studies..

The three Innovation Input factors are: R&D expenditure is defined as the natural logarithm of total R&D investment, which accounts for conscious knowledge-creation investments (Griliches, 1990). Capital input, expressed as the logarithm of total assets, indicates the total resource foundation for innovation. Labor input is the logarithm of the total number of employees, which represents the human capital that generates new knowledge (Cohen & Levinthal, 1990; Moreira et al., 2024). All of the inputs are in log form and consistent with the Cobb-Douglas function.

The first two are conventional ratio indicators. Ratio 1 is the raw patent-to-R&D ratio ($\mathrm{Patent}_{it}/\mathrm{RD}_{it}$), indicating the number of patents per unit of R&D investment. Ratio 2 is the log-transformed ratio (ln (1+Patent_{it})/ln (RD_{it})), which reduces skewness and is more suitable for the log-log SFA structure. They are used to determine the efficiency score of SFA.

4.3 Descriptive Statistics

Table 1 presents descriptive statistics. Innovation output, ln(1+Patent), has a mean of 1.332 (SD = 0.278), with some firms filing no patents and the most active reaching 1.792. Inputs display wide variation: ln (RD) has a standard deviation of 1.510, reflecting large differences in R&D scale. The SFA innovation efficiency score has a mean of 0.787 (SD = 0.132), ranging from 0.161 to 0.980. The mean efficiency of 0.787 implies that, on average, firms could increase innovation output by approximately 21% without additional inputs by operating at the best-practice frontier.

Table 1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ln(1+Patent))	37,658	1.332	0.278	0.000	1.792
ln(R&D)	37,658	17.928	1.510	13.607	21.937
ln(Capital)	37,658	20.152	1.741	10.804	27.298
ln(Labor)	37,658	7.615	1.248	2.398	13.464
Innovation efficiency	37,658	0.787	0.132	0.161	0.980

Notes: Sample consists of Chinese A-share listed firms, 2012–2023. Efficiency estimated via SFA. All continuous variables winsorized at 1st and 99th percentiles.

The distribution of efficiency (Figure 1) is nearly unimodal and concentrated in the range of 0.70-0.90. The mass of the distribution is significantly below the frontier value of 1.0; thus, it is considerably inefficient. A right-skewed distribution indicates that fewer enterprises are located in the forward area. The distribution is relatively even at a low end and does not have any sudden large dips, which is in line with the noise-filtering property of SFA (Coelli et al., 2005).

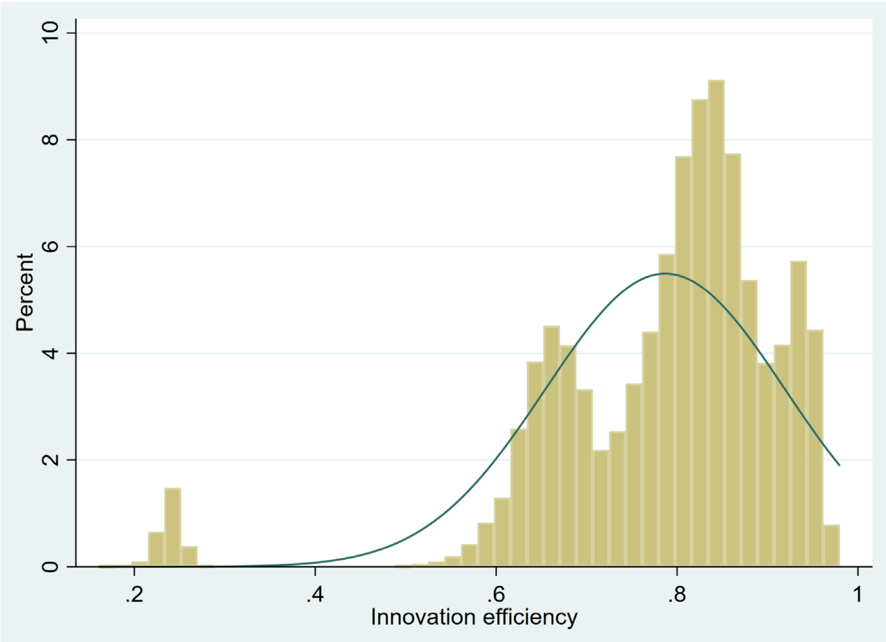

Figure 1: Distribution of innovation efficiency

Most firms cluster around efficiency levels between 0.75 and 0.90, while a smaller group of firms exhibits substantially lower efficiency levels.

5. Empirical Results

5.1 Stochastic Frontier Estimation

Table 2 reports the maximum likelihood estimation results. All three input coefficients are positive and significant at the 1% level. The coefficient on ln(R&D) is 0.0285, the largest among the three elasticities, confirming the central role of R&D in generating innovation output. The sum of elasticities is approximately 0.065, indicating strongly decreasing returns to scale—consistent with the inherent uncertainty and high risk of innovation (Griliches, 1990).

Table 2: Stochastic frontier estimation

Variable	Coefficient	Std. Error	z-stat
ln(R&D)	0.0285***	0.0008	35.85
Ln (Capital)	0.0189***	0.0008	22.36
Ln (Labor)	0.0172***	0.0014	12.67
Constant	0.5712***	0.0159	35.89

Table 3: Frontier parameters

Parameter	Estimate
σ_u	0.3589
σ_v	0.0862
σ^2	0.1363
λ	4.1637

Table 4: Model statistics

Statistic	Value
Observations	37,658
Log-likelihood	4334.71
Wald χ^2	6789.57
LR test (σ_u = 0)	$p < 0.001$

*Notes: *** p<0.01p<0.01. Dependent variable: ln(1+Patent).*

The estimate of γ is 0.945, indicating that approximately 94.5% of total variance in the composite error is attributable to inefficiency rather than random noise. This demonstrates that inefficiency is the dominant source of deviation from the frontier and provides strong justification for SFA over OLS. The LR test rejects the null hypothesis of no inefficiency ($p<0.001$). The parameter λ=4.164 reinforces the conclusion that systematic inefficiency, rather than random variation, is the primary source of firms' deviations from the frontier.

5.2 Distribution of Innovation Efficiency

Based on SFA estimates, firm-level efficiency scores are obtained as $TE_{it} = exp(-u_{it})$. As noted, mean efficiency is 0.787 (SD = 0.132). The right-skewed distribution (Figure 1) indicates that while most firms operate at moderate efficiency, very few achieve near-frontier performance. For an average firm with efficiency of 0.787, the output shortfall relative to the frontier is approximately 21.3%, suggesting that improving innovation resource utilization may be as important as increasing inputs themselves.

5.3 Comparison with Conventional Indicators

Table 5 presents Spearman rank correlations among the three efficiency measures.

Table 5: Spearman rank correlations

	SFA efficiency (TE)	Ratio 1 (Patent/RD)	Ratio 2 (ln(1+Patent)/ln(RD))
SFA efficiency (TE)	1.000		
Ratio 1	0.387***	1.000	
Ratio 2	0.621***	0.782***	1.000

*Notes: *** p<0.01*p*<0.01. All correlations computed on 37,658 observations.

SFA efficiency scores are positively correlated with both conventional indicators and thus belong to the same group. The correlations of Ratio 1 and Ratio 2 with it are relatively small: 0.387 and 0.621, respectively. The first result is that the above correlations are less than 0.90, so SFA cannot merely replicate the ranking of a simple model. A correlation of 0.621 shows that some companies are significantly more or less efficient under different measures.

These two are the different traits of SFA. First, SFA considers multiple inputs at the same time and is not a single input-output relationship. Second, SFA separates inefficiency from random noise. Firms that have been adversely affected by random shocks will be penalized in line with the ratio-based indicator, and SFA partially mitigates this noise. Firms that have received favorable shocks are considered relatively efficient under the above-mentioned indicators.

The relatively weak rank correlations do not support the main conclusion that a different measurement mode was used. Based on the theoretical strengths of SFA and empirical evidence that the proportion of error attributable to inefficiency is relatively large (γ=0.945), these differences are likely to reflect an actual innovation inefficiency of the firm.

5.4 Robustness Tests

Three Robustness Checks are conducted. First, we re-estimate the SFA model with a translog production function, and the efficiency scores are highly correlated with those obtained from the Cobb–Douglas model (Spearman ρ>0.95), and the rank correlations with traditional indicators remain unchanged. Second, we limit the sample to observations with at least one patent application; the rank correlation between SFA efficiency and Ratio 2 is 0.598 (compared to 0.621 in the full sample), and the qualitative conclusion remains unchanged. Third, we build an alternative index Ratio3=Patent/Total AssetsRatio3=Patent/Total Assets, which also has a rank correlation of 0.412 with SFA efficiency and is thus considered moderate. The above checks confirm that the main results are not due to particular model selection.

6. Discussion

6.1 Interpreting the Divergence

The moderate rank correlation (Spearman ρ=0.621) between SFA efficiency and conventional indicators reflects two distinguishing features of SFA. First, SFA accounts for multiple inputs simultaneously, whereas ratio indicators capture only a single input-output relationship. Second, and more fundamentally, SFA separates inefficiency from random noise. The estimated γ of 0.945 validates that efficiency differences are real, while the fact that approximately 5.5% of total error variance is attributable to noise implies that deterministic methods produce distorted rankings. For researchers and policymakers who rely on efficiency measures to identify best practices or make resource allocation decisions, such ranking differences have meaningful consequences.

6.2 Research Methodology

The three results have been revealed. First, the selected mode of measurement is not solely based on technology. Ratio-based indicators and DEA are different from those in SFA, and therefore may show different pictures of firm efficiency. Secondly, SFA does not need to be very complicated. The framework shown here is a Cobb-Douglas function with three inputs, estimated using maximum likelihood, and has transparent and reproducible diagnostic parameters (γ, LR test) to assess model suitability. Third, as shown in the comparison, the method is open. Research on the effectiveness of innovation should be sensitive to all kinds of changes in measurement.

6.3 Limitations and Future Research

Some deficiencies will also be listed. Patent counts do not cover all dimensions of innovation (OECD/Eurostat, 2018), and a simple count fails to differentiate between high-value and low-value inventions. Future studies can add quality-adjusted patent indicators or several innovation outputs. The SFA framework is for a single output; multi-output SFA models and distance-function approaches offer good extensions. The sample is restricted to Chinese listed companies, and cross-country comparative studies may not be generalizable. Problems of endogeneity in the estimation of the production function can be addressed by instrumental variable or dynamic panel SFA methods. Finally, other functional forms for Cobb-Douglas and translog were not used. Despite the above deficiencies, the main content remains unchanged: accounting for stochastic noise does not alter the distribution of firm innovation performance.

7. Conclusion

The following study will address a long-standing problem in research methodology: how to measure firm-level innovation efficiency in the presence of inherent noise and uncertainty in the innovation process. Panel data of Chinese A-share listed companies from 2012 to 2023 were taken as the sample for an SFA-based estimation of innovation efficiency. Frontier estimation shows significant differences in efficiency; the mean is 0.787, so generally speaking, an increase of about 21% in innovation output per unit of input can be achieved. The variance parameter γ was estimated at 0.945, demonstrating that inefficiency—rather than random noise—is the dominant source of deviation from the frontier.

The first result of this paper is an introduction to the SFA efficiency index. Spearman's rank correlation between SFA efficiency and the logarithm of the patent-to-R&D ratio is 0.621; thus, the selection of a different indicator may have yielded a significantly different result. The Division of SFA can be attributed to its collection of various indicators to distinguish inefficiency from randomness in the unpredictable environment of innovation. The study has shown that, in terms of improving the efficiency of innovation research, methods should be more open, and a practical, verifiable model has been proposed that can be used or adapted by others in the future.

Ethics Declaration

No ethical approval was required for this study because the research used publicly available secondary data from Chinese A-share listed firms.

AI Declaration

AI tools were used only for language polishing, grammar checking, and improving readability. All academic content, analysis, and conclusions were developed and verified by the author.

References

Aigner, D. J., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6(1), 21–37.

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, 20(2), 325–332.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research*, 2(6), 429–444.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis* (2nd ed.). Springer.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1), 128–152.

Dosi, G. (1988). Sources, procedures, and microeconomic effects of innovation. *Journal of Economic Literature*, 26(3), 1120–1171.

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, 28(4), 1661–1707.

Griliches, Z. (1994). Productivity, R&D, and the data constraint. *American Economic Review*, 84(1), 1–23.

Hall, B. H., Jaffe, A., & Trajtenberg, M. (2005). Market value and patent citations. *RAND Journal of Economics*, 36(1), 16–38.

Hirshleifer, D., Hsu, P.-H., & Li, D. (2013). Innovative efficiency and stock returns. *Journal of Financial Economics*, 107(3), 632–654.

Holl, A., Peters, B., & Rammer, C. (2023). Local knowledge spillovers and innovation persistence of firms. *Economics of Innovation and New Technology*, 32(6), 826–850.

Kong, D., Yang, Y., & Wang, Q. (2023). Innovative efficiency and firm value: Evidence from China. *Finance Research Letters*, 52, 103557.

Kumbhakar, S. C., & Lovell, C. A. K. (2000). *Stochastic frontier analysis*. Cambridge University Press.

Li, C., Xu, Y., Zheng, H., Wang, Z., Han, H., & Zeng, L. (2023). Artificial intelligence, resource reallocation, and corporate innovation efficiency. *Resources Policy*, 81, 103324.

Meeusen, W., & van den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review*, 18(2), 435–444.

Moreira, A., Navaia, E., & Ribau, C. (2024). Innovation capabilities and their dimensions: A systematic literature review. *European Journal of Innovation Management*, 27(3), 901–930.

OECD/Eurostat. (2018). *Oslo Manual 2018: Guidelines for collecting, reporting and using data on innovation* (4th ed.). OECD Publishing.

Ponta, L., Puliga, G., Oneto, L., & Manzini, R. (2022). Identifying the determinants of innovation capability with machine learning and patents. *IEEE Transactions on Engineering Management*, 69, 2144–2154.
Todorov, L., Shopova, M., Panteleeva, I. M., & Todorova, L. (2024). Innovation metrics: A critical review. *Economies*, 12(12), 1–28.
Zhou, H., Zhang, X., & Ruan, R. (2023). Firm's perception of economic policy uncertainty and corporate innovation efficiency. *Journal of Innovation & Knowledge*, 8(3), 100371.