FACTOR PRODUCTIVITY AND GROWTH ELASTICITY OF THE FOOD PROCESSING INDUSTRY IN ODISHA: A TRANSLOG PRODUCTION FUNCTION APPROACH

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Abstract: The food processing industry occupies a strategic position in Odisha's industrial economy as the principal link between the state's large agricultural, horticultural, and fisheries base and its manufacturing sector. This study estimates factor productivity and the growth elasticities of labour and capital in the food processing industry of Odisha over a twenty-five-year period (1998–99 to 2022–23) using a transcendental logarithmic (translog) production function. Secondary data on gross value of output (GVO), the number of persons engaged, and fixed capital were compiled from the Annual Survey of Industries (ASI), Ministry of Statistics and Programme Implementation, Government of India. Output and capital were converted to constant (2011–12) prices using spliced wholesale price indices of manufactured food products and of machinery and equipment, respectively. Real GVO grew at a trend compound annual growth rate (CAGR) of 7.72 per cent, real fixed capital at 10.62 per cent, and employment at 3.40 per cent, indicating pronounced capital deepening. The translog specification is preferred to the Cobb–Douglas restriction, $F(3, 19) = 3.10$, $p = 0.051$, and explains 92.1 per cent of the variation in log real output. At the geometric mean of the data, the output elasticity of labour is 0.435 and that of capital is 0.502, yielding a scale elasticity of 0.937 that is statistically indistinguishable from constant returns to scale. Total factor productivity (TFP) grew at an average of 3.48 per cent per annum but decelerated sharply, from 5.85 per cent in 1998–99 to 2010–11 to 1.10 per cent in 2010–11 to 2022–23, implying that recent output growth has been increasingly input-driven, particularly capital-driven. The findings support policy emphasis on technological upgradation, skill formation, and improved capacity utilisation rather than capital accumulation alone.

IndexTerms – Translog production function; factor productivity; growth elasticity; food processing industry; Odisha; Annual Survey of Industries.
JEL Classification: D24; L66; O47.

1. INTRODUCTION

The food processing industry is widely regarded as the natural first rung of industrialisation for agrarian economies because it raises the value of primary produce, curtails post-harvest losses, stabilises farm incomes, and generates employment along the entire value chain from farm gate to retail shelf. In India, the sector has attracted sustained policy attention through instruments such as the Pradhan Mantri Kisan Sampada Yojana, the Production Linked Incentive Scheme for Food Processing, and state-level agro-processing policies, reflecting its dual role in agricultural transformation and manufacturing growth. Yet the growth of the sector has been geographically uneven, and the constraints on its expansion—infrastructure gaps, supply-chain fragmentation, limited access to credit and technology, and regulatory burden—remain binding in many states (Singh et al., 2022).

Odisha presents a particularly instructive case. The state possesses one of the country's richest raw-material bases for food processing—rice, pulses, oilseeds, fruits and vegetables, milk, and marine and inland fisheries—and the Government of India's sectoral profiling has projected substantial growth potential for food processing in the state (Ministry of Food Processing Industries [MoFPI]). At the same time, Odisha's registered food processing industry has historically been dominated by rice milling and other primary processing with comparatively low value addition, so that the efficiency with which the industry converts labour and capital into output is of direct policy relevance. Whether output growth in the industry has been driven by the accumulation of inputs or by improvements in productivity determines whether the current growth path is sustainable and what form public support should take. Production function analysis provides the standard analytical framework for such questions. Since the pioneering work of Cobb and Douglas (1928), economists have used estimated production functions to recover the output elasticities of factors, returns to scale, and—following Solow (1957)—the residual growth of total factor productivity (TFP). The restrictive assumptions of the Cobb–Douglas form, notably unitary elasticity of substitution and fixed output elasticities, prompted the development of more flexible specifications, including the constant elasticity of substitution (CES) function (Arrow et al., 1961) and, ultimately, the transcendental logarithmic (translog) function introduced by Christensen, Jorgenson, and Lau (1971, 1973). The translog form imposes no prior restrictions on substitution possibilities or homotheticity and permits output elasticities and returns to scale to vary with input levels (Kim, 1992), which makes it especially suitable for studying an industry undergoing rapid structural change.

This paper applies the translog production function to a twenty-five-year annual series (1998–99 to 2022–23) on the registered food processing industry of Odisha compiled from the Annual Survey of Industries (ASI). The specific objectives of the study are:

(i) to estimate the factor productivity of the food processing industry in Odisha using the translog production function; and (ii) to analyse the growth elasticity of labour and capital in the industry. In addition, the study documents the trends and compound annual growth rates (CAGR) of gross value of output, persons engaged, and fixed capital over the study period.

The contribution of the paper is twofold. First, while the productivity of India's food processing industry has been examined at the national level, chiefly with non-parametric methods (Ali et al., 2009; Kumar & Basu, 2008; Meena, 2024), no published study, to the best of our knowledge, applies a translog production function to ASI data for the food processing industry of Odisha; the nearest state-level antecedent is a data envelopment analysis for Assam (Das et al., 2024), and the nearest Odisha-specific productivity work concerns agriculture rather than food processing (Kadam et al., 2022). Second, by combining deflated ASI aggregates with a flexible functional form and a growth-accounting decomposition, the paper separates the contributions of labour, capital, and TFP to the industry's output growth and thereby speaks directly to the design of state industrial policy.

The remainder of the paper is organised as follows. Section 2 reviews the literature. Section 3 describes the data and methodology. Section 4 presents the empirical results, and Section 5 discusses them in the light of previous findings. Sectio n 6 concludes with policy implications and limitations.

2. REVIEW OF LITERATURE

2.1 Production functions, flexible forms, and the translog

The empirical production function literature originates with Cobb and Douglas (1928), who fitted the function $P = bL^{k}C^{1-k}$ to United States manufacturing data for 1899–1922 and found that a labour exponent of about 0.75 tracked both output and observed factor shares remarkably well. The Cobb–Douglas form, however, constrains the elasticity of substitution between capital and labour to unity and fixes the output elasticities irrespective of scale or factor proportions. Arrow et al. (1961) relaxed th e first constraint with the CES function, presenting international evidence that the elasticity of substitution is typically positive but below unity, and Kmenta (1967) provided a Taylor-series linearisation of the CES function around the Cobb–Douglas case that can be estimated by ordinary least squares and that is structurally a restricted translog.

The decisive step towards flexibility was taken by Christensen, Jorgenson, and Lau (1971, 1973), who proposed the transcendental logarithmic production frontier as a second-order approximation to an arbitrary production function that imposes neither additivity nor homotheticity, and rejected those restrictions for aggregate United States data for 1929–1969. Berndt and Christensen (1973) supplied the first major empirical application, using the translog to test capital aggregation and to document substantial differences in partial elasticities of substitution among equipment, structures, and labour in United States manufacturing. Subsequent methodological work clarified the behaviour of the form: Kim (1992) showed that returns to scale in a translog function vary with output and input levels and derived conditions for a well-behaved specification, and Kymn and Hisnanick (2001) derived returns-to-scale and Allen elasticity expressions for the CES–translog family. Solow (1957) supplied the complementary growth-accounting apparatus, decomposing output growth into movements along the production function and shifts of the function itself—the TFP residual—and attributing roughly seven-eighths of the growth of United States output per man-hour between 1909 and 1949 to technical change.

2.2 Productivity in Indian manufacturing: the ASI tradition

A large Indian literature estimates productivity from ASI data. Ahluwalia (1991) documented stagnant or declining TFP in Indian manufacturing through the 1960s and 1970s followed by a turnaround in the first half of the 1980s, which she associated with early deregulation. Balakrishnan and Pushpangadan (1994) showed that this celebrated turnaround is sensitive to the deflation procedure: once value added is double-deflated to account for changes in relative input prices, the improvement of the 1980s largely disappears—a caution that continues to shape how ASI series are deflated. Goldar (1986) found that import substitution was associated with slower, and demand expansion with faster, productivity growth across Indian industries, while Goldar and Kumari (2003) reported a deceleration of TFP growth in the 1990s despite trade liberalisation, attributing it partly to underutilisation of capacity. Trivedi, Prakash, and Sinate (2000), in a Reserve Bank of India study covering 1973–74 to 1997–98, found modest aggregate TFP growth with substantial inter-industry variation, and Unel (2003) reported an acceleration of productivity growth in most industry groups after the 1991 reforms. Kathuria, Raj, and Sen (2010) extended the comparison to the unorganised sector and found rising labour productivity in organised (ASI) manufacturing during the early 2000s alongside a slowdown in the unorganised segment. Within this tradition, flexible functional forms have a long pedigree in India: Kazi (1980) rejected the constancy of the elasticity of substitution for Indian manufacturing using a variable elasticity of substitution specification, Kar and Chakraborty (1986) applied the translog form to interfuel substitution in Indian industry, and Sahoo (1999) compared frontier translog and data envelopment estimates of returns to scale and efficiency.

2.3 Productivity of the Indian food processing industry

Studies of the Indian food processing industry have relied mainly on index-number and frontier methods. Ali et al. (2009) computed Malmquist TFP indices for twelve segments of Indian food manufacturing over 1980–81 to 2001–02, decomposed productivity change into efficiency change and technical change, and analysed its determinants. Kumar and Basu (2008) likewise found, using data envelopment analysis, that technological progress rather than efficiency catch-up was the principal driver of productivity growth in the Indian food industry. More recently, Meena (2024) reported that TFP growth in the organised food processing industry stems mainly from technical progress, with technical-efficiency change playing an insignificant role, and recommended that technology adoption be matched by adaptation. Sub-sectoral evidence points in the same direction: Ohlan (2013) found significant TFP growth in Indian dairy processing over 1980–2008, with mean technical efficiency of 72 per cent and scale inefficiency arising mainly from increasing returns to scale. The edited volume by Bathla and Kannan (2021) consolidates much of this evidence: Bathla (2021) links TFP growth in the organised food industry to the structure of trade protection, Bathla and Jee (2021) document pronounced temporal and inter-state variation in employment and productivity growth in the organised food industry, and Kukreja (2021) shows that labour-market regulation conditions employment growth in the industry across states. At the state level, Das et al. (2024) applied Malmquist–DEA methods to ASI data for Assam (2008–09 to 2019–20) and found a capital-intensive industry operating below the best-practice frontier with no clear TFP improvement.

2.4 The research gap

Three gaps emerge from this literature. First, the Indian food-processing productivity literature is dominated by non-parametric DEA and index-number techniques; parametric flexible-form evidence, which yields output elasticities and returns to scale directly, is scarce. Second, state-level analyses are rare, despite the strong spatial heterogeneity documented by Bathla and Jee (2021), and no study estimates factor productivity or growth elasticities for the food processing industry of Odisha; the only Odisha-specific factor productivity study located concerns agriculture (Kadam et al., 2022). Third, few studies extend the analysis beyond the mid-2010s. The present paper addresses all three gaps by estimating a translog production function on a 1998–99 to 2022–23 ASI series for Odisha's food processing industry.

3. DATA AND METHODOLOGY

3.1 Data and variables

The study uses secondary annual time-series data for the registered (organised) food processing industry of Odisha for the twenty-five years from 1998–99 to 2022–23, compiled from the Annual Survey of Industries, Ministry of Statistics and Programme Implementation (MoSPI), Government of India (MoSPI, various years). The ASI is the principal source of industrial statistics for the registered manufacturing sector in India and covers factories registered under the Factories Act, 1948. Three variables are used. The dependent variable is the gross value of output (GVO), measured in rupees million at current prices. The two independent variables are labour, measured as the total number of persons engaged, and capital, measured as fixed capital in rupees million at current prices. Persons engaged is preferred to workers alone because it includes supervisory, managerial, and other employees who contribute to production.

3.2 Price deflation

Because GVO and fixed capital are reported at current prices, both series were converted to constant 2011–12 prices before estimation. GVO was deflated by the wholesale price index (WPI) for manufactured food products and fixed capital by the WPI for machinery and equipment, following the standard practice in the ASI-based productivity literature. Since the official WPI base year changed from 1993–94 to 2004–05 and then to 2011–12 during the study period, continuous deflators were constructed by splicing the three base series using overlap-year linking factors, with annual (financial-year average) indices taken from the statistical appendices of the Economic Survey (Government of India, 2008, 2018, 2024) and the linking factors validated against those published by the Office of the Economic Adviser (2017). The use of a single deflator for gross output is a recognised limitation of single deflation (Balakrishnan & Pushpangadan, 1994), and is noted again in Section 6.

3.3 Trend and compound annual growth rates

For each variable X_t, the compound annual growth rate is estimated from the semi-logarithmic trend regression

$$\ln X_t = a + bt + u_t, \qquad (1)$$

with CAGR = $(e^b - 1) \times 100$. The trend estimator uses all observations and is therefore robust to the choice of endpoints; endpoint-based CAGRs, computed as $[(X_T/X_1)^{1/(T-1)} - 1] \times 100$, are reported alongside for comparison.

3.4 The translog production function

The translog production function with two inputs is specified as

$$\ln Y_t = \beta_0 + \beta_L \ln L_t + \beta_K \ln K_t + \tfrac{1}{2}\beta_{LL}(\ln L_t)^2 + \tfrac{1}{2}\beta_{KK}(\ln K_t)^2 + \beta_{LK} \ln L_t \ln K_t + \varepsilon_t, \qquad (2)$$

where Y_t is real GVO, L_t is persons engaged, K_t is real fixed capital, and ε_t is the disturbance term. The Cobb–Douglas function is nested within Equation (2) under the restriction $\beta_{LL} = \beta_{KK} = \beta_{LK} = 0$, which is tested with an F-test. All log variables are mean-centred prior to estimation; this reduces the multicollinearity inherent in translog regressors and gives the first-order coefficients a direct interpretation as output elasticities evaluated at the geometric mean of the data (Kim, 1992).

The output elasticities of labour and capital—the growth elasticities, measuring the percentage change in output associated with a one per cent change in the respective input—are obtained as

$$\varepsilon_{L,t} = \partial \ln Y/\partial \ln L = \beta_L + \beta_{LL} \ln L_t + \beta_{LK} \ln K_t, \qquad (3)$$

$$\varepsilon_{K,t} = \partial \ln Y/\partial \ln K = \beta_K + \beta_{KK} \ln K_t + \beta_{LK} \ln L_t, \qquad (4)$$

and the elasticity of scale (returns to scale, RTS) as $RTS_t = \varepsilon_{L,t} + \varepsilon_{K,t}$ (Kim, 1992; Kymn & Hisnanick, 2001). At the geometric mean the centred log variables are zero, so $\varepsilon_L = \beta_L$, $\varepsilon_K = \beta_K$, and RTS = $\beta_L + \beta_K$; the hypothesis of constant returns to scale, $\beta_L + \beta_K = 1$, is examined with a Wald test.

Total factor productivity growth is measured as the Solow (1957) residual using the translog elasticities evaluated at the geometric mean as weights:

$$\Delta \ln TFP_t = \Delta \ln Y_t - \varepsilon_L \Delta \ln L_t - \varepsilon_K \Delta \ln K_t. \qquad (5)$$

Equation (2) is estimated by ordinary least squares. Because annual time-series residuals may be serially correlated and heteroscedastic, statistical inference is reported both with conventional standard errors and with heteroscedasticity- and autocorrelation-consistent (HAC, Newey–West) standard errors with two lags. Residual diagnostics include the Durbin–Watson statistic, the Jarque–Bera normality test, and the Breusch–Pagan heteroscedasticity test.

4. RESULTS

4.1 Trends and compound annual growth

Table 1 reports the nominal ASI series together with the constant-price series used in estimation, and Figures 1–3 display their movement over 1998–99 to 2022–23. Nominal GVO expanded more than twentyfold, from Rs. 11,611 million in 1998–99 to Rs. 238,713 million in 2022–23; in real (2011–12 price) terms output grew roughly sevenfold, from Rs. 20,456 million to Rs. 144,675 million. The output series shows a slow-growth phase up to 2007–08—including absolute declines in 2002–03, 2006–07, and especially 2007–08—followed by a marked and sustained acceleration from 2008–09 onwards. Employment fell sharply in 1999–00, recovered unevenly during the 2000s, and rose fairly steadily after 2010–11 to reach 40,897 persons in 2022–23, only about 1.6 times its 1998–99 level. Real fixed capital, by contrast, grew more than sixfold over the period, with especially rapid accumulation after 2007–08.

Table 1: gross value of output, persons engaged, and fixed capital in the food processing industry of Odisha, 1998–99 to 2022–23

Year	GVO, current prices (Rs. million)	Persons engaged (number)	Fixed capital, current prices (Rs. million)	GVO, 2011–12 prices (Rs. million)	Fixed capital, 2011–12 prices (Rs. million)
1998–99	11,611	26,333	4,381.7	20,456.3	6,609.9
1999–00	14,193	14,315	2,948.2	24,839.0	4,447.4
2000–01	17,240	19,381	4,220.4	31,203.6	6,004.3
2001–02	23,446	19,457	3,836.3	42,436.2	5,204.6
2002–03	20,813	22,129	3,569.9	35,946.5	4,805.4
2003–04	21,496	19,890	4,036.6	34,012.7	5,311.3
2004–05	21,903	18,930	5,377.3	33,071.1	6,721.6
2005–06	28,765	22,168	6,286.5	43,003.4	7,555.9
2006–07	27,771	22,855	7,225.1	39,191.4	8,210.3
2007–08	20,397	19,575	7,104.7	27,998.6	7,790.2
2008–09	40,637	22,458	11,688.9	51,135.0	12,488.1
2009–10	41,008	27,864	13,794.4	45,529.0	14,612.7
2010–11	57,510	29,257	12,941.9	61,587.1	13,369.7
2011–12	67,956	24,872	14,575.2	67,956.0	14,575.2
2012–13	70,815	35,217	18,566.1	64,967.9	17,852.0
2013–14	74,789	26,835	20,630.3	65,604.4	19,462.5
2014–15	92,108	26,868	21,856.2	79,403.4	20,237.2
2015–16	1,00,514	30,378	26,309.4	87,403.5	24,137.1
2016–17	1,03,356	31,534	31,319.7	82,684.8	28,999.7
2017–18	1,11,073	33,790	36,130.5	87,459.1	33,147.2
2018–19	1,44,367	38,468	38,371.2	1,11,912.4	34,568.6
2019–20	1,60,054	36,343	43,363.3	1,19,443.3	38,374.6
2020–21	1,63,995	36,452	40,074.5	1,16,308.5	35,153.1
2021–22	2,36,320	39,381	43,610.5	1,49,569.6	36,342.1
2022–23	2,38,713	40,897	53,056.1	1,44,674.5	42,108.0

Note. Constant-price series obtained by deflating GVO with the spliced WPI for manufactured food products and fixed capital with the spliced WPI for machinery and equipment (2011–12 = 100). *Source.* Compiled from the Annual Survey of Industries, MoSPI, Government of India; deflators from Government of India (2008, 2018, 2024) and Office of the Economic Adviser (2017); author's calculations.

Table 2 summarises the growth rates. The trend CAGR of real GVO is 7.72 per cent per annum, against 3.40 per cent for persons engaged and 10.62 per cent for real fixed capital; all trend coefficients are significant at the one per cent level. Real capital has thus grown roughly three times as fast as employment, and the real capital–labour ratio rose about fourfold, from approximately Rs. 0.25 million per person engaged in 1998–99 to Rs. 1.03 million in 2022–23—clear evidence of sustained capital deepening in the industry.

Table 2: compound annual growth rates, 1998–99 to 2022–23 (per cent per annum)

Variable	Endpoint CAGR	Trend CAGR	R^2 of trend
GVO (current prices)	13.42	13.09***	0.971
GVO (2011–12 prices)	8.49	7.72***	0.928
Persons engaged	1.85	3.40***	0.781
Fixed capital (current prices)	10.95	13.50***	0.970
Fixed capital (2011–12 prices)	8.02	10.62***	0.953

Note. Trend CAGR from the semi-logarithmic regression in Equation (1); endpoint CAGR from first and last observations. *** $p < 0.01$.
Source.
Author's calculations based on ASI (MoSPI) data.

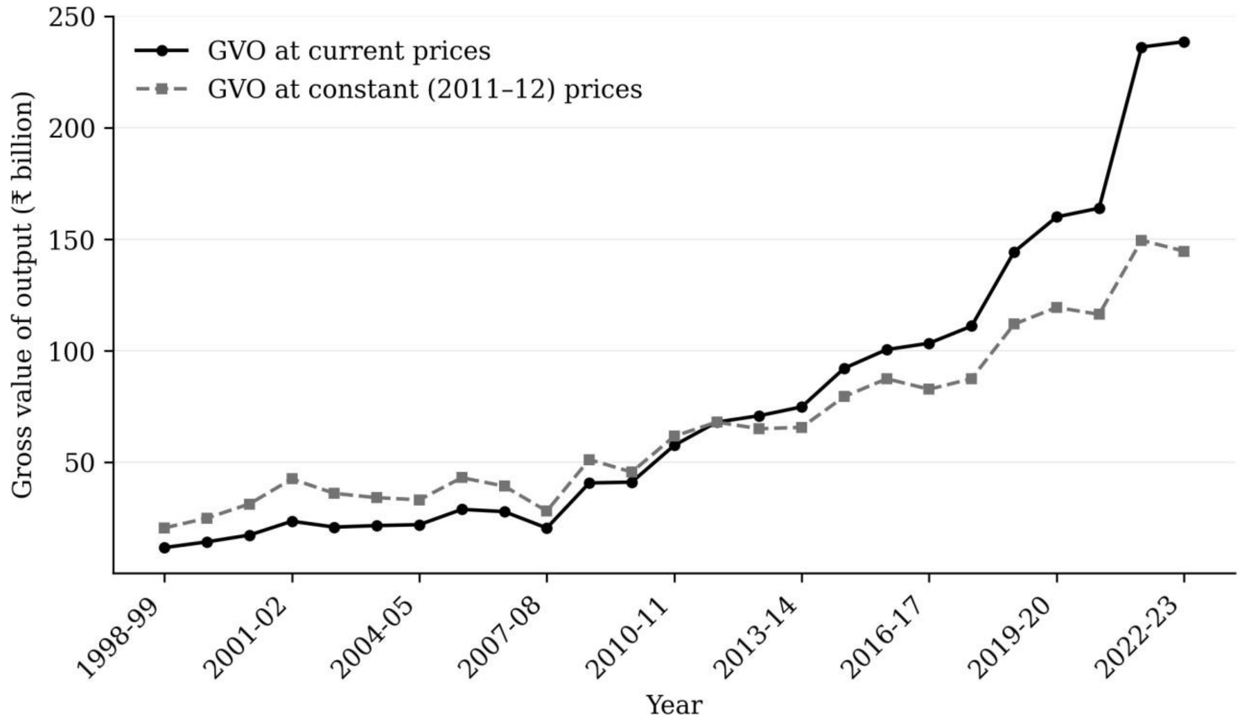

Figure 1: gross value of output of the food processing industry in Odisha, 1998–99 to 2022–23
Source. Author's construction from ASI (MoSPI) data.

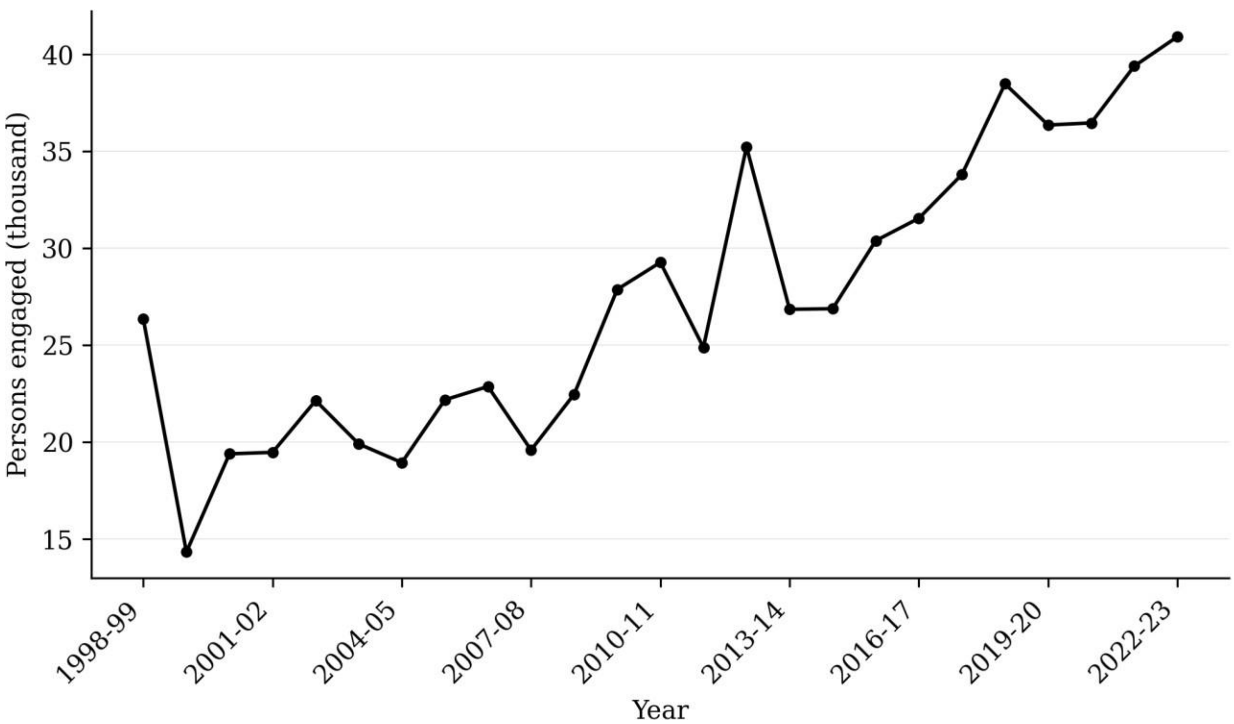

Figure 2: persons engaged in the food processing industry in Odisha, 1998–99 to 2022–23
Source. Author's construction from ASI (MoSPI) data.

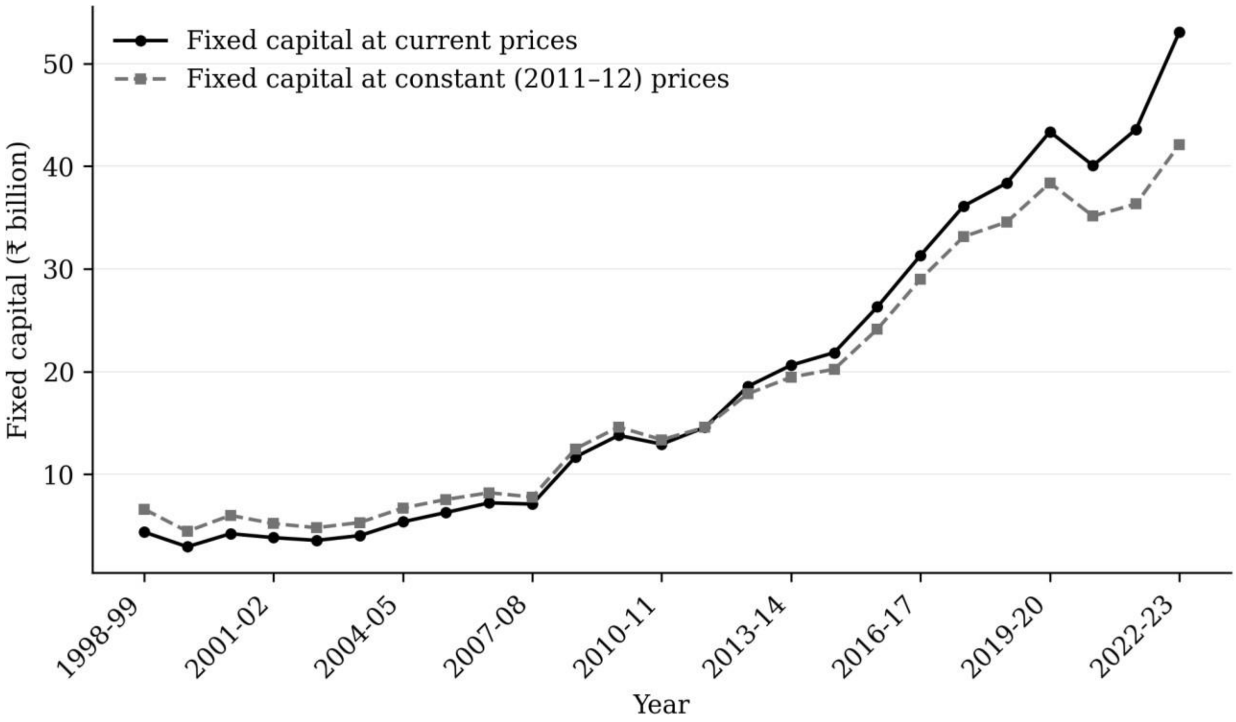

Figure 3: fixed capital of the food processing industry in Odisha, 1998–99 to 2022–23
Source. Author's construction from ASI (MoSPI) data.

4.2 Translog production function estimates

Table 3 presents the estimates of the translog production function of Equation (2) and of the nested Cobb–Douglas specification, both on mean-centred logarithms of the constant-price data. The translog model fits the data well: it explains 92.1 per cent of the variation in log real output (adjusted $R^2 = 0.900$), and the regression is highly significant, $F(5, 19) = 44.37$, $p < 0.001$. The three second-order terms are individually significant—β_{LL} at the five per cent level, β_{LK} at the five per cent level, and β_{KK} at the ten per cent level—and the F-test of the joint Cobb–Douglas restriction $\beta_{LL} = \beta_{KK} = \beta_{LK} = 0$ yields $F(3, 19) = 3.10$ with $p = 0.051$, rejecting the Cobb–Douglas form at the ten per cent level and just short of the five per cent level. The residual diagnostics of the translog model are satisfactory: the Durbin–Watson statistic of 1.824 indicates no first-order autocorrelation, the Jarque–Bera test does not reject normality ($p = 0.631$), and the Breusch–Pagan test does not reject homoscedasticity ($p = 0.179$). By contrast, the Cobb–Douglas residuals display positive autocorrelation (DW = 1.219) and significant heteroscedasticity (Breusch–Pagan $p = 0.020$), reinforcing the preference for the flexible form. Mean-centring keeps multicollinearity manageable (condition number 158).

Table 3: translog and Cobb–Douglas production function estimates, dependent variable ln (real GVO), 1998–99 to 2022–23 (n = 25)

Variable	**Translog: coefficient (SE)**	**Translog: HAC p-value**	**Cobb–Douglas: coefficient (SE)**	**Cobb–Douglas: HAC p-value**
Constant	10.944 (0.068)***	< 0.001	10.956 (0.041)***	< 0.001
ln L	0.435 (0.411)	0.082	0.098 (0.376)	0.846
ln K	0.502 (0.155)***	< 0.001	0.669 (0.138)***	0.002
½(ln L)²	−12.236 (5.005)**	0.003	—	—
½(ln K)²	−1.362 (0.764)*	0.097	—	—
ln L × ln K	4.530 (1.859)**	0.012	—	—
R^2	0.921		0.883	
Adjusted R^2	0.900		0.872	
F-statistic	44.37***		82.63***	
Durbin–Watson	1.824		1.219	
Jarque–Bera (p)	0.631		0.261	
Breusch–Pagan (p)	0.179		0.020	

Note. All log variables are mean-centred, so first-order coefficients are output elasticities at the geometric mean. Conventional standard errors in parentheses; HAC p-values use Newey–West standard errors with two lags. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (conventional). F-test of the Cobb–Douglas restriction: $F(3, 19) = 3.10$, $p = 0.051$. *Source.* Author's calculations based on ASI (MoSPI) data.

4.3 Growth elasticities of labour and capital and returns to scale

Because the log variables are mean-centred, the first-order translog coefficients in Table 3 are the output elasticities at the geometric mean of the sample, summarised in Table 4. The growth elasticity of labour is 0.435: a one per cent increase in persons engaged raises real output by about 0.44 per cent, holding capital constant. The estimate is imprecise under conventional standard errors ($p = 0.304$) but significant at the ten per cent level with HAC inference ($p = 0.082$). The growth elasticity of capital is 0.502 and strongly significant (HAC $p < 0.001$): a one per cent increase in real fixed capital raises real output by about 0.50 per cent. Capital is thus the marginally dominant source of output growth at the margin, though the two elasticities are of broadly similar magnitude.

The elasticity of scale at the geometric mean is 0.937. The Wald test of constant returns to scale ($\beta_L + \beta_K = 1$) yields $t = -0.233$ with $p = 0.819$ (HAC $p = 0.683$), so constant returns to scale cannot be rejected; the 95 per cent confidence interval for the scale elasticity, [0.371, 1.503], is wide, reflecting the modest sample size. The positive and significant interaction term ($\beta_{LK} = 4.530$) indicates complementarity between labour and capital in the sense that the marginal productivity of each factor rises with the level of the other, while the negative own second-order terms imply diminishing output elasticities in each factor—both consistent with a well-behaved technology in the neighbourhood of the sample mean (Kim, 1992). It should be noted, as is common in translog estimation on short annual series, that the fitted year-specific elasticities of Equations (3) and (4) vary widely away from the mean and violate monotonicity in some years; inference is therefore confined to the neighbourhood of the geometric mean.

Table 4: output (growth) elasticities and returns to scale at the geometric mean

Parameter	**Estimate**	**Inference**
Growth elasticity of labour (ε_L)	0.435	HAC $p = 0.082$
Growth elasticity of capital (ε_K)	0.502	HAC $p < 0.001$
Returns to scale ($\varepsilon_L + \varepsilon_K$)	0.937	95% CI [0.371, 1.503]
Wald test of constant returns (H_0: $\varepsilon_L + \varepsilon_K = 1$)	$t = -0.233$	$p = 0.819$ (HAC $p = 0.683$)

Source. Author's calculations based on ASI (MoSPI) data.

4.4 Total factor productivity growth and the sources of output growth

Table 5 decomposes the growth of real output into the contributions of labour, capital, and TFP using Equation (5). Over the full period, real output grew at an average (log-difference) rate of 8.15 per cent per annum, of which labour contributed 0.80 percentage points, capital 3.88 percentage points, and TFP 3.48 percentage points. Factor accumulation—overwhelmingly capital accumulation—thus accounts for about 57 per cent of output growth and productivity improvement for about 43 per cent.

The sub-period pattern is striking. During 1998–99 to 2010–11, output growth of 9.18 per cent per annum was propelled by TFP growth of 5.85 per cent, with capital contributing 2.95 points and labour only 0.38 points. During 2010–11 to 2022–23, output growth moderated to 7.12 per cent, but its composition changed fundamentally: the capital contribution rose to 4.80 points and the labour contribution to 1.21 points, while TFP growth collapsed to 1.10 per cent per annum. The industry's more recent expansi on has therefore been increasingly input-driven, and especially capital-driven, rather than productivity-driven.

Table 5: sources of real output growth in the food processing industry of Odisha (average annual log-difference growth, per cent)

Period	**Output growth**	**Contribution of labour**	**Contribution of capital**	**TFP growth**
1998–99 to 2010–11	9.18	0.38	2.95	5.85
2010–11 to 2022–23	7.12	1.21	4.80	1.10
1998–99 to 2022–23	8.15	0.80	3.88	3.48

Note. Contributions are $\varepsilon_L \Delta \ln L$ and $\varepsilon_K \Delta \ln K$ with elasticities held at their geometric-mean values (0.435 and 0.502); TFP growth is the residual of Equation (5). Components may not sum exactly to output growth because of rounding. *Source.* Author's calculations based on ASI (MoSPI) data.

5. DISCUSSION

Three findings merit discussion. First, the near-unitary scale elasticity indicates that Odisha's food processing industry operates, on average, under approximately constant returns to scale. This differs from the increasing returns detected in Indian dairy processing by Ohlan (2013), but is unsurprising for an industry aggregate dominated by primary processing activities such as rice milling, where plant-level scale economies are quickly exhausted. Practically, constant returns imply that proportional expansion of the industry is feasible without efficiency penalties, so that the binding constraints on growth are more likely to lie in raw material supply chains, infrastructure, and market access than in technology-imposed scale limits (Singh et al., 2022).

Second, the capital elasticity (0.502) exceeds the labour elasticity (0.435), and the observed input mix has shifted markedly towards capital, with real fixed capital growing at 10.62 per cent per annum against 3.40 per cent for employment. The dominance of capital accumulation in recent output growth parallels the capital-intensive character of the food processing industry documented for Assam by Das et al. (2024) and the inter-state patterns reported by Bathla and Jee (2021). The comparatively low—and imprecisely estimated—labour elasticity is consistent with an industry whose employment is concentrated in low-skill primary processing; Kukreja (2021) shows, in addition, that labour-market regulation shapes employment growth in the organised food industry, which may help explain why employment has responded sluggishly even as output accelerated.

Third, the pronounced deceleration of TFP growth after 2010–11—from 5.85 to 1.10 per cent per annum—echoes, at the state-industry level, the deceleration narratives in the broader Indian literature (Goldar & Kumari, 2003) and the finding for the national food processing industry that productivity growth depends chiefly on technical progress rather than efficiency change (Ali et al., 2009; Kumar & Basu, 2008; Meena, 2024). The pattern suggests that the easy productivity gains of the 2000s—likely associated with the post-2008 step-up in output, better capacity utilisation, and the modernisation of milling capacity—have been exhausted, and that the industry has since grown mainly by adding capital of roughly average productivity. If so, the policy priority is not further undifferentiated capital subsidy but the diffusion of superior processing technologies, an upgraded product mix towards higher value addition, and complementary investment in worker skills.

6. CONCLUSION AND POLICY IMPLICATIONS

This paper provides, to our knowledge, the first translog production function estimates for the food processing industry of Odisha, using ASI data for 1998–99 to 2022–23. Real gross value of output grew at a trend CAGR of 7.72 per cent per annum, sustained by rapid capital accumulation (10.62 per cent) and modest employment growth (3.40 per cent). The translog specification is preferred to the Cobb–Douglas restriction and yields growth elasticities of 0.435 for labour and 0.502 for capital at the geometric mean, with a scale elasticity of 0.937 that is statistically indistinguishable from constant returns to scale. Total factor productivity grew at 3.48 per cent per annum on average but decelerated sharply after 2010–11, so that recent growth has been predominantly capital-driven.

Four policy implications follow. First, because returns to scale are approximately constant, the industry can expand proportionally without efficiency loss, and policy should concentrate on relieving external constraints—raw material aggregation, cold chains, logistics, and credit—rather than on plant scale per se. Second, the slowdown in TFP growth argues for reorienting support from capital subsidy towards technology upgradation, quality certification, and the movement of the product mix from primary towards secondary and tertiary processing, in line with the direction of national schemes for the sector (MoFPI, n.d.). Third, the positive labour–capital interaction implies that investment raises the productivity of labour, so that skill development programmes for food technologists, machine operators, and quality-control personnel would raise the return to the capital already installed. Fourth, the sluggish response of employment to output growth cautions against relying on the industry for large direct employment gains without deliberate promotion of labour-using segments such as fruit and vegetable processing and marine products.

The study has limitations that qualify these conclusions. The analysis uses gross output with only two inputs, so intermediate inputs are subsumed in the residual; single deflation is used, which is known to affect measured productivity (Balakrishnan & Pushpangadan, 1994); fixed capital is a book-value stock rather than a capital-services measure; and, with twenty-five observations, the translog estimates are locally reliable at the sample mean but imprecise away from it. Extensions using plant-level ASI microdata, value added with double deflation, and stochastic frontier or DEA methods for the same period would allow the robustness of the elasticity and TFP findings to be assessed.

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