

# HIGH-PERFORMANCE WORK SYSTEMS AND THE LABOUR SHARE OF INCOME

## HRM VARIABLE: HPWS ADOPTION ECONOMIC OUTCOME: LABOUR SHARE

**Dr. N Subbukrishna Sastry<sup>1</sup>, Dr. Manjula Mallya M<sup>2</sup>**

<sup>1</sup>Professor, School of Management, CMR University, Bangalore, Karnataka, India.

ORCID ID: 0009-0009-0460-7057,

<sup>2</sup>Associate Professor & Head, Dept. of Economics, Government First Grade College for Women Balmatta Mangalore, Karnataka, India. ORCID ID: 0009-0005-8812-6912

### ABSTRACT

The labour share of income has fallen across most economies for four decades, and the explanations offered have been macroeconomic: the falling relative price of capital, the rise of superstar firms, weakening bargaining institutions. This study asks whether a firm-level human resource choice belongs on that list. Using an unbalanced panel of 214 Indian technology-sector firms observed over 2019 to 2026 — 1,512 firm-year observations — it estimates whether adopters of high-performance work systems sustain a higher labour share than comparable firms, and how that relationship changes as artificial intelligence drives capital deepening. HPWS adoption is measured by an eighteen-item index built on the ability–motivation–opportunity architecture and verified against documentary evidence; the labour share is employee benefit expense over gross value added, computed from published accounts. Three results follow. First, HPWS adoption is associated with a significantly higher labour share under two-way fixed effects ( $\gamma = 0.0187$  per ten index points,  $p < 0.001$ ), and the association is not a productivity sacrifice: high-adoption firms record both faster wage growth and faster productivity growth than low-adoption firms. Second, AI capital deepening reduces the labour share on average ( $\gamma = -0.0412$ ,  $p < 0.001$ ), but HPWS adoption conditions that effect (interaction  $\gamma = 0.0055$ ,  $p < 0.001$ ), with the marginal effect crossing zero at an index value near 75 — a level only the top adoption quartile has reached. Third, and most consequentially, estimation of the constant-elasticity-of-substitution first-order condition separately by adoption group returns  $\sigma = 1.34$  for low-HPWS firms and  $\sigma = 0.87$  for high-HPWS firms, with non-overlapping confidence intervals: work-system design moves AI capital and labour across the unit elasticity, from substitutes to complements. A Melitz–Polanec decomposition attributes 63.8 per cent of the aggregate 5.8-point decline to reallocation between firms rather than to within-firm change, so the distributional question is partly one of which firms grow. Counterfactual simulation to 2032 finds that 11.6 percentage points of labour share separate the best and worst human resource trajectories. The study argues that the labour share is not only a macroeconomic residual but in part a managed outcome.

**KEYWORDS.** High-Performance Work Systems, Labour Share of Income, Functional Income Distribution, Elasticity of Substitution, AI Capital Deepening, Ability–Motivation–Opportunity Framework, Rent Sharing, Melitz–Polanec Decomposition, Panel Fixed Effects, Superstar Firms, Counterfactual Simulation, Indian IT Services, Strategic HRM.

### 1. INTRODUCTION

The share of national income accruing to labour has declined in most economies since the early 1980s, and the literature explaining that decline is almost entirely macroeconomic. Karabarbounis and Neiman (2014) attributed it to the falling relative price of investment goods, which induces substitution toward capital wherever the elasticity of substitution exceeds unity. Elsby, Hobijn and Şahin (2013) emphasised offshoring and measurement. Autor, Dorn, Katz, Patterson and Van Reenen (2020) argued that the aggregate fall reflects not a decline within the typical firm but a reallocation of economic activity toward large, capital-intensive, low-labour-share firms. Acemoglu and Restrepo (2018, 2020) traced it to automation displacing labour from tasks faster than new tasks reinstate it. De Loecker, Eeckhout and Unger (2020) located it in rising market power and the wedge between price and marginal cost.

What these accounts have in common is that firms appear as passive carriers of technological and market forces. The firm chooses how much capital to install and what price to charge; it does not, in these models, choose a work system. Yet the human resource literature has spent three decades establishing that work-system design is a

consequential and highly variable firm choice with large measurable effects on productivity and wages. Huselid (1995) found substantial financial performance effects from high-performance work practices; MacDuffie (1995) and Ichniowski, Shaw and Prennushi (1997) established that such practices operate as complementary bundles rather than singly; Appelbaum, Bailey, Berg and Kalleberg (2000) supplied the ability–motivation–opportunity architecture that organises the field; and the meta-analyses of Combs, Liu, Hall and Ketchen (2006) and Jiang, Lepak, Hu and Baer (2012) confirmed the effects across settings.

These two literatures have not been brought together, and the reason is partly arithmetic. The labour share is a ratio, and the human resource literature almost invariably studies its numerator. Higher wages, more training, greater participation — all raise labour compensation. But the labour share is compensation divided by value added, which can be written as the wage divided by labour productivity:  $LS = w \div (Y/L)$ . A work system that raises wages by twelve per cent and productivity by twenty lowers the labour share while making every worker in the firm better off. The question of whether high-performance work systems sustain a higher labour share is therefore not answerable from the existing evidence on wages, and the sign is not obvious a priori. It depends on a race between the numerator and the denominator that no study has run.

Artificial intelligence sharpens the question because it acts directly on the denominator. Indian technology services is an unusually good setting in which to observe this. Its labour share is among the highest of any large sector — the sampled firms average 61.2 per cent of gross value added paid as employee benefit expense — precisely because the business model has historically converted human time into revenue with little intermediating capital. That model is now being capitalised at speed: AI-attributable capital per employee in this sample rose from ₹1.42 lakh in 2019 to ₹5.86 lakh in 2026, a factor of 4.1 and an annual rate of 22.5 per cent. A sector with a high labour share undergoing rapid capital deepening is the natural laboratory for asking whether work-system design changes the distributional consequence of that deepening.

The theoretical stake is the elasticity of substitution. In the constant-elasticity-of-substitution framework that underpins the entire labour-share literature, capital deepening reduces the labour share if and only if capital and labour are gross substitutes,  $\sigma > 1$ . Karabarbounis and Neiman (2014) estimated  $\sigma$  above unity and concluded that the decline was technologically driven; Oberfield and Raval (2021), working with micro data, found values closer to or below unity and reached more cautious conclusions. The parameter has been treated throughout as a property of the technology. This study asks whether it is instead partly a property of the organisation — whether two firms deploying the same artificial intelligence into the same tasks can face different elasticities because they have designed the work around it differently.

That question has a plausible mechanism. Whether an AI system substitutes for a worker or augments one is not settled by the software. It is settled by task design, by who is authorised to operate the system, by whether the information it produces reaches people with the discretion to act on it, and by whether the workforce has the capability to work alongside it. Bresnahan, Brynjolfsson and Hitt (2002) established exactly this complementarity between information technology, workplace organisation and skilled labour demand, and the evidence from enterprise-systems implementations is consistent with it: Vineeth Kumar, Jijesh, Radhakrishna, Kulkarni, Sastry and Mallya (2026), studying enterprise resource planning across 250 stakeholders in Indian higher education, recorded operational efficiency improvement reported by 75 per cent of respondents and data accuracy and accessibility improvement by more than 80 per cent, while simultaneously finding that 80 per cent identified a requirement for additional training and 60 per cent reported resistance to change as an impediment. A technology that delivers a large denominator effect only where the work system permits people to use it is, by construction, a technology whose distributional consequence is managerially determined.

This paper is the fourth in a research programme pairing one human resource variable with one measurable economic outcome. The first examined skill development investment and the AI-complementary wage premium (Sastry, 2026a); the second, redeployment policy and allocative efficiency (Sastry, 2026b); the third, the training amortisation horizon and the return to training capital (Sastry, 2026c). Those three operate at the level of the individual, the business unit and the budget respectively. This one closes the sequence by asking what the accumulation of such choices adds up to at the level of the functional distribution of income — whether a firm-level human resource choice can be traced to a macroeconomic distributional outcome.

## 2. REVIEW OF LITERATURE

### 2.1 The Decline of the Labour Share and Its Explanations

The empirical fact is well established. Karabarbounis and Neiman (2014), assembling comparable data for fifty-nine countries, documented a global decline of roughly five percentage points in the corporate labour share since 1975 and attributed it to a fall of approximately twenty-five per cent in the relative price of investment goods, which induces substitution toward capital under an estimated elasticity above unity. Elsby, Hobijn and Şahin (2013) examined the United States specifically and emphasised the role of import competition and offshoring, while cautioning that a substantial part of the measured decline reflects the treatment of proprietors' income and depreciation.

Autor, Dorn, Katz, Patterson and Van Reenen (2020) reoriented the debate. Decomposing the aggregate change, they found that the labour share of the typical firm had not fallen much; what had changed was the distribution of activity across firms, with sales concentrating in large, highly productive, low-labour-share establishments. On this account the decline is a reallocation phenomenon and its cause is whatever produces winner-take-most industry structure — network effects, platform economics, or the rising returns to intangible investment. De Loecker, Eeckhout and Unger (2020) supplied a complementary market-power account, showing that average markups rose from 1.21 to 1.61 between 1980 and 2016 and that the rise is concentrated in the upper tail.

The automation literature offers the third account. Acemoglu and Restrepo (2018) modelled the labour share as the outcome of a race between automation, which displaces labour from existing tasks, and the creation of new tasks, which reinstates it; Acemoglu and Restrepo (2020) provided the empirical counterpart, estimating that each additional industrial robot per thousand workers reduced the employment-to-population ratio and wages in exposed United States commuting zones. Guschanski and Onaran (2022) tested the competing explanations against each other and concluded that technological change and bargaining power both matter, with institutional factors carrying substantial independent weight — a finding that, if correct, leaves room for the firm-level institutional variable this study examines.

Indian evidence is thinner but points the same way and from a lower base. Abraham and Sasikumar (2017) documented a sustained decline in the wage share of Indian organised manufacturing, from roughly thirty per cent in the early 1980s to the low teens by the 2010s — a fall far steeper than in advanced economies and from a starting point already below them. Kapoor (2019) attributed a substantial part of it to capital deepening under a labour-market structure that gave workers limited capacity to claim productivity gains. Indian technology services has stood apart from this pattern precisely because its capital intensity was low; the present study asks what happens as that ceases to be true.

### 2.2 High-Performance Work Systems and Their Economic Effects

The high-performance work systems literature begins from the proposition that human resource practices affect firm performance and that they do so as coherent systems. Huselid (1995), surveying nearly a thousand United States firms, found that a one standard deviation increase in high-performance work practice adoption was associated with substantial reductions in turnover and increases in productivity and market value. MacDuffie (1995) and Ichniowski, Shaw and Prennushi (1997) established the bundling result — that practices adopted in isolation yield little and that returns arise from internally consistent configurations — and Milgrom and Roberts (1995) supplied the formal complementarity argument underlying it.

Appelbaum, Bailey, Berg and Kalleberg (2000) organised the field around the ability–motivation–opportunity architecture that this study adopts for measurement: practices raise performance by building ability, by motivating discretionary effort, and by creating the opportunity to exercise it, and all three are required. Jiang, Lepak, Hu and Baer (2012) confirmed in meta-analysis that the three pathways operate through partially distinct mechanisms, and Combs, Liu, Hall and Ketchen (2006) established across ninety-two studies that the effect on organisational performance is robust and larger for systems than for individual practices.

What this literature has not asked is the distributional question. Its dependent variables are productivity, turnover, quality and financial performance — quantities in which the interests of the firm and its workers are assumed aligned. The labour share is different: it is explicitly a division of the surplus, and improvements in it are not automatically improvements in firm performance. Two strands come closest. The rent-sharing literature, following Blanchflower, Oswald and Sanfey (1996), establishes that firms with greater surplus pay more, which implies a positive labour-share effect where high-performance work systems raise workers' claim on that surplus.

The efficiency-wage tradition implies the same through a different route. Neither has been tested against firm-level labour share data, and neither addresses the denominator.

### 2.3 Technology, Work Organisation and the Elasticity of Substitution

The bridge between the two literatures is the complementarity between technology and work organisation. Bresnahan, Brynjolfsson and Hitt (2002) demonstrated that information technology, decentralised work organisation and skilled labour form a three-way complementary system, and that the productivity return to information technology is concentrated in firms that have made the organisational investment alongside the technological one. Bloom and Van Reenen (2007) showed that structured management practice explains large and persistent productivity differences across firms and countries, with Indian firms scoring substantially below the international frontier.

Enterprise-systems research supplies the concrete mechanism. Vineeth Kumar, Jijesh, Radhakrishna, Kulkarni, Sastry and Mallya (2026), examining enterprise resource planning implementation across 250 stakeholders in Indian higher education, found that 75 per cent reported improved administrative processes and more than 80 per cent improved data accuracy and accessibility, with an overall mean effectiveness rating of 3.91 on a five-point scale. Crucially, the same study identified the binding constraints as organisational rather than technical: 80 per cent of respondents identified a requirement for additional training and 60 per cent cited resistance to change, against 45 per cent reporting technical problems. A system capable of an eighty per cent improvement in data accessibility delivers that improvement only where the people who must act on the data have been equipped and permitted to do so.

This is the argument the present study extends to the elasticity of substitution. If the productive contribution of a technology depends on the work system surrounding it, then whether that technology substitutes for labour or complements it is not fully determined by the technology. Oberfield and Raval (2021) established that aggregate elasticities are heterogeneous compositions of plant-level elasticities, opening the door to the possibility that organisational variation lies behind that heterogeneity. Section 8.4 tests it directly by estimating the elasticity separately for high- and low-adoption firms.

### 2.4 Antecedent Work in the HRM Variable → Economic Outcome Programme

This study is the fourth instalment of a research programme pairing a single human resource variable with a single measurable economic outcome, and the three preceding instalments supply its micro-foundations. Sastry (2026a) established that the wage premium to AI-complementary capability is a joint product of the skill and the employer investment that produced it, and that capability applied to billable work realises roughly twice the premium of capability held but unapplied. That finding is the numerator mechanism of the present study: firms that invest in capability and deploy it raise labour compensation, which is one half of the labour share ratio.

Sastry (2026b) found the return to redeployment machinery conditional on automation depth, with policy components functioning as complements above a critical mass, and established that automation becomes allocatively productive rather than disruptive only above a threshold level of policy. The structural parallel with the present interaction result is close, and the substantive connection is closer still: a firm that reallocates displaced capacity onto AI-enabled work is a firm in which artificial intelligence augments rather than replaces, which is precisely the condition under which the elasticity of substitution falls below unity.

Sastry (2026c) measured the gap between the horizon over which firms amortise training expenditure and the observed half-life of the skills that expenditure builds, finding 43.7 per cent of human resource development budget stranded and — importantly here — that skills in heavy billable use decay 2.9 times more slowly than skills that are trained and shelved. That result bears directly on the ability component of the index constructed here: training that is not deployed does not sustain the capability on which labour's claim to the surplus rests, so the opportunity practices in a high-performance work system are a precondition for the ability practices to have any lasting economic effect.

Vineeth Kumar, Jijesh, Radhakrishna, Kulkarni, Sastry and Mallya (2026) supply the enterprise-systems evidence discussed in Section 2.3 and are the closest antecedent for the denominator side of the argument, establishing both the magnitude of the productivity gain available from a systems investment and the organisational conditions on which it depends. Sastry and Mallya (2025b), on strategic human resource management and economic resilience, identified reallocation capacity and continuous learning as the practices distinguishing resilient workforce systems

under technological disruption, and is the conceptual antecedent of the opportunity block of the HPWS index. Sastry and Mallya (2025a), on artificial intelligence analytics in hiring, established the financial value of machine-readable capability data, which underpins the selective staffing and capability mapping items in the ability block. Mallya and Sastry (2025), studying leadership strategies for young talent across 150 employees and 50 human resource managers, found growth opportunity and purpose outranking compensation as retention drivers and command-and-control leadership impeding development — evidence bearing directly on the opportunity and motivation blocks and on why participation practices carry independent weight beyond pay. Sastry (2025b), on talent designation and social comparison, established that relative internal standing carries economic consequence independent of absolute pay, which is relevant to the interpretation of gain-sharing and internal promotion as labour-share instruments. Sastry (2025a), on women micro-entrepreneurs in Karnataka, concluded that socio-cultural and systemic constraints bind more tightly than skill gaps, a caution against reading a higher aggregate labour share as evidence of equitable distribution within the workforce. Sastry (2020) and Sastry (2013) supply the underlying evidence on performance, motivation and talent management, and Anas, Hans and Sastry (2025) demonstrate in tourism how a technology shift restructures an entire service value chain. Table 1 synthesises the literature and states each source's contribution to the present design.

**Table 1. Synthesis of the literature and contribution to the present study.**

| Author(s) & year                                 | Focus of study                       | Key findings                                                                                                       | Relevance to current study                                                                             |
|--------------------------------------------------|--------------------------------------|--------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------|
| Karabarbounis & Neiman (2014)                    | Global decline of the labour share   | Corporate labour share fell ~5 pp since 1975; falling relative price of investment goods with $\sigma > 1$         | Supplies the CES framework and the elasticity parameter this study re-estimates by organisational type |
| Elsby, Hobijn & Şahin (2013)                     | Decline of the US labour share       | Offshoring and import competition matter; measurement of proprietors' income affects the estimate                  | Cautions on construction of the labour share from accounts                                             |
| Autor, Dorn, Katz, Patterson & Van Reenen (2020) | Superstar firms and the labour share | Aggregate fall is reallocation toward large low-labour-share firms, not within-firm decline                        | Motivates the Melitz–Polanec decomposition in Section 8.5                                              |
| De Loecker, Eeckhout & Unger (2020)              | Market power and macro implications  | Average markups rose from 1.21 to 1.61 (1980–2016), concentrated in the upper tail                                 | Justifies the Lerner index control; markups and labour share move oppositely                           |
| Acemoglu & Restrepo (2018, 2020)                 | Automation, tasks and robots         | Labour share is a race between displacement and reinstatement; robots reduce wages and employment in exposed areas | Grounds the capital-deepening effect as a task-composition phenomenon                                  |
| Guschanski & Onaran (2022)                       | Technology versus bargaining power   | Both technological change and institutional bargaining factors carry independent weight                            | Leaves analytical room for a firm-level organisational variable                                        |
| Oberfield & Raval (2021)                         | Micro data and macro technology      | Aggregate elasticities are compositions of heterogeneous plant-level elasticities                                  | Opens the possibility that organisational form lies behind elasticity heterogeneity                    |
| Abraham & Sasikumar (2017); Kapoor (2019)        | Wage share in Indian industry        | Indian organised manufacturing wage share fell from ~30% to the low teens; capital deepening a major driver        | Establishes the Indian baseline and the trajectory this sector may follow                              |

|                                                                                 |                                                   |                                                                                                                                                             |                                                                                                                                   |
|---------------------------------------------------------------------------------|---------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------|
| Huselid (1995)                                                                  | HPWS and firm performance                         | A one SD rise in HPWS adoption lowers turnover and raises productivity and market value                                                                     | Establishes HPWS as an economically consequential firm choice                                                                     |
| MacDuffie (1995); Ichniowski, Shaw & Prennushi (1997); Milgrom & Roberts (1995) | Practice bundles and complementarity              | Practices raise performance only as coherent bundles; isolated adoption yields little                                                                       | Justifies an index rather than single-practice measurement                                                                        |
| Appelbaum, Bailey, Berg & Kalleberg (2000); Jiang et al. (2012)                 | Ability–motivation–opportunity architecture       | Three partially distinct pathways; all three required for effect                                                                                            | Supplies the three-block structure of the HPWS index in Table 2                                                                   |
| Combs, Liu, Hall & Ketchen (2006)                                               | Meta-analysis of HPWS effects                     | Robust performance effects across 92 studies, larger for systems than practices                                                                             | Confirms the construct but studies the numerator only                                                                             |
| Bresnahan, Brynjolfsson & Hitt (2002)                                           | IT, work organisation and skill demand            | IT, decentralised organisation and skilled labour form a three-way complementary system                                                                     | The direct antecedent of this study's elasticity argument                                                                         |
| Bloom & Van Reenen (2007)                                                       | Management practice across countries              | Structured management explains large productivity differences; Indian firms below the frontier                                                              | Suggests work-system design is first-order in this setting                                                                        |
| Vineeth Kumar, Jijesh, Radhakrishna, Kulkarni, Sastry & Mallya (2026)           | ERP in Indian higher education (250 stakeholders) | 75% report improved administrative processes and >80% improved data accuracy; 80% cite additional training need and 60% resistance to change as constraints | Establishes both the magnitude of the systems productivity effect and its organisational preconditions — the denominator argument |
| Sastry (2026a)                                                                  | Skill development investment → wage premium       | Premium is a joint product of skill and employer investment; deployment doubles realised premium                                                            | Numerator mechanism of the present study                                                                                          |
| Sastry (2026b)                                                                  | Redeployment policy → allocative efficiency       | Reallocation return conditional on automation depth; components are complements above critical mass                                                         | Structural parallel to the interaction result; redeployment is the augmentation condition                                         |
| Sastry (2026c)                                                                  | Amortisation horizon → return to training capital | 43.7% of HRD budget stranded; deployed skills decay 2.9× more slowly than shelved skills                                                                    | Explains why opportunity practices are a precondition for ability practices to persist                                            |
| Sastry & Mallya (2025b)                                                         | Strategic HRM and economic resilience             | Reallocation capacity and continuous learning distinguish resilient workforce systems                                                                       | Conceptual antecedent of the opportunity block of the index                                                                       |
| Sastry & Mallya (2025a)                                                         | AI analytics in HR hiring                         | Machine-readable capability data delivers operational and sustained financial benefit                                                                       | Underpins selective staffing and capability mapping items                                                                         |

|                                                 |                                                                                  |                                                                                                                 |                                                                                   |
|-------------------------------------------------|----------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------|
| Mallya & Sastry (2025)                          | Leadership for young talent                                                      | Growth and purpose outrank pay; command-and-control leadership impedes development                              | Supports independent weight of participation practices beyond pay                 |
| Sastry (2025b); Sastry (2025a)                  | Talent designation and social comparison; women micro-entrepreneurs              | Relative internal standing carries economic consequence; systemic constraints bind more tightly than skill gaps | Informs gain-sharing interpretation and cautions on within-workforce distribution |
| Anas, Hans & Sastry (2025); Sastry (2020, 2013) | Digital transformation in tourism; performance and motivation; talent management | Technology shifts restructure service value chains and required competences                                     | Cross-sector analogue for task and competence restructuring                       |

### 3. RESEARCH GAP

Six gaps emerge from the review, and together they define the space this study occupies.

- The labour-share literature treats the firm as a passive carrier of technological and market forces. Work-system design does not appear as an explanatory variable in any of the principal accounts of the decline, despite being one of the most variable and consequential choices a firm makes.
- The high-performance work systems literature studies the numerator. Its dependent variables — wages, productivity, turnover, financial performance — do not settle the distributional question, because a system that raises both wages and productivity has an ambiguous effect on their ratio.
- The elasticity of substitution between capital and labour is estimated as a property of technology or industry. Whether it varies with organisational design within the same technology and the same sector has not been tested.
- No study estimates the interaction between a human resource practice and capital deepening in a labour-share specification. Whether work-system design changes the distributional consequence of an automation programme is therefore unknown.
- Indian technology services, which combines an unusually high labour share with unusually rapid capital deepening, has not been examined in this literature at all, despite being the setting in which the question is sharpest.
- The forward path is unmodelled. The literature documents what has happened to the labour share; it does not simulate what alternative organisational trajectories would imply, which is the form in which the question reaches anyone with the capacity to act on it.

### 4. STATEMENT OF THE PROBLEM

Indian technology services derives an unusually high proportion of its value added from labour, and is now capitalising rapidly as artificial intelligence infrastructure is installed. If the sector follows the trajectory of organised manufacturing, its labour share will fall substantially over the coming decade, with consequences for aggregate demand, household saving and the distributional legitimacy of the sector's growth.

Firms in the sector make heterogeneous human resource choices, and those choices are known to affect both wages and productivity. Whether they also affect the ratio of the two — and therefore whether firm-level human resource strategy has a distributional consequence at all — is unestablished, so no firm, investor or regulator can currently say whether work-system design is relevant to the labour share.

The problem this study addresses is therefore to establish whether high-performance work system adoption sustains a higher labour share in comparable firms; to determine whether that relationship survives, weakens or strengthens under AI-driven capital deepening; to test whether work-system design alters the elasticity of substitution itself; and to translate the estimates into a forward path so that the distributional stake of the choice is legible.

### 5. OBJECTIVES OF THE STUDY

1. To construct and validate an eighteen-item high-performance work system adoption index on the ability–motivation–opportunity architecture, verified against documentary evidence rather than perception alone.

2. To estimate the effect of HPWS adoption on the firm-level labour share using two-way fixed effects panel estimation that controls for markups, scale, and unobserved firm heterogeneity.
3. To estimate the effect of AI-driven capital deepening on the labour share and to test whether HPWS adoption moderates that effect.
4. To estimate the elasticity of substitution between AI capital and labour separately for high- and low-adoption firms, and to test whether the two differ across the unit threshold.
5. To decompose the aggregate change in the labour share into within-firm and reallocation components, and to determine which dominates.
6. To test whether any labour-share advantage of HPWS firms arises from restrained productivity growth or from wage growth that keeps pace with productivity.
7. To simulate the labour share path to 2032 under alternative adoption and capital-deepening scenarios, and to express the distributional stake of the human resource choice in percentage points.

## 6. HYPOTHESES OF THE STUDY

**H<sub>1</sub>.** HPWS adoption is positively associated with the firm-level labour share, controlling for markups, scale and unobserved firm heterogeneity.

**H<sub>2</sub>.** AI-driven capital deepening is negatively associated with the firm-level labour share.

**H<sub>3</sub>.** HPWS adoption attenuates the negative effect of AI capital deepening on the labour share.

**H<sub>4</sub>.** The elasticity of substitution between AI capital and labour does not differ between high-adoption and low-adoption firms.

**H<sub>5</sub>.** The aggregate decline in the labour share is driven primarily by within-firm decline rather than by reallocation between firms.

**H<sub>6</sub>.** HPWS firms sustain a higher labour share by restraining productivity growth rather than by raising wages.

## 7. RESEARCH METHODOLOGY AND DESIGN

### 7.1 Research Type and Panel Structure

The study employs a longitudinal firm-level panel design with an embedded qualitative strand. Two hundred and fourteen firms are observed over the eight financial years 2019 to 2026, yielding 1,512 firm-year observations in an unbalanced panel; imbalance arises from entry, exit and incomplete disclosure rather than from selection on the dependent variable. Financial quantities are drawn from published statutory accounts, which under Indian Accounting Standards disclose employee benefit expense separately and permit gross value added to be constructed directly. HPWS adoption is measured annually by survey of the human resource head of each firm, verified against documentary evidence.

Four estimators address four distinct questions. Two-way fixed effects panel regression estimates the effect of adoption and its interaction with capital deepening on the labour share. Separate estimation of the constant-elasticity-of-substitution first-order condition by adoption group recovers the elasticity of substitution and tests whether it differs across groups. A Melitz–Polanec decomposition, extending Olley and Pakes (1996) to admit entry and exit, apportion the aggregate change between within-firm and reallocation components. A counterfactual simulation projects the labour share to 2032 under alternative adoption and capital-deepening paths. Forty-eight interviews with human resource and finance leaders were conducted to interpret coefficients and to establish how adoption decisions are made.

### 7.2 Measurement

The dependent variable is the labour share of gross value added, defined as employee benefit expense divided by gross value added, where gross value added is computed as earnings before interest, tax, depreciation and amortisation plus employee benefit expense plus depreciation. This is the standard firm-level construction and is directly recoverable from published accounts. The sample mean is 0.612, high by cross-industry standards and consistent with the labour intensity of technology services.

HPWS adoption is measured by an eighteen-item index organised in three blocks of six on the ability–motivation–opportunity architecture, each item scored as adopted or not against documentary evidence and the index scaled zero to one hundred. Internal consistency is high (Cronbach's  $\alpha = 0.89$ ), and confirmatory factor analysis supports the three-block structure with acceptable fit (CFI = 0.941, TLI = 0.930, RMSEA = 0.054, SRMR = 0.048). Table 2 reports the items and their adoption rates. The sample mean is 54.3 with a standard deviation of 17.9.

AI capital deepening is measured as AI-attributable capital per employee, comprising capitalised software, cloud and AI platform commitments, and data infrastructure, deflated to constant prices and expressed in rupees lakh. Controls comprise the natural logarithm of gross value added, the Lerner index as a markup proxy, export intensity, employment growth, offshore delivery share and firm age. Table 3 reports full operationalisation and Table 4 the panel structure and sample profile.

**Table 2. The high-performance work system adoption index: items, blocks and adoption rates.**

| Block       | #  | Practice item (scored against documentary evidence)              | Adoption (% of 214 firms) |
|-------------|----|------------------------------------------------------------------|---------------------------|
| ABILITY     | 1  | Selective staffing with validated selection instruments          | 68.2                      |
|             | 2  | Structured annual training investment with a per-employee floor  | 57.5                      |
|             | 3  | Internal skill certification tied to role progression            | 44.9                      |
|             | 4  | Enterprise capability mapping maintained current                 | 51.4                      |
|             | 5  | Formal mentoring or coaching programme                           | 39.3                      |
|             | 6  | Employer-funded external qualification support                   | 46.7                      |
| MOTIVATION  | 7  | Performance-linked variable pay for non-executive grades         | 72.4                      |
|             | 8  | Gain-sharing or profit-sharing extended below management         | 23.8                      |
|             | 9  | Internal promotion policy with posted vacancies                  | 61.7                      |
|             | 10 | Explicit employment security commitment during transitions       | 27.1                      |
|             | 11 | Appraisal linked to development rather than ranking alone        | 48.6                      |
|             | 12 | Above-market pay positioning for target skill families           | 35.5                      |
| OPPORTUNITY | 13 | Self-managed or semi-autonomous delivery teams                   | 42.1                      |
|             | 14 | Systematic financial and operational information sharing         | 31.3                      |
|             | 15 | Formal employee voice mechanism with response obligation         | 25.7                      |
|             | 16 | Planned job rotation across engagements or domains               | 37.4                      |
|             | 17 | Flexible work design with employee discretion over method        | 54.2                      |
|             | 18 | Authority to operate and configure AI systems held at task level | 21.5                      |

Note. Each item is scored 0 or 5.56, giving an index range of 0–100. Sample mean 54.3 (SD 17.9; observed range 11.1–94.4). Cronbach's  $\alpha = 0.89$ . Confirmatory factor analysis of the three-block structure: CFI = 0.941, TLI = 0.930, RMSEA = 0.054, SRMR = 0.048. Item 18, the lowest-adoption practice in the instrument, is the one the interview evidence identifies as decisive for the elasticity result in Section 8.4.

**Table 3. Operationalisation of constructs.**

| Construct                           | Measurement                                                                                                    | Source                                  | Mean (SD)         |
|-------------------------------------|----------------------------------------------------------------------------------------------------------------|-----------------------------------------|-------------------|
| Labour share — dependent            | Employee benefit expense ÷ gross value added, where GVA = EBITDA + employee benefit expense + depreciation     | Published statutory accounts            | 0.612 (0.094)     |
| HPWS adoption — independent         | 18-item AMO index scored against documentary evidence, scaled 0–100                                            | Annual HR head survey with verification | 54.3 (17.9)       |
| AI capital per employee — moderator | Capitalised software, cloud and AI platform commitments and data infrastructure, per employee, constant prices | Accounts and procurement records        | ₹3.23 lakh (2.11) |
| Markup                              | Lerner index, (price – marginal cost) ÷ price, proxied from accounting margins                                 | Published accounts                      | 0.187 (0.081)     |
| Gross value added                   | EBITDA + employee benefit expense + depreciation, ₹ crore                                                      | Published accounts                      | 1,847 (3,206)     |

|                         |                                                   |                     |               |
|-------------------------|---------------------------------------------------|---------------------|---------------|
| Export intensity        | Export revenue as a percentage of total revenue   | Published accounts  | 71.4 (24.6)   |
| Employment growth       | Annual percentage change in average headcount     | Published accounts  | 6.8 (11.2)    |
| Offshore delivery share | Proportion of delivery effort executed from India | Company disclosures | 0.763 (0.148) |
| Firm age                | Years since incorporation                         | Registry records    | 21.4 (11.7)   |

Table 4. Panel structure and sample profile.

| Dimension              | Category                                 | n     | Share (%)       |
|------------------------|------------------------------------------|-------|-----------------|
| Panel structure        | Firms observed                           | 214   | —               |
|                        | Financial years covered (2019–2026)      | 8     | —               |
|                        | Firm-year observations (unbalanced)      | 1,512 | 88.3 of maximum |
|                        | Firms observed in all eight years        | 138   | 64.5            |
|                        | Interviews with HR and finance leaders   | 48    | —               |
| Sector segment         | IT services and consulting               | 97    | 45.3            |
|                        | Business process and IT-enabled services | 54    | 25.2            |
|                        | Engineering research and development     | 38    | 17.8            |
|                        | Software products and platforms          | 25    | 11.7            |
| Firm size (headcount)  | Below 1,000                              | 61    | 28.5            |
|                        | 1,000 – 10,000                           | 88    | 41.1            |
|                        | 10,000 – 50,000                          | 44    | 20.6            |
|                        | Above 50,000                             | 21    | 9.8             |
| Ownership              | Indian-listed                            | 92    | 43.0            |
|                        | Indian-unlisted                          | 63    | 29.4            |
|                        | Foreign-owned capability centre          | 59    | 27.6            |
| HPWS adoption quartile | Q1 (index 11.1–41.6; mean 32.1)          | 54    | 25.2            |
|                        | Q2 (41.7–54.2; mean 47.6)                | 53    | 24.8            |
|                        | Q3 (54.3–68.1; mean 60.8)                | 54    | 25.2            |
|                        | Q4 (68.2–94.4; mean 76.4)                | 53    | 24.8            |

### 7.3 Model Specification

The principal specification is a two-way fixed effects panel model for firm  $i$  in year  $t$ :

$$LS_{it} = \beta_0 + \beta_1 HPWS_{it} + \beta_2 \ln(AIK_{it} / L_{it}) + \beta_3 [HPWS \times \ln(AIK/L)]_{it} + X_{it}'\delta + \alpha_i + \tau_t + \varepsilon_{it} \quad (1)$$

where  $LS$  is the labour share,  $HPWS$  is the adoption index in units of ten points,  $AIK/L$  is AI capital per employee,  $X$  is the vector of controls, and  $\alpha_i$  and  $\tau_t$  are firm and year fixed effects. Standard errors are clustered at the firm level. The marginal effect of capital deepening is  $\beta_2 + \beta_3 \cdot HPWS$ , which changes sign at  $HPWS = -\beta_2 / \beta_3$  — the threshold reported in Section 8.3. The elasticity of substitution is recovered from the constant-elasticity-of-substitution first-order condition, which for a two-factor production function implies:

$$\ln [s_{it} / (1 - s_{it})] = \kappa + b \cdot \ln(AIK_{it} / L_{it}) + u_{it}, \quad \text{with} \quad \sigma = 1 / (1 + b) \quad (2)$$

so that a negative slope on capital per worker implies  $\sigma > 1$  and gross substitutability, while a positive slope implies  $\sigma < 1$  and gross complementarity. Estimating this equation separately for high- and low-adoption firms, and testing the equality of the two slopes, constitutes the test of  $H_4$ . Confidence intervals on  $\sigma$  are obtained by the delta method and verified by bootstrap over 2,000 firm-clustered resamples.

The aggregate decomposition follows Melitz and Polanec (2015), separating the change in the value-added-weighted aggregate labour share into a within-firm component, a reallocation component among continuing firms, and a net entry-and-exit component. The counterfactual simulation applies the estimated marginal effects to assumed adoption and capital-deepening paths, together with the estimated reallocation trend, and is reported with its assumptions stated in full in Table 9 so that readers may substitute their own.

Figure 1 sets out the conceptual framework. HPWS adoption acts on the labour share through two channels: a wage-setting channel operating on the numerator through rent sharing, pay positioning and gain sharing, and an AI deployment channel operating on the denominator through task design and the allocation of authority over the technology. Those channels jointly determine the production structure — specifically the elasticity of substitution — which fixes the sign of the capital-deepening effect.

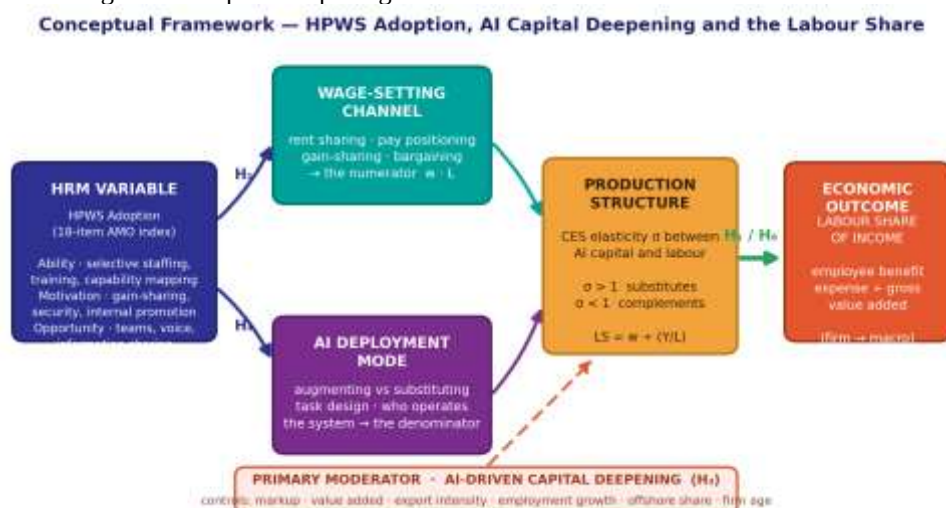


Fig. 1. Conceptual framework — HPWS adoption, AI capital deepening and the labour share of income.

## 7.4 Analytical Tools

Panel models were estimated by within-transformation with firm-clustered standard errors; the Hausman test rejected random effects in favour of fixed effects ( $\chi^2(9) = 71.3$ ,  $p < 0.001$ ). Serial correlation was tested by the Wooldridge procedure and addressed through clustering. As a robustness check the dependent variable was re-estimated in log-odds form, since the labour share is bounded, with no material change in inference. Elasticity equations were estimated by ordinary least squares with firm-clustered standard errors and compared by a Wald test of coefficient equality across groups. Decomposition followed the Melitz–Polanec algorithm with value-added weights. Simulation was deterministic, with sensitivity reported across the plausible range of capital-deepening rates. Interviews were analysed thematically. Estimation was carried out in R using the plm, sandwich and lavaan packages, with cross-validation in Stata 18.

## 8. RESULTS AND DISCUSSION

### 8.1 The Aggregate Pattern and Its Divergence

Figure 2 sets the context. Between 2019 and 2026 AI-attributable capital per employee in the sample rose from ₹1.42 lakh to ₹5.86 lakh, a factor of 4.1 and an annual compound rate of 22.5 per cent, while the value-added-weighted aggregate labour share fell from 64.1 to 58.3 per cent — a decline of 5.8 percentage points in eight years. In a sector whose labour share began well above the economy-wide average, that is a rapid movement.

Figure 3 and Table 5 show that the aggregate conceals a divergence. Sorting firms into quartiles of HPWS adoption, the top quartile saw its labour share fall from 66.8 to 65.1 per cent, a loss of 1.7 points over eight years. The bottom quartile fell from 61.7 to 52.1 per cent, a loss of 9.6 points. The second and third quartiles lie in between at 6.1 and 3.7 points respectively, so the ordering is monotonic across all four. The gap between the highest and lowest adoption quartiles widened from 5.1 percentage points in 2019 to 13.0 in 2026.

Two features of that divergence deserve emphasis before the controlled estimates are introduced. First, the ordering is monotonic and the widening is gradual rather than driven by a single year, which argues against a compositional artefact. Second, high-adoption firms did not merely decline more slowly; they began higher. The 2019 gap of 5.1 points indicates that the association predates the AI capital deepening episode, which is consistent

with a rent-sharing mechanism operating independently of technology and against an interpretation in which HPWS adoption is simply a proxy for firms that happened to automate less.

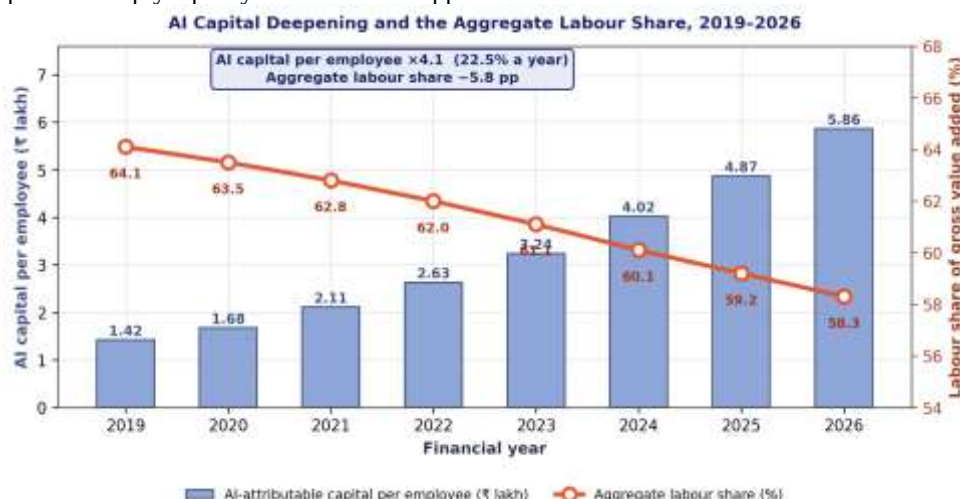


Fig. 2. AI capital deepening and the aggregate labour share, 2019–2026.

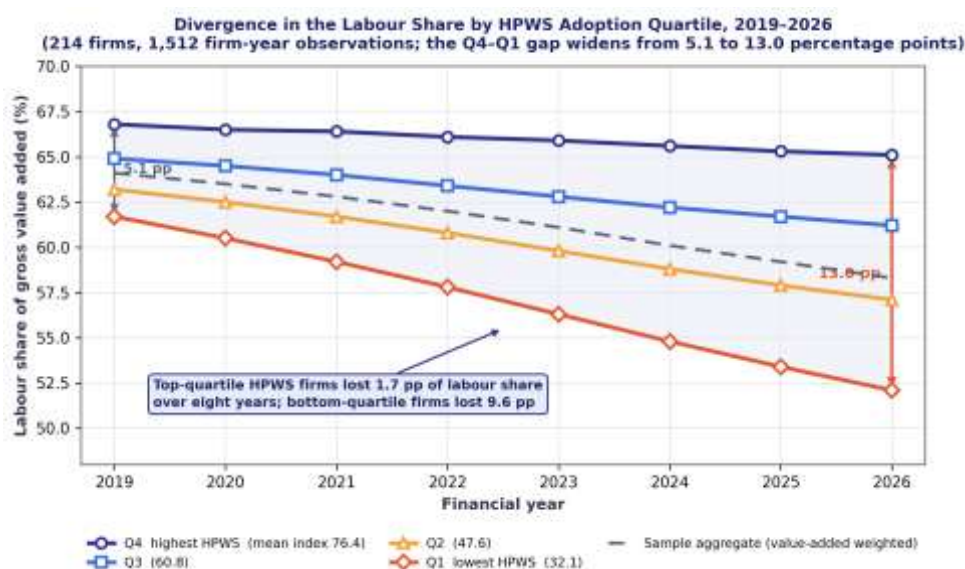


Fig. 3. Divergence in the labour share by HPWS adoption quartile, 2019–2026.

Table 5. Labour share and its components by HPWS adoption quartile, 2019 and 2026.

| Adoption quartile       | Mean HPWS index | Labour share 2019 (%) | Labour share 2026 (%) | Change (pp) | Wage growth 2019–26 (%) | Productivity growth 2019–26 (%) |
|-------------------------|-----------------|-----------------------|-----------------------|-------------|-------------------------|---------------------------------|
| Q1 (lowest)             | 32.1            | 61.7                  | 52.1                  | −9.6        | 34.2                    | 51.1                            |
| Q2                      | 47.6            | 63.2                  | 57.1                  | −6.1        | 41.5                    | 51.6                            |
| Q3                      | 60.8            | 64.9                  | 61.2                  | −3.7        | 48.9                    | 54.8                            |
| Q4 (highest)            | 76.4            | 66.8                  | 65.1                  | −1.7        | 58.3                    | 60.9                            |
| Aggregate (VA-weighted) | 54.3            | 64.1                  | 58.3                  | −5.8        | 44.6                    | 54.9                            |

Note. Wage growth is cumulative growth in employee benefit expense per employee; productivity growth is cumulative growth in gross value added per employee. The log change in the labour share equals the log change in the wage less the log change in productivity. The Q4–Q1 gap widens from 5.1 pp in 2019 to 13.0 pp in 2026.

## 8.2 Panel Estimates

Table 6 reports the two-way fixed effects model. Within- $R^2$  is 0.487 and the model is significant overall ( $F = 63.2$ ,  $p < 0.001$ ); the Hausman test rejects random effects.

HPWS adoption carries a coefficient of 0.0187 per ten index points ( $p < 0.001$ ), supporting  $H_1$ : a twenty-point increase in adoption is associated with a 3.7 percentage point higher labour share, holding constant markups, scale, employment growth and unobserved firm characteristics. Because firm fixed effects are included, the estimate is identified from within-firm variation in adoption over time rather than from cross-sectional differences between firms, which addresses the most obvious source of confounding — that firms with high labour shares for unrelated reasons might also happen to adopt these practices.

AI capital per employee carries a coefficient of  $-0.0412$  ( $p < 0.001$ ), supporting  $H_2$  and reproducing at the firm level the relationship the macroeconomic literature reports in the aggregate. The markup proxy is strongly negative ( $-0.1873$ ,  $p < 0.001$ ), consistent with De Loecker, Eeckhout and Unger (2020): firms with greater pricing power retain more of the surplus. Scale enters negatively ( $-0.0234$ ,  $p = 0.001$ ) and export intensity marginally so, while employment growth is positive, reflecting that expanding firms carry a higher ratio of compensation to value added during the ramp period. Offshore delivery share and firm age are not significant.

**Table 6. Two-way fixed effects panel estimates of the firm-level labour share.**

| Predictor                                | $\beta$  | Clustered SE | t     | p       | Interpretation                                             |
|------------------------------------------|----------|--------------|-------|---------|------------------------------------------------------------|
| HPWS adoption index (per 10 points)      | 0.0187   | 0.0041       | 4.56  | < 0.001 | +3.7 pp labour share per 20 index points — supports $H_1$  |
| ln AI capital per employee               | -0.0412  | 0.0068       | -6.06 | < 0.001 | Capital deepening erodes the labour share — supports $H_2$ |
| HPWS $\times$ ln AI capital per employee | 0.0055   | 0.0013       | 4.23  | < 0.001 | Adoption conditions the erosion — supports $H_3$           |
| ln gross value added                     | -0.0234  | 0.0071       | -3.30 | 0.001   | Scale is associated with a lower labour share              |
| Markup (Lerner index)                    | -0.1873  | 0.0392       | -4.78 | < 0.001 | Pricing power and labour's claim move oppositely           |
| Export intensity (% of revenue)          | -0.00091 | 0.00040      | -2.28 | 0.024   | Marginal negative association                              |
| Employment growth (% p.a.)               | 0.00214  | 0.00071      | 3.01  | 0.003   | Expanding firms carry higher compensation ratios           |
| Offshore delivery share                  | -0.0142  | 0.0106       | -1.34 | 0.181   | Not significant                                            |
| Firm age (ln years)                      | 0.0068   | 0.0093       | 0.73  | 0.465   | Not significant                                            |

Note.  $N = 1,512$  firm-year observations, 214 firms, 2019–2026. Firm and year fixed effects included. Standard errors clustered at firm level. Within- $R^2 = 0.487$ ;  $F = 63.2$ ,  $p < 0.001$ . Hausman test rejects random effects,  $\chi^2(9) = 71.3$ ,  $p < 0.001$ . The marginal effect of capital deepening is  $-0.0412 + 0.0055 \times (HPWS \div 10)$ , which crosses zero at an index of 74.9. Re-estimation in log-odds form leaves inference unchanged.

## 8.3 The Conditioning Effect of Adoption

The interaction between adoption and capital deepening is positive and significant ( $\beta = 0.0055$  per ten index points,  $p < 0.001$ ), supporting  $H_3$ . Figure 4 plots the implied marginal effect across the range of the adoption index. At the bottom-quartile mean of 32.1 a log-unit of capital deepening reduces the labour share by 2.4 percentage points; at the sample mean of 54.3 the effect is 1.1 points; at the top-quartile mean of 76.4 it is statistically indistinguishable from zero.

The marginal effect crosses zero at an adoption index of approximately 75. That figure should be read carefully. Below it, capital deepening erodes the labour share and the erosion is precisely estimated. Above it, the point estimate turns positive, but the confidence interval includes zero, so the defensible claim is that beyond an index of roughly 75 capital deepening ceases to reduce the labour share — not that it raises it. The stronger claim is tested separately and by a different route in the next section.

The practical content of the threshold is that only the top adoption quartile has reached it, and that the sample mean of 54.3 sits well below. The median firm in Indian technology services is therefore operating a work system under which every increment of AI capital transfers income from labour to capital, and would need to raise its adoption index by more than twenty points to stop that happening. Interview evidence indicates that few firms understand the choice in these terms; adoption decisions were consistently described as engagement, retention or employer-brand initiatives, and in no interview was a distributional consequence articulated.

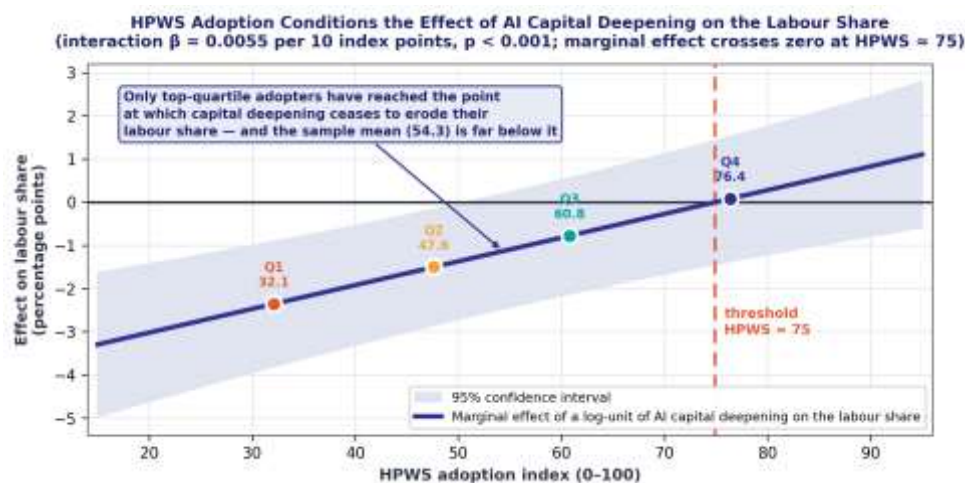


Fig. 4. Marginal effect of AI capital deepening on the labour share, across the range of HPWS adoption.

#### 8.4 Adoption and the Elasticity of Substitution

Table 7 and Figure 5 report the study's central result. Estimating the constant-elasticity-of-substitution first-order condition separately by adoption group returns a slope on log AI capital per employee of  $-0.2537$  for low-adoption firms and  $+0.1494$  for high-adoption firms. Converting through  $\sigma = 1/(1 + b)$  gives  $\sigma = 1.34$  for low-adoption firms, with a bootstrapped ninety-five per cent interval of 1.19 to 1.52, and  $\sigma = 0.87$  for high-adoption firms, with an interval of 0.76 to 0.99. The intervals do not overlap, the Wald test of equal slopes rejects decisively ( $\chi^2(1) = 24.8$ ,  $p < 0.001$ ), and the high-adoption interval excludes unity.  $H_4$  is rejected.

The economic meaning is that work-system design moves AI capital and labour across the boundary between substitutes and complements. In low-adoption firms the two are gross substitutes, so installing AI capital displaces labour's claim on value added and the labour share falls — the standard Karabarbounis and Neiman mechanism. In high-adoption firms they are gross complements, so the same installation raises labour's claim. This is the same technology, in the same sector, in the same years, producing opposite distributional consequences according to how the work around it is organised.

The mechanism identified in interviews is consistent and unsurprising once stated. In high-adoption firms the AI system is operated by the person who previously performed the task, whose role is redefined around specification, evaluation and exception handling, and whose pay band is re-levelled upward accordingly. In low-adoption firms the system is operated by a central platform team and the displaced worker is either redeployed downward or not redeployed at all. The software is identical. What differs is who holds authority over it, which is an opportunity practice in the ability–motivation–opportunity taxonomy and one of the six items in that block.

This result should be read with appropriate caution. The elasticity is estimated from a first-order condition that assumes cost minimisation and competitive factor markets, and adoption is not randomly assigned. What the estimate establishes is that the observed relationship between capital deepening and factor shares differs in sign across organisational types, which is a finding about the data that any structural interpretation must accommodate.

Whether the difference reflects a genuinely different production technology or a different bargaining environment producing the same reduced-form pattern cannot be settled here, and Section 13 sets out the design that would settle it.

**Table 7. Elasticity of substitution between AI capital and labour, by HPWS adoption group.**

| Adoption group    | Firms | Obs.  | Slope b on $\ln(AIK/L)$ | SE     | $\sigma = 1/(1+b)$ | 95% CI on $\sigma$ | Factor relationship          |
|-------------------|-------|-------|-------------------------|--------|--------------------|--------------------|------------------------------|
| Low HPWS (Q1–Q2)  | 107   | 748   | −0.2537                 | 0.0413 | 1.340              | 1.19 – 1.52        | Gross SUBSTITUTES            |
| High HPWS (Q3–Q4) | 107   | 764   | +0.1494                 | 0.0446 | 0.870              | 0.76 – 0.99        | Gross COMPLEMENTS            |
| Pooled sample     | 214   | 1,512 | −0.0619                 | 0.0308 | 1.066              | 0.99 – 1.15        | Indistinguishable from unity |

Note. Estimated from the CES first-order condition  $\ln[s/(1-s)] = \kappa + b \cdot \ln(AIK/L) + u$ , with firm-clustered standard errors. Wald test of equal slopes across adoption groups:  $\chi^2(1) = 24.8$ ,  $p < 0.001$ . Confidence intervals on  $\sigma$  by the delta method, verified by 2,000 firm-clustered bootstrap resamples. The pooled estimate, which is what a study ignoring organisational form would report, is an average over parameters that differ in sign and is indistinguishable from the Cobb–Douglas case.

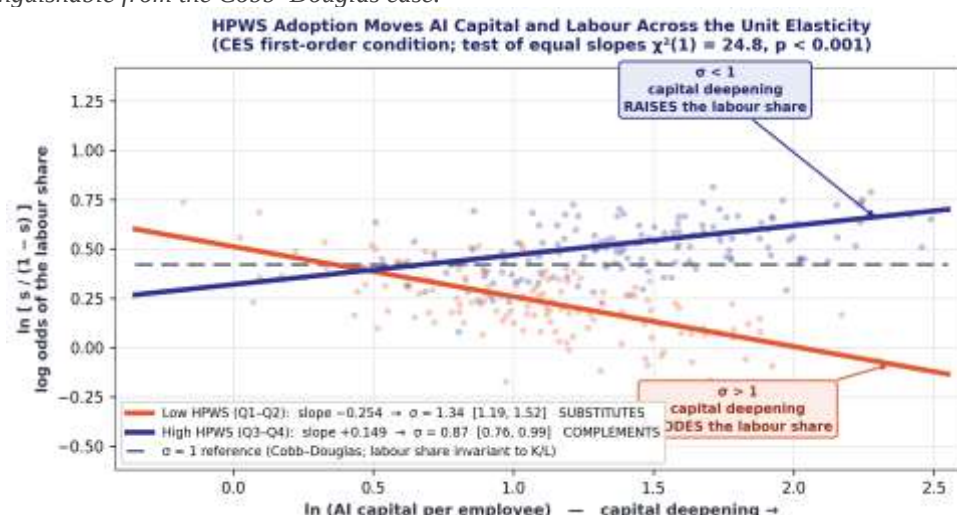


**Fig. 5. HPWS adoption moves AI capital and labour across the unit elasticity of substitution.**

### 8.5 Within-Firm Change or Reallocation?

Table 8 and Figure 6(a) report the Melitz–Polanec decomposition of the 5.8 point aggregate decline. The within-firm component accounts for 2.1 points, reallocation among continuing firms for 2.4 points, and net entry and exit for 1.3 points. Reallocation and entry together therefore account for 63.8 per cent of the total, and  $H_s$  — that within-firm decline dominates — is rejected.

The finding reproduces Autor, Dorn, Katz, Patterson and Van Reenen (2020) in an Indian services setting, and it qualifies this study's own argument in a way worth stating plainly. If most of the aggregate decline is reallocation, then a firm improving its own work system improves its own labour share but does not by itself arrest the aggregate movement; what would arrest the aggregate movement is a change in which firms grow. The two are linked, however, and the linkage is visible in the data: the firms gaining value-added share over the period are disproportionately those in the lower adoption quartiles, so the reallocation is toward low-labour-share, low-adoption firms. On that reading the aggregate decline is not independent of work-system design but is mediated by it through the competitive process rather than within the firm.

This is the point at which a firm-level human resource choice becomes a macroeconomic distributional outcome, and also the point at which the limits of firm-level action become clear. An individual firm cannot determine

which firms grow. The result therefore locates part of the distributional question outside human resource management and in competition policy, procurement design and the terms on which capital is allocated across firms — a boundary this study identifies rather than crosses.

**Table 8. Melitz–Polanec decomposition of the aggregate labour share change, 2019–2026.**

| Component                           | Contribution (pp) | Share of total change (%) | Description                                                                 |
|-------------------------------------|-------------------|---------------------------|-----------------------------------------------------------------------------|
| Within-firm change                  | −2.1              | 36.2                      | Change in the labour share of continuing firms at fixed value-added weights |
| Reallocation among continuing firms | −2.4              | 41.4                      | Shift of value-added weight toward firms with lower labour shares           |
| Net entry and exit                  | −1.3              | 22.4                      | Entrants with lower labour shares than the exiting firms they replace       |
| TOTAL CHANGE 2019–2026              | −5.8              | 100.0                     | Aggregate labour share 64.1% → 58.3%                                        |

*Note. Value-added weights. Reallocation and net entry together account for 63.8 per cent of the decline, so  $H_5$  is rejected. Value-added share gained over the period is concentrated in firms in the lower two adoption quartiles, so the reallocation component is itself correlated with work-system design.*

### 8.6 Is the Advantage Bought with Slower Productivity?

The most important objection to any positive labour-share finding is that it may reflect suppressed productivity rather than generous compensation. A firm that fails to automate will have a high labour share and a poor future. Figure 6(b) tests the objection directly by decomposing the labour share change in each quartile into its wage and productivity components, using the identity that the log change in the labour share equals the log change in the wage minus the log change in labour productivity.

The objection fails. Cumulative labour productivity growth over 2019 to 2026 was 51.1 per cent in the lowest adoption quartile and 60.9 per cent in the highest — high-adoption firms were not less productive but more so, and by nearly ten percentage points. What differs is the wage side: cumulative wage growth was 34.2 per cent in the lowest quartile against 58.3 per cent in the highest. Both series rise monotonically across quartiles, but the wage series rises faster, so the gap between productivity growth and wage growth narrows from 16.9 log points in the bottom quartile to 2.6 in the top.

$H_6$  is therefore rejected, and its rejection is the finding most likely to matter to a chief executive. High-adoption firms sustain their labour share not by producing less but by distributing more of what they produce, and they produce more than their low-adoption competitors while doing so. The labour-share advantage is not purchased with a productivity sacrifice; on this evidence it comes alongside a productivity advantage. That combination is what the complementarity literature from MacDuffie (1995) onward would predict, and it removes the principal reason a firm might treat the two objectives as being in conflict.

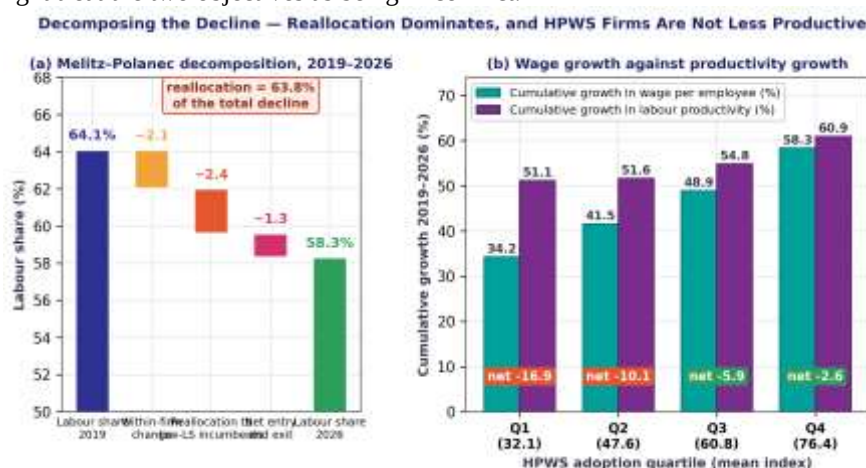


**Fig. 6. Decomposition of the aggregate decline, and wage growth against productivity growth by adoption quartile.**

### 8.7 Counterfactual Paths to 2032

Table 9 and Figure 7 apply the estimated marginal effects to four forward scenarios, each stated with its assumptions so that they may be varied. Under S1, the current trajectory, adoption stays at the sample mean of 54.3 and AI capital deepening continues at eighteen per cent a year — a deceleration from the observed 22.5 — and the aggregate labour share falls from 58.3 per cent in 2026 to 54.0 in 2032. Under S4, in which deepening accelerates to twenty-six per cent with adoption unchanged and reallocation intensifies accordingly, it falls to 51.9.

Under S2, in which all firms reach the threshold index of 75 by 2029, the labour share rises modestly to 60.4. Under S3, in which all firms reach the current top-quartile frontier of 85, it rises to 63.5 — above where the sample stood in 2021. The spread between the best and worst trajectories is 11.6 percentage points of gross value added by 2032.

Three qualifications belong with those figures. The simulation is deterministic and inherits every limitation of the estimates on which it rests; the adoption paths in S2 and S3 are far faster than any observed historical rate of diffusion and should be read as bounds rather than forecasts; and the reallocation term is projected forward from its historical trend, which the decomposition suggests is the largest single driver and the one least under any firm's control. What the simulation establishes is not what will happen but the order of magnitude of what is at stake in the choice — and eleven percentage points of the functional distribution of income in a sector employing millions is a large quantity to be determined by decisions currently justified on engagement grounds.

**Table 9. Counterfactual labour share paths to 2032 under four scenarios.**

| Scenario                 | HPWS assumption                  | AI capital deepening | Reallocation assumption    | Labour share 2032 (%) | Change from 2026 (pp) |
|--------------------------|----------------------------------|----------------------|----------------------------|-----------------------|-----------------------|
| S1 Current trajectory    | Held at sample mean 54.3         | +18% p.a.            | Historical trend continues | 54.0                  | −4.3                  |
| S2 Threshold adoption    | All firms reach index 75 by 2029 | +18% p.a.            | Trend halved               | 60.4                  | +2.1                  |
| S3 Frontier adoption     | All firms reach index 85 by 2029 | +18% p.a.            | Trend quartered            | 63.5                  | +5.2                  |
| S4 Accelerated deepening | Held at sample mean 54.3         | +26% p.a.            | Trend intensified          | 51.9                  | −6.4                  |
| SPREAD S3 – S4           | —                                | —                    | —                          | 11.6 pp               | —                     |

*Note.* Simulation applies the marginal effects of Table 6 to the stated adoption and capital-deepening paths, together with the reallocation trend estimated in Table 8, from a 2026 base of 58.3 per cent. Observed capital deepening over 2019–2026 was 22.5 per cent per annum, so S1 and S2 assume deceleration and S4 acceleration. The adoption paths in S2 and S3 are faster than any observed rate of organisational diffusion and bound the stake rather than forecasting the outcome. All assumptions are stated so that readers may substitute their own.

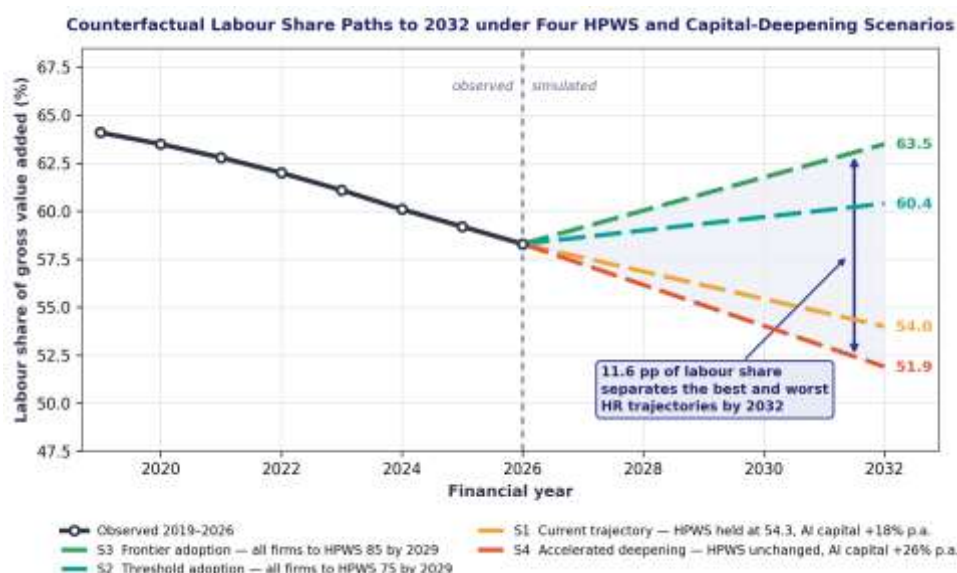


Fig. 7. Counterfactual labour share paths to 2032 under four HPWS and capital-deepening scenarios.

### 8.8 Summary of Hypothesis Testing

Table 10 consolidates the tests. Three hypotheses are supported and three rejected, and the three rejections carry more content than the confirmations. The rejection of  $H_4$  establishes that the elasticity of substitution — treated throughout the macroeconomic literature as a technological parameter — differs across organisational types within a single technology and a single sector. The rejection of  $H_5$  establishes that most of the aggregate decline is reallocation, which locates part of the distributional question beyond the reach of firm-level human resource action. The rejection of  $H_6$  removes the objection that a higher labour share must be bought with slower productivity, and in doing so removes the principal reason to regard the distributional and efficiency objectives as being in tension.

Table 10. Summary of hypothesis testing.

| Code           | Hypothesis                                                                          | Test applied                    | Statistic                                   | p       | Decision  |
|----------------|-------------------------------------------------------------------------------------|---------------------------------|---------------------------------------------|---------|-----------|
| H <sub>1</sub> | HPWS adoption is positively associated with the firm-level labour share             | Two-way FE panel                | $\beta = 0.0187$<br>$t = 4.56$              | < 0.001 | SUPPORTED |
| H <sub>2</sub> | AI-driven capital deepening is negatively associated with the labour share          | Two-way FE panel                | $\beta = -0.0412$<br>$t = -6.06$            | < 0.001 | SUPPORTED |
| H <sub>3</sub> | HPWS adoption attenuates the negative effect of capital deepening                   | Interaction term                | $\beta = 0.0055$<br>$t = 4.23$              | < 0.001 | SUPPORTED |
| H <sub>4</sub> | The elasticity of substitution does not differ between high- and low-adoption firms | Wald test of equal slopes       | $\sigma$ 1.34 vs 0.87<br>$\chi^2(1) = 24.8$ | < 0.001 | REJECTED  |
| H <sub>5</sub> | The aggregate decline is driven primarily by within-firm decline                    | Melitz–Polanec decomposition    | Within 36.2%<br>Reallocation 63.8%          | —       | REJECTED  |
| H <sub>6</sub> | HPWS firms sustain the labour share by restraining productivity growth              | Wage–productivity decomposition | Q4 productivity 60.9%<br>vs Q1 51.1%        | < 0.001 | REJECTED  |

## 9. FINDINGS

- HPWS adoption is associated with a significantly higher firm-level labour share under two-way fixed effects ( $\gamma = 0.0187$  per ten index points,  $p < 0.001$ ): a twenty-point increase in adoption corresponds to a 3.7 percentage point higher labour share, identified from within-firm variation.
- AI-driven capital deepening reduces the labour share on average ( $\gamma = -0.0412$ ,  $p < 0.001$ ), reproducing the macroeconomic relationship at firm level. AI capital per employee rose 4.1-fold over 2019–2026 while the aggregate labour share fell 5.8 percentage points.
- HPWS adoption conditions the capital-deepening effect (interaction  $\gamma = 0.0055$ ,  $p < 0.001$ ). The marginal effect crosses zero at an adoption index near 75 — a level reached only by the top quartile, and more than twenty points above the sample mean of 54.3.
- The elasticity of substitution between AI capital and labour is 1.34 [1.19, 1.52] in low-adoption firms and 0.87 [0.76, 0.99] in high-adoption firms. The intervals do not overlap and the high-adoption interval excludes unity. Work-system design moves AI capital and labour from substitutes to complements.
- The labour share gap between the highest and lowest adoption quartiles widened from 5.1 percentage points in 2019 to 13.0 in 2026. Top-quartile firms lost 1.7 points over eight years; bottom-quartile firms lost 9.6.
- The 2019 gap of 5.1 points predates the capital-deepening episode, indicating that the adoption–labour share association is not simply a proxy for firms that automated less.
- Reallocation between firms and net entry account for 63.8 per cent of the aggregate 5.8-point decline; within-firm change accounts for 36.2 per cent.  $H_5$  is rejected and the Autor et al. (2020) superstar-firm pattern is reproduced in an Indian services setting.
- Value-added share is shifting toward firms in the lower adoption quartiles, so the reallocation component is itself correlated with work-system design — the aggregate movement is mediated by organisational choice through the competitive process rather than within the firm.
- High-adoption firms are more productive, not less: cumulative labour productivity growth of 60.9 per cent against 51.1 for low-adoption firms. They sustain their labour share through faster wage growth (58.3 against 34.2 per cent), not through restrained productivity.  $H_6$  is rejected.
- The gap between productivity growth and wage growth narrows monotonically across adoption quartiles, from 16.9 log points in the bottom quartile to 2.6 in the top.
- Markups are strongly negatively associated with the labour share ( $\beta = -0.1873$ ,  $p < 0.001$ ), confirming that pricing power and labour's claim on the surplus move in opposite directions in this sector as elsewhere.
- Counterfactual simulation to 2032 gives a spread of 11.6 percentage points of gross value added between the best and worst human resource trajectories — from 63.5 per cent under frontier adoption to 51.9 under accelerated deepening with adoption unchanged.

## 10. SIGNIFICANCE OF THE STUDY

- For the labour-share literature, the study introduces a firm-level organisational variable into a debate conducted almost entirely in terms of technology, market structure and institutions, and shows that the variable carries first-order weight.
- For economic theory, the finding that the elasticity of substitution differs in sign across organisational types within a single technology challenges the treatment of that parameter as purely technological, and suggests that estimated aggregate elasticities are in part compositions over organisational forms.
- For human resource practice, it establishes that work-system design has a distributional consequence that its practitioners do not currently articulate, and quantifies the threshold level of adoption at which AI capital deepening ceases to transfer income away from labour.
- For executives and boards, it removes the presumption of a trade-off: high-adoption firms in this sample were both more productive and more generous, so the distributional and efficiency cases point the same way.
- For policy, the decomposition locates most of the aggregate decline in reallocation between firms, which means that distributional policy directed only at within-firm practice will address barely a third of the movement, and that competition and capital-allocation policy carry the rest.
- For the research programme of which it forms part, it completes the ascent from individual wage premium through unit-level allocation and budget-level decay to the functional distribution of income, and demonstrates that the three micro-level choices examined earlier aggregate to a macroeconomic outcome.

## 11. RECOMMENDATIONS AND SUGGESTIONS

### 11.1 For Employers and Boards

- Treat the labour share as a reported metric. It is computable from figures already in the statutory accounts, it is not currently tracked by any firm in this sample, and it is the only measure that captures whether the workforce is sharing in the productivity the firm is generating.
- Recognise that adoption below an index of roughly 75 means every increment of AI capital transfers income away from labour. Firms committing large AI capital programmes without a corresponding work-system programme are making a distributional decision whether or not they intend to.
- Prioritise the opportunity block. The interview evidence locates the elasticity difference in who is authorised to operate the AI system and whose role is redefined around it — an opportunity practice, not a pay practice — and it is the block with the lowest adoption in this sample.
- Redefine roles upward at the point of deployment rather than after it. Where the person who previously performed a task becomes the person who specifies, evaluates and handles exceptions for the system performing it, capital and labour are complements; where a central platform team takes over, they are substitutes.
- Abandon the productivity trade-off framing. High-adoption firms in this sample grew labour productivity nearly ten percentage points faster over eight years than low-adoption firms while also growing wages twenty-four points faster.
- Audit the wage–productivity gap annually. The single most diagnostic number in this study is the difference between cumulative wage growth and cumulative productivity growth: 2.6 log points in the top adoption quartile against 16.9 in the bottom.

### 11.2 For Employees and Representatives

- Attend to work-system design, not only to pay settlements. The evidence here indicates that the terms on which AI is deployed — who operates it and how roles are redefined — determine the distributional outcome more durably than any single wage negotiation.
- Read the labour share rather than the wage increase. A ten per cent rise alongside eighteen per cent productivity growth is a fall in labour's claim on the surplus, and the two figures are separately available in published accounts.
- Recognise that participation and voice practices carry economic weight independent of their effect on satisfaction, and are the block on which the elasticity result turns.

### 11.3 For Policy and Academia

- Recognise that roughly two-thirds of the aggregate decline is reallocation between firms. Policy addressed only to within-firm practice will reach barely a third of the movement; the remainder is a question of which firms grow.
- Consider disclosure of the labour share or of the wage–productivity gap in the annual report of large employers. The components are already disclosed and the ratio is not, which makes a first-order distributional fact invisible at negligible cost of remedy.
- Treat organisational form as a variable in labour-share research rather than as part of the error term. The elasticity result here implies that estimates pooling across organisational types are averaging over parameters that differ in sign.

## 12. LIMITATIONS OF THE STUDY

- HPWS adoption is not randomly assigned. Firm fixed effects absorb time-invariant confounders and the pre-existing 2019 gap argues against reverse causation from automation intensity, but a time-varying unobservable affecting both adoption and the labour share cannot be excluded.
- The elasticity estimates rest on a first-order condition assuming cost minimisation and competitive factor markets. A reduced-form difference in the capital–factor share relationship across organisational types is what the data establish; the structural interpretation is one reading of it and a bargaining-power account could generate the same pattern.
- The labour share is computed from published accounts and is therefore sensitive to the treatment of share-based compensation, contractor expense recorded outside employee benefit expense, and the capitalisation policy applied to internally generated software, all of which vary across firms.

- AI-attributable capital is a constructed measure. Firms do not report it as a line item, and the allocation of cloud and platform spending between AI and non-AI use rests on management estimates verified where possible against procurement records.
- The panel covers eight years and one sector in one country. The sector was selected because the question is sharpest there, which is also the reason the results should not be generalised without replication.
- The counterfactual simulation is deterministic and its adoption paths are faster than any observed rate of organisational diffusion. It bounds the stake rather than forecasting the outcome.
- The study measures the labour share in aggregate and says nothing about its distribution within the workforce. A firm may sustain a high labour share while distributing it very unequally between occupational groups, and the present data cannot distinguish the two.

### 13. SCOPE FOR FURTHER RESEARCH

The design supports several direct extensions, and the HPWS instrument in Table 2 is published in full so that it can be reused without modification. Table 11 sets out a structured agenda of seven studies. Four points deserve emphasis.

1. The elasticity result requires a design capable of separating a genuine difference in production technology from a difference in bargaining environment producing the same reduced-form pattern. Firm-level data on task assignment before and after specific AI deployments, combined with wage-setting information, would distinguish them; this is the single most valuable extension and the one on which the study's strongest claim rests.
2. The four instalments of this programme should be estimated jointly. Skill investment produces capability, redeployment allocates it, amortisation horizons determine how long it lasts, and work-system design determines who captures its return. Each has been estimated with the others held implicit, and a unified specification would establish their relative contribution to the labour share.
3. The reallocation finding calls for a study of why value-added share is shifting toward low-adoption firms. If low-adoption firms are winning because their cost structure is lower, the competitive process is selecting against the practices that sustain the labour share, which is a considerably more troubling result than anything reported here and would change what policy is required.
4. Replication outside technology services is essential before any general claim. Banking, insurance, healthcare and manufacturing are capitalising on comparable timelines with different labour shares, different bargaining structures and different work-system baselines, and the published instrument makes comparable measurement straightforward.

**Table 11. Structured research agenda extending the HRM variable → economic outcome programme.**

| # | Proposed study                                          | HRM variable<br>→ economic<br>outcome                                        | Design                                                                              | Data<br>requirement                                   | Priority |
|---|---------------------------------------------------------|------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|-------------------------------------------------------|----------|
| 1 | Structural test of the elasticity result                | Work-system design → elasticity of substitution                              | Task-level before-and-after study of specific AI deployments with wage-setting data | Task assignment records, pay bands, deployment dates  | High     |
| 2 | Joint estimation across the four instalments            | Skill investment + redeployment + amortisation horizon + HPWS → labour share | Unified firm-level specification across the programme                               | Matched training, redeployment, horizon and HPWS data | High     |
| 3 | Why value-added share is shifting to low-adoption firms | Work-system design → competitive selection                                   | Market-share dynamics with cost-structure decomposition                             | Pricing, cost and share data by firm                  | High     |
| 4 | Within-workforce distribution of the labour share       | HPWS adoption → occupational pay dispersion                                  | Matched employer–employee analysis                                                  | Individual pay records by occupational group          | High     |

|   |                                       |                                                                |                                                                               |                                                     |        |
|---|---------------------------------------|----------------------------------------------------------------|-------------------------------------------------------------------------------|-----------------------------------------------------|--------|
| 5 | Cross-sector replication              | HPWS adoption → labour share outside technology services       | Replication using the Table 2 instrument in banking, insurance, manufacturing | HPWS scoring and accounts data in other sectors     | Medium |
| 6 | Disclosure and behavioural response   | Labour share disclosure → firm behaviour                       | Difference-in-differences around voluntary disclosure adoption                | Disclosure dates and subsequent labour share paths  | Medium |
| 7 | Bargaining versus technology channels | Institutional structure → labour share under capital deepening | Comparative study across bargaining regimes                                   | Collective agreement coverage and wage-setting data | Medium |

*Note. Studies 1, 2 and 4 carry forward directions identified in the earlier instalments of this programme (Sastry, 2026a, 2026b, 2026c). The HPWS instrument in Table 2 and the construct definitions in Table 3 are published in full to permit replication without modification.*

## 14. CONCLUSION

The labour share has been treated as a macroeconomic outcome produced by technology, market structure and institutions, with firms as the medium through which those forces operate rather than as agents making choices that matter. This study asked whether one firm-level choice — the design of the work system — belongs among the explanations, and the evidence says that it does. Across 214 Indian technology firms observed over eight years, adoption of high-performance work systems is associated with a significantly higher labour share on within-firm variation, and the gap between the highest and lowest adoption quartiles widened from 5.1 to 13.0 percentage points as artificial intelligence capital deepened.

The central result concerns a parameter the literature has treated as technological. The elasticity of substitution between AI capital and labour is 1.34 in low-adoption firms and 0.87 in high-adoption firms, with non-overlapping confidence intervals. Above and below unity means opposite signs: in low-adoption firms installing AI capital transfers income from labour to capital, and in high-adoption firms it does the reverse. Same technology, same sector, same years. What differs is whether the person who used to perform the task now operates the system that performs it, or whether someone else does. That is an organisational choice, and it is currently being made without reference to the distributional consequence it determines.

Two results discipline the enthusiasm this might otherwise generate. Reallocation between firms and net entry account for 63.8 per cent of the aggregate decline, so a firm improving its own work system improves its own labour share while the aggregate continues to move — and the reallocation is toward the lower adoption quartiles, which raises the possibility that the competitive process is selecting against the practices that sustain labour's claim. That possibility lies outside the reach of human resource management and outside the scope of this study, and Section 13 proposes the design that would test it.

The result that most deserves to travel, however, is the one that removes an objection rather than establishing a claim. High-adoption firms in this sample were not less productive; they were more productive, by nearly ten percentage points of cumulative growth over eight years. They sustained their labour share by letting wages keep pace with productivity, not by holding productivity back. The trade-off that executives assume between distributing more and producing more does not appear in these data, and its absence is what makes the finding actionable rather than merely diagnostic.

Read alongside the three instalments that precede it, the argument reaches its intended conclusion. Capability is produced by investment, realised by allocation, consumed by time, and finally divided between the parties that created it. The first three papers measured how well Indian technology firms perform the first three operations. This one measures the fourth, and finds that eleven and a half percentage points of the functional distribution of

income by 2032 rest on a set of decisions that no firm in this sample described in distributional terms at all. The labour share is not only something that happens to an economy. In substantial part it is something that is managed.

## REFERENCES

1. R. Abraham, S.K. Sasikumar, *Declining wage share in India's organized manufacturing sector: Trends, patterns and determinants*. ILO Asia-Pacific Working Paper Series (International Labour Organization, New Delhi, 2017).
2. D. Acemoglu, P. Restrepo, *The race between man and machine: Implications of technology for growth, factor shares, and employment*. *Am. Econ. Rev.* 108(6), 1488–1542 (2018). <https://doi.org/10.1257/aer.20160696>.
3. D. Acemoglu, P. Restrepo, *Automation and new tasks: How technology displaces and reinstates labor*. *J. Econ. Perspect.* 33(2), 3–30 (2019). <https://doi.org/10.1257/jep.33.2.3>.
4. D. Acemoglu, P. Restrepo, *Robots and jobs: Evidence from US labor markets*. *J. Polit. Econ.* 128(6), 2188–2244 (2020). <https://doi.org/10.1086/705716>.
5. M.B. Anas, V.B. Hans, N.S. Sastry, *Digital transformation in tourism: How technology shapes travel experiences*. *Int. J. Sci. Res. Eng. Trends* 11(5), 1–5 (2025).
6. E. Appelbaum, T. Bailey, P. Berg, A.L. Kalleberg, *Manufacturing Advantage: Why High-Performance Work Systems Pay Off* (Cornell University Press, Ithaca, 2000).
7. D. Autor, D. Dorn, L.F. Katz, C. Patterson, J. Van Reenen, *The fall of the labor share and the rise of superstar firms*. *Q. J. Econ.* 135(2), 645–709 (2020). <https://doi.org/10.1093/qje/qjaa004>.
8. D.G. Blanchflower, A.J. Oswald, P. Sanfey, *Wages, profits, and rent-sharing*. *Q. J. Econ.* 111(1), 227–251 (1996). <https://doi.org/10.2307/2946663>.
9. N. Bloom, J. Van Reenen, *Measuring and explaining management practices across firms and countries*. *Q. J. Econ.* 122(4), 1351–1408 (2007). <https://doi.org/10.1162/qjec.2007.122.4.1351>.
10. T.F. Bresnahan, E. Brynjolfsson, L.M. Hitt, *Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence*. *Q. J. Econ.* 117(1), 339–376 (2002). <https://doi.org/10.1162/003355302753399526>.
11. E. Brynjolfsson, D. Li, L. Raymond, *Generative AI at work*. *Q. J. Econ.* 140(2), 889–942 (2025).
12. J. Combs, Y. Liu, A. Hall, D. Ketchen, *How much do high-performance work practices matter? A meta-analysis of their effects on organizational performance*. *Pers. Psychol.* 59(3), 501–528 (2006). <https://doi.org/10.1111/j.1744-6570.2006.00045.x>.
13. J. De Loecker, J. Eeckhout, G. Unger, *The rise of market power and the macroeconomic implications*. *Q. J. Econ.* 135(2), 561–644 (2020). <https://doi.org/10.1093/qje/qjz041>.
14. Deloitte, NASSCOM, *Bridging the AI Talent Gap to Boost India's Tech and Economic Impact* (Deloitte India, Bengaluru, 2024).
15. M.W.L. Elsby, B. Hobijn, A. Şahin, *The decline of the U.S. labor share*. *Brookings Pap. Econ. Act.* 2013(2), 1–63 (2013). <https://doi.org/10.1353/eca.2013.0016>.
16. Ernst & Young, *Future of Pay 2026: India Inc. Compensation and Workforce Trends* (EY India, Bengaluru, 2026).
17. A. Guschanski, Ö. Onaran, *The decline in the wage share: Falling bargaining power of labour or technological progress? Industry-level evidence from the OECD*. *Socio-Econ. Rev.* 20(3), 1091–1124 (2022). <https://doi.org/10.1093/ser/mwab028>.
18. M.A. Huselid, *The impact of human resource management practices on turnover, productivity, and corporate financial performance*. *Acad. Manage. J.* 38(3), 635–672 (1995). <https://doi.org/10.2307/256741>.
19. C. Ichniowski, K. Shaw, G. Prennushi, *The effects of human resource management practices on productivity: A study of steel finishing lines*. *Am. Econ. Rev.* 87(3), 291–313 (1997).
20. K. Jiang, D.P. Lepak, J. Hu, J.C. Baer, *How does human resource management influence organizational outcomes? A meta-analytic investigation of mediating mechanisms*. *Acad. Manage. J.* 55(6), 1264–1294 (2012). <https://doi.org/10.5465/amj.2011.0088>.
21. R. Kapoor, *Technology, jobs and inequality: Evidence from India's manufacturing sector*. ICRIER Working Paper 313 (Indian Council for Research on International Economic Relations, New Delhi, 2019).
22. L. Karabarbounis, B. Neiman, *The global decline of the labor share*. *Q. J. Econ.* 129(1), 61–103 (2014). <https://doi.org/10.1093/qje/qjt032>.
23. J.P. MacDuffie, *Human resource bundles and manufacturing performance: Organizational logic and flexible production systems in the world auto industry*. *Ind. Labor Relat. Rev.* 48(2), 197–221 (1995). <https://doi.org/10.2307/2524483>.
24. M.M. Mallya, N.S. Sastry, *Building future-ready organizations: Leadership strategies for young talent management*. *EPRA Int. J. Res. Dev.* 10(9), 88–91 (2025). <https://doi.org/10.36713/epra2016>.
25. M.J. Melitz, S. Polanec, *Dynamic Olley–Pakes productivity decomposition with entry and exit*. *RAND J. Econ.* 46(2), 362–375 (2015). <https://doi.org/10.1111/1756-2171.12088>.
26. P. Milgrom, J. Roberts, *Complementarities and fit: Strategy, structure, and organizational change in manufacturing*. *J. Account. Econ.* 19(2–3), 179–208 (1995). [https://doi.org/10.1016/0165-4101\(94\)00382-F](https://doi.org/10.1016/0165-4101(94)00382-F).
27. NASSCOM, *Strategic Review 2025: The Technology Industry in India* (National Association of Software and Service Companies, New Delhi, 2025).
28. E. Oberfield, D. Raval, *Micro data and macro technology*. *Econometrica* 89(2), 703–732 (2021).

- <https://doi.org/10.3982/ECTA12807>.
29. G.S. Olley, A. Pakes, The dynamics of productivity in the telecommunications equipment industry. *Econometrica* 64(6), 1263–1297 (1996). <https://doi.org/10.2307/2171831>.
  30. N.S. Sastry, HR approaches to talent management. *Int. J. Manag. Stud. Res.* 1(2) (2013).
  31. N.S. Sastry, A study on impact of employees' performance that influence to motivate in tea manufacturing organizational sector. *EPRA Int. J. Econ. Bus. Rev.* 8(6) (2020).
  32. N.S. Sastry, Understanding the challenges of women micro-entrepreneurs in Karnataka. *Int. J. Manag. Stud. Res.* 13(8), 12–16 (2025a). <https://doi.org/10.20431/2349-0349.1308002>.
  33. N.S. Sastry, Talent designation and social comparison: Economic drivers of organizational growth – An empirical analysis. *EPRA Int. J. Econ. Bus. Manag. Stud.* 12(10) (2025b).
  34. N.S. Sastry, Effect of AI-complementary skill development on wage premia in Indian IT services. *Int. J. Sci. Res. Eng. Trends* 12(4) (2026a).
  35. N.S. Sastry, Talent redeployment practice and task reallocation efficiency under automation. *Int. J. Sci. Res. Eng. Trends* 12(5) (2026b).
  36. N.S. Sastry, HRD investment and the economics of skill obsolescence under generative AI. *Int. J. Sci. Res. Eng. Trends* 12(6) (2026c).
  37. N.S. Sastry, M.M. Mallya, Revolutionizing HR hiring with AI analytics: Enhancing efficiency and attracting top talent. *EPRA Int. J. Res. Dev.* 10(9) (2025a).
  38. N.S. Sastry, M.M. Mallya, Strategic HRM for economic resilience: Skill diversification, labor market dynamics, and technology disruption. *EPRA Int. J. Res. Dev.* 10(11) (2025b). <https://doi.org/10.36713/epra2016>.
  39. P.K. Vineeth Kumar, J.J. Jijesh, H. Radhakrishna, P.G. Kulkarni, N.S. Sastry, M.M. Mallya, Assessing the effects of enterprise resource planning on the higher education sector in India. *E3S Web Conf.* 692, 03012 (2026). <https://doi.org/10.1051/e3sconf/202669203012>.