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Impact of Firms' Characteristics on Total Factor Productivity: Evidence from Pakistan

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Abstract

This study has two objectives: First, it measures the firm-level total factor productivity of Pakistan's industrial sector for a panel of 161 firms listed on the Pakistan Stock Exchange over the period 1997-2017. Second, it examines the impact of cost of goods sold, firm size, total borrowings, return on assets, and interest rate on total factor productivity using a multinomial logit model. In order to calculate firm-level total factor productivity, we estimated a variant of the firm-level production function. The results indicate that firm size and return on assets are significantly positively associated with total factor productivity, whereas cost of goods sold and interest rate are significantly negatively related to total factor productivity. Results on the association between total borrowings and total factor productivity show mixed evidence. The findings of the study are important as aggregated total factor productivity at the macro level is a reflection of micro-level total factor productivity. Therefore, to prevent the negative effects of the cost of goods sold, it is recommended that the government formulate policies such as an industry-friendly energy policy, as well as reduce raw materials and tariff rates. Similarly, to reduce detrimental effects on total factor productivity, the State Bank of Pakistan ought to reconsider its interest rate policies.

Keywords: Total Factor Productivity, Growth, Industrial sector, Pakistan

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1 Introduction

The industrial sector plays a vital role in economic growth by contributing to national income, investment, employment, and consumption. More precisely, long-term economic development depends partly on industrial productivity, which is central to modern economic growth (Kuznets, 1966). Improvements in productivity allow an economy to produce more output from a given combination of inputs, including capital and labor (Solow, 1956; Syverson, 2011). Young (1992) and Krugman (1994) distinguish between input-driven and productivity-driven economic growth. Input-driven growth depends on the accumulation of factors of production that may face diminishing returns in the long run. However, productivity-driven growth reflects improvements in knowledge, technology transfer, information technology, and the efficient allocation and use of inputs (Young, 1992; Krugman, 1994). Similarly, Van Beveren (2012), Syverson (2011), and Ghosh (2013) discuss technological and operational differences that help explain industrial TFP, whereas Mahadevan and Kim (2003) examine whether manufacturing output growth arises from inputs or productivity improvements. These distinctions underline the importance of examining productivity at the firm level.

Productivity shocks are generally unobservable to researchers and may influence both firm output and input decisions. Firms may respond to favorable shocks by expanding production and increasing input use; however, adverse shocks can reduce output and constrain future operations. Therefore, productivity shocks may affect firms' survival, entry, and exit, especially when demand changes alter expected returns. In addition, productivity improvements can strengthen industrial competitiveness in domestic and international markets (Syverson, 2011; Bournakis & Mallick, 2018).

Empirical research identifies several determinants of industrial TFP, including research and development, human capital, investment in information and communication technologies (ICT), and international trade (Aghion & Howitt, 2006; Syverson, 2011). At the macroeconomic level, innovation, market efficiency, infrastructure, and institutions may also shape productivity outcomes. Furthermore, productivity differences contribute to variations in income per capita across economies (Hall & Jones, 1999; Hsieh & Klenow, 2009). Nevertheless, aggregate estimates can obscure substantial differences among firms within the same economy. Consequently, firm-level analysis can complement the macroeconomic literature by examining how firms' own characteristics relate to productivity (Melitz, 2003; Khan et al., 2020).

Given the importance of TFP, researchers have estimated productivity through data envelopment analysis (DEA), index-number methods, and parametric or semiparametric production-function approaches. These methods involve different assumptions about technology, measurement error, and unobservable productivity shocks (Del Gatto et al., 2011; Van Beveren, 2012). In addition, the generalized method of moments (GMM) can address certain endogeneity problems when suitable moment conditions and instruments are available (Wooldridge, 2009). A central estimation challenge is the possible correlation between firms' input choices and productivity observed by managers but not by researchers. Pakistan's industrial sector has also faced persistent constraints, including energy shortages, inflation, exchange-rate instability, policy uncertainty, and high input costs. Therefore, examining firm-level TFP and its correlates is especially relevant to understanding productivity differences in this setting.

Research on Pakistan has examined the role of industrial inputs, trade liberalization, and other factors in productivity performance. Some studies report that output increases reflect growth in capital and labor inputs rather than sustained improvements in TFP. Similarly, Ahmed et al. (2017), as discussed in the existing study, examined the relationship between trade policy and industrial productivity, while Khan et al. (2020) investigated firm-level productivity in Pakistan. However, macroeconomic and industry-level findings do not necessarily explain why productivity differs among individual firms. Therefore, the present study focuses on firm-specific production costs, size, borrowing, and profitability, together with interest rates, to provide a complementary perspective. Despite the importance of TFP for economic growth, the combined relationships between firm-level characteristics—namely, cost of goods sold, firm size, total borrowings, and return on assets—and the macroeconomic interest rate and firm-level productivity require further examination in the Pakistani

industrial setting. These characteristics may differ substantially across firms and sectors. Therefore, the present study investigates the following research questions:

- How does cost of goods sold affect TFP?
- How does firm size affect TFP?
- What is the impact of firm total borrowings on TFP?
- What is the impact of return on assets on TFP?
- What is the impact of interest rates on TFP?

This study contributes to the literature by examining TFP among Pakistan Stock Exchange-listed industrial firms using the stated firm-level production-function framework. First, it draws on the productivity-estimation tradition of Olley and Pakes (1996), which emphasizes the need to consider unobserved productivity and selection processes. Second, it augments the industrial production function by considering raw materials and overhead costs alongside capital and labor. Third, it examines how cost of goods sold, firm size, return on assets, total borrowings, and interest rates relate to the reported binary TFP outcome. These linked stages provide evidence on both production inputs and firm characteristics without changing the study's central research objectives (Levinsohn & Petrin, 2003; Van Beveren, 2012).

The remainder of the article is organized as follows. Section 2 reviews the relevant literature and theoretical foundations. Section 3 describes the model, data, and methods. Section 4 presents and interprets the empirical findings, including their relevance to comparable research. Section 5 discusses the conclusions, policy implications, limitations, and directions for future investigation.

2 Literature Review

The conceptual origins of TFP lie in early growth-accounting and production-function research, including Solow (1956). Subsequent studies developed a range of theoretical and empirical methods for estimating firm- and industry-level productivity. In particular, Olley and Pakes (1996), Levinsohn and Petrin (2003), Wooldridge (2009), Del Gatto et al. (2011), Van Beveren (2012), and Bournakis and Mallick (2018) discuss or apply alternative approaches to productivity estimation. Some research has focused on aggregate performance; however, firm-level analysis recognizes that producers operating within the same industry can differ substantially in input use, technology, and efficiency (Melitz, 2003; Khan et al., 2020).

Common econometric approaches to production-function estimation include ordinary least squares (OLS), fixed-effects (FE), and random-effects (RE) models. However, estimates can be affected when input choices respond to unobserved productivity shocks or when firms enter or exit the observed sample. Olley and Pakes (1996) introduced an investment-based proxy approach designed to address such problems under specific assumptions. Subsequent studies have explored alternative proxy variables and estimation procedures, including intermediate inputs and GMM formulations (Levinsohn & Petrin, 2003; Wooldridge, 2009; Van Beveren, 2012). It is therefore important to distinguish the conceptual motivation for these methods from the particular estimator ultimately reported in the empirical analysis.

Levinsohn and Petrin (2003) developed an approach that uses intermediate inputs to account for unobserved productivity in production-function estimation. Similarly, Wooldridge (2009) proposed a one-step GMM treatment of proxy-variable estimation. Van Beveren (2012) and Del Gatto et al. (2011) provide comparative reviews of alternative TFP estimators and their underlying assumptions. These methods differ in data requirements, identification conditions, and sensitivity to measurement error. Consequently, the choice of estimator can influence the interpretation and comparability of firm-level productivity estimates.

Correlation between observed production inputs and unobserved productivity may generate simultaneity and endogeneity problems. Therefore, production-function estimators must be interpreted in light of their identifying assumptions (Olley & Pakes, 1996; Levinsohn & Petrin, 2003). The existing literature also distinguishes input accumulation from productivity-driven growth. For example, the contributions of technological change, management, and resource allocation may differ

across industries and countries (Solow, 1956; Syverson, 2011). In addition, Wooldridge (2009) shows how proxy-variable and moment-based methods can be combined to control for unobservables under appropriate conditions. These methodological considerations inform the estimation strategy adopted in the present study.

The literature identifies research and development, trade openness, human capital, technological capabilities, and ICT investment as potential determinants of TFP (Aghion & Howitt, 2006; Syverson, 2011). Trade-related research additionally highlights the contribution of firm heterogeneity and market participation to productivity outcomes (Melitz, 2003; Kasahara & Lapham, 2013). In Pakistan, studies have examined industrial productivity and the roles of input accumulation, trade policy, and firm characteristics (Raheman et al., 2008; Khan et al., 2020). However, this manuscript devotes relatively little attention to examining production costs, firm scale, borrowings, profitability, and interest rates together across listed industrial firms. Building on this literature, the present study examines firm-specific characteristics as correlates of TFP in Pakistan. In particular, it considers cost of goods sold, total borrowings, return on assets, and firm size alongside the prevailing interest rate. This emphasis complements research on productivity estimation and resource allocation by focusing on observable financial and operational differences among firms (Melitz, 2003; Van Beveren, 2012; Khan et al., 2020).

2.1 Theoretical Foundations and Firm Heterogeneity

Differences in firm-level productivity can be understood through production technology, resource allocation, and unequal access to financial and operational resources. The production-function perspective treats TFP as the component of output not accounted for by measured inputs, subject to the assumptions of the chosen estimation method (Solow, 1956; Van Beveren, 2012). However, firms may make different choices about technology, intermediate inputs, and capital intensity, generating heterogeneous productivity outcomes (Olley & Pakes, 1996; Syverson, 2011). Accordingly, cost of goods sold and overhead costs are relevant to analyzing production conditions, while firm size and return on assets may reflect differences in scale and operating performance.

Similarly, resource-allocation theories emphasize that differences across firms can affect aggregate industrial productivity (Melitz, 2003; Hsieh & Klenow, 2009). Firm size may be associated with economies of scale and access to productive assets; however, larger size does not guarantee greater efficiency. In addition, borrowings and interest rates may influence firms' financing conditions, investment choices, and ability to maintain operations (Duval et al., 2020). These mechanisms offer plausible interpretations of the study's variables, although the empirical associations reported below cannot establish their causal operation.

The distinction between measured inputs and productivity matters when firms use different combinations of capital, labor, and intermediate goods. Two enterprises can record similar sales yet differ in their use of machinery, materials, and energy. Consequently, a firm-level production function helps to assess how much observed output is associated with each input, while the residual captures variation that the measured inputs do not explain. However, the residual is not a pure measure of technological innovation: pricing differences, measurement choices, and omitted inputs may also be reflected in it (Van Beveren, 2012). Recognizing this limitation makes the present analysis more useful for researchers comparing productivity measures across industries, ownership structures, or countries. In addition, how operational conditions interact with firm characteristics links production-function analysis to the study's subsequent examination of financial variables.

Firm size and profitability may relate to TFP through different channels. Larger firms may have greater access to production facilities and be better positioned to absorb fixed costs, yet size may also be associated with organizational complexity and inefficient investment. Return on assets reflects an accounting-based relationship between earnings and assets, which is conceptually distinct from productivity estimated using a production function. Therefore, a positive association between profitability and a TFP indicator should not be treated as evidence that one variable mechanically causes the other. Similarly, total borrowings may support investment in productive capacity but can also increase financial obligations and exposure to changing interest rates. These competing explanations provide a basis for evaluating mixed borrowing results without assuming that all forms of debt influence firms in the same way (Duval et al., 2020; Syverson, 2011).

3 Model, Data, and Research Methodology

3.1 Modeling framework

This study uses an augmented Cobb–Douglas production function to estimate firm-specific production relationships. In industrial production, observed inputs may be correlated with productivity shocks that are known to managers but unobserved by researchers. This correlation can create endogeneity and selection problems. Therefore, the study draws on the semiparametric productivity-estimation literature initiated by Olley and Pakes (1996). The empirical procedure has two stages: estimating the production function and recovering a firm-level productivity measure from the estimated input coefficients, following the general approach described in the manuscript (Olley & Pakes, 1996; Levinsohn & Petrin, 2003; Khan et al., 2020). The augmented production function is specified as follows:

$$Y_{it} = A_{it} K_{it}^{\propto} L_{it}^{\beta} OH_{it}^{\gamma} RM_{it}^{\delta} \quad (1)$$

In Equation (1), Y denotes firm output, operationalized in the dataset by total sales; TFP denotes total factor productivity; K represents the capital stock; L denotes labor; OH represents overhead costs, including energy consumption; and RM indicates raw materials. The subscripts i and t identify firms and years, respectively. The logarithmic transformation of the production function is presented in Equation (2):

$$lnY_{it} = lnA_{it} + \propto lnK_{it} + \beta lnL_{it} + \gamma lnOH_{it} + \delta lnRM_{it} + u_{it} + \varepsilon_{it} \quad (2)$$

Following Bournakis and Mallick (2018), the technical-efficiency component is decomposed as shown in Equation (3):

$$lnA_{it} = a_0 + \omega_{it} \quad (3)$$

Equation (2) can therefore be rewritten as follows:

$$Y_{it} = a_0 + \alpha lnK_{it} + \beta lnL_{it} + \gamma lnOH_{it} + \delta lnRM_{it} + \omega_{it} \quad (4)$$

ω_{it} $a_0\omega_{it}$Equation (4) distinguishes unobserved demand shocks from average firm efficiency and accommodates firm-specific and time-specific components of unobserved influences. These components are incorporated in Equation (5):

$$y_{it} = a_0 + \alpha k_{it} + \beta l_{it} + \gamma oh_{it} + (\eta_i + \lambda_{it}) + u_{it} \quad (5)$$

For estimation purposes, Equation (5) can be expressed more compactly as follows:

$$y_{it} = a_0 + \alpha k_{it} + \beta l_{it} + \gamma oh_{it} + \omega_{it} + u_{it} + \epsilon_{it} \quad (6)$$

Lowercase letters denote variables expressed in natural logarithms. Estimating the production function by OLS may produce biased coefficients if input decisions are correlated with unobserved productivity shocks. Accordingly, alternative estimators have been developed to address the resulting simultaneity and endogeneity concerns (Olley & Pakes, 1996; Levinsohn & Petrin, 2003; Wooldridge, 2009). The following equations present the productivity measure used in the study.

The final form of total factor productivity (TFP) can be expressed in Equation (7):

$$(\omega_it)\hat{}=y_it-\alpha k_it-\beta l_it-\gamma\ 〚rm〛_it-\delta\ 〚oh〛_it+u_it=a_it \quad (7)$$

In Equation (7), the estimated productivity component is obtained as the difference between observed log output and the contributions of the measured inputs. Equation (8) expresses the corresponding calculation using the estimated function:

$$(\omega_it)\hat{}=(\varphi_it)\hat{}\ (〚rm〛_it,K_it)-\gamma\hat{}\ 〚rm〛_it-\alpha\hat{}k_it \quad (8)$$

Following the firm-characteristics literature discussed above, firm size is proxied by the book value of total fixed assets. Return on assets (ROA), total borrowings (TBr), cost of goods sold (CGS), and the interest rate (INT) are also included to examine associations with TFP. The functional relationship is shown in Equation (9):

$$〚TFP〛_it=f(〚TA〛_it,〚TBr〛_it,〚CGS〛_it,〚ROA〛_it,〚INT〛_it) \quad (9)$$

The subsequent analysis converts the estimated TFP measure into a dichotomous indicator. In the description associated with Equation (9), the indicator distinguishes positive from negative productivity growth, whereas Section 4.5 specifies 1 for zero or positive estimated TFP and 0 otherwise. The estimates in Table 5 are therefore interpreted as odds ratios for the reported binary TFP classification. Although the original discussion refers to a multinomial logit model, an outcome with two categories is ordinarily analysed using binary logistic regression; the precise estimation specification would need to be established from the underlying analysis records. Firm size, production costs, profitability, borrowings, and interest rates are considered as explanatory variables (Syverson, 2011; Duval et al., 2020).

3.2 Data Description

The study examines firm-level characteristics and TFP using panel observations for companies listed on the Pakistan Stock Exchange during 1997–2017. Data sources include audited annual accounts, Pakistan Stock Exchange records, the Federal Board of Revenue (FBR), and the Pakistan Bureau of Statistics (PBS). Missing observations were treated using linear interpolation. The manuscript's data description identifies 153 industrial firms selected from a population of 374 listed firms, based on listing continuity and compliance with exchange requirements. However, the abstract, conclusion, and Table 5 report a total of 161 firms. This numerical discrepancy is retained as a documented feature of the supplied study rather than reconciled without access to the underlying dataset. The empirical coverage should therefore be interpreted alongside the sample counts reported for each analysis.

3.3 Variables Description

Firm output is operationalized by total sales, defined as the sum of local sales and exports. The principal production inputs are capital, labor, raw materials, and overhead costs. Capital stock comprises property, plant, and equipment, whereas labor represents workers directly involved in production. Overhead costs include expenditures associated with the production process, such as energy and alternative energy sources. The variables were deflated using the wholesale price index (WPI), with WPI data obtained from the World Bank database. In addition, the analysis of TFP determinants uses total fixed assets (TFA), total borrowings (TBr), cost of goods sold (COGS), return on assets (ROA), and interest rates. Total sales should be distinguished from the conventional measure of value added, and this measurement choice should be considered when interpreting the estimated productivity residual (Van Beveren, 2012).

The distinction between sales and value added affects the interpretation of the production-function coefficients. Total sales reflect revenue generated by a firm, whereas conventional value added subtracts intermediate inputs from gross output. When intermediate goods are also included as explanatory inputs, this distinction can influence the apparent contribution of materials and other costs. Therefore, interpret the estimates reported here according to the operational definition given in the data section, rather than assuming they are directly interchangeable with value-added-based estimates from other studies (Van Beveren, 2012). In addition, using the wholesale price index applies a common price adjustment that may not fully capture firm- or product-specific price changes. These considerations do not invalidate the stated research questions; however, they underscore the importance of reporting measurement conventions when comparing results with alternative productivity datasets.

The firm-year structure also deserves attention. Observations differ across the variables in Table 1, indicating that the analytic sample is not balanced for every measure. Linear interpolation can retain information in an incomplete panel, but it introduces estimated values for unobserved outcomes and may smooth short-term movements. Consequently, tests using complete observations or alternative treatments of missing data would be valuable in future analyses. In interpreting the current estimates, it is appropriate to distinguish the number of firms included in the descriptive TFP classification from the number of observations used in each regression. Moreover, the results for smaller sectors should be read cautiously because large odds ratios can arise when events are rare or the model has limited information. These concerns affect the reliability of inference but do not require changing the figures presented in the manuscript (Wooldridge, 2009; Van Beveren, 2012).

4 Results and Discussion

4.1 Descriptive Statistics

Table 1 reports descriptive statistics for the variables used in the empirical analysis. The reported mean values are positive, although their magnitudes depend on measurement scales and transformations and should not be treated as indicators of relative importance. COGS, TFA, and TBR have comparatively large reported means, whereas ROA has a smaller mean on its stated scale. In addition, the interest-rate variable has a higher reported standard deviation than the other listed variables. Nevertheless, standard deviations across differently scaled variables cannot be compared directly as evidence of greater economic volatility. The number of observations also differs across variables, which is relevant when interpreting subsequent regression sample sizes.

Table 1: Descriptive Statistics of Variables

Variables	Observations	Mean	Median	Maximum	Minimum	Std. Dev.
TFP	2848	0.631	1	1	0	0.482
COGS	2829	8.121	8.031	13.593	-1.101	1.497
TFA	2789	7.613	7.585	12.454	-4.993	1.787
TBR	2774	7.817	7.764	12.361	1.153	1.536
ROA	2789	0.056	0.050	0.669	-0.529	0.095
INT	2115	1.841	2.879	8.321	-6.774	4.479

Source: Author

4.2 Correlation Analysis

Table 2 presents pairwise correlations among TFP and the explanatory variables. TFP is positively correlated with TFA (0.041) and ROA (0.095), while it is negatively correlated with COGS (−0.141), TBR (−0.027), and INT (−0.066). Similarly, COGS is strongly correlated with TBR (0.832) and TFA (0.729), and TBR is strongly correlated with TFA (0.8831). These high correlations among some explanatory variables warrant caution when interpreting their individual regression coefficients because multicollinearity may affect precision. However, the correlations alone do not demonstrate causal relationships.

Table 2: Correlation among Variables

Variables	TFP	COGS	TBR	TFA	ROA	INT
TFP	1.000	.				
COGS	-0.141	1.000				
TBR	-0.027	0.832	1.000			
TFA	0.041	0.729	0.8831	1.000		
ROA	0.095	0.084	-0.0121	-0.022	1.000	
INT	-0.066	0.014	-0.011	0.014	0.003	1.000

Source: Author

4.3 Estimation Results on Firm-Level Production Function

The firm-level production function is estimated using panel least squares (PLS), fixed effects (FE), and random effects (RE) specifications. These models examine the associations of capital, labor, raw materials, and overhead costs with firm output. Table 3 reports the corresponding coefficient estimates and diagnostic statistics. The Hausman test is reported as 0.00, which appears to be a rounded probability rather than the test statistic itself; on the manuscript's interpretation, this result favors FE over RE. Therefore, the discussion focuses on the FE estimates while recognizing that this model does not automatically resolve all potential forms of simultaneity or input endogeneity (Wooldridge, 2009).

In the FE specification, the coefficient on raw materials (RM) is positive (0.05), while those for capital stock (PPE) and labor (L) are negative (−0.03 and −0.02, respectively). If the dependent and explanatory variables are in logarithms, these coefficients are interpreted as elasticities: a 1% increase in raw materials is associated with approximately a 0.05% increase in sales, whereas the estimated coefficients for capital and labor imply reductions of approximately 0.03% and 0.02%, respectively, holding other included variables constant. These estimates indicate conditional associations rather than proving that

additional capital or labor reduces productivity. The unexpected negative signs may reflect input utilization, measurement, firm heterogeneity, or other specification-related factors and merit cautious interpretation (Syverson, 2011; Van Beveren, 2012).

Table 3: Firm-level Production Function (Dependent variable TS)

Variables	FE	RE	PLS
Constant	-0.95*	-0.43*	-0.21*
	(-13.86)	(-10.00)	(-7.34)
RM	0.05*	0.03*	0.01*
	(6.54)	(4.71)	(2.62)
PPE	-0.03*	-0.01*	0.01
	(-4.57)	(-2.70)	1.34
L	-0.02*	-0.01**	0.01
	(-3.96)	(-1.95)	1.05
OH	1.12*	1.06**	1.02*
	(84.44)	(104.10)	(114.70)
Adjusted R^2	0.98	0.95	0.98
F-Stat	937.22	10410.91	24385.59
Hausman Test		0.00	

Source: Author. Note. FE = fixed effects; RE = random effects; PLS = panel least squares. Values in parentheses are reported t-statistics. * p < .01; ** p < .05, as designated in the original table. The reported Hausman entry is retained in its original numerical form.

$\beta = 1.12, \mathrm{t} =$The FE coefficient for labor is negative and statistically significant at the level indicated in Table 3. Overhead costs (OH), including energy expenditure, have the largest positive estimated coefficient (1.12) among the included inputs; however, the reported t statistic of 84.44 is not itself an effect size. One possible explanation the study offers is that some firms use in-house electricity generation, which may reduce disruption from unreliable energy supplies. Nevertheless, the model does not separately identify the causal effect of alternative electricity generation. Thus, the findings are consistent with the importance of energy-related inputs in industrial production, while the precise mechanism remains open to further investigation (Khan et al., 2020; Syverson, 2011).

4.4 Firm-Level Total Factor Productivity

Following the production-function approach discussed by Levinsohn and Petrin (2003) and the study's cited Pakistani literature, firm-level TFP is calculated from estimated input elasticities after accounting for the production inputs. The reported estimation uses the FE coefficients and the productivity expression presented in Equation (10). Because how unobserved shocks are treated influences productivity measurement, the resulting estimates should be understood within the assumptions of the reported specification (Van Beveren, 2012).

$$TFP_{it} = TS_{it} - \beta_K K_{it} - \beta_{RM} RM_{it} - \beta_L L_{it} - \beta_{OH} OH_{it} \quad (10)$$

Equation (10) is used to calculate TFP for individual firms over 1997–2017. The study subsequently reports average TFP for the sampled firms and industries. Figure 1 illustrates industry-level averages and allows comparisons across the industrial groups included in the sample. Figure 1 reports positive average estimated TFP for firms in cement, engineering, paper and board, pharmaceuticals, and chemicals, whereas several other industries report negative averages, including automobiles, construction, food, oil and gas, textiles, telecommunications, and tobacco. The paper and board industry has the highest positive reported average, followed by cement and other positively performing sectors. These patterns may reflect differences in demand, production processes, competition, input costs, and technology adoption. However, because the figure is descriptive, it does not establish which factors caused the observed sectoral differences. The sectoral variation nevertheless demonstrates the relevance of firm and industry heterogeneity for productivity analysis (Melitz, 2003; Syverson, 2011).

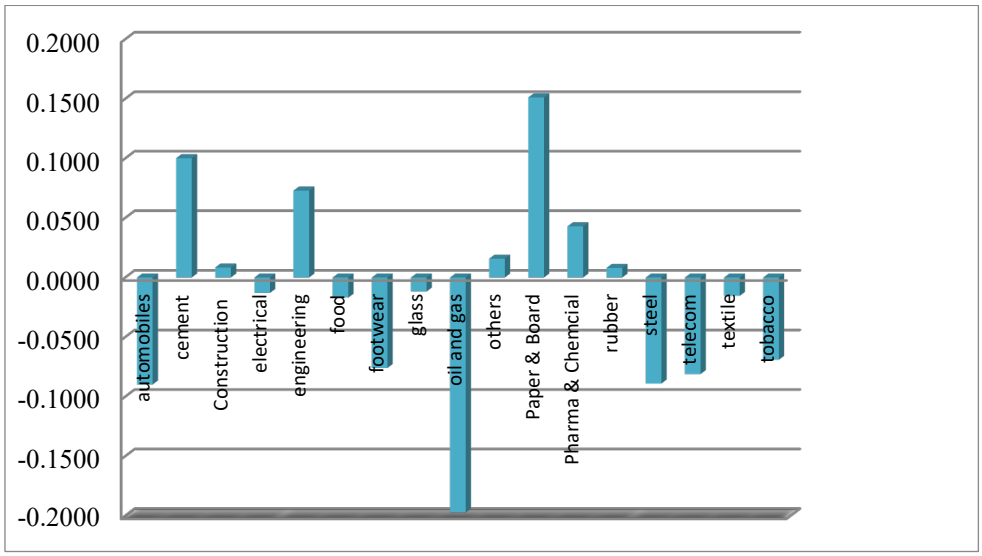


Figure 1: Industry-wise average TFP

The negative average estimated TFP for oil and gas firms may reflect fluctuations in international energy prices, taxation, and regulatory duties. Similarly, the automobile industry's estimated productivity may have been affected by competitive pressure from imported vehicles, while firms in textiles and footwear faced production costs, raw-material constraints, and energy supply interruptions. The manuscript also discusses taxation and illicit trade as possible challenges for tobacco producers. These explanations are plausible contextual interpretations rather than effects the empirical model identifies independently. In particular, without firm-level measures of the proposed mechanisms, the results should not be taken as demonstrating that any single factor caused a sector's negative average TFP.

The sectoral estimates indicate that negative average TFP is common across several industries in the study sample. As the literature on resource allocation suggests, persistent productivity differences between firms can matter for aggregate industrial performance (Melitz, 2003; Hsieh & Klenow, 2009). Table 4 reports 62 firms with positive average TFP, 78 with negative average TFP, and 13 with zero average TFP, giving a total of 153 firms. The firm-level estimates are also reported in Appendices A and B. These counts should be distinguished from the figure of 161 firms shown elsewhere in the manuscript.

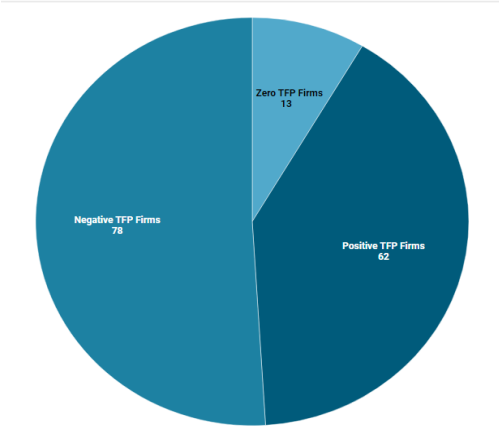


Figure 2: Summary of Firm-Level TFP

Table 4: Summary of Firm-Level TFP

No. of Zero TFP Firms	No. of firms with positive TFP	No. of firms with negative TFP	Total No of firms
13	62	78	153

Source: Author

4.5 Estimation Results on the Determinants of Firm-level TFP

The study constructs a binary TFP indicator equal to 1 when estimated TFP is zero or positive and 0 when it is negative. Table 5 reports odds ratios for cost of goods sold, firm size, return on assets, borrowings, and the interest rate. Column 1 represents the pooled sample, whereas Columns 2–8 provide estimates for industrial sectors. Given the two-category response, we discuss the reported model as a logit specification for a binary outcome, without altering the numerical results. In interpreting Table 5, an odds ratio above 1 indicates higher conditional odds of being in the zero-or-positive TFP category, whereas an odds ratio below 1 indicates lower conditional odds; it does not directly quantify a change in the probability or a causal effect.

The pooled results in Column 1 indicate that higher cost of goods sold is associated with lower odds of zero-or-positive TFP (odds ratio = 0.508), holding the other model variables constant. This finding may reflect the burden of production costs, including energy and raw materials. However, the reported association does not, on its own, establish the channels through which such costs operate. Firm size, proxied by total fixed assets, is positively associated with the outcome in the pooled sample (odds ratio = 1.456). Similarly, several sector estimates show positive size associations, although the signs and statistical precision vary. The unusual estimates reported for communication services require particular caution because that sector has a few observations.

Table 5: Logit Model Results

Sector								
Variables	**Overall**	**Industrial**	**Materials**	**Consumer Discretion**	**Health Care**	**Consumer Staples**	**Comm Services**	**Energy**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
COGS	[0.508]	[0.138]	[0.505]	[0.409]	[0.313]	[0.703]	[1.59E+21]	[0.151]
	(0.034)*	(0.063)*	(0.083)*	(0.066)*	(0.159)*	(0.122)**	(8.20E+22)	(0.075)*
TFA	[1.456]	[1.739]	[3.07]	[2.291]	[15.09]	[0.766]	[7.8E-31]	[2.38]
	(0.088)*	(0.361)*	(0.525)*	(0.357)*	(9.779)*	(0.099)**	(5.1E-29)	(0.916)**
ROA	[19.71]	[30.651]	[6973.23]	[22.489]	[0.001]	[0.115]	[2.31E+28]	[0.0003]
	(15.64)*	(66.71)*	(8903.61)*	(25.72)*	(0.007)*	(0.141)	(9.85E+29)	(0.001)*
TBr	[1.115]	[1.671]	[0.456]	[0.584]	[0.083]	[1.451]	[1.04E+27]	[8.61]
	(0.096)	(0.755)	(0.097)*	(0.11)*	(0.064)*	(0.265)**	(5.67E+28)	(5.92)*
Int	[0.968]	[0.989]	[24.62]	[0.935]	[0.953]	[0.931]	[0.353]	[0.923]
	(0.01)*	(0.046)	(16.56)	(0.021)*	(0.05)	(0.022)*	(0.369)	(0.054)
Constant	6.495	[8337.01]	[(24.626]	[101.526]	12822.93]	[8.21]	[2.6E-142]	[0.0004]
	(1.835)*	(15960.85)*	(16.561)*	(62.053)*	34173.72)*	(7.602)**	(7.9E-140)	(0.001)*
Observations	2014	156	605	593	112	371	40	137
Number of Firms	161	11	44	47	8	31	10	10
Pseudo R-Squared	0.069	0.263	0.147	0.142	0.246	0.161	0.751	0.491
Chi² Stats	193.76	53.05	113.31	112.93	36.69	26.71	22.1	90.29

*Source: Author. Note. Values in square brackets are reported odds ratios; values in parentheses are robust standard errors. The original significance convention identifies * p < .01 and ** p < .05. Extremely large or small sector-level odds ratios should be interpreted cautiously in light of limited observations and possible separation or numerical instability.*

The positive association between total fixed assets and TFP status may be consistent with benefits from productive equipment and economies of scale. However, a higher book value of fixed assets does not necessarily demonstrate that a firm uses newer machinery. Table 5 reports a particularly large size odds ratio for the health-care sector (15.09). This estimate may indicate substantial heterogeneity, although it should be assessed alongside the sector's limited number of firms and the large reported standard error. Similarly, the manuscript's discussion of research and development as a possible explanation should be treated as a hypothesis, because the reported model does not separately test R&D expenditure (Syverson, 2011; Van Beveren, 2012).

Return on assets (ROA) is positively associated with the binary TFP outcome in the pooled sample (odds ratio = 19.71). However, because ROA is measured on a fractional scale, interpretation of this

odds ratio depends on the unit change specified in the model. Total borrowings are not statistically significant in the pooled specification, although some sector-specific associations are reported. In consumer staples and energy, the positive borrowing associations may reflect different financing needs and access to credit. Nevertheless, the estimates do not directly measure credit availability or liquidity; these mechanisms should therefore be treated as possible explanations rather than confirmed effects (Duval et al., 2020).

The findings also speak to the relationship between firm-level heterogeneity and industrial competitiveness. Because firms differ in capital intensity, input use, and access to finance, uniform policies may affect sectors differently. Consequently, policy design could benefit from evidence on which types of firms face the greatest constraints rather than relying exclusively on sector-wide averages. Nevertheless, the current study does not estimate the effects of a particular subsidy, tariff reform, or monetary-policy change, and policy recommendations must be interpreted in that light. Comparative studies of productivity and resource misallocation suggest that the distribution of productive resources among firms is an important dimension of industrial performance (Hsieh & Klenow, 2009; Melitz, 2003). Thus, the empirical patterns reported for Pakistan may be relevant to the broader discussion of emerging-economy industrial development, while remaining specific to the firms and period examined.

For researchers seeking to extend this work, the joint treatment of production conditions and financial characteristics provides several concrete avenues for further testing. One approach is to examine whether the relationship between borrowing and productivity varies by firm size or interest rates. Another would be to assess whether energy-intensive industries exhibit stronger associations between production costs and productivity outcomes. In addition, researchers could compare continuous TFP measures with binary classifications to determine how results depend on the definition of the dependent variable. Such extensions should retain a clear distinction between productivity estimation and the subsequent modelling of its correlates (Olley & Pakes, 1996; Wooldridge, 2009). They would also help establish which empirical findings are robust to alternative specifications rather than dependent on a single classification rule.

The interest rate is negatively associated with zero- or positive TFP in the pooled sample (odds ratio = 0.968), consistent with the possibility that financing conditions matter for productive activity (Duval et al., 2020). Sector estimates for consumer discretionary and consumer staples firms also show odds ratios below 1 (0.935 and 0.931, respectively), with significance at the levels indicated in Table 5. However, the estimates for several other sectors are not statistically significant. Accordingly, the evidence supports a negative conditional association in the pooled data but does not imply that the relationship has the same magnitude or precision across industries.

An important feature of the descriptive results is that the direction of a simple correlation may not match the strength of a conditional regression association. In Table 2, for instance, the correlation of TFP with firm size is positive but small, while the pooled logit model reports an odds ratio above one after controlling for other observed variables. This difference is not inherently contradictory because the estimates summarize different relationships and, in the reported models, involve distinct specifications and possibly different sets of observations. Similarly, the strong correlations between size, borrowings, and costs indicate that regression results may depend on which variables are included simultaneously. Therefore, the estimated odds ratios should be considered alongside their standard errors, the number of firms per sector, and the sample definition, rather than interpreted as stand-alone measures of economic importance.

The sectoral evidence also raises questions about why firms exposed to broadly similar macroeconomic conditions experience different productivity outcomes. For example, a common interest rate may affect enterprises differently depending on their financing requirements, debt structure, or capacity to finance investment internally. Similarly, higher energy or material costs may have different implications for industries with distinct technologies and input intensities. However, the present models do not directly test such mechanisms. Future sectoral work could measure exposure to energy interruptions, imported intermediate inputs, and specific financing arrangements. This would allow researchers to distinguish broad associations with the binary TFP classification from the channels through which firm behavior and policy conditions may affect productivity. The existing evidence is thus a starting point for more detailed explanations of industrial heterogeneity, not a final account of those mechanisms.

4.6 Comparison with Evidence from Other Economies

The associations observed for Pakistani firms can be compared with research on productivity differences in other economies. Hsieh and Klenow (2009), for example, examine resource misallocation and manufacturing productivity in China and India, whereas Ghosh (2013) considers manufacturing productivity in India. Although these studies use different data, research designs, and outcomes, they provide a basis for considering how firm heterogeneity and resource allocation may shape industrial performance. Therefore, the present study contributes historically situated evidence from listed Pakistani firms rather than estimates that can be transferred directly to other countries.

In addition, Melitz (2003) and Kasahara and Lapham (2013) link productivity to trade participation and firm selection, while Duval et al. (2020) investigate the relationship between financial frictions and productivity. The associations of size, borrowings, and interest rates reported here can therefore inform comparative discussions of financing and industrial competitiveness. However, differences in sample composition and identification strategies require caution, and the current regressions should not be interpreted as establishing causality.

4.7 Implications for Productivity Research and Industrial Competitiveness

The study links firm-level production characteristics to broader questions about industrial productivity, financing conditions, and the allocation of productive resources. In particular, combining production-function estimates with a binary TFP classification provides a basis for subsequent investigations into why productivity outcomes vary across firms and industries. However, meaningful comparison requires careful attention to the TFP definition, the underlying output proxy, and the econometric specification (Van Beveren, 2012; Wooldridge, 2009). In addition, researchers may use the reported sectoral contrasts to develop testable hypotheses on energy reliability, operating costs, and access to finance, while employing research designs suited to causal identification (Syverson, 2011; Duval et al., 2020).

5 Conclusion and Policy Recommendations

This study examines firm-level total factor productivity among industrial firms listed on the Pakistan Stock Exchange during 1997–2017. It estimates an augmented Cobb–Douglas production function using the reported fixed-effects specification and then derives firm-level TFP from estimated input elasticities. It then uses a logit model to examine associations between cost of goods sold, firm size, return on assets, total borrowings, and interest rates and the reported binary TFP classification. The empirical tables show that many sampled firms have negative average TFP, whereas others have zero or positive values. The discussion identifies high production costs, outdated machinery, and unreliable energy supplies as plausible contextual constraints. However, the reported regressions do not identify these mechanisms as separate causal effects. The findings therefore provide firm-level evidence relevant to industrial productivity and motivate closer examination of operational and financial constraints.

The empirical results indicate that firm size and return on assets are positively associated with the likelihood of belonging to the zero-or-positive TFP category, whereas the cost of goods sold and the interest rate are negatively associated with that outcome in the pooled estimates. Total borrowings display a weaker association in the pooled sample and more heterogeneous results across sectors. In addition, the production-function estimates demonstrate that measured inputs have differing coefficients, highlighting variation in firms' production processes. These findings should be interpreted as associations within the historical sample, not evidence of universal or causal relationships.

The findings have several policy implications. First, reliable and affordable industrial energy may help firms manage overhead costs and production interruptions. Therefore, policies that improve the predictability of energy supply and the efficiency of industrial energy use merit attention. Second, access to appropriate-quality raw materials at competitive prices may help contain production costs, while trade policy can affect the affordability of imported inputs. Similarly, policies supporting productive investment and access to efficient machinery could encourage technological upgrading. Finally, the negative association between interest rates and the TFP outcome suggests that financing conditions are relevant to industrial policy debates. However, the present evidence alone does not establish the appropriate level of interest rates or the effects of any specific monetary-policy intervention. Future policy evaluations would benefit from more recent data and designs that distinguish correlation from causation.

5.1 Limitations and Directions for Future Research

The analysis focuses on listed industrial firms over 1997–2017. Consequently, the findings should be interpreted as historical evidence from the sampled firms rather than as a direct measure of the current productivity of all Pakistani enterprises. Firms that remained listed and satisfied the data requirements may differ systematically from unlisted, newly established, or exiting businesses. Moreover, interpolated observations and the use of total sales as the output proxy may affect the interpretation of estimated productivity levels. The distinction between a binary TFP indicator and a continuous productivity measure is also important when comparing findings across studies (Van Beveren, 2012; Wooldridge, 2009).

Future investigations could extend the observation period, compare listed and unlisted enterprises, and examine whether the reported relationships differ across technology-intensive and energy-intensive industries. Similarly, sensitivity checks using alternative production-function estimators and alternative measures of firm-level productivity could clarify the robustness of the estimates (Olley & Pakes, 1996; Levinsohn & Petrin, 2003; Wooldridge, 2009). In addition, comparative research across emerging economies could investigate how financing conditions, energy costs, and firm size interact with institutional and industrial characteristics. These extensions follow from the current research questions and do not alter the study's original objectives.

Further limitations follow from the nature of the data and the reported estimators. The historical panel draws on publicly listed industrial companies, so its findings cannot automatically represent unlisted and informal enterprises. In addition, firm-level sales and costs may be influenced by market conditions, accounting measurement, and physical productivity. Using a binary TFP classification simplifies heterogeneous productivity outcomes into two categories and may conceal variation among firms with substantially different estimated values. Likewise, the sector regressions include different numbers of firms, making comparisons of their odds ratios sensitive to estimation precision. Therefore, future work should consider alternative output definitions, continuous productivity measures, and diagnostic checks for influential observations or separation in small samples. By clarifying these issues, later investigations can build on the substantive questions addressed here while strengthening comparability and inference (Van Beveren, 2012; Wooldridge, 2009).

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Appendix A

Firms with Estimated Negative TFP

S.No.	Name of Firm	TFP	S.No.	Name of Firm	TFP
1	Atlas Honda Limited	-0.14	40	Wyeth Pakistan Limited	-0.07
2	Ghani Automobile Industries Limited	-0.14	41	sanofi-aventis Pakistan Limited	-0.05
3	Hinopak Motors Limited	-0.08	42	Berger Paints Pakistan Limited	-0.05
4	Al-Ghazi Tractors Limited	0.00	43	ZIL Limited	-0.05
5	Power Cement Limited	-0.01	44	Nimir Industrial Chemicals Limited	-0.04
6	Dandot Cement Company Limited	-0.32	45	Dynea Pakistan Limited	-0.02
7	Pakistan Cables Limited	-0.03	46	Buxly Paints Limited	-0.01
8	Siemens (Pakistan) Engineering Co. Ltd.	-0.08	47	Crescent Steel and Allied Products Limited	-0.09
9	Waves Singer Pakistan Limited	-0.03	48	Telecard Limited	-0.08
10	KSB Pumps Company Limited	-0.01	49	Dewan Textile Mills Limited	-0.21
11	Fauji Foods Limited	-0.13	50	Dar Es Salaam Textile Mills Limited	-0.11
12	Dewan Sugar Mills Limited	-0.12	51	Dewan Khalid Textile Mills Limited	-0.11
13	Haseeb Waqas Sugar Mills Limited	-0.09	52	Chakwal Spinning Mills Limited	-0.08
14	Husein Sugar Mills Limited	-0.08	53	Ghazi Fabrics International Limited	-0.07
15	Faran Sugar Mills Limited	-0.05	54	Rupali Polyester Limited	-0.07
16	Shezan International Limited	-0.05	55	The Crescent Textile Mills Limited	-0.07
17	Shahtaj Sugar Mills Limited	-0.04	56	Jubilee Spinning & Weaving Mills Limited	-0.06
18	National Foods Limited	-0.03	57	Gul Ahmed Textile Mills Limited	-0.05
19	Jauharabad Sugar Mills Limited	-0.03	58	Ibrahim Fibres Limited	-0.05
20	Noon Sugar Mills Limited	-0.03	59	Gatron (Industries) Limited	-0.05
21	Mehran Sugar Mills Limited	-0.02	60	Quetta Textile Mills Limited	-0.04
22	Baba Farid Sugar Mills Limited	-0.02	61	Nishat Mills Limited	-0.04
23	Chashma Sugar Mills Limited	-0.02	62	International Industries Limited	-0.04
24	Habib Sugar Mills Limited	-0.01	63	Gadoon Textile Mills Limited	-0.03
25	Al-Noor Sugar Mills Limited	0.00	64	Dewan Mushtaq Textile Mills Limited	-0.03
26	Mitchell's Fruit Farms Limited	0.00	65	Sapphire Textile Mills Limited	-0.03
27	Service Industries Limited	-0.08	66	Indus Dyeing & Manufacturing Company Limited	-0.02
28	Bata Pakistan Limited	-0.02	67	Shadab Textile Mills Limited	-0.02
29	Balochistan Glass Limited	-0.17	68	Feroze1888 Mills Limited	-0.01
30	Pakistan Refinery Limited	-0.25	69	Nagina Cotton Mills Limited	-0.01
31	Shell Pakistan Limited	-0.25	70	Kohinoor Mills Limited	-0.01
32	Attock Refinery Limited	-0.23	71	GlaxoSmithKline Pakistan Limited	-0.01
33	National Refinery Limited	-0.22	72	Shams Textile Mills Limited	-0.01
34	Burshane LPG (Pakistan) Limited	-0.04	73	Elahi Cotton Mills Limited	-0.01
35	Packages Limited	-0.06	74	Faisal Spinning Mills Limited	-0.00
36	Nestlé Pakistan Limited	-0.05	75	Ismail Industries Limited	-0.01
37	Colgate-Palmolive (Pakistan) Limited	-0.02	76	Bhanero Textile Mills Limited	-0.01
38	Bolan Castings Limited	-0.01	77	Philip Morris (Pakistan) Limited	-0.11
39	ICI Pakistan Limited	-0.07	78	Pakistan Tobacco Company Limited	-0.03

Appendix B

Firms with Estimated Positive TFP

S.No.	Name of Firm	TFP	S.No.	Name of Firm	TFP
1	Fecto Cement Limited	0.03	32	Clover Pakistan Limited	0.04
2	Gharibwal Cement Limited	0.03	33	EcoPack Limited	0.05
3	Maple Leaf Cement Factory Limited	0.12	34	Century Paper & Board Mills Limited	0.01
4	Cherat Cement Company Limited	0.13	35	Pakistan Paper Products Limited	0.17
5	Lucky Cement Limited	0.16	36	Security Papers Limited	0.28
6	D.G. Khan Cement Company Limited	0.17	37	Otsuka Pakistan Limited	0.00
7	Pioneer Cement Limited	0.18	38	Highnoon Laboratories Limited	0.01
8	Fauji Cement Company Limited	0.22	39	The Searle Company Limited	0.05
9	Kohat Cement Company Limited	0.24	40	Sana Industries Limited	0.05
10	Bestway Cement Limited	0.25	41	Archroma Pakistan Limited	0.05
11	Dawood Hercules Corporation Limited	0.11	42	Abbott Laboratories (Pakistan) Limited	0.06
12	GOC (Pak) Limited	0.21	43	Wah Nobel Chemicals Limited	0.09
13	Pakistan Engineering Company Limited	0.23	44	Pakistan Oxygen Limited	0.11
14	Pak Elektron Limited	0.01	45	Sitara Chemical Industries Limited	0.11
15	Dadex Eternit Limited	0.01	46	Ferozsons Laboratories Limited	0.19
16	Fauji Fertilizer Company Limited	0.17	47	Biafo Industries Limited	0.32
17	Fauji Fertilizer Bin Qasim Limited	0.00	48	The General Tyre and Rubber Company of Pakistan Limited	0.01
18	Engro Corporation Limited	0.00	49	Pakistan Services Limited	0.15
19	JDW Sugar Mills Limited	0.01	50	Reliance Cotton Spinning Mills Limited	0.08
20	Al-Abbas Sugar Mills Limited	0.01	51	Artistic Denim Mills Limited	0.10
21	Tandlianwala Sugar Mills Limited	0.01	52	Bannu Woollen Mills Limited	0.18
22	Ansari Sugar Mills Limited	0.02	53	Shahtaj Textile Limited	0.00
23	Shahmurad Sugar Mills Limited	0.03	54	Salfi Textile Mills Limited	0.00
24	Tri-Pack Films Limited	0.07	55	Reliance Weaving Mills Limited	0.01
25	Habib-ADM Limited	0.07	56	Premium Textile Mills Limited	0.02
26	Rafhan Maize Product Company Limited	0.08	57	Pakistan Synthetics Limited	0.02
27	Tariq Glass Industries Limited	0.02	58	Nishat (Chunian) Limited	0.03
28	Ghani Glass Limited	0.11	59	Dewan Cement Limited	0.03
29	Treet Corporation Limited	0.01	60	Tata Textile Mills Limited	0.03
30	Merit Packaging Limited	0.02	61	Island Textile Mills Limited	0.04
31	Cherat Packaging Limited	0.03	62	Sapphire Fibres Limited	0.05