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"Export as a driver of productivity: Myth or Reality?"

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Abstract

This study analysis firm level productivity in the Indian Automobile sector for the period 2014-2024 with the help of panel data for 1864 firms. Total factor productivity in the sector is estimated with Levinsohn -Petrin model, and robustness checks are done by Ackerberg -Frazer model and Wooldridge model. The study shows the variations in productivity like in Levinsohn- Petrin model it reflects absolute productivity levels while ACF and Wooldridge gives estimation for relative efficiency. The analysis reveals exports as the most robust and consistent determinant of productivity I the automobile sector which follows learning by doing hypothesis. It also analysis heterogeneity across industry segments. Scale based productivity in OEM's input efficiency in component manufacturers. Trends analysis shows a break with the Covid-19 shock in 2020, but the sector recovered by 2024 which reflects restructuring, flexibility and adaptability. The results shows that the emphasis should be on external market exposure as a determinant of productivity, compared to internal characteristics of firms in the sector.

JEL codes – C23, D24, F14, L20, L25, L60, O14

Keywords -Exports, Total Factor Productivity, Firm Performance, IndianManufacturing, panel Data, Learning -by-Exporting

1 Introduction

A firm level Total factor productivity gives the efficiency with which factor inputs such as capital ,labour transformed into output it indicates total factor productivity and resource allocation(Hulten, 2000). In Developing countries like India , discussing firm level productivity is important because of structural changes in manufacturing due to liberalisation and global integration(Goldar & Kumari, 2003; Virmani, n.d.) productivity estimates differ depending upon different models (Kathuria, n.d.) .Productivity measurement is a challenge ,traditional Ordinary least square method estimation suffers from simultaneous bias and heterogeneity because firm adjust input choices on expectations of productivity (Griliches & Mairesse, 1995). To tackle this issue semi -parametric methods like Levinsohn- Petrin 2003, Ackerberg -Frazer 2015 & Wooldridge 2009 has been used widely. These methods different in endogeneity and in identification, Levinsohn -Petron method solves simultaneous bias problem but have its own limitations then it's important to run robustness checks with ACF & Wooldridge method. In this study of Indian automobile sector, we systematically compare all the methods in a single empirical framework. More productive firms likely to enter exports markets which supports self – selection and learning by exporting mechanism (Clerides et al., 1998) . Macro-economic shocks also plays important role in changing dynamics of productivity ,semi- conductor shortages, logistic disturbances ,rising input costs, social distancing have affected the level of productivity(Bloom et al., 2020) ,But these effects are short-term ,there is recovery post pandemic period and adaptations to the structural changes in the sector. Evidence of firm level productivity during and after the covid period is limited, these three gaps remain unattended,

1. Limited comparative estimation of total factor productivity with a single empirical framework in Indian automobile sector.
2. External factors like exports versus internal factor size & research and development as determining factor of productivity
3. Limited evidence of Industry segment variation in productivity over time especially after covid-19 shock.

This study tries to fill these gaps by providing firm level productivity estimation in Indian automobile sector for the period 2014-2024. Panel data of firms are prepared, for estimating total factor productivity from Levinsohn - Petrin, ACF and Wooldridge method to examine both scale & efficiency-based productivity. It also examines determinants of productivity by using regression model with fixed effects which focus on export, firm size & Research & Development. It explains heterogeneity between different segments over time, and provide evidence for shock and recovery. Comparative methodical difference between different estimation of Total factor productivity and how different technique changes interpretation.

Four Research Questions are framed for the study-

1 Are Different total factor productivity estimation method consistent for productivity and its determinants?
2 Explain Key determinants of firm level productivity in Indian automobile sector?
3 How does Productivity vary in industry segments like component manufactures or OEMs?
4 How productivity adapts over time pre and post covid-19 shock?

2 Literature Review

Long -term economic growth not only depends on labour and capital but also needs improvements in technology & efficiency level. Total factor productivity introduced from (Solow, 1957) that unexplained growth which is not explained by capital & labour reflects total productivity is accounted as total factor productivity. It lays foundation for modern production methods. After Solow, (Hulten, 2000) argues that total factor productivity captures managerial efficiency ,innovation ,resource allocation, total factor productivity not only reflect total productivity but more than that.

Firms choose inputs labour, capital and material after productivity stocks, because of this traditional production function estimation methods can be biased. To tackle this Olley&Pakes 1996, a semi- parametric method which uses Investment has been used as a proxy for unobserved productivity. Levinsohn-Petrin 2003 uses intermediate inputs as a proxy which is an improved as many firms does not disclose investment & it creates selection bias. ACF 2015 further improved the estimation by modifying timing assumptions for proxy variable, it fixes identification problem of both Olley and Pakes &Levinsohn- Petrin. Wooldridge 2009 proposed a one-step GMM estimation which improves efficiency, it also reduces estimation inconsistency. Comparative review of production function and examines the importance of identification bias & simultaneity in the firm level analysis(Van Beveren, 2012). Different method produce different productivity interpretations ,which shows that there is a need to compare Levisohn - Petrin, ACF and Wooldridge (Rovigatti & Mollisi, 2018) .It made real world datasets estimation more stable, practical and efficient. Misallocation of resources majorly affects productivity in developing countries (Hsieh & Klenow, 2009).Two firms in the same industry can have different productivity story (Bartelsman & Doms, 2000).(Virmani, n.d.) Analysis that economic liberalization and lesser government controls ,improved productivity in India Manufacturing sectors while other studies (Pulapre Balakrishnan et al., 2000) bit caution that productivity follows by liberalisation , productivity changes partly reflect changes in input intensity and utilization of capital.(Topalova & Khandelwal, 2011) provides evidence that liberal trade policy improved firm level productivity by better access to inputs and increase in competitiveness.(Krishna & Mitra, 1998) after liberalization firms experienced the market discipline effect which increases competitiveness among firms which further improves productivity. These studies provide the framework for Indian manufacturing Industries for firm level analysis of automobile sector, because of its contribution in manufacturing sector automobile industry gets special attention.(Sharma & Mishra, 2011) highlights the role of upgradation of technology ,liberalisation ,exports for improving manufacturing productivity in the post reform period (Meier & Pinto, 2024) analysis that productivity like covid -19 are interconnected with supply chains disruptions which resulted in decrease in production ,employment& exports and Imports. It supports our finding of sharp decline in 2020 and gradual recovery in 2022-24. Overall, Literature suggests following gaps-:

1 Most studies do not compare Total factor Productivity estimation together in one study.

2 Most studies focus on total factor productivity, lesser attention to scale based versus efficiency based productivity.

3 Exports, firm size & Research & Development at firm level are not explored.

4 Post covid-19 recovery still underexplored in this sector.

Our study addresses these gaps by estimating Total factor productivity using Levensohn -Petrin, ACF and Wooldridge method. It focuses on heterogeneity of Industry segments and factor determining productivity of Indian automobile Industry.

3 Research Methodology and Data

3.1 Data

This study uses firm level panel data of 1864 firms from CMIE Prowess for Indian Automobile Industry for the period 2015-2024. Firstly, Variables from raw data constructed then total factor productivity is calculated by Levisohn Petrein model& for robustness check ACF model and Wooldridge model has been used. After that second regression model with fixed effect is run to find the determinants of TFP in the automobile Industry.

3.2Variable Construction

Before using LP, model Brief definition of variable is constructed from standard definitions of productivity-

Variable	Definition	Why it is used for TFP
Capital	PIM capital stock-built year by year with firm's own investment & depreciation, values are deflated to 2013-2014 prices.	PIM is been used because book value of assets (GFA/NFA) gives overestimation of the productive capital.
Output	Real value added= Sales minus intermediate inputs, deflated to 2013-2014 prices	It measures what firm actually produced, removes double counting
Labour	Labour is defined as Wage bill = Value Added minus PBDITA (profit before depreciation, interest, tax, amortisation), deflated to 2013-14 prices	Employee headcount has only 7% coverage in CMIE. Wage bill is a reliable proxy available for 51% of the sample.
Materials	It includes Raw materials, stores & spares, power, fuel & water — all deflated to 2013-14 prices	It is used as the "proxy variable" in TFP estimation — to identify the unobservable productivity of the firm.

Details of variable construction mentioned in Appendix -A

3.3 Total Factor Productivity estimation Methods

- **Levinsohn -Petrin Method (2003)**

In this study firm level total factor productivity (TFP) is measured by Levinsohn -Petrin method which uses semi parametric approach. It overcomes the simultaneous bias that arises when firms choose inputs based on unobserved productivity.

The production function is assumed to follow cobb Douglas functional form: -

- **Ackerberg -Caves -Frazer (ACF-TFP)**

Ackerberg -TFP produces more accurate method for efficiency modifies the process to identify properly labour coefficients for Robustness check. Following (Rovigatti & Mollisi, 2018) firm level productivity is estimated by control function approach implemented through prodeststata. They emphasize on the importance of identifying and correcting selection bias and endogeneity problems in measuring firm level productivity.

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- **Wooldridge GMM TFP (WRDG -TFP)**

It is one step GMM framework. It addresses the endogeneity problem and improves efficiency. This method is used for robustness check.

Heterogeneity of Industry segment – Study analysis Industry segment & difference in their efficiency level andProductivity level

Trend and structural Analysis -The study Analysis the trends over the years, how with the time sector is evolving

Interpretation

1 Measurement Analysis

Are three methods produce same Total factor Productivity or Different

2 Determinants of productivity

Exports, firm size & Research & Development which factor explains productivity.

3 Time period analysis and heterogeneity of Industry Segment

Trend analysis and different productivity analysis in the industry segment.

Descriptive statistics

Fig-1 Shows year wise TFP trends

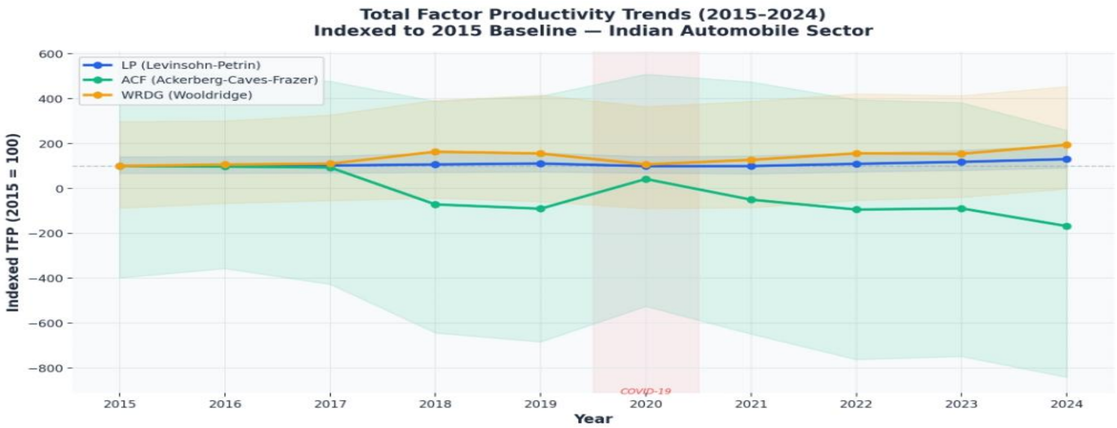

Figure -1 shows Total factor productivity estimates obtained by LP, ACF&Wooldridge method. LP & Wooldridge shows trend gradual decline in 2017 & recovery after Covid -19. But ACF shows lower productivity & Divergence trend which highlights the measurement sensitivity of different methods**.**

Figure-2

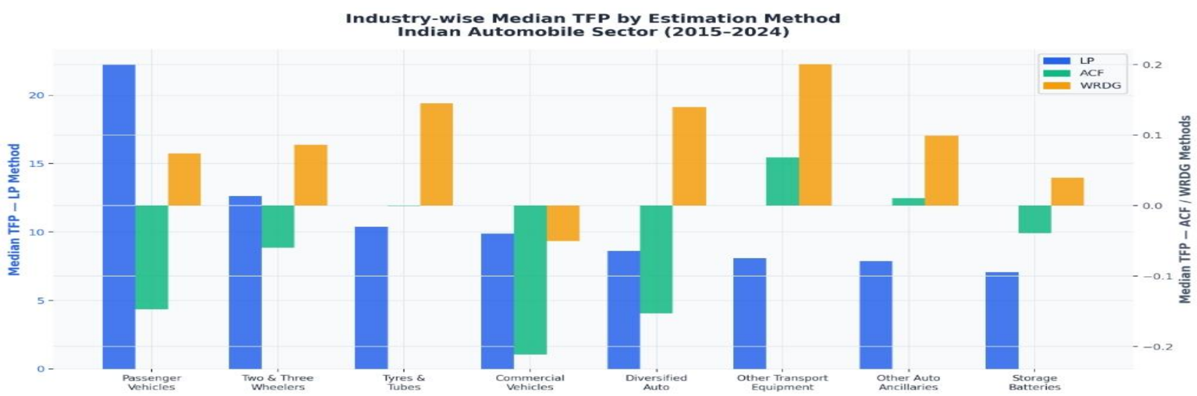

Figure -2shows Industry -wise Median TFP by Estimation Method.

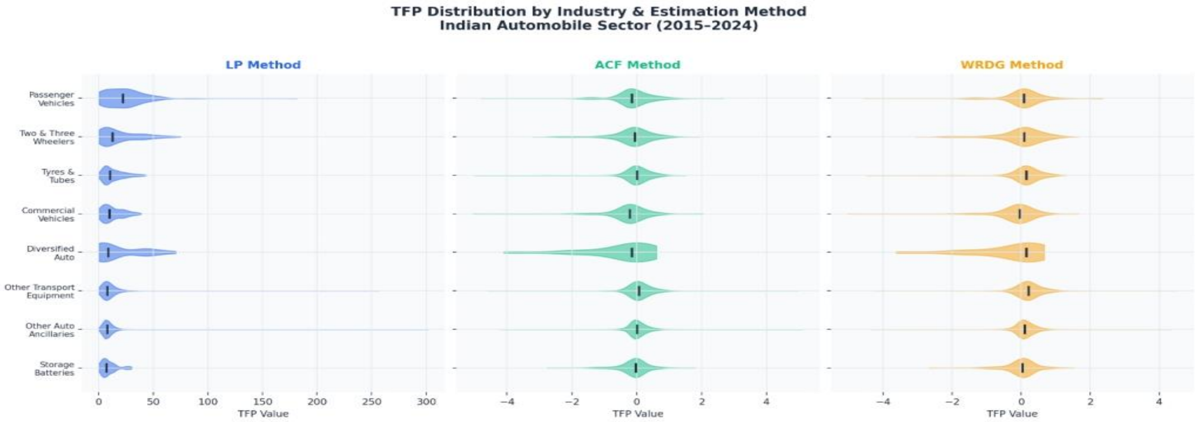

Figure-3 shows violin plots of TFP distribution across automobile Industries using LP, ACF &WRDG methods.

Figure -4

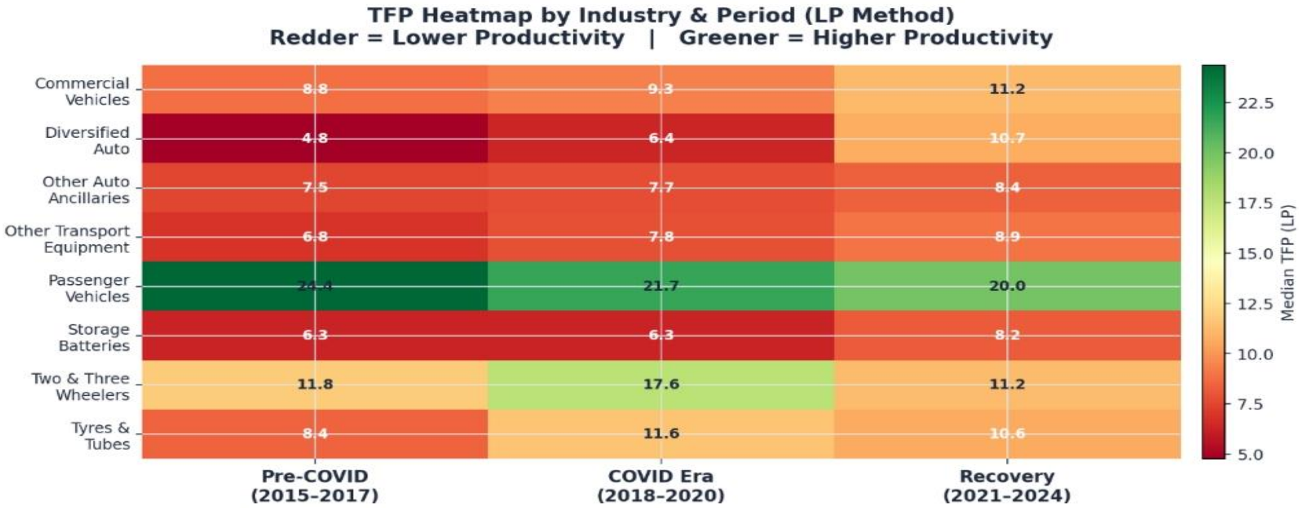

Figure-4 shows heterogeneity in productivity across automobile Industries over period of time.

Table 1: TFP Summary Statistics and Year-Wise Trends

Panel A: Descriptive Statistics of TFP Estimates

Main specification — Value Added + PIM Capital

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Method	Specification	+	Mean	SD	p25	Median	p75	Corr LP	Corr ACF	Corr WRDG	Scale
LP (Levinsohn-Petrin)	*VA + PIM Capital*	**9,414**	**9.8391**	**9.5121**	**5.4031**	**8.0207**	**11.5137**	**1.000**	**0.456*******	**0.475*****	***Absolute level***
ACF (Ackerberg-Caves-Frazer)	*VA + PIM Capital*	**9,411**	**0.0265**	**0.4617**	**-0.1366**	**0.0080**	**0.1914**	**0.456*****	**1.000**	**0.971*****	***Residual (0=avg)***

International Journal of Economic Practices and Theories (IJEPT)
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//Wooldridge GMM	*VA + PIM Capital*	9,411	0.1154	0.4438	-0.0445	0.1033	0.2888	0.475***	0.971***	1.000	*Residual (0=avg)*

*LP TFP = absolute productivity level. ACF and Wooldridge = log residuals centered near zero. *** = significant at 1% level. Correlation between ACF and Wooldridge = 0.971 — both identify the same productivity variation*

Panel B: Year-Wise Mean TFP

Year	LP Mean	LP SD	LP Med.	LP N	ACF Mean	ACF SD	ACF Med.	ACF N	WRDG Mean	WRDG SD	WRDG N
2015	8.8593	10.4658	7.4344	798	-0.0102	0.4086	-0.0315	797	0.0870	0.3948	797
2016	8.7805	6.1219	7.5589	841	-0.0234	0.4253	-0.0307	841	0.0853	0.4157	841
2017	8.8909	6.5226	7.6178	930	-0.0258	0.4298	-0.0294	930	0.0849	0.4266	930
2018	9.7616	8.7386	7.9754	968	0.0231	0.4827	0.0224	968	0.1166	0.4653	968
2019	10.2493	10.4365	8.2810	964	0.0407	0.4874	0.0284	964	0.1234	0.4747	964
2020	8.9966	7.1233	7.3930	1,013	-0.0103	0.4352	-0.0133	1,011	0.0837	0.4261	1,011
2021	9.1474	7.7873	7.4358	998	0.0167	0.4882	0.0157	998	0.0974	0.4745	998
2022	10.4311	12.1984	8.1749	993	0.0700	0.4921	0.0296	993	0.1447	0.4639	993
2023	10.8427	9.1900	8.8154	991	0.0620	0.4810	0.0280	991	0.1360	0.4563	991
2024	12.2298	13.2550	9.7338	918	0.1118	0.4426	0.0528	918	0.1897	0.4058	918

Red row (2020) = COVID-19 year. 2014 has no TFP estimates — base year for PIM capital (no lagged values available). Med. = Median.

TFP Levels and Distribution

1 LP TFP (mean=9.84, SD=9.51): Absolute productivity levels. Right-skewed (max=302) because a few very large OEMs (Maruti, Tata Motors, Hero MotoCorp) have very high absolute TFP. The median (8.02) is a better central tendency for this measure. Most firms cluster between 5.4 and 11.5 (p25–p75).

2 ACF TFP (mean=0.027, SD=0.46) and Wooldridge TFP (mean=0.115, SD=0.44): Residual productivity estimates centred near zero. A positive value means the firm produces MORE output than predicted by its inputs alone — it is operating above the average efficiency frontier. A negative value means it produces less than predicted — inefficiency relative to peers

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3 CORRELATIONS: ACF and Wooldridge are almost identical (r=0.971, p<0.001). Different GMM approaches shows same productive variation LP gives absolute scale efficiency component which other methods removed.

Empirical Results

Table 2: Production Function Coefficients | LP, ACF & Wooldridge | Indian Automobile Sector | 2014–2024

*Dep. var: ln(Real Value Added). Main spec uses PIM capital stock (Perpetual Inventory Method) and wage bill as labour proxy. Robustness checks use Gross Output and NFA capital. Std. errors in parentheses. *** p<0.01 ** p<0.05 * p<0.10*

Specification	Variable	Coefficient	(Std. Error)	z-stat	p-value	N obs	Wald CRS Test
LP (Levinsohn-Petrin, 2003)							
Main — Value Added + PIM Capital	Labour (ln real wage bill)	**0.7074*** **	*(0.0174)*	40.66	**<0.001**	9,411	*Chi²=246.07 p=0.0000*
	Capital (ln real PIM stock)	**0.0096** **	*(0.0045)*	2.14	**0.032**		
Robustness — Gross Output + PIM Capital	Labour (ln real wage bill)	**0.3308*** **	*(0.0235)*	14.08	**<0.001**	9,525	*Chi²=729.63 p=0.0000*
	Capital (ln real PIM stock)	0.0121	*(0.0086)*	1.41	0.159		
Robustness — Value Added + NFA Capital	Labour (ln real wage bill)	**0.7077*** **	*(0.0134)*	52.66	**<0.001**	9,406	*Chi²=3.51 p=0.0609*
	Capital (ln real NFA)	**0.2241*** **	*(0.0365)*	6.14	**<0.001**		
ACF (Ackerberg-Caves-Frazer, 2015)							
Main — Value Added + PIM Capital	Labour (ln real wage bill)	**0.8806*** **	*(0.0411)*	21.44	**<0.001**	8,088	*Chi²=13.84 p=0.0002*
	Capital (ln real PIM stock)	0.0006	*(0.0058)*	0.10	0.923		
	Materials (ln real inputs)	**0.1568*** **	*(0.0385)*	4.07	**<0.001**		
Robustness — Gross Output + PIM Capital	Labour (ln real wage bill)	**0.3375** **	*(0.1549)*	2.18	**0.029**	8,163	*Chi²=0.04 p=0.8501*
	Capital (ln real PIM stock)	-0.0107	*(0.0068)*	-1.57	0.117		
	Materials (ln real inputs)	**0.6777*** **	*(0.1369)*	4.95	**<0.001**		
Robustness — Value Added + NFA Capital	Labour (ln real wage bill)	**0.5140** **	*(0.2087)*	2.46	**0.014**	8,086	*Chi²=2.25 p=0.1333*

	Capital (ln real NFA)	0.0912	*(0.0776)*	1.18	0.240		
	Materials (ln real inputs)	0.2114	*(0.1319)*	1.60	0.109		
Wooldridge GMM (Wooldridge, 2009)							
Main — Value Added + PIM Capital	Labour (ln real wage bill)	**0.7628*****	*(0.0055)*	137.89	**<0.001**	8,027	*Chi²=0.49 p=0.4800*
	Capital (ln real PIM stock)	0.0006	*(0.0032)*	0.20	0.840		
	Materials (ln real inputs)	**0.2441*****	*(0.0098)*	24.90	**<0.001**		
Robustness — Gross Output + PIM Capital	Labour (ln real wage bill)	**0.3454*****	*(0.0040)*	86.82	**<0.001**	8,149	*Chi²=14.66 p=0.0000*
	Capital (ln real PIM stock)	**-0.0056****	*(0.0022)*	-2.54	**0.011**		
	Materials (ln real inputs)	**0.6322*****	*(0.0065)*	97.19	**<0.001**		
Robustness — Value Added + NFA Capital	Labour (ln real wage bill)	**0.7606*****	*(0.0054)*	141.55	**<0.001**	8,024	*Chi²=39.72 p=0.0000*
	Capital (ln real NFA)	**0.1105*****	*(0.0142)*	7.76	**<0.001**		
	Materials (ln real inputs)	**0.2259*****	*(0.0102)*	22.24	**<0.001**		
**** p<0.01 ** p<0.05 * p<0.10 | All monetary variables in ln(real Rs. Million), Base FY2013-14 | CRS = Constant Returns to Scale | Labour measured by ln(real wage bill = VA − PBDITA)*							

Table-2 shows production function coefficient -

- Each coefficient is the output elasticity of that input: -1% increase in the input leads to a coefficient-% increase in real value added, holding all other inputs constant. All variables are in natural logs, so coefficients are directly interpretable as elasticities.
- **LABOUR COEFFICIENT** (LP = 0.707***, ACF = 0.881***, Wooldridge = 0.763***)
- Labour is the dominant factor of production. Consistent and highly significant ($p < 0.001$) across all three methods. A 1% increase in the real wage bill raises real value added by 0.71–0.88%. The automobile sector is strongly labour-intensive at the value-added level.
- **CAPITAL COEFFICIENT** (PIM: LP = 0.010*, ACF = 0.001, WRDG = 0.001 | NFA: LP = 0.224***, WRDG = 0.111***)
- Under PIM capital the coefficient is very small and mostly insignificant. In NFA both LP and Wooldridge are significant. PIM take into account accumulated depreciation, which reduces Net capital. Capital is productive in NFA robustness check.
- **RETURNS TO SCALE (Wald CRS Test)**

Rejected (decreasing returns) in most specifications — LP gross output (Chi²=729.6***), Wooldridge NFA (Chi²=39.7***). Wooldridge main spec does NOT reject CRS (Chi²=0.49, p=0.48). Overall interpretation: the sector operates with slightly decreasing returns to scale — doubling all inputs produces less than double the output.

Table 3: Industry-Wise Mean TFP | All Three Methods | Sorted by LP Mean TFP Descending						
LP TFP = absolute productivity level (higher = more productive). ACF & Wooldridge TFP = residual productivity (positive = above-average efficiency; negative = below-average). Green = positive / productive. Red = negative / below average.						
Industry Segment	**LP Mean TFP**	**ACF Mean TFP**	**WRDG Mean TFP**	**Obs**	**LP Rank**	**Key Insight**
Passenger Vehicles	**23.850**	-0.1142	0.0694	174	#1	*Highest absolute LP TFP — Maruti, Tata, Honda (large-scale). Negative ACF/WRDG means below own efficiency frontier*
Two & Three Wheelers	**19.310**	-0.1702	-0.0154	160	#2	*Very high LP TFP — Hero, Bajaj, TVS. Negative ACF/WRDG suggests under-utilised productivity potential*
Diversified Automobile	**18.229**	-0.5329	-0.3602	32	#3	*High LP but most negative ACF/WRDG — resource allocation across segments may reduce input efficiency*
Tyres & Tubes	**13.663**	-0.0202	0.1169	284	#4	*Positive WRDG (+0.117) — Apollo, MRF show consistent above-average input efficiency*
Commercial Vehicles	**12.717**	-0.2658	-0.1646	108	#5	*Below-average ACF/WRDG — cyclical demand and capital intensity suppress relative efficiency*
Other Transport Equip.	**10.209**	0.0726	0.1954	730	#6	*Second highest ACF/WRDG (+0.195) — specialised makers extract maximum value from inputs*
Storage Batteries	**9.349**	-0.1047	-0.0245	200	#7	*Negative ACF/WRDG — EV battery makers in heavy capital investment / scale-up phase*
Other Auto Ancillaries	**9.090**	0.0409	0.1210	7,726	#8	*Largest sub-sample (7,726 obs). Positive ACF (+0.041) & WRDG (+0.121) — component sector shows strong input efficiency*

Table-**3 Industry Segment trends**

- LP RANKING (high to low): Passenger Vehicles (23.85) > Two & Three Wheelers (19.31) > Diversified (18.23) > Tyres & Tubes (13.66) > Commercial Vehicles (12.72) > Other Transport (10.21) > Storage Batteries (9.35) > Other Auto Ancillaries (9.09).
- Large OEMs dominate because LP captures absolute scale — Maruti or Tata simply process more value added in absolute terms than a small component maker.
- ACF / WRDG RANKING (high to low): Other Transport Equipment (+0.195) > Other Auto Ancillaries (+0.121) > Tyres & Tubes (+0.117) > Passenger Vehicles (+0.069) > ...

- Ranking is done by relative efficiency of inputs, higher rank assumed by specialized component ad equipment makers.

Key point (why ranking of LP and ACF/WRDG are different):

Passenger vehicle OEMs attained highest LP signifies absolute productivitybut in ACF its efficiency is negative because it operates below its efficiency frontier. It shows that large firms have large absolute TFP but they may not be utilizing inputs at their best level.Smaller firms show relative higher efficiency incomparison of large firms

Storage Batteries and Commercial Vehicles are the two segments which shows negative ACF and WooldridgeTFP.Electric vehicle investment depressed the present efficiency levels. Commercialvehicle segment faces cyclical weak demand and they adopt electric vehicle transition slowly.

Table 4: Determinants of TFP | Fixed-Effects Panel Regression | Robust Std. Errors Clustered by Firm

*Dep. var: TFP estimated by each method. Covariates: ln(R&D), ln(Exports), ln(Total Assets). Year fixed effects (2015 base). Std. errors clustered by firm_id (257 clusters). N=968 obs / 257 firms. *** p<0.01 ** p<0.05 * p<0.10*

Variable	LP (Levinsohn-Petrin)		ACF (Ackerberg-Caves-Frazer)		Wooldridge GMM	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
ln(R&D expenditure)	0.1908	*(0.2221)*	0.0025	*(0.0157)*	0.0046	*(0.0134)*
ln(Export earnings)	**0.3043****	*(0.1315)*	**0.0317*****	*(0.0107)*	**0.0313*****	*(0.0110)*
ln(Total Assets) — firm size	**2.3488*****	*(0.7650)*	0.0217	*(0.0792)*	0.0263	*(0.0686)*
Year Fixed Effects	**Yes**		**Yes**		**Yes**	
Observations	968		968		968	
Number of Firms	257		257		257	
R^2 Within	0.0614		0.0465		0.0473	
R^2 Between	0.7141		0.0026		0.0307	
R^2 Overall	0.5858		0.0126		0.0426	
Hausman Test (FE vs RE)	*Chi²(12) = 15.66, p = 0.207 → Fail to reject H0 → FE and RE are consistent. FE preferred: controls for all time-invariant firm heterogeneity.*					

**** p<0.01 ** p<0.05 * p<0.10 | Year 2020 (COVID) may be driving some instability in year FE — consider robustness check excluding 2020.*

Table 4 Determinants of Total factor Productivity (TFP)

EXPORTS — MOST ROBUST FINDING (significant in ALL three methods)

LP: +0.304** (p=0.021) ACF: +0.032*** (p=0.003) Wooldridge: +0.031*** (p=0.005)

Firms that export more have significantly higher TFP across all estimation methods. This is the single most robust finding in the analysis. It supports the "learning by exporting" hypothesis — exposure to global markets forces quality upgrading, process improvements, and technology adoption that raise productivity

FIRM SIZE (Total Assets) — ONLY SIGNIFICANT IN LP (p=0.002)

LP: +2.35*** (p=0.002) ACF: +0.022 (p=0.784) Wooldridge: +0.026 (p=0.701)

LP-measured TFP rises with firm size, but this effect vanishes in ACF and Wooldridge. This confirms that LP captures a scale effect that the more sophisticated methods correct for. Size per se does not drive input efficiency — large firms use more inputs, not fewer per unit of output.

R&D EXPENDITURE — POSITIVE BUT INSIGNIFICANT IN ALL METHODS

LP: +0.191 (p=0.391)   ACF: +0.002 (p=0.875)   Wooldridge: +0.005 (p=0.733)

Only 11.6% of firms in the sample report R&D expenditure — insufficient coverage to detect a statistically significant effect. The positive sign is theoretically consistent with innovation theory but cannot be confirmed statistically with this sample.

HAUSMAN TEST: $Chi^2(12)=15.66$, $p=0.207$ — Fail to reject H0. Fixed Effects and Random Effects estimates are statistically consistent. FE is the preferred model: it controls for all time-invariant firm characteristics (ownership, founding year, location, historical capital vintage) without needing to specify a distributional assumption for the unobserved heterogeneity.

TFP – trends

- 2015-2017 – STABLE GROWTH, TFP is flat across all three methods. Wooldridge mean ≈ 0.085. No significant productivity growth — the sector was recovering from the 2013-14 downturn and consolidating.
- 2017-2019 - PRE-COVID, TFP rose to 0.117–0.123 (Wooldridge), LP reached 9.76–10.25. High vehicle sales in FY2018-19, improved capacity utilisation &strong export growth in auto components in the sector.
- 2020 - COVID-19 SHOCK — DECADE LOW, all methods show the single-year decline. Wooldridge fell to 0.084 (lowest in sample), LP to 8.997. Production shutdowns (April–June 2020 near-zero output), supply chain collapse, and demand destruction combined to crush productivity. This is the clearest event-study signal in the entire dataset.
- 2021-2022- UNEVEN RECOVERY, TFP partially recovered but was constrained by global semiconductor shortages — automobile production worldwide was disrupted by chip supply gaps. Recovery visible but below pre-COVID peak in ACF/Wooldridge.
- 2022-2024- NEW DECADE HIGH, Wooldridge TFP = 0.136–0.190, LP = 10.84–12.23. Post-COVID normalisation, EV investment cycles, digital manufacturing adoption, and export diversification drove the sector to its best productivity in the 2014–2024 periodd

Conclusion

A key finding of the study is that different estimation techniques yield different economic interpretation.Levisohn -Petrin model more sensitive to scale of the firm while ACF&Wooldridge gave emphasis on input efficiency .(Van Beveren, 2012)argued that proxy variables may analysis different dimension of productivity which depends on input choices and endogeneity are treated. Our study reinforce that total factor productivity depends estimation techniques. Large firm plays a dominate role when productivity analysis through scale effect, smaller firm improves input efficiency compared to larger firms. Exports as the dominant factor in determining productivity. The most robust and key finding is that export is positive and sufficient across all methods, which supports (Melitz, 2003)more productive firms catch up early and supports self -selection hypotheses. Learning by exporting (De Loecker, 2007) remains significant after controlling fixed effect, shows firm learning by doing effect dominates. This is consistent with empirical studies(Wagner, n.d.) which emphasis that global integration plays important role in technology adoption and firm efficiency improvement. It also highlights the heterogeneity of Industry segment. The trend analysis shows a structural change during covid-19 and improvement after 2020 shows adaptation and re-silence of the automobile sector.

The study concludes that external factor plays a important role in determining the productivity of the sector in comparison of Internal factors. We need to combine scale and efficiency for extracting best from all firms.

Policy Implications

1 Export -Oriented policy should be formed as it is the important driver of productivity

2Global Integration is important as it improves supply chains in the industry.

3 Focus should be on improving efficiency of small and medium firms, they focusing on only large firms for scale benefits.

Future Research

We can extend this study by adding

- Innovative measure
- Dynamic models
- Interaction models can be framed in future
- Heterogeneity between ownership structures and regions can be studied.

Appendix -A

How the Key Variables Were Built

1 Sales (Output)

Formula: Sales = Revenue from Products + Revenue from Services

Both revenue lines come directly from CMIE Prowess (File 2). If a firm earns only from products, the services revenue is treated as zero — not missing. If both are absent, the firm-year is excluded from that calculation.

Why: Some automobile firms earn a portion of revenue from after-sales services, maintenance contracts, or financing. Including both gives the complete picture of what the firm sold.

2 Value Added

Formula: Value Added = Sales − Materials

Where Materials = Raw materials consumed + Stores & spares + Power, fuel & water charges

Value added is the preferred output measure for TFP because it strips out the cost of bought-in inputs, leaving only what the firm created. This avoids giving credit for productivity to a firm that simply buys more inputs.

Why not use Sales directly? A firm that doubles sales by doubling raw material purchases has not become more productive. Value added correctly isolates the firm's own contribution.

3 Labour Cost (Wage bill proxy)

Formula: Labour Cost = Value Added − PBDITA

Where PBDITA = Profit Before Depreciation, Interest, Tax & Amortisation — reported directly by CMIE Prowess

CMIE Prowess does not have a separate "staff costs" or "wages" line item for most firms in this sector. Employee headcount is available for only 7% of the sample — too sparse to use directly. The wage bill approach solves this: Value Added minus operating profit equals all operating costs paid to labour.

Is this accurate? Yes — for TFP estimation purposes. The wage bill (w × L) identifies the same labour elasticity as headcount (L) because the market wage rate (w) is set externally and is not controlled by the firm. This is standard practice in Indian firm-level productivity studies.

4 Capital stock and Depreciation -Why we don't use book Value

The most important methodological decision in this analysis is how to measure capital. There are three options — and each gives a different answer.

Approach	What it uses	Problem
GFA (Gross Fixed Assets)	Book value of all fixed assets ever purchased, at original cost	Includes fully depreciated, non-functioning assets. Overstates productive capital.
NFA (Net Fixed Assets)	GFA minus accumulated depreciation on the balance sheet	Accounting depreciation depends on the firm's chosen method (WDV vs SLM). Not comparable across firms.

PIM Capital Stock ✓ USED	Built year by year from investment flows using the firm's own depreciation rate	Reflects actual productive capital in use. Comparable across firms. Recommended in the literature.

5 The PIM formula

K(t) = K(t−1) × (1 − δ) + I(t)

Term	Meaning	How it was measured
K(t)	Capital stock in the current year	Calculated — this is what we are building
K(t−1)	Capital stock in the previous year	Starting point: GFA in the first year the firm appears in data
δ (delta)	Depreciation rate	Firm-specific: Depreciation ÷ GFA(t−1), capped between 1% and 30%. See Section 3.2.
I(t)	Net investment in the current year	GFA(t) − GFA(t−1) + Depreciation(t)

6 Why Firm -Specific Depreciation not a fixed rate

The standard approach in academic research is to use a fixed depreciation rate — commonly 5% or 10%. We chose a firm-specific rate instead. Here is why.

Fixed rate (e.g. 5% or 10%)	Firm-specific rate ✓ USED
Same rate applied to all firms regardless of asset type	Each firm's rate comes from its own accounts: Depreciation ÷ GFA(t−1)
A tyre maker and a two-wheeler OEM get the same depreciation assumption	A tyre maker depreciates assets differently from a two-wheeler OEM — and the data reflects that
Our sample median depreciation rate is 7.39% — a fixed 5% rate would understate capital consumption for most firms	Rates are capped at 1% (minimum) and 30% (maximum) to remove data errors and outliers
Faster to compute	Follows: Topalova& Khandelwal (2011) and other standard Indian TFP studies

Sample median depreciation rate: 7.39% (not 5%). Using a fixed 5% would systematically understate capital consumption for the majority of automobile firms and bias the capital stock estimates upward.

7 Price Deflators

All financial figures in CMIE Prowess are in nominal rupees — they include the effect of price inflation over time. A firm whose sales grew from Rs. 500 crore in 2015 to Rs. 1,000 crore in 2024 may have simply benefited from price increases rather than producing more. To measure real productivity, we must remove the price effect.

Deflation formula: Real Value(t) = Nominal Value(t) × (Base Index / WPI Index(t))

Base year: FY2013-14 | Source**:** Office of Economic Adviser (OEA), DPIIT, Government of India | **Series:** Annual Average WPI, Financial Year (Base: 2011-12 = 100)

Variable Deflated	WPI Series Used	NIC Code	Why This Series
Sales / Value Added / Wage Bill	Manufacture of Motor Vehicles, Trailers & Semi-Trailers	1319000000	Output price index for the automobile sector directly
Materials (raw materials + stores + spares)	Manufactured Products (all)	1300000000	Broad manufactured goods index — matches the mix of inputs purchased
Power, fuel & water charges	Fuel & Power	1200000000	Energy-specific price index — more accurate than general manufacturing WPI for energy costs
Capital stock (PIM / NFA)	Manufacture of Machinery & Equipment	1318000000	Investment goods (machinery) have a different price trend than output — using output price for capital would mismeasure real investment
Variable	Coverage (firm-years)	Coverage (%)	Note
Total sample	18,669	100%	1,864 firms × ~10 years
Sales (output)	14,098	75.5%	—
PIM capital stock	15,216	81.5%	—
Wage bill (labour proxy)	9,588	51.4%	VA & PBDITA both needed
Materials (proxy variable)	10,044	53.8%	—
Complete cases for TFP estimation (all 4 variables present)	9,411	50.4%	1,172 firms
Employee headcount (not used as primary)	1,296	6.9% — too sparse	Used only for subsample check

Whywe use sector-specific deflators rather than general CPI or GDP deflator? The general CPI includes services, food, and housing — none of which are relevant to automobile manufacturing input and output prices. Sector-specific WPI series track the actual price movements of what automobile firms buy and sell, giving a more accurate conversion to real terms.

8**Summary of Sample Coverage**

Variable	Coverage (firm-years)	Coverage (%)	Note
Total sample	18,669	100%	1,864 firms × ~10 years
Sales (output)	14,098	75.5%	—
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Complete cases for TFP estimation (all 4 variables present)	**9,411**	**50.4%**	1,172 firms
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