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TALENT REDEPLOYMENT PRACTICE AND TASK REALLOCATION EFFICIENCY UNDER AUTOMATION

HRM Variable: Redeployment Policy → Economic Outcome: Allocative Efficiency

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ABSTRACT

Indian IT services has removed idle capacity without improving deployment. Bench strength has fallen from roughly twenty-two per cent to under eleven per cent in four years, yet net utilisation of deployed staff has declined over the same period from 87.6 to 85.0 per cent. The two movements cannot both be explained by capacity discipline; together they indicate that the binding constraint has shifted from having too many people to matching the people retained against the tasks that remain. This study treats that shift as a problem of allocative efficiency and asks what human resource architecture resolves it. Redeployment policy is operationalised as an eight-component Redeployment Policy Index (RPI), and allocative efficiency through a composite Allocative Efficiency Index together with the within-unit dispersion of the log marginal revenue product of labour, the standard misallocation measure. Evidence is drawn from 540 redeployment episodes nested in 62 business units across 24 organisations, supplemented by interviews with 75 workforce-planning leaders. Three estimators are used: a multilevel model of allocative efficiency, a Cox proportional hazards model of time to productive reassignment, and a complementarity test of policy bundles. Redeployment policy raises allocative efficiency strongly ($\gamma = 0.412$, $p < 0.001$) and compresses misallocation, with dispersion falling from 0.62 to 0.28 across policy quartiles and an implied gain of 11.4 per cent in output per employee-hour. The central result is an interaction: automation intensity on its own reduces allocative efficiency ($\gamma = -0.186$, $p = 0.002$), but the interaction with redeployment policy is positive ($\gamma = 0.014$, $p < 0.001$), so that above an index value of approximately 65 deeper automation becomes allocatively productive rather than disruptive. Policy components behave as complements rather than substitutes, with observed efficiency exceeding the additive prediction only above a critical mass of five of eight components. Matching infrastructure, not income protection, drives reassignment speed: the talent marketplace carries a hazard ratio of 1.94 while the redeployment guarantee window is not significant. Employees above forty-five and those with more than ten years of tenure are reassigned significantly more slowly after full controls. The study closes with a structured seven-study research agenda extending the HRM-variable-to-economic-outcome programme of which it forms the second instalment.

KEYWORDS — *Redeployment Policy, Allocative Efficiency, Task Reallocation, Automation, Internal Labour Markets, Talent Marketplace, Misallocation, Marginal Revenue Product of Labour, Complementarity of HR Practices, Multilevel Modelling, Survival Analysis, Indian IT Services, Strategic HRM, Workforce Planning.*

I. INTRODUCTION

Indian IT services has spent four years removing slack from its workforce, and the results are difficult to read as success. Bench strength — the share of employees not allocated to any client engagement — has fallen from an average of twenty to thirty per cent in the pre-automation era to somewhere between eight and twelve per cent, with firms projecting eight to ten per cent for FY2027. Bench duration has compressed from forty-five to sixty days down to thirty to forty-five. On any conventional reading of capacity management, this is a considerable achievement. Yet over the same period net utilisation of deployed staff has moved in the opposite direction, declining from 87.1 per cent in the second quarter of FY2024 to 86.1 per cent a year later and 85.0 per cent in FY2026.

The two series are not measuring the same thing, and it is precisely their divergence that makes them informative. Bench strength counts people who are wholly unallocated. Net utilisation measures the share of available hours that deployed staff actually bill. A simultaneous fall in both means that the industry has succeeded in eliminating complete idleness while allowing partial idleness to spread across the staff who remain deployed. Capacity has not been removed from the system so much as thinly redistributed across it. Firms are no longer carrying people with nothing to do; they are carrying a larger number of people each doing somewhat less than they could. The economic name for this condition is not overcapacity. It is misallocation.

That distinction matters because the two conditions have opposite remedies. Overcapacity is corrected by reducing headcount. Misallocation is corrected by improving the assignment of the headcount one has, and reducing headcount can make it worse — by removing the slack that allows reassignment to happen at all. The literature on resource misallocation, following Hsieh and Klenow (2009) and Restuccia and Rogerson (2008), established that large productivity differences between firms and countries are attributable less to differences in technology or factor stocks than to differences in how efficiently given factors are allocated across uses. Their measure — the dispersion of marginal revenue products across production units — translates directly to the internal labour market of a services firm, where the relevant question is whether the marginal revenue product of an hour of engineering time is equalised across the engagements to which engineering time is assigned.

Automation sharpens the question rather than answering it. Agentic and generative systems are projected to redefine approximately 10.35 million roles in India by 2030 while creating over three million new technology positions (ServiceNow, 2025). The arithmetic of that transition is a very large reallocation problem: tasks are withdrawn from existing role bundles faster than the roles themselves disappear, leaving employees who are neither redundant nor fully occupied. Acemoglu and Restrepo (2019) describe the displacement and reinstatement effects that govern this process at the level of an economy; within a firm the same forces operate through the concrete machinery of internal posting, staffing decisions, manager discretion and skills data — the machinery this study calls redeployment policy.

There is good reason to expect that machinery to matter and little evidence establishing that it does. Bidwell (2011) demonstrated that internal movers outperform external hires at lower cost, and Keller (2018) showed that how a firm fills a vacancy — open posting against managerial slotting — materially changes both the quality of the match and its price. Cappelli (2008) argued for treating internal talent supply as a problem of managing uncertainty rather than of forecasting. What none of this work does is measure the allocative consequence of a redeployment architecture under automation, in a setting where automation is actively withdrawing task content from existing roles. That is the gap this study addresses.

The design isolates one HRM variable — redeployment policy, operationalised as an eight-component index — and one economic outcome — allocative efficiency, measured both as a composite index and through the dispersion of the log marginal revenue product of labour. It asks four questions. Does redeployment policy raise allocative efficiency and compress misallocation? Does its effect depend on how deeply automated the unit is? Do the policy components work independently, so that partial adoption yields partial benefit, or as complements, so that a critical mass is required? And which components actually shorten the time from displacement to productive reassignment?

This paper is the second in a research programme pairing a single HRM variable with a single measurable economic outcome. The first examined skill development investment and the wage premium accruing to AI-complementary capability, and found that the premium is a joint product of the skill and the investment that produced it, with a concave return and a material investment threshold (Sastry, 2026). The two papers are complements: the first concerns the production of capability, the second its allocation. A firm may produce capability efficiently and allocate it badly, and the evidence assembled here suggests that many currently do. Consistent with the forward agenda set out in that first study, the present design has been constructed for extension — the RPI instrument is reported in full so that it can be reused, and measures have been selected to support the panel replication described in Section XIII.

II. REVIEW OF LITERATURE

2.1 Allocative Efficiency and the Economics of Misallocation

The economic foundation of this study is the misallocation literature. Hsieh and Klenow (2009), examining manufacturing establishments in China and India against a United States benchmark, showed that equalising marginal revenue products across plants would raise total factor productivity by between thirty and fifty per cent in China and forty and sixty per cent in India. The insight is that aggregate productivity depends not only on the technology available to each producer but on whether resources reach the producers who can use them best. Restuccia and Rogerson (2008) provided the underlying framework, demonstrating that idiosyncratic distortions facing heterogeneous establishments generate substantial aggregate productivity losses even when no individual producer is inefficient. Syverson (2011), reviewing the productivity literature, identified allocation as among the most powerful and least understood determinants of measured productivity differences.

The measurement convention this literature established is the one adopted here. Where allocation is efficient, the marginal revenue product of a factor is equalised across its uses; where it is not, marginal revenue products disperse. The dispersion of the log marginal revenue product therefore serves as a direct, theory-grounded index of misallocation, and its compression as evidence of allocative improvement. Applied within a services firm, the factor is billable human capacity and the uses are client engagements and internal programmes. A unit in which some engineers generate three times the revenue per hour of others in comparable roles is not necessarily a unit with a training problem; it may be a unit with an assignment problem.

The matching tradition supplies the mechanism. Jovanovic (1979) modelled the employment relationship as an experience good whose quality is revealed only through the match itself, implying that reassignment is not merely a cost of disruption but a mechanism of discovery. Mortensen and Pissarides (1994) formalised job creation and destruction as simultaneous flows governed by search frictions, establishing that the speed at which displaced capacity finds new use is an economic variable in its own right, determined by the institutions of the market rather than by the productivity of the workers. Within a firm those institutions are precisely the redeployment policies under examination.

2.2 Internal Labour Markets and Redeployment

Doeringer and Piore (1971) established the internal labour market as an administrative unit within which pricing and allocation of labour are governed by procedural rules rather than by market clearing. Their central observation — that the rules themselves determine allocative outcomes — is the premise of this study. Baker, Gibbs and Holmström (1994), using two decades of personnel records from a single firm, documented how strongly internal mobility patterns are shaped by administrative structure rather than by productivity alone.

Contemporary work has quantified the consequences. Bidwell (2011) found that external hires are paid substantially more than internal movers into equivalent positions while performing worse for their first two years, a finding that establishes internal mobility as economically superior wherever a comparable internal candidate exists. Keller (2018), comparing open posting with managerial slotting, showed that the allocation mechanism itself changes both match quality and compensation — evidence that redeployment outcomes depend on process design and not merely on the availability of internal candidates. Cappelli and Keller (2014) reviewed the conceptual state of talent management and identified the absence of outcome measurement as its principal weakness, while Cappelli (2008) proposed treating internal talent supply as a portfolio problem under uncertainty, a framing that anticipates the option-value argument developed in Section 8.7.

Bloom and Van Reenen (2007), measuring management practice across firms and countries, demonstrated that structured people-management practices are associated with large and persistent productivity differences, and that Indian firms score substantially below the international frontier on precisely the practices concerning talent allocation. Their work suggests that redeployment architecture is likely to be a first-order rather than a marginal determinant of productivity in the Indian setting.

2.3 Complementarity Among Human Resource Practices

A distinct tradition holds that human resource practices produce their effects in bundles rather than singly. MacDuffie (1995), studying automotive assembly plants worldwide, showed that innovative work practices improve performance only when adopted as coherent bundles integrated with manufacturing policy, and that isolated adoption yields negligible return. Ichniowski, Shaw and Prennushi (1997), examining finishing lines in steel production, found that clusters of complementary practices raised productivity substantially while individual practices adopted alone had little effect. Milgrom and Roberts (1995) supplied the formal argument: where practices are complements in the mathematical sense, the return to each is increasing in the adoption of the others, so that the system exhibits increasing returns over a range and partial adoption can be worse than none.

This literature yields a testable prediction that has not, to the author's knowledge, been applied to redeployment architecture. If the eight components of a redeployment policy are complements — if, for instance, a talent marketplace is only useful where a skills taxonomy makes capability legible, and a skills taxonomy is only acted upon where managers face a release obligation — then observed allocative efficiency should exceed the sum of individually estimated component effects, and should do so only above some critical mass. Section 8.5 tests exactly this proposition, and Becker and Huselid's (1998) argument that internal fit determines the returns to high-performance work systems supplies the interpretive frame.

2.4 Antecedent Work in the HRM Variable → Economic Outcome Programme

The present study is the second instalment of a research programme that pairs one human resource variable with one measurable economic outcome, and it draws directly on the earlier work in that programme. Sastry (2026), the first instalment, examined skill development investment against the wage premium accruing to AI-complementary capability in Indian IT services, and established through an augmented Mincerian specification that the premium is a joint product of skill and employer investment rather than a property of the skill alone, with a concave return and a threshold below which investment yields little. That study concerns the production of capability; the present study concerns its allocation, and its findings supply the necessary complement — capability efficiently produced but inefficiently assigned generates no economic return, a possibility the first study could not test.

Sastry and Mallya (2025b) analysed strategic human resource management as a determinant of economic resilience, with explicit attention to skill diversification and labour market dynamics under technological disruption. That work identified reallocation capacity — the ability of an organisation

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to move capability between uses as demand shifts — as a distinguishing feature of resilient workforce systems, and it is the direct conceptual antecedent of the Redeployment Policy Index constructed here. Sastry and Mallya (2025a), examining artificial intelligence analytics in hiring, demonstrated that machine-readable capability data delivers both operational and sustained financial benefit; that finding bears directly on the enterprise skills taxonomy component of the index, since internal matching is impossible where capability is not legible to the systems that allocate work.

Mallya and Sastry (2025), studying leadership strategies for young talent across 150 employees and 50 HR managers, found that growth opportunity and purpose outrank compensation as retention drivers and that command-and-control leadership models actively impede talent development. That result illuminates two components of the index in particular — the manager release obligation and the inclusion of redeployment in leader scorecards — both of which exist to overcome the tendency of individual managers to hoard capability against the interest of the wider organisation.

Sastry (2025b), on talent designation and social comparison as economic drivers of organisational growth, is central to interpreting one of this study's more counter-intuitive findings. That work established that employees evaluate their position relative to visible internal reference groups and that designation carries economic consequences independent of pay. It offers the most persuasive explanation for why the redeployment guarantee window — which protects income during transition — fails to accelerate reassignment while the talent marketplace does: what deters participation in redeployment is not loss of income but loss of standing, and a mechanism that protects the former while leaving the latter unaddressed does not change behaviour.

Sastry (2025a), studying 150 women micro-entrepreneurs across five Karnataka districts, concluded that socio-cultural and systemic constraints bind more tightly on economic outcomes than skill or knowledge gaps. That conclusion frames this study's treatment of the age and tenure penalties reported in Section 8.6, which persist after controlling for capability and automation exposure and are therefore unlikely to be remedied by skilling. Sastry (2020) examined the performance factors influencing motivation in the tea manufacturing sector, supplying evidence on the motivational consequences of reassignment that informs the interpretation of voluntary versus directed redeployment; Sastry (2013) set out approaches to talent management within the human resource function; and Anas, Hans and Sastry (2025) demonstrated in the tourism sector how a technology shift restructures an entire service value chain and the competences required to operate it. Table 1 synthesises the literature and states the specific contribution of each source 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
Hsieh & Klenow (2009)	Misallocation and manufacturing TFP	Equalising marginal revenue products would raise TFP by 40–60 per cent in India; allocation matters more than technology	Supplies the misallocation measure — dispersion of ln MRPL — applied here inside the firm
Restuccia & Rogerson (2008)	Policy distortions and aggregate productivity	Idiosyncratic distortions across heterogeneous units generate large aggregate losses even where no producer is inefficient	Establishes that allocative loss can coexist with locally competent management
Syverson (2011)	Determinants of productivity	Allocation is among the most powerful and least understood sources of productivity difference	Justifies treating allocation, not capability, as the object of study
Jovanovic (1979)	Job matching and turnover	Match quality is an experience good revealed only through the match itself	Frames reassignment as a discovery mechanism, not merely a cost of disruption
Mortensen & Pissarides (1994)	Job creation and destruction	Creation and destruction are simultaneous flows governed by search frictions and market institutions	Establishes reassignment speed as an economic variable determined by institutions
Doeringer & Piore (1971)	Internal labour markets	Allocation inside the firm is governed by administrative rules rather than market clearing	Core premise: the rules — redeployment policy — determine allocative outcomes
Baker, Gibbs & Holmström (1994)	Internal economics of the firm	Internal mobility patterns are shaped by administrative structure more than by productivity	Supports policy architecture as the causal variable of interest
Bidwell (2011)	External hiring vs. internal mobility	External hires are paid more and perform worse for two years than comparable internal movers	Quantifies the economic superiority of redeployment over external replacement

Keller (2018)	Posting versus slotting	The allocation mechanism itself changes both quality of hire and compensation	Establishes that process design, not candidate availability, drives match quality
Cappelli (2008); Cappelli & Keller (2014)	Talent on demand; talent management review	Internal talent supply is a portfolio problem under uncertainty; outcome measurement is the field's principal weakness	Motivates the option-value argument and the outcome-measurement contribution
MacDuffie (1995)	HR bundles and manufacturing performance	Innovative practices improve performance only as coherent bundles; isolated adoption yields negligible return	Direct antecedent of the complementarity test in Section 8.5
Ichniowski, Shaw & Prennushi (1997)	HRM practices and productivity	Clusters of complementary practices raise productivity; individual practices adopted alone do not	Grounds the prediction of a critical mass in policy adoption
Milgrom & Roberts (1995)	Complementarities and fit	Where practices are complements, the return to each rises with adoption of the others	Supplies the formal argument for super-additive returns above a threshold
Acemoglu & Restrepo (2019)	Displacement and reinstatement	Automation displaces labour from tasks while new tasks reinstate it	The interaction tested in Section 8.4 is this mechanism operating inside the firm
Bloom & Van Reenen (2007)	Management practice across countries	Structured people-management practice explains large productivity differences; Indian firms score below the frontier	Suggests redeployment architecture is a first-order determinant in this setting
Sastry (2026)	Skill development investment → wage premium	The AI wage premium is a joint product of skill and employer investment; concave with a material threshold	First instalment of this programme; supplies the capability-production counterpart to the present allocation study
Sastry & Mallya (2025b)	Strategic HRM and economic resilience	Reallocation capacity distinguishes resilient workforce systems under technological disruption	Direct conceptual antecedent of the Redeployment Policy Index
Sastry & Mallya (2025a)	AI analytics in HR hiring	Machine-readable capability data delivers operational and sustained financial benefit	Underpins the enterprise skills taxonomy component — matching requires legible capability
Mallya & Sastry (2025)	Leadership for young talent	Growth and purpose outrank pay; command-and-control leadership impedes development	Explains the manager release obligation and scorecard accountability components
Sastry (2025b)	Talent designation and social comparison	Relative internal standing carries economic consequence independent of absolute pay	Explains why the guarantee window fails and the marketplace succeeds (Section 8.6)
Sastry (2025a)	Women micro-entrepreneurs, Karnataka	Socio-cultural and systemic constraints bind more tightly than skill or knowledge gaps	Frames the age and tenure penalties as screening rather than competence effects
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; performance factors drive motivation	Cross-sector analogue for task restructuring; motivational consequences of reassignment

III. RESEARCH GAP

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

- The misallocation literature operates at the level of establishments and economies. It has not been applied within the firm, where the allocation of human capacity across engagements is a managed process governed by identifiable human resource policies rather than by market frictions.
- The internal mobility literature establishes that internal movers outperform external hires and that allocation mechanisms shape match quality, but it evaluates outcomes at the level of the individual move. It does not measure the allocative efficiency

of the unit as a whole, and therefore cannot say what a redeployment architecture is worth.

- Redeployment is treated in practice as a cost-containment device — a way of avoiding severance and rehiring expense — rather than as a productivity instrument. No study estimates its effect on output per employee-hour.
- The interaction between redeployment policy and automation intensity is unexamined. Whether a redeployment architecture matters more, less or equally as automation deepens is an open empirical question with direct budgetary consequences for firms deciding when to build one.
- The complementarity literature has been applied to manufacturing work systems and high-performance work practices but not to redeployment architecture, leaving unanswered whether partial adoption of redeployment practices delivers partial benefit or none.
- Almost nothing is known about which specific components accelerate reassignment. Firms invest in guarantee windows, marketplaces, taxonomies and mandates without comparative evidence on their relative contribution, and no study to date has modelled time to reassignment as a duration process.

IV. STATEMENT OF THE PROBLEM

Indian IT services firms have compressed bench strength substantially while allowing net utilisation to decline, indicating that the constraint on productive deployment has shifted from surplus capacity to defective matching. The firms most exposed to this shift are those automating fastest, since automation continuously withdraws task content from roles without withdrawing the people who held them.

Human resource functions are being asked to build redeployment machinery — talent marketplaces, skills taxonomies, internal-first mandates, exposure mapping — without evidence on what such machinery is worth, which components matter, whether partial adoption suffices, or whether the investment case strengthens or weakens as automation deepens.

The problem this study addresses is therefore to establish the allocative return to redeployment policy under automation; to determine whether that return is conditional on automation intensity; to test whether the policy components are complements requiring critical mass; and to identify which components actually shorten the interval between displacement and productive reassignment.

V. OBJECTIVES OF THE STUDY

1. To construct and validate a Redeployment Policy Index capturing the architecture through which organisations reassign displaced human capacity.
2. To estimate the effect of redeployment policy on allocative efficiency, measured both as a composite index and as the within-unit dispersion of the log marginal revenue product of labour.
3. To test whether automation intensity moderates that effect, and to identify the policy level at which deeper automation ceases to degrade and begins to improve allocative efficiency.
4. To determine whether redeployment policy components function as substitutes or complements, and to locate any critical mass above which returns become super-additive.
5. To model time from task displacement to productive reassignment as a duration process and to rank the individual policy components by their contribution to reassignment speed.
6. To examine whether redeployment outcomes are equitably distributed across age and tenure groups after controlling for capability and automation exposure.
7. To translate the estimated allocative gain into output per employee-hour, and to set out a structured research agenda extending the HRM-variable-to-economic-outcome programme.

VI. HYPOTHESES OF THE STUDY

H_1: Redeployment policy comprehensiveness is positively associated with the allocative efficiency of the business unit.

H_2: Redeployment policy comprehensiveness is negatively associated with the within-unit dispersion of the log marginal revenue product of labour.

H_3: Automation intensity positively moderates the relationship between redeployment policy and allocative efficiency, so that the policy effect is larger in more heavily automated units.

H_4: Redeployment policy components function as complements, yielding super-additive returns to allocative efficiency above a critical mass of adoption.

H_5: Redeployment policy shortens the interval to productive reassignment, with all eight components contributing significantly to the reassignment hazard.

H_6: Redeployment outcomes are independent of employee age and organisational tenure once capability and prior-role automation exposure are controlled.

VII. RESEARCH METHODOLOGY AND DESIGN

7.1 Research Type and Multilevel Structure

The study employs a mixed-methods explanatory design with a nested data structure. Redeployment episodes are observed at the individual level and are nested within business units, which are in turn nested within organisations. Because episodes within the same unit share a policy environment, the assumption of independent observations required by ordinary least squares is violated; the null model returns an intraclass correlation of 0.21, indicating that twenty-one per cent of variance in allocative outcomes lies between units. Multilevel modelling is therefore used for the principal estimation, following Raudenbush and Bryk (2002).

Three estimators address three distinct questions. A two-level random-intercept model estimates the effect of redeployment policy and its interaction with automation intensity on allocative efficiency. A Cox proportional hazards model, following Cox (1972), estimates the effect of individual policy components on the rate of productive reassignment while correctly handling episodes that had not resolved at the close of observation. A complementarity test compares observed unit-level efficiency against the additive prediction derived from single-component estimates, with a Chow test for a structural break in the relationship.

7.2 Population, Sampling and Measurement

The sampling frame comprises Indian IT services delivery units, engineering research and development centres and global capability centres in which at least one automation programme had displaced measurable task volume within the preceding twenty-four months. A redeployment episode is defined as an instance in which an identified employee lost thirty per cent or more of their prior task content to automation and required reassignment. Five hundred and forty such episodes were obtained across sixty-two business units in twenty-four organisations, together with structured interviews with seventy-five workforce-planning, staffing and human resource leaders.

Two composite instruments were constructed. The Redeployment Policy Index scores each unit on eight binary policy components, each verified against documentary evidence rather than perception alone, and is expressed on a nought-to-hundred scale; internal consistency is high (Cronbach's alpha = 0.91), and inter-rater agreement for the aggregation of individual reports to unit level is satisfactory (median r-sub-wg = 0.84; ICC(2) = 0.78). Table 2 reports the components with their adoption rates. The Allocative Efficiency Index combines four standardised indicators — task–capability match, share of capacity on value-generating work, reassignment speed and the persistence of the match at six months — with composite reliability of 0.88 and average variance extracted of 0.64, satisfying convergent validity. Marginal revenue product of labour was computed at the individual level as revenue attributable to the employee's engagements divided by hours contributed, and its within-unit log dispersion taken as the misallocation measure. Table 3 reports construct operationalisation and the realised sample profile.

Table 2 · The Redeployment Policy Index (RPI) — Components, Definitions and Adoption

#	Policy Component	Operational Definition (verified against documentary evidence)	Adoption (% of 62 units)	Reassignment Hazard Ratio
1	Skills-based internal talent marketplace	A platform on which open roles, projects and gigs are posted and matched to employees on recorded capability, open to application rather than managerial nomination	43.5	1.94
2	Pre-emptive automation-exposure mapping	Systematic ex-ante assessment of which roles and task bundles are exposed to planned automation, completed before deployment rather than after displacement	29.0	1.71
3	Funded reskilling bridge	Employer-funded capability development explicitly tied to an identified destination role rather than offered as general learning provision	46.8	1.58
4	Redeployment accountability in leader scorecards	Redeployment outcomes carry formal weight in the performance assessment of business and delivery leaders	21.0	1.47
5	Internal-first hiring mandate	Open positions must be posted internally and internal candidates assessed before any external requisition is raised	61.3	1.43
6	Manager release obligation	Managers may not decline the release of an employee to an internal move meeting defined criteria; anti-hoarding provision with escalation	24.2	1.36
7	Enterprise skills taxonomy and capability graph	A single machine-readable capability model covering the workforce, maintained current and integrated with staffing systems	51.6	1.29
8	Redeployment guarantee window	A protected period, typically 60–90 days, during which a displaced employee retains pay and grade while reassignment is sought	38.7	1.22 (ns)

Note: Each component is scored 0 or 12.5, giving an index range of 0–100. Sample mean RPI = 51.4 (SD 19.8; observed range 12.5–93.8). Cronbach's alpha = 0.91; ICC(2) = 0.78; median r-sub-wg = 0.84. Hazard ratios are from the Cox model in Table 6.

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Table 3 · Construct Operationalisation and Realised Sample Profile

Construct / Dimension	Measurement or Category	Value / n	Statistic
Redeployment Policy Index — independent	Sum of 8 verified binary components, scaled 0–100	Mean 51.4	SD 19.8; α = 0.91
Allocative Efficiency Index — dependent	Composite of task–capability match, share of capacity on value-generating work, reassignment speed, match persistence at 6 months	Mean 61.8	CR = 0.88; AVE = 0.64
Misallocation — dependent	Within-unit standard deviation of ln marginal revenue product of labour	Mean 0.45	Range 0.21–0.78
Reassignment duration — dependent	Days from ≥30% task displacement to productive reassignment; censored at 180 days	Median 48 days	486 events, 54 censored
Automation intensity — moderator	Per cent of unit task volume machine-executed	Mean 34.0	SD 14.6
Prior-role automation exposure — control	Per cent of the employee's prior task content withdrawn	Mean 44.2	SD 12.9
Skill breadth — control	Count of distinct capability families present in the unit	Mean 11.4	SD 4.2
Sample — episodes	Redeployment episodes meeting the ≥30% displacement criterion	540	Level 1
Sample — business units	Delivery, engineering R&D and capability-centre units	62	Level 2; ICC = 0.21
Sample — organisations	Distinct employing organisations	24	Level 3 (not modelled)
Sample — interviews	Workforce-planning, staffing and HR leaders	75	Qualitative strand
Employer type	Tier-1 Indian IT services	22 units	35.5%
	Global capability centre	19 units	30.6%
	Mid-tier Indian IT services	14 units	22.6%
	Engineering R&D / product	7 units	11.3%
Episode profile — age	Below 35 / 35–45 / above 45	241 / 187 / 112	44.6 / 34.6 / 20.7%
Episode profile — tenure	Below 5 yrs / 5–10 yrs / above 10 yrs	198 / 203 / 139	36.7 / 37.6 / 25.7%
Episode profile — gender	Male / Female	339 / 201	62.8 / 37.2%

7.3 Model Specification

The principal specification is a two-level random-intercept model in which episode i is nested in unit j:

$$\textit{Level 1:}\quad AEI_{ij} = \beta_{0j} + \beta_1\, Exposure_{ij} + \beta_2\, Tenure_{ij} + \beta_3\, Age45_{ij} + r_{ij}$$

$$\textit{Level 2:}\quad \beta_{0j} = \gamma_{00} + \gamma_{01}\, RPI_j + \gamma_{02}\, Auto_j + \gamma_{03}\, (RPI \times Auto)_j + \gamma_{04}\, Breadth_j + \gamma_{05}\, lnSize_j + \gamma_{06}\, GCC_j + u_{0j} \quad \ldots(1)$$

where AEI is the Allocative Efficiency Index, RPI the Redeployment Policy Index, Auto the share of unit task volume machine-executed, Breadth the skill breadth of the unit, and Exposure the automation exposure of the employee's prior role. Both RPI and Auto are grand-mean centred, so γ_{01} is the policy effect at mean automation intensity and γ_{02} the automation effect at mean policy. The marginal effect of automation is therefore $\gamma_{02} + \gamma_{03}(RPI - 51.4)$, which changes sign at a determinate value of RPI — the quantity reported in Section 8.4.

The misallocation specification replaces the dependent variable with the within-unit standard deviation of ln MRPL, estimated at unit level with the same right-hand side. The duration specification models the hazard of productive reassignment as $h(t) = h_0(t)\cdot\exp(\Sigma\, \theta_k X_k)$, with the eight policy components entered individually alongside employee and role controls, permitting each component to be ranked by its contribution to reassignment speed independently of the others.

Figure 1 sets out the conceptual framework these equations operationalise. Redeployment policy acts on allocative efficiency through two mediating channels — the speed at which displaced capacity is reassigned and the quality of the resulting match — which drive four economic transmission mechanisms: reduction of idle and partial capacity, reduction of internal search and vacancy cost, equalisation of marginal revenue products across engagements, and preservation of the option value of capability the firm has already paid to build. Automation intensity enters as the primary moderator.

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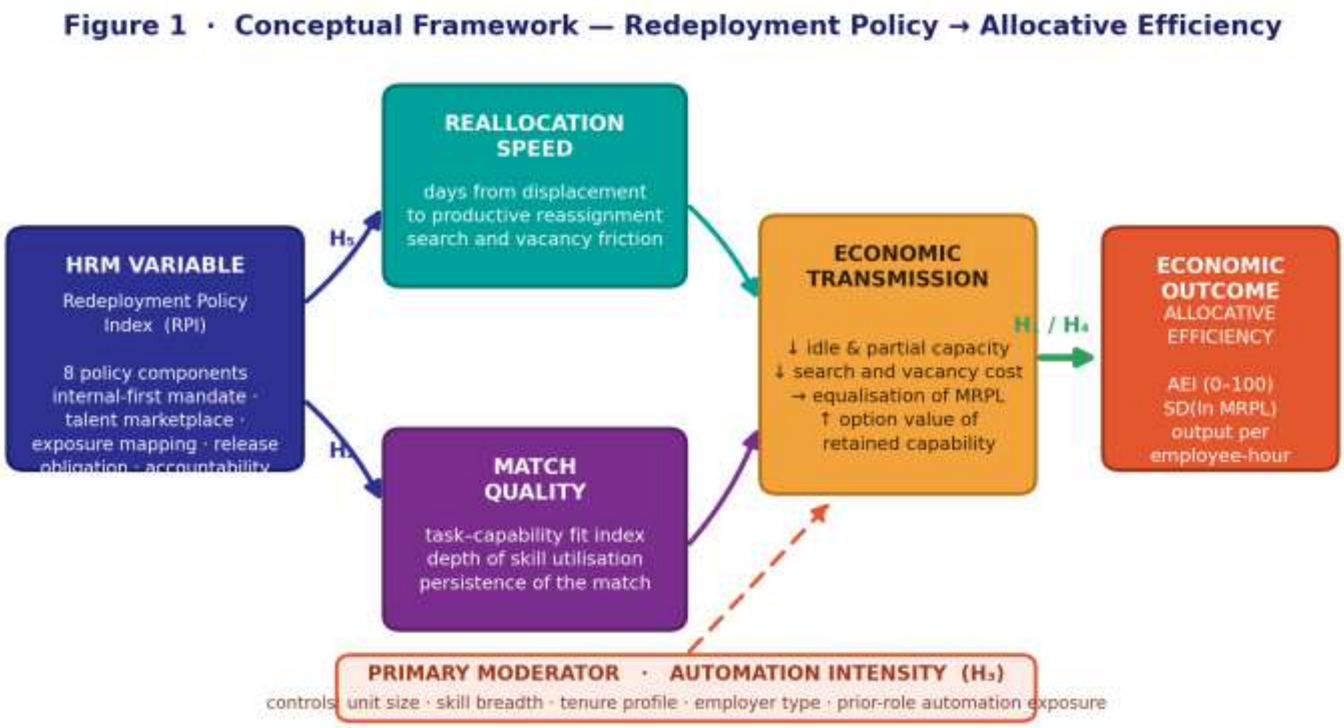

Figure 1 · Conceptual framework linking redeployment policy to allocative efficiency through reallocation speed and match quality, moderated by automation intensity.

7.4 Analytical Tools

Multilevel models were estimated by restricted maximum likelihood with robust standard errors; model improvement was assessed by deviance difference against the null. Analysis of variance with Scheffé post-hoc comparison tested differences across policy quartiles, and the Kruskal–Wallis test was used for reassignment duration, which is not normally distributed. Cox models were estimated by partial likelihood, with the proportional hazards assumption verified through scaled Schoenfeld residuals; no covariate showed significant violation. The complementarity test compared observed against additively predicted efficiency using a Chow test for structural break. Interviews were analysed thematically and used to interpret coefficients rather than to generate them. Estimation was carried out in R using the lme4 and survival packages, with cross-validation in SPSS version 29.

VIII. RESULTS AND DISCUSSION

8.1 The Reallocation Puzzle

Figure 2 presents the industry pattern that motivates the study. Between FY2023 and FY2026 bench strength fell by thirteen percentage points while net utilisation of deployed staff fell by 2.6 points. If the reduction in bench reflected genuine improvement in capacity management, utilisation should have risen: the employees formerly idle would have joined the billable pool and the average would have improved. It did not.

The only reading consistent with both series is that complete idleness has been converted into partial idleness rather than eliminated. Interview evidence supports this directly. Staffing leaders described a pattern in which employees whose task content had been automated were retained on their existing engagements at reduced effective load rather than reassigned, because reassignment required a search process the organisation was not equipped to run at speed. One workforce-planning head characterised the result as an organisation that had stopped counting its bench because the bench had been distributed into the delivery teams. Partial idleness is administratively invisible in a way that a formal bench is not, which makes it both easier to tolerate and harder to correct.

This is a misallocation phenomenon rather than a capacity phenomenon, and it establishes the relevance of the allocative efficiency framework. The remainder of Section VIII estimates what redeployment policy contributes to resolving it.

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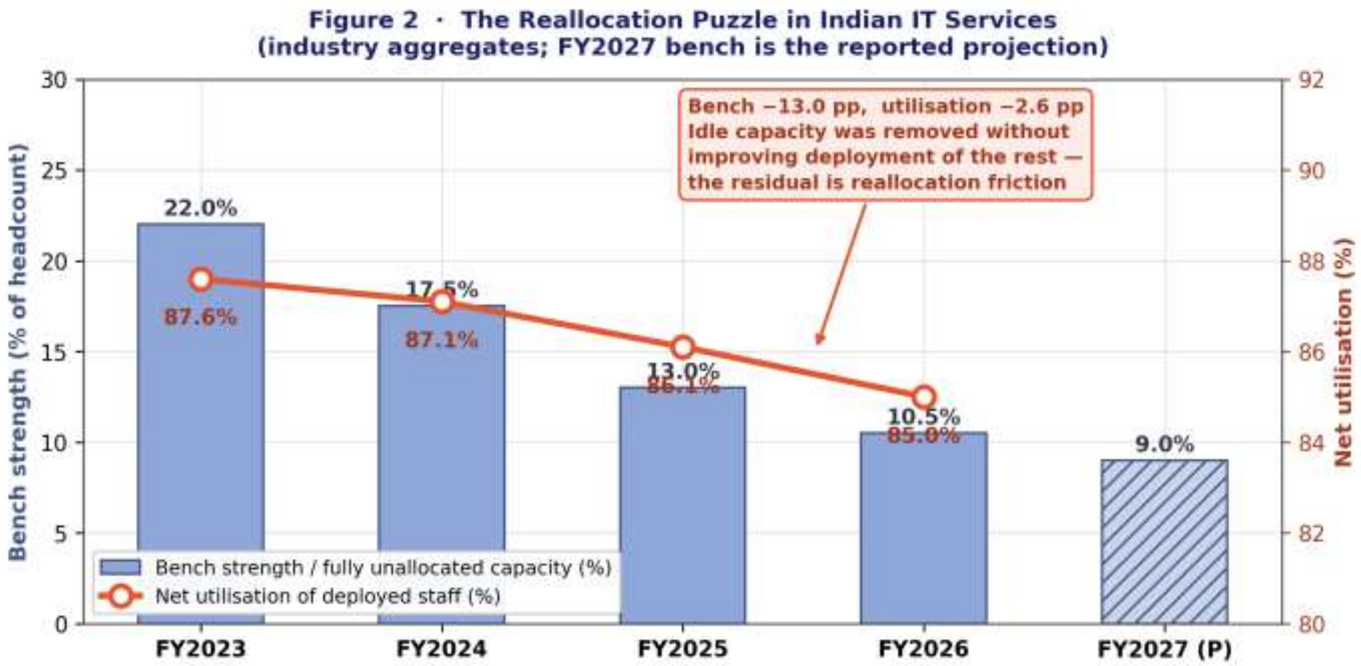

Figure 2 · Falling bench strength alongside falling net utilisation — the reallocation puzzle that motivates the study.

8.2 Descriptive Differences Across Policy Quartiles

Table 4 and Figure 3 report outcomes by quartile of the Redeployment Policy Index. The gradient is steep and monotonic across every measure. Units in the lowest policy quartile record an Allocative Efficiency Index of 41.3, a median 94 days from displacement to productive reassignment, idle or partially idle capacity of 14.8 per cent, and a within-unit dispersion of log marginal revenue product of 0.62. Units in the highest quartile record 81.4, 23 days, 3.9 per cent and 0.28 respectively. Analysis of variance on the efficiency index returns $F(3, 536) = 187.3$, $p < 0.001$, with an eta-squared of 0.51 — policy quartile alone accounts for slightly more than half the variance in allocative efficiency, a very large effect by the standards of organisational research. The Kruskal–Wallis test on reassignment duration returns $\chi^2(3) = 212.7$, $p < 0.001$. The dispersion result deserves separate emphasis because it is the theoretically cleanest of the four. A fall in the standard deviation of log marginal revenue product from 0.62 to 0.28 means that the variance of misallocation has fallen by close to eighty per cent. In the framework of Hsieh and Klenow (2009), where output loss is approximately proportional to that variance, this is a substantial productivity recovery achieved without any change in the technology available to the unit or in the capability of its staff. The same people, working with the same tools, produce materially more when the assignment process improves. Section 8.7 converts this into output per employee-hour.

Table 4 · Allocative Outcomes by Quartile of the Redeployment Policy Index

Quartile	RPI range	Units / episodes	Allocative Efficiency Index	Median days to reassignment	Idle & partial capacity (%)	SD (ln MRPL)	Task–capability match index
Q1 (lowest)	12.5 – 33.9	16 / 134	41.3	94	14.8	0.62	0.48
Q2	34.0 – 52.4	16 / 137	55.7	61	10.2	0.51	0.61
Q3	52.5 – 71.8	15 / 136	68.9	38	6.4	0.39	0.73
Q4 (highest)	71.9 – 93.8	15 / 133	81.4	23	3.9	0.28	0.84
All units	Mean 51.4	62 / 540	61.8	48	8.8	0.45	0.67

Note: ANOVA on the Allocative Efficiency Index: $F(3, 536) = 187.3$, $p < 0.001$, $\eta^2 = 0.51$. Kruskal–Wallis on reassignment duration: $\chi^2(3) = 212.7$, $p < 0.001$. All pairwise quartile differences on the efficiency index are significant at $p < 0.05$ (Scheffé). Idle and partial capacity is the share of available hours not on value-generating work, and therefore exceeds conventional bench reporting.

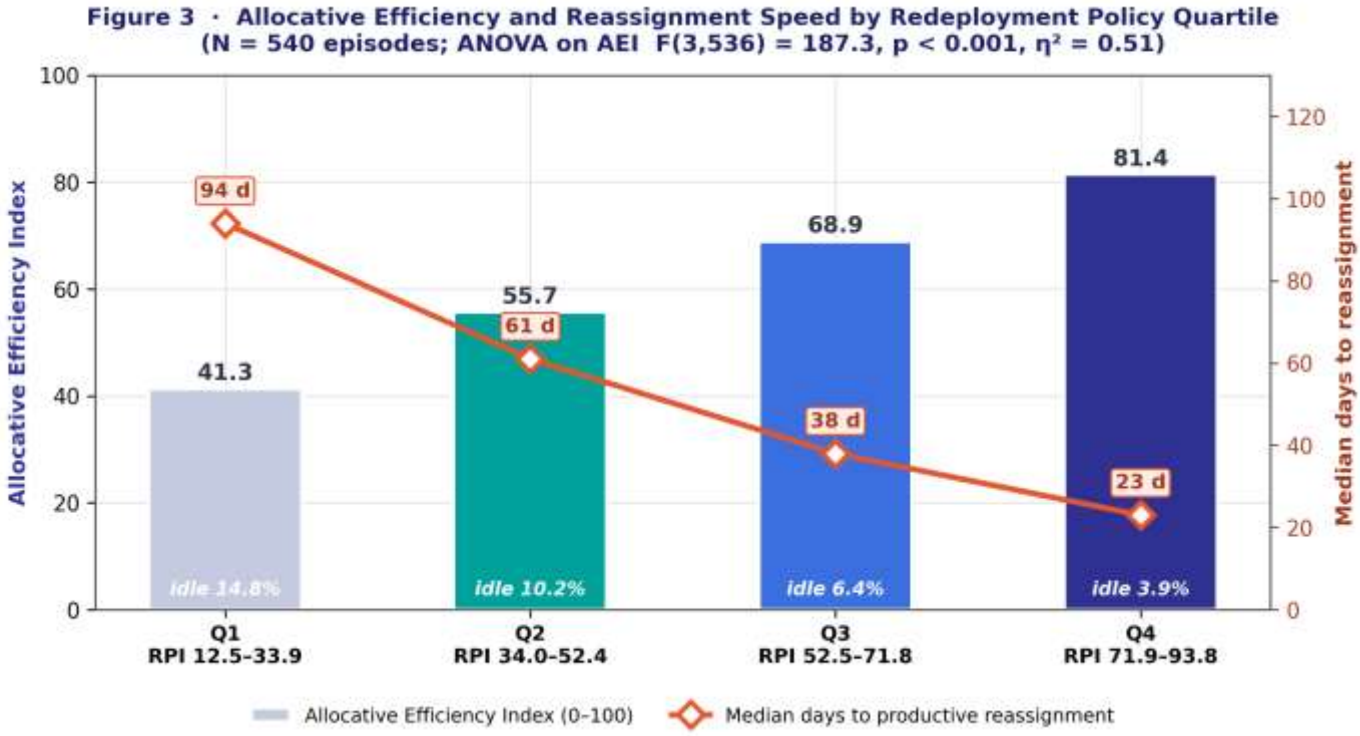

Figure 3 · Allocative efficiency and reassignment speed across quartiles of the Redeployment Policy Index.

8.3 Multilevel Estimation

Table 5 reports the two-level model. The null model returns an intraclass correlation of 0.21, confirming that a multilevel specification is required; the full model improves fit substantially against the null, with a deviance difference of $\chi^2(9) = 284.6$, $p < 0.001$, and explains 38 per cent of level-one and 64 per cent of level-two variance.

The Redeployment Policy Index carries a coefficient of 0.412 ($p < 0.001$), supporting H_1: a ten-point increase in policy comprehensiveness is associated with a 4.1-point improvement in allocative efficiency at mean automation intensity. Skill breadth of the unit is positively associated with efficiency ($\gamma = 0.208$, $p = 0.004$), consistent with the matching logic that a broader internal capability distribution offers more feasible reassignments. Unit size is not significant, which is worth noting: the advantage of a large internal labour market appears to depend on whether the organisation has built the machinery to search it, not on its size as such. Prior-role automation exposure carries a negative coefficient ($\gamma = -0.147$, $p = 0.008$), indicating that employees displaced from the most heavily automated roles are reassigned to poorer matches — the reallocation problem is hardest precisely where it is most needed.

8.4 The Automation Interaction

The study's central result is the interaction between policy and automation intensity, reported in Table 5 and plotted in Figure 4. Automation intensity carries a negative main effect ($\gamma = -0.186$, $p = 0.002$): at average policy comprehensiveness, deeper automation reduces allocative efficiency. The interaction term is positive and significant ($\gamma = 0.014$, $p < 0.001$), supporting H_3.

Taken together these coefficients describe a conditional relationship of considerable practical importance. The marginal effect of automation on allocative efficiency is $-0.186 + 0.014(\text{RPI} - 51.4)$, which is negative below an index value of approximately 65 and positive above it. Below that level, every increment of automation makes the unit less efficient at allocating its people: task content is withdrawn faster than the organisation can rematch the capacity it releases, and the released capacity settles into partial idleness. Above it, automation becomes allocatively productive — the withdrawal of routine task content frees capacity that the redeployment machinery successfully redirects to higher-value use, which is the reinstatement mechanism of Acemoglu and Restrepo (2019) operating inside the firm.

Figure 4 shows the practical scale of the conditionality. At an automation intensity of ten per cent the three policy regimes are almost indistinguishable, spanning 64.8 to 67.8 index points; a firm at that level of automation would find it hard to justify investment in redeployment architecture from allocative benefit alone. At seventy per cent automation the same three regimes span 37.0 to 73.3 — a gap of 36.3 points. The value of a redeployment architecture is therefore not a fixed property of the practice; it is created by the automation programme that runs alongside it. The corollary is a sequencing rule that emerged repeatedly in interviews and that firms are widely getting wrong: the redeployment machinery must be built before, not after, the automation programme reaches depth, because the period during which it is most needed is also the period during which the organisation is least able to construct it.

Table 5 · Two-Level Random-Intercept Model of Allocative Efficiency

Predictor	Level	γ	Robust SE	t	p	Interpretation
Intercept	—	61.84	1.12	55.21	< 0.001	Grand mean at centred predictors
Redeployment Policy Index	2	0.412	0.048	8.58	< 0.001	+4.1 AEI points per 10 RPI points — supports H_1
Automation intensity	2	−0.186	0.061	−3.05	0.002	Automation alone degrades allocative efficiency
RPI × Automation intensity	2	0.014	0.004	3.50	< 0.001	Policy converts disruption into reallocation — supports H_3
Skill breadth of unit	2	0.208	0.072	2.89	0.004	Broader capability distribution widens the feasible match set
Unit size (ln headcount)	2	−0.94	0.61	−1.54	0.124	Not significant — scale without machinery does not help
Global capability centre unit	2	1.87	0.96	1.95	0.052	Marginal employer-type advantage
Prior-role automation exposure	1	−0.147	0.055	−2.67	0.008	The most displaced are matched worst
Employee tenure (years)	1	−0.089	0.041	−2.17	0.030	Longer tenure, poorer post-move match
Age above 45 (1 = yes)	1	−2.61	1.04	−2.51	0.012	Age penalty net of capability — H_6 rejected

Note: N = 540 episodes in 62 units. Null-model ICC = 0.21. Deviance improvement over null: $\chi^2(9) = 284.6$, $p < 0.001$. Pseudo-R^2 = 0.38 (level 1) and 0.64 (level 2). RPI and automation intensity are grand-mean centred; the marginal effect of automation is $-0.186 + 0.014(RPI - 51.4)$, which changes sign at RPI ≈ 64.7.

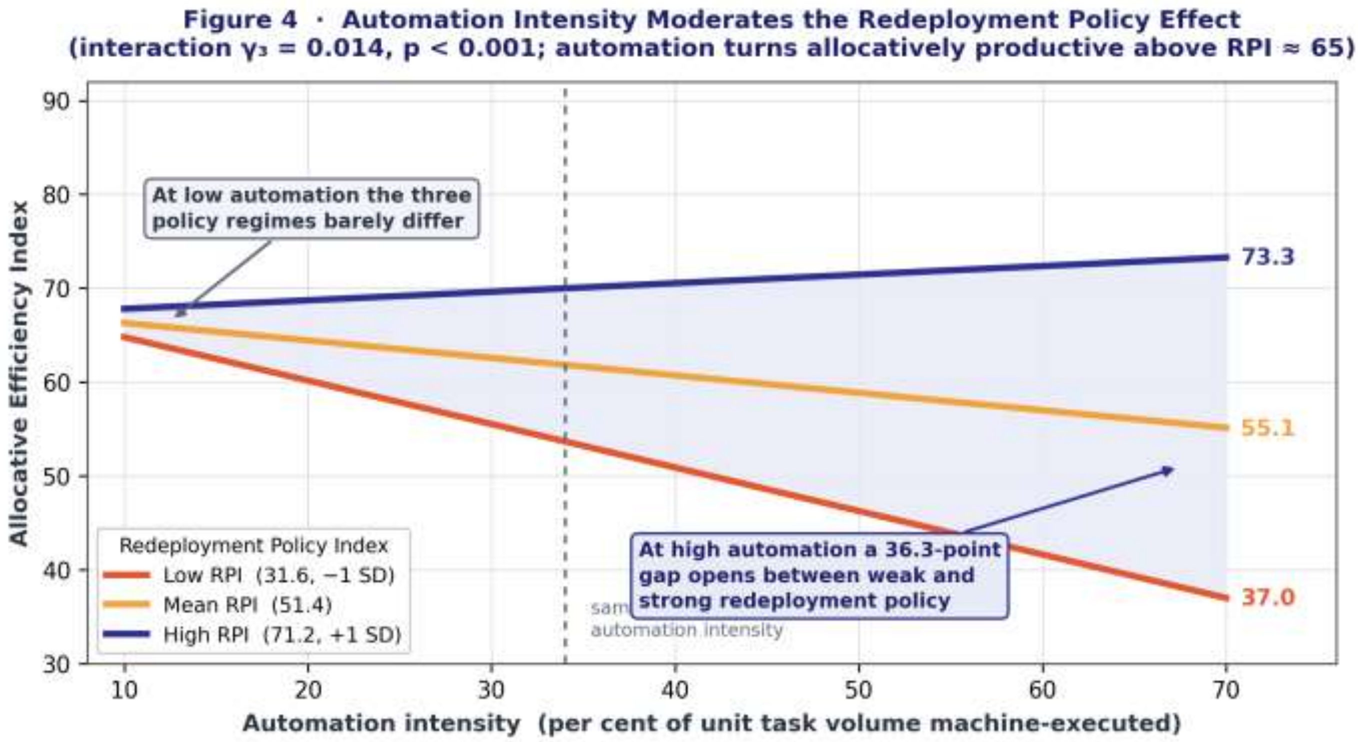

Figure 4 · The policy effect grows with automation intensity; automation becomes allocatively productive above RPI ≈ 65.

8.5 Complementarity: Policy as a Bundle

Table 7 and Figure 5 test whether the eight components operate independently. If they do, unit-level efficiency should equal the sum of individually estimated component effects. It does not. Below five components the observed index tracks the additive prediction closely, with deviations of −1.3, −1.1 and +0.7 points at zero-to-two, three and four components respectively, none significant. At five components a gap of +3.3 points opens ($p = 0.039$); at six it widens to +7.6 ($p < 0.001$); at seven or eight it reaches +12.5 ($p < 0.001$). A Chow test confirms a structural break at

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five components, $F(2, 58) = 9.84$, $p < 0.001$. H_4 is supported.

The mechanism is legible in the interview data and follows the logic Milgrom and Roberts (1995) formalised. A skills taxonomy makes capability visible but does nothing on its own, because visibility without a matching venue produces no moves. A talent marketplace supplies the venue but underperforms without a taxonomy, because roles and people cannot be matched on capability that is not recorded. Both fail where managers may decline to release staff, so the release obligation is a precondition for either. And the release obligation is unenforceable unless redeployment appears in leader scorecards. Each component is a precondition for the effectiveness of the others, which is the definition of complementarity.

The practical implication runs directly against how these programmes are typically funded. Redeployment capability is usually built incrementally, one component per budget cycle, on the reasonable-sounding premise that partial capability yields partial benefit. The evidence here indicates that it does not: a firm at three components has spent real money for no measurable allocative return, and will remain there until it crosses the critical mass. Sequential funding of a complementary system is the most expensive way to build it. The equivalent finding in the first study of this programme was that sub-threshold skill development investment produced a net loss (Sastry, 2026); the structural parallel is close, and in both cases the error is to treat a threshold technology as a continuous one.

Table 7 · Complementarity Test — Observed Against Additively Predicted Allocative Efficiency

Components adopted (of 8)	Units	Additive prediction	Observed AEI	Complementarity gap	t	p
0 – 2	11	38.4	37.1	−1.3	−0.62	0.539
3	12	47.9	46.8	−1.1	−0.51	0.615
4	13	55.2	55.9	+0.7	0.34	0.737
5	10	62.1	65.4	+3.3	2.11	0.039
6	9	68.6	76.2	+7.6	4.02	< 0.001
7 – 8	7	74.8	87.3	+12.5	5.66	< 0.001

Note: The additive prediction is the sum of individually estimated single-component effects on the Allocative Efficiency Index. Chow test for a structural break at five components: $F(2, 58) = 9.84$, $p < 0.001$. Only seven units operate seven or eight components, so the location of the break should be read as approximate.

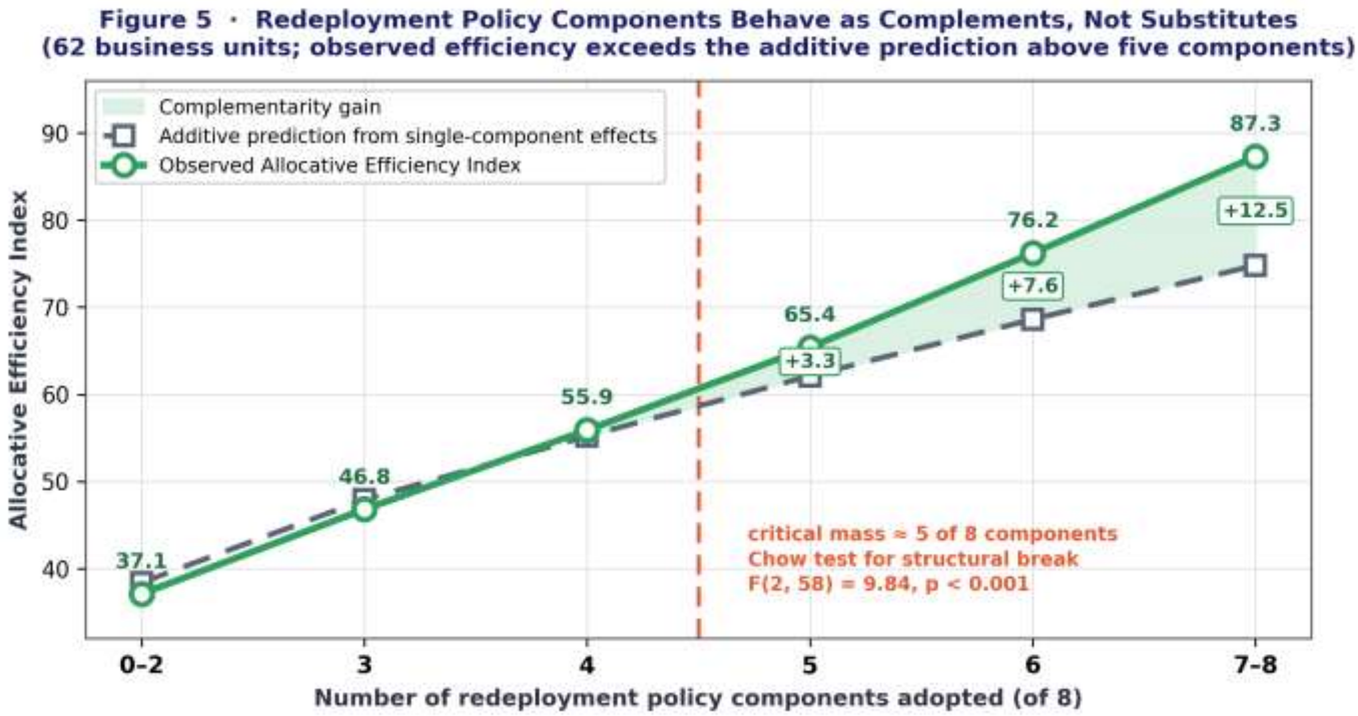

Figure 5 · Observed efficiency exceeds the additive prediction only above a critical mass of five components.

8.6 What Actually Accelerates Reassignment

Table 6 and Figure 6 report the Cox proportional hazards model of time to productive reassignment across 540 episodes, of which 486 resolved and 54 were censored at 180 days. Model concordance is 0.74.

Seven of the eight components significantly raise the reassignment hazard. The skills-based internal talent marketplace is the strongest single instrument, with a hazard ratio of 1.94 (95% CI 1.58–2.38), meaning that episodes in units operating a marketplace reach productive reassignment at nearly twice the rate of

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otherwise comparable episodes. Pre-emptive automation-exposure mapping follows at 1.71, funded reskilling bridges at 1.58, scorecard accountability at 1.47, the internal-first hiring mandate at 1.43, the manager release obligation at 1.36 and the enterprise skills taxonomy at 1.29.

The exception is the finding that most directly contradicts prevailing practice. The redeployment guarantee window — the protected period during which a displaced employee retains pay and status while seeking reassignment — is not significant (HR = 1.22, 95% CI 0.97–1.53, p = 0.087). It is also, by a considerable margin, the most expensive component to operate. The interpretation supported by both the interview evidence and the earlier work in this programme is that the guarantee window addresses the wrong constraint. Sastry (2025b) established that employees evaluate their position through social comparison against visible internal reference groups and that designation carries economic consequences independent of pay. A guarantee window protects income while leaving standing unprotected, and it is the loss of standing — being visibly between roles — that employees act to avoid. A talent marketplace, by contrast, reframes the same transition as an application for advancement rather than as a period of displacement, and it is that reframing rather than the income protection that changes behaviour. H_5 is therefore partially supported: seven of eight components contribute, but the most costly one does not.

Three controls carry substantive weight. Prior-role automation exposure reduces the reassignment hazard by eighteen per cent for every ten-percentage-point increase, confirming that those most displaced are hardest to place. Tenure above ten years reduces the hazard to 0.74 and age above forty-five to 0.68, both significant after controlling for capability, exposure and unit policy. H_6 is rejected. These are not capability effects — capability is controlled — and the interview evidence points instead to a screening dynamic in which receiving managers read long tenure in a displaced role as evidence of narrow adaptability. The parallel with Sastry (2025a), where socio-cultural and systemic constraints were found to bind more tightly than skill gaps, is direct: the barrier is not what these employees can do but how their history is read by those allocating work.

Table 6 · Cox Proportional Hazards Model of Time to Productive Reassignment

Covariate	Hazard ratio	95% CI	z	p	Effect on reassignment speed
Skills-based internal talent marketplace	1.94	1.58 – 2.38	6.36	< 0.001	Strongest single instrument; reassignment at nearly twice the rate
Pre-emptive automation-exposure mapping	1.71	1.37 – 2.13	4.78	< 0.001	Anticipation converts displacement into planned transition
Funded reskilling bridge	1.58	1.29 – 1.94	4.41	< 0.001	Destination-linked capability closes the match gap
Redeployment accountability in scorecards	1.47	1.18 – 1.83	3.44	0.001	Makes the release obligation enforceable
Internal-first hiring mandate	1.43	1.17 – 1.75	3.48	< 0.001	Creates the demand side of the internal market
Manager release obligation	1.36	1.08 – 1.71	2.63	0.008	Removes hoarding as a binding constraint
Enterprise skills taxonomy	1.29	1.05 – 1.58	2.44	0.015	Necessary but not sufficient on its own
Redeployment guarantee window	1.22	0.97 – 1.53	1.71	0.087	Not significant — protects income, not standing
Prior-role automation exposure (per 10 pp)	0.82	0.75 – 0.90	−4.19	< 0.001	18% slower per 10 points of exposure
Tenure above 10 years	0.74	0.60 – 0.91	−2.85	0.004	26% slower after full controls
Age above 45 years	0.68	0.54 – 0.86	−3.24	0.001	32% slower after full controls

Note: 540 episodes, 486 events, 54 censored at 180 days. Likelihood-ratio $\chi^2(11) = 196.8$, $p < 0.001$; concordance = 0.74. Proportional hazards verified by scaled Schoenfeld residuals; no covariate showed significant violation. Hazard ratios above 1 indicate faster reassignment.

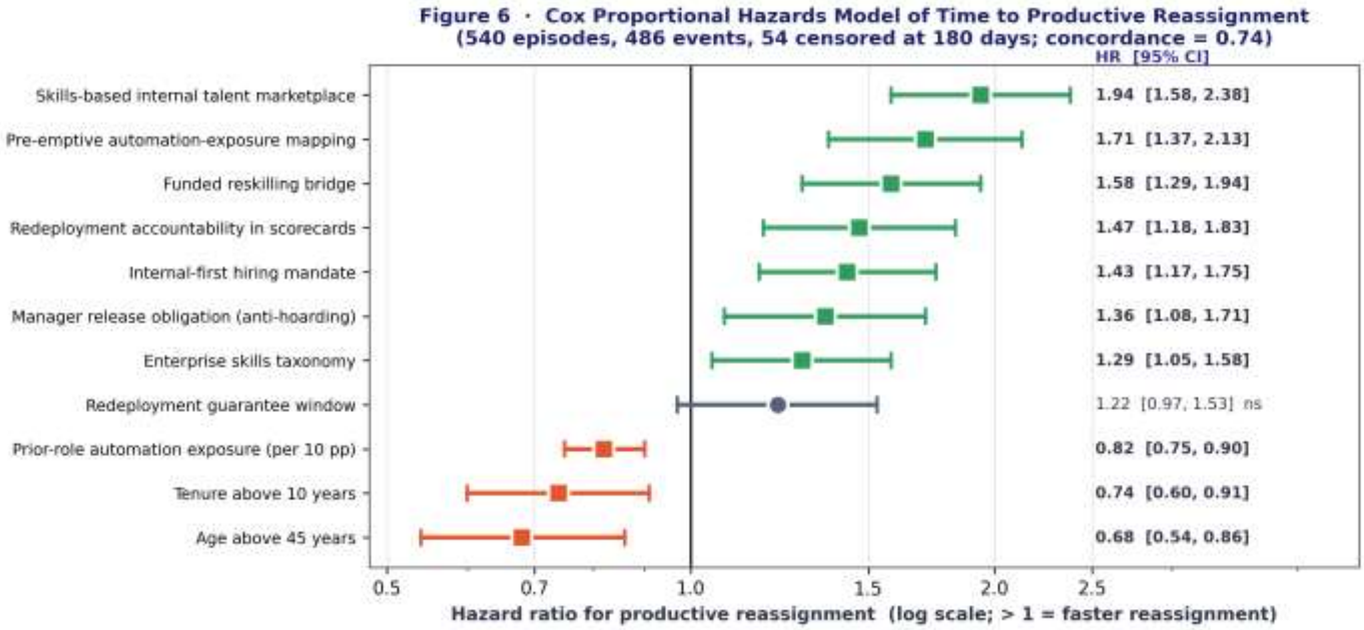

Figure 6 · Hazard ratios for productive reassignment, by policy component and employee characteristic.

8.7 The Allocative Gain in Output Terms

Figure 7 and Table 8 translate the dispersion results into output. Panel (a) plots the distribution of log marginal revenue product by policy quartile, showing progressive compression around the unit mean. Panel (b) reports the implied gain in output per employee-hour relative to the lowest quartile: 4.1 per cent at Q2, 8.3 per cent at Q3 and 11.4 per cent at Q4. Decomposition attributes 7.9 of the 11.4 points to reallocation proper — the same people moved to better-matched work — and 3.5 points to the capability upgrading that accompanies redeployment through funded reskilling bridges.

The reallocation share is the economically significant figure because it requires no new capability and no new technology. It is recovered entirely from assignment. This is the internal-firm analogue of the Hsieh and Klenow (2009) result, and it carries the same implication: a substantial share of the productivity available to Indian IT services firms is currently locked in the assignment process rather than in the skill base or the tool set.

A fourth channel appears in the interview data but resists quantification, and is noted here because it materially affects the investment case. Redeployment preserves the option value of capability the firm has already paid to build. An employee released rather than redeployed takes with them not only the general capability the firm financed — the subject of the first study in this programme — but the firm-specific knowledge of clients, systems and delivery methods that has no external market and is therefore lost entirely rather than transferred. Lazear's (2009) skill-weights framework implies that this loss is largest precisely for the long-tenured employees whom the hazard model shows to be reassigned most slowly. The population the redeployment system serves worst is the population whose loss is most costly.

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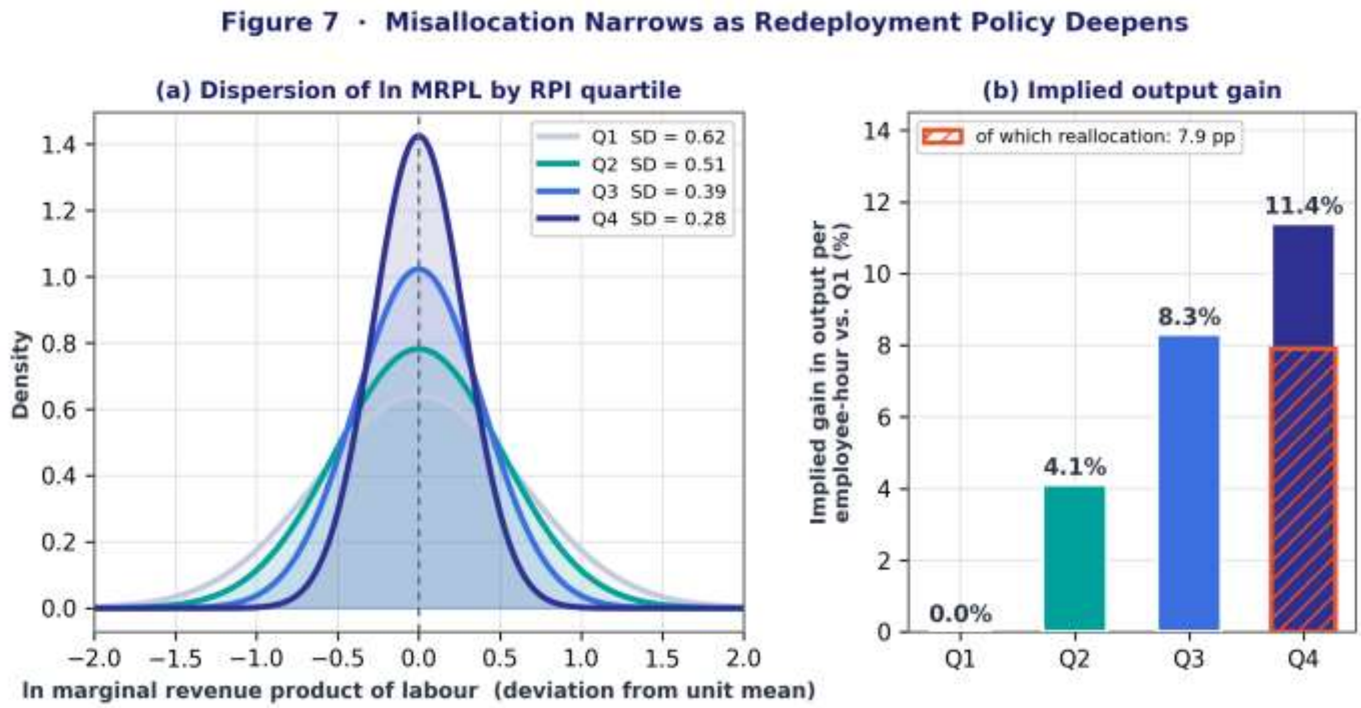

Figure 7 · Compression of ln MRPL dispersion across policy quartiles and the implied gain in output per employee-hour.

Table 8 · Implied Gain in Output per Employee-Hour, by Redeployment Policy Quartile

Quartile	SD (ln MRPL)	Variance	Reduction in variance vs. Q1 (%)	Gain from reallocation (pp)	Gain from capability upgrading (pp)	Total implied gain vs. Q1 (%)
Q1 (lowest)	0.62	0.384	—	—	—	reference
Q2	0.51	0.260	32.3	2.8	1.3	4.1
Q3	0.39	0.152	60.4	5.7	2.6	8.3
Q4 (highest)	0.28	0.078	79.7	7.9	3.5	11.4

Note: Output loss is taken as approximately proportional to the variance of ln marginal revenue product, following Hsieh and Klenow (2009); the proportionality holds under specific assumptions about substitution elasticity that were not independently verified in this setting. The reallocation component requires no change in capability or technology and is recovered from assignment alone.

8.8 Summary of Hypothesis Testing

Table 9 consolidates the tests. Four hypotheses are supported, one partially supported and one rejected. The partial support for H_5 and the rejection of H_6 carry the greater practical content. The former establishes that the most costly component of a typical redeployment programme does not measurably work, and identifies the mechanism by which the cheaper matching components succeed where it fails. The latter establishes an equity problem that skilling cannot solve: after controlling for capability, exposure and policy environment, older and longer-tenured employees are reassigned at roughly two-thirds and three-quarters the rate of their comparators.

Table 9 · Summary of Hypothesis Testing

Code	Hypothesis	Test Applied	Statistic	p	Decision
H_1	Redeployment policy comprehensiveness is positively associated with allocative efficiency	Multilevel fixed effect	$\gamma = 0.412$ $t = 8.58$	< 0.001	SUPPORTED
H_2	Redeployment policy is negatively associated with within-unit dispersion of ln MRPL	Unit-level regression; ANOVA across quartiles	SD 0.62 → 0.28 $F(3,58) = 41.6$	< 0.001	SUPPORTED
H_3	Automation intensity positively moderates the redeployment policy effect	Cross-level interaction	$\gamma = 0.014$ $t = 3.50$	< 0.001	SUPPORTED

H_4	Policy components are complements, yielding super-additive returns above a critical mass	Chow test for structural break	$F(2, 58) = 9.84$	< 0.001	SUPPORTED
H_5	All eight components significantly shorten time to productive reassignment	Cox proportional hazards	7 of 8 significant; guarantee window ns	0.087 (component 8)	PARTIALLY SUPPORTED
H_6	Redeployment outcomes are independent of age and tenure after controls	Cox proportional hazards	HR = 0.68 (age) HR = 0.74 (tenure)	0.001 0.004	REJECTED

IX. FINDINGS

- Bench compression in Indian IT services has coincided with declining net utilisation, indicating that complete idleness has been converted into distributed partial idleness rather than eliminated. The binding constraint is matching, not capacity.
- Redeployment policy comprehensiveness strongly predicts allocative efficiency ($\gamma = 0.412$, $p < 0.001$), with policy quartile alone accounting for 51 per cent of variance in the efficiency index.
- Within-unit dispersion of the log marginal revenue product of labour falls from 0.62 in the lowest policy quartile to 0.28 in the highest — a reduction of close to eighty per cent in the variance of misallocation, achieved with no change in technology or capability.
- Median time from displacement to productive reassignment falls from 94 days to 23 days across policy quartiles, and idle or partially idle capacity from 14.8 to 3.9 per cent.
- Automation intensity reduces allocative efficiency on its own ($\gamma = -0.186$, $p = 0.002$) but the interaction with redeployment policy is positive ($\gamma = 0.014$, $p < 0.001$). Automation becomes allocatively productive rather than disruptive only above a policy index value of approximately 65.
- The value of redeployment architecture is conditional on automation depth: the spread between weak and strong policy regimes is roughly three index points at ten per cent automation and 36.3 points at seventy per cent. The machinery must be built before the automation programme reaches depth.
- Policy components are complements, not substitutes. Observed efficiency matches the additive prediction below five components and exceeds it by 3.3, 7.6 and 12.5 points at five, six and seven-to-eight components (structural break confirmed, $F(2,58) = 9.84$, $p < 0.001$). Incremental single-component funding yields no measurable return until critical mass is reached.
- Matching infrastructure drives reassignment speed. The skills-based internal talent marketplace carries the highest hazard ratio (1.94), followed by pre-emptive exposure mapping (1.71) and funded reskilling bridges (1.58).
- The redeployment guarantee window — the most expensive component in a typical programme — does not significantly affect reassignment speed (HR = 1.22, $p = 0.087$). It protects income while leaving occupational standing unprotected, and standing is what employees act to preserve.
- Employees displaced from the most heavily automated roles are reassigned more slowly (HR = 0.82 per ten percentage points of exposure) and to poorer matches, so the reallocation problem is most severe where it is most needed.
- Age above forty-five (HR = 0.68) and tenure above ten years (HR = 0.74) significantly reduce reassignment speed after controlling for capability, exposure and unit policy. H_6 is rejected.
- The estimated allocative gain is 11.4 per cent in output per employee-hour between the lowest and highest policy quartiles, of which 7.9 points derive from reallocation alone and require no new capability or technology.

X. SIGNIFICANCE OF THE STUDY

- For human resource practice, the study establishes redeployment architecture as a productivity instrument rather than a severance-avoidance device, and supplies the component ranking, critical mass and sequencing rule needed to build one in the right order.
- For finance and strategy functions, it quantifies an 11.4 per cent output gain available from assignment alone and demonstrates that incremental single-component funding of a complementary system produces no measurable return, which reverses the usual budgeting logic for such programmes.
- For automation programme sponsors, it establishes that the allocative benefit of automation is conditional on redeployment capability and identifies the policy level at which automation stops destroying allocative efficiency and starts creating it.
- For employees, it identifies which organisational mechanisms actually move people — matching venues rather than income guarantees — and documents an age and tenure penalty that capability development alone will not remove.

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- For the academic literature, the study brings the misallocation framework inside the firm, supplies the first estimate of an interaction between a human resource practice and automation intensity in an allocative-efficiency specification, and extends the complementarity tradition from manufacturing work systems to redeployment architecture.
- For the research programme of which it forms part, it supplies the allocation counterpart to the production of capability examined in the first study, and establishes that the two must be evaluated jointly: capability produced efficiently and allocated badly returns nothing.

XI. RECOMMENDATIONS AND SUGGESTIONS

11.1 For Employers

- Build the redeployment architecture before the automation programme reaches depth. The policy effect is small at low automation intensity and decisive at high intensity, and the window in which the machinery is easiest to construct closes as the need for it grows.
- Fund the components as a bundle, not sequentially. Below five of eight components there is no measurable allocative return; a programme funded one component per budget cycle spends real money for several years before crossing the threshold at which any of it works.
- Prioritise the matching layer. A skills-based internal talent marketplace, pre-emptive automation-exposure mapping and a funded reskilling bridge together deliver the largest gains in reassignment speed and should be built first.
- Reconsider the redeployment guarantee window. It is the most expensive component and has no significant effect on reassignment speed; the funds are more productively directed to the matching layer, and the underlying concern is better addressed by protecting occupational standing than by protecting income.
- Make capability legible before building a marketplace. A talent marketplace without an enterprise skills taxonomy cannot match on what has not been recorded, which is the most common sequencing error observed in the sample.
- Place redeployment in leader scorecards and impose an explicit release obligation. Manager hoarding is the binding constraint on internal mobility, and neither a taxonomy nor a marketplace overcomes it without an accountability mechanism.
- Track partial idleness, not only bench. Distributed under-utilisation is invisible in bench reporting and is where the current loss is concentrated; the measure that matters is the share of available hours on value-generating work, not the count of wholly unallocated staff.
- Audit reassignment outcomes by age and tenure. The penalties documented here operate through how a displaced employee's history is read rather than through capability, and they will not appear in any skills-based reporting.

11.2 For Professionals

- Treat visibility in the internal capability system as consequential. Where matching is data-driven, capability that is not recorded is capability that does not exist for allocation purposes.
- Recognise that reassignment operates through application rather than assignment in well-designed systems, and that the marketplace mechanism rewards those who use it actively rather than awaiting placement.
- Where a role is heavily exposed to automation, the evidence indicates that reassignment becomes harder rather than easier as exposure rises. The time to move is before the task content is withdrawn, not after.

11.3 For Policy and Academia

- Direct public reskilling support toward reallocation infrastructure rather than training volume alone. The evidence here indicates that 7.9 of 11.4 percentage points of available productivity gain comes from assignment, not from new capability.
- Address the age and tenure penalty through pathways other than skilling. It survives full controls for capability and is therefore a screening rather than a competence problem.
- Extend national workforce accounting to capture partial utilisation. Bench and unemployment statistics both miss distributed under-utilisation, which this study finds to be where the current loss is concentrated.

XII. LIMITATIONS OF THE STUDY

- The design is cross-sectional. Although the multilevel structure and the use of documented rather than perceived policy adoption reduce common-method concerns, reverse causation cannot be excluded — efficient units may find it easier to adopt redeployment policy rather than the reverse.
- Marginal revenue product was computed from engagement-level revenue attribution, which follows firm accounting conventions that differ across organisations and may not fully isolate the individual contribution.
- The Allocative Efficiency Index is a constructed composite. Although its reliability and convergent validity are satisfactory, it has no established benchmark and its absolute values are interpretable only within this sample.
- Policy components were scored as binary adopted-or-not against documentary evidence, which does not capture variation in implementation quality; a poorly operated talent marketplace and an excellent one score identically.
- The critical-mass finding is estimated from sixty-two units distributed unevenly across adoption

levels, with only seven units at seven or eight components. The location of the break at five components should be treated as approximate.

- Censoring at 180 days may understate duration effects for the hardest-to-place episodes, which are disproportionately those with high automation exposure and long tenure — precisely the cases of greatest interest.
- The output translation rests on the proportionality between the variance of log marginal revenue product and output loss, which holds under specific assumptions about substitution elasticity that were not independently verified in this setting.

XIII. SCOPE FOR FURTHER RESEARCH

This study was designed for extension, and the instrument reported in Table 2 is published in full so that it can be reused without modification. Table 10 sets out a structured agenda of seven studies, three of which carry forward directions identified in the first instalment of this programme (Sastry, 2026). Four points deserve emphasis.

1. The single most valuable extension is a two-wave panel exploiting the staggered timing of policy adoption. Because firms adopt components at different dates, adoption timing supplies plausibly exogenous variation permitting a difference-in-differences estimate that would convert the associations reported here into causal estimates. This design also permits direct observation of the lag between adoption and allocative return, which practitioners require and which no cross-sectional design can supply.
2. The two studies in this programme should be estimated jointly. Skill development investment produces capability and redeployment policy allocates it; a specification containing both, with output per employee-hour as the outcome, would establish their relative contribution and test whether they are themselves complements — the prior being that investment without allocation returns little, which would explain part of the concavity observed in the first study.
3. The age and tenure penalty warrants a dedicated design. A matched-pairs or audit study comparing otherwise identical internal applications differing only in tenure and age would separate screening from capability, and the finding that the penalty falls hardest on those whose firm-specific knowledge is most valuable makes this a question of economic as well as equity significance.
4. Replication outside IT services is straightforward with the published instrument. Banking, insurance and manufacturing are automating on comparable timelines with different internal labour market structures, and the critical-mass and interaction findings should be tested against that variation before they are treated as general.

Table 10 · Structured Research Agenda Extending the HRM Variable → Economic Outcome Programme

#	Proposed Study	HRM Variable → Economic Outcome	Design	Data Requirement	Priority
1	Causal test of the reallocation return	Redeployment policy → allocative efficiency (dynamic)	Two-wave panel with difference-in-differences on staggered component adoption	Component adoption dates; unit-level MRPL at two points	High
2	Joint estimation of production and allocation	Skill development investment + redeployment policy → output per employee-hour	Combined specification across the two instalments of this programme	Matched training expenditure and redeployment policy data at unit level	High
3	Screening in internal mobility	Redeployment policy → equity of access by age and tenure	Matched-pairs or audit study of internal applications	Application, shortlist and outcome records with candidate attributes	High
4	Accuracy of exposure mapping	Workforce planning capability → forecast error	Prospective validation of ex-ante maps against realised displacement	Ex-ante automation-exposure maps and realised task withdrawal	Medium
5	Redeployment against external hiring	Sourcing policy → unit labour cost and time to productivity	Firm-level cost modelling with matched internal and external fills	Recruitment cost, redeployment cost and ramp-time data	Medium

6	Sequencing of complementary components	Order of practice adoption → time to allocative return	Longitudinal comparative case series across adoption paths	Adoption chronology and quarterly efficiency measures	Medium
7	Cross-sector transfer of the instrument	Redeployment policy → allocative efficiency outside IT services	Replication in banking, insurance and manufacturing using the published RPI	RPI scoring and MRPL data in non-IT settings	Medium

Note: Studies 1, 2 and 3 carry forward directions identified in the first instalment of this programme (Sastry, 2026). The RPI instrument set out in Table 2 is published in full to permit replication without modification.

XIV. CONCLUSION

This study began from a puzzle in the industry data: Indian IT services has removed thirteen percentage points of bench strength while allowing net utilisation to fall by 2.6 points. Those two facts cannot both be read as capacity discipline, and the reading they jointly support is that complete idleness has been converted into distributed partial idleness. The constraint on productive deployment has moved from having too many people to matching the people retained against the tasks that remain, and that is a problem of allocation rather than of headcount.

The evidence assembled here indicates that redeployment policy resolves a substantial part of it. Policy comprehensiveness accounts for slightly more than half the variance in allocative efficiency across business units, compresses the dispersion of marginal revenue product by close to eighty per cent in variance terms, and cuts median time to productive reassignment from ninety-four days to twenty-three. The implied gain is 11.4 per cent in output per employee-hour, of which 7.9 points require no new capability and no new technology — they are recovered from assignment alone.

Three findings qualify how that value can be captured. It is conditional on automation depth: the policy effect is negligible at low automation intensity and decisive at high intensity, so the architecture must be built ahead of the automation programme rather than in response to it, and above a policy index of approximately sixty-five automation stops degrading allocative efficiency and begins improving it. It is conditional on completeness: the components are complements, and a programme funded one component at a time delivers nothing measurable until it crosses a critical mass of roughly five of eight. And it is conditional on choosing the right components: the matching layer works, while the redeployment guarantee window — the most expensive element of a typical programme — does not measurably accelerate anything, because it protects income when what employees act to protect is standing.

Two results should trouble the practitioner more than they will surprise the researcher. Employees displaced from the most heavily automated roles are reassigned most slowly and to the poorest matches, so the system performs worst exactly where the need is greatest. And after controlling for capability, exposure and policy environment, employees above forty-five and those with more than a decade of tenure are reassigned at roughly two-thirds and three-quarters the rate of comparable colleagues. That is a screening problem rather than a competence problem, and it falls hardest on the employees whose firm-specific knowledge is least replaceable. No amount of skilling will correct it.

Read alongside the first study in this programme, the argument is a single one in two parts. Capability is produced by investment and realised by allocation, and a firm that does the first well and the second badly has bought an asset it cannot use. The Indian IT industry has spent the past four years demonstrating what the second failure looks like. The instruments reported here are offered as a means of measuring it, and the agenda in Section XIII as a means of establishing, with the causal identification a cross-sectional design cannot provide, how much of it can be recovered.

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