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Human Capital and the Productivity Payoff to R&D: Evidence from Egyptian Establishment Microdata

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Abstract

Productivity gains from technology expenditure are not automatic. Their size depends on whether firms can absorb and implement new knowledge. This study examines that margin using firm-level microdata from Egypt's Fifth Economic Census (2017/2018), covering roughly 166,000 establishments across 82 two-digit industries. The empirical framework is derived from a Cobb–Douglas production structure in which research expenditure is a productive input, and human capital raises its productivity elasticity, giving the interaction term a clear structural interpretation rather than the status of a control. The baseline outcome is net value added per worker; gross value added and gross output per worker are used as alternative measures. Across specifications with two-digit industry fixed effects, research expenditure is positively and precisely associated with productivity, and the association is significantly stronger in firms with more educated workers. The complementarity holds whether human capital is measured by a broad post-secondary skill share or by a tighter university-educated share, and is sharper for value-added outcomes than for gross output — the ranking the framework predicts. The results provide the first establishment-population evidence on R&D–human-capital complementarity in Egypt and translate into a concrete policy lesson: support for firm-level innovation is likely to be more effective when paired with strengthening of workforce skills, technical training, and complementary capacity building.

Keywords: Egypt; productivity; research and development; human capital; absorptive capacity; firm-level microdata.

JEL classification: D24; J24; L25; O14; O32; O33.

[1]The views expressed in this paper are those of the author and do not necessarily represent the views of Damanhour University or Innovation, Science and Economic Development Canada.

1 Introduction

Productivity growth is central to development, but it is hard to manufacture at the firm level.[2] For middle-income economies, better performance depends not only on accumulating capital but on how effectively firms reorganize production, adapt technologies, and solve implementation problems. Research and development is at the heart of that story: it is the most visible form of deliberate technology investment. Yet the returns to research spending are rarely automatic. They depend on whether the firm has the internal capability to understand, adapt, and use what that spending produces.

That idea is the absorptive-capacity argument. In the classic formulation of Cohen and Levinthal (1990), prior knowledge makes new knowledge more useful. The same logic runs through the broader work on technology transfer and growth. Borensztein et al. (1998) show that the gains from foreign technology depend on the human capital of the recipient economy, while Griffith et al. (2004) document that the productivity payoff from R&D in OECD industries is larger where domestic absorptive capacity is stronger. At the establishment level, the implication is direct: the productivity payoff from research expenditure should be larger where the workforce has the skills needed to implement and scale new ideas.

Why Egypt, and why now. Egypt is a uniquely informative setting in which to test that mechanism, for three reasons. First, the country has placed technology upgrading and scientific research at the centre of its development strategy. The 2014 Constitution explicitly commits the state to devote at least 1% of gross national product to scientific research and to increase that share over time (Constitute Project, 2014). The Global Innovation Index reports gross expenditure on R&D at about 1.02% of GDP in Egypt in 2022, compared with 1.32% in Türkiye in the same year (World Intellectual Property Organization, 2024a,b). OECD reporting indicates that business-enterprise R&D nonetheless accounts for a relatively small share of total R&D spending in Egypt, with most activity still concentrated in the public and higher-education sectors, and that weaknesses in measurement and classification, especially for firm-level and applied innovation, make it difficult to identify which activities are being supported and whether policy is effectively targeted (OECD, 2025).

Second, the human-capital constraint is equally important. Egypt's Human Capital Index was 0.49 in 2020, indicating that future worker productivity is substantially below its potential under prevailing health and education conditions; the gap between expected years of schooling and learning-adjusted years of schooling further suggests that formal schooling does not translate

[2]The unit of observation in the Economic Census is the establishment. Throughout the paper, "firm" is used as shorthand for the establishment-level production unit observed in the data.

fully into effective skills (World Bank, 2020).[3] Together, the policy push toward innovation, the modest scale of private-sector R&D, and persistent concerns about workforce skills make Egypt a natural setting in which to ask whether technology spending is associated with higher productivity and whether that association varies with human capital. Current policy initiatives point in the same direction: Egypt's entrepreneurship and digital-upgrading programs explicitly emphasize not only technology adoption but also the skills and capabilities needed to use that technology effectively (Information Technology Industry Development Agency, 2026).

Third, the Egyptian Economic Census provides exactly the data the question requires. It records research and experimental expenditure as a separate cost item rather than relying on technology dummies or qualitative survey questions, it records the educational composition of the workforce in enough detail to construct meaningful skill shares, and it spans the full establishment population at the two-digit ISIC level. This combination is rare in the developing-economy firm literature, where direct measurement of R&D is usually limited to manufacturing surveys or to small samples of large firms. The census makes the absorptive-capacity question observable for an establishment population of roughly 166,000 active producing units across 82 two-digit industries, including not only manufacturing but also trade, services, transport, professional activities, education, and health.

Research questions and approach. The paper studies two related questions. First, is firm-level research expenditure associated with higher productivity in Egypt? Second, does human capital strengthen that association, as an absorptive-capacity view would predict? The empirical specification is derived from a production structure in which research expenditure is a productive input and the elasticity of productivity with respect to research expenditure is itself a function of the workforce skill share. This means the interaction between research expenditure and human capital is not an auxiliary control: it is the structural counterpart of the absorptive-capacity parameter, and a positive estimate is a direct test of the model's central prediction. The baseline productivity measure is net value added per worker. Gross value added per worker and gross output per worker are used as alternative outcomes, but the discussion keeps net value added at the centre because that measure is closer to the underlying productivity concept and less directly driven by intermediate-input intensity.

What the data say. Two patterns emerge from the estimates. Firms that report higher research expenditure tend to have higher productivity, and the relationship is significantly stronger

[3] Expected years of schooling measure the number of years of education a child is expected to complete under current enrollment patterns. Learning-adjusted years of schooling discount this measure by actual learning outcomes.

in firms with more educated workers. The direct R&D coefficient and the interaction term both fall within the indicative ranges suggested by the firm-level R&D and absorptive-capacity literatures (Hall et al., 2010; Aw et al., 2007; Yang et al., 2010; Yasar, 2013). The interaction is economically gradual, which is exactly what a census cross-section dominated by small firms with limited formal R&D would predict, but it is statistically robust for value-added outcomes and stable across alternative human-capital measures. It is sharper for value added than for gross output, which is the theoretically expected ranking, since gross output loads more heavily on intermediate-input intensity and product mix. Capital elasticities sit close to conventional capital-share benchmarks.

Contribution. The paper makes three contributions. First, on *measurement and coverage*, it provides the first census-wide, establishment-level evidence on R&D–human-capital complementarity for Egypt, using direct monetary measures of research expenditure and direct measures of workforce education rather than qualitative innovation indicators or restricted manufacturing samples. Second, on *framework*, the empirical interaction term has a structural interpretation: it is the absorptive-capacity parameter σ_1 from a constant-returns production technology in which research expenditure is a productive input. This anchors the interpretation of the coefficient and makes the empirical exercise a genuine test of the model rather than a pattern detection exercise. Third, on *policy*, the paper supplies a quantitative basis for a policy distinction that Egypt's industrial and digital strategies are increasingly making in qualitative terms: that technology support and capability building are complements, not substitutes, and that programs targeting one without the other are likely to underperform (OECD, 2025; Information Technology Industry Development Agency, 2026). Existing Egyptian work has shown that knowledge, technology, finance, and business conditions matter for firm performance (Sami and El Bedawy, 2019; Chaffai and Plane, 2017; Sami and Abdallah, 2022; Saadi et al., 2024), but it has not directly estimated whether measured research expenditure is associated with productivity and whether that relationship is conditioned by workforce skill within the same establishment population.

Interpretation and scope. Two scope conditions are stated up front. The estimates are conditional associations from a large cross-section, identified within two-digit industries; they are not interpreted as quasi-experimental treatment effects, and selection on unobservables remains a possibility. The paper is correspondingly transparent about what the cross-section can and cannot show, and the policy discussion is framed in those terms. The qualitative pattern, however, is robust to the alternative outcome and human-capital definitions a referee would naturally request, lines up across sectors, and reproduces the sign and rough magnitude predicted

by the absorptive-capacity literature. That, plus the policy timeliness in Egypt, is what the paper offers.

Roadmap. Section 2 reviews the related literature. Section 3 lays out the theoretical framework leading to the empirical specification, with the full derivation in Appendix A. Section 4 describes the census data, variable construction, and empirical method. Section 5 reports the main results and the robustness exercises. Section 6 turns to policy discussion. Section 7 concludes.

2 Related literature

The paper sits at the intersection of two literatures. One asks how technology investment and knowledge-related activity shape firm productivity. The other argues that human capital raises the payoff to those investments by strengthening absorptive capacity. The Egypt-specific evidence is informative but incomplete on the precise margin studied here.

A first strand shows that knowledge-related capabilities matter for Egyptian firms even when direct measures of R&D are scarce. Using Economic Census data, Sami and El Bedawy (2019) document a positive relationship between knowledge-management intensity and total factor productivity. Chaffai and Plane (2017) show that technology heterogeneity and export status help explain productivity differences across Egyptian manufacturing firms, with considerable variation across sectors. Sami and Abdallah (2022) find that knowledge variables help account for productivity differences across private Egyptian firms once endogeneity is addressed with an instrumental-variables strategy. Other contributions emphasize technology type, operating structure, and industry dynamics rather than formal research expenditure itself (El-Shinnawy, 2010; Abulezz and Sherief, 2020). Taken together, these studies leave little doubt that technology and knowledge matter for Egyptian firms. What they say less directly is whether *research spending itself* is associated with higher productivity and whether that association depends on workforce skill.

A second set of studies points to finance and business conditions as important mediators of innovation effort. Using Enterprise Survey data, Saadi et al. (2024) show that access to bank credit increases the likelihood of innovation activity in Egypt. At the regional level, Giovanis and Ozdamar (2018) find that business-climate constraints are associated with weaker firm performance across the MENA region. This matters for the present paper because the observed R&D–productivity relationship in a census cross-section may reflect not only technology but also differences in financing capacity, local business conditions, and managerial quality. Those

concerns do not undermine reduced-form associations, but they discipline the way the estimates are interpreted, and the paper engages with them explicitly in the identification discussion.

Evidence from other emerging economies helps clarify the mechanism. In Tunisia, Ben Khalifa (2023) links R&D and information-and-communication-technology investment to innovation outcomes and then to productivity, stressing that technology inputs tend to work together rather than in isolation. Using Chinese electronics firms, Yang et al. (2010) show that R&D and human-capital investment are both positively associated with productivity. Aw et al. (2007) find that R&D, worker training, and export-market participation jointly shape productivity dynamics in Taiwanese electronics. Griffith et al. (2004) document, at the industry level across the OECD, that the productivity payoff to R&D is larger where absorptive capacity is stronger. The recurring lesson is that technology investment often pays off, but the magnitude of the payoff varies systematically with complementary capabilities.

That complementarity is precisely what the absorptive-capacity literature predicts. Cohen and Levinthal (1990) argue that firms invest in research not only to generate knowledge internally but also to improve their ability to evaluate and use external knowledge. Dai and Yu (2013) show that learning-by-exporting is stronger in firms that had already invested in research before export entry. Yasar (2013) finds that the productivity payoff to imported capital inputs is larger in firms with stronger absorptive capacity. López-Acevedo and Tan (2003) and Moreira Vaz (2013) likewise emphasize complementarities between workforce training, research, and productivity performance. The recurring message is that technology spending does not operate in a vacuum: firms need some stock of internal capability before external exposure or formal R&D can translate into efficiency gains.

What remains limited for Egypt is direct evidence that combines research expenditure, workforce composition, and firm productivity in a single establishment-population setting. That is the gap this paper addresses. The objective is not to claim that Egypt is unique. It is to bring direct evidence to a policy question that is increasingly central in Egypt's development strategy: whether innovation support is likely to deliver larger productivity payoffs when it is paired with skill formation inside the firm.

3 Theoretical framework

The model provides a microfoundation for the estimating equation by treating research expenditure as a productive input whose elasticity depends on human capital. The point is not to build a full dynamic growth model. It is to derive the regression equation from an equilibrium production problem and to make the interaction between research expenditure and human cap-

ital a *prediction* of the model rather than an imposed empirical device. Appendix A provides the full derivation, including all proofs.

Consider a firm i in industry j. The final good is the numeraire, so its price is normalized to one. Output is produced with physical capital K_i, labor L_i, and research expenditure M_i. The technology is

$$Y_i = A_i K_i^{\alpha} L_i^{\beta_i}, \qquad A_i = A_0 \mu_i, \qquad \mu_i = \Phi_j \exp(\psi h_i) M_i^{\sigma(h_i)}. \tag{1}$$

A useful way to read (1) is to write it in unwrapped Cobb-Douglas form,

$$Y_i = A_0 \Phi_j \exp(\psi h_i) K_i^{\alpha} L_i^{\beta_i} M_i^{\sigma(h_i)}, \tag{2}$$

where $h_i \in [0, 1]$ is the human-capital share of the workforce, Φ_j is an industry-level technology shifter, and A_0 is common baseline technology. The research elasticity is the affine function

$$\sigma(h_i) = \sigma_0 + \sigma_1 h_i, \qquad \sigma_0 > 0, \qquad \sigma_1 > 0. \tag{3}$$

This is the absorptive-capacity channel of the model. Research expenditure raises technology, and the elasticity of technology with respect to research is larger when the workforce has stronger human capital. The formulation is close in spirit to the treatment of research effort as a costly input into innovation in Aghion and Howitt (2008), with the additional feature that the productivity of research depends on internal capability, in the spirit of Cohen and Levinthal (1990).

Why an affine $\sigma(h)$. The affine form (3) is the simplest specification that delivers the model's qualitative prediction (positive cross-derivative of productivity with respect to research and human capital) while remaining log-linear after taking logs of the intensive-form productivity function. It can be read as the first-order term in a Taylor expansion of an arbitrary smooth elasticity $\sigma(h)$ around $h = 0$; richer functional forms would generate the same testable comparative static under standard regularity conditions, at the cost of additional parameters that the cross-section cannot identify separately.

Because research expenditure is part of the productive technology, the constant-returns-to-scale restriction is

$$\alpha + \beta_i + \sigma(h_i) = 1, \qquad \beta_i \equiv 1 - \alpha - \sigma(h_i) > 0. \tag{4}$$

Since $\sigma(h_i)$ varies with human capital, the labor exponent is firm-specific. A fixed labor exponent would be consistent with constant returns for all firms only if $\sigma_1 = 0$, which would shut down

the absorptive-capacity mechanism.

The firm chooses inputs taking the wage W_i and the rental rate of capital R_i as given. One unit of research expenditure costs one unit of the final good, following Aghion and Howitt (2008). The production-stage problem is

$$\max_{K_i, L_i, M_i} \Pi_i = A_0 \Phi_j \exp(\psi h_i) K_i^{\alpha} L_i^{\beta_i} M_i^{\sigma_i} - R_i K_i - W_i L_i - M_i, \tag{5}$$

where $\sigma_i \equiv \sigma(h_i)$ and $\beta_i = 1 - \alpha - \sigma_i$. With constant returns, a competitive interior equilibrium pins down input ratios rather than scale. The first-order conditions are

$$R_i = \alpha \frac{Y_i}{K_i}, \qquad W_i = \beta_i \frac{Y_i}{L_i}, \qquad 1 = \sigma_i \frac{Y_i}{M_i}. \tag{6}$$

Hence the equilibrium capital intensity and research intensity satisfy

$$\frac{K_i^*}{L_i^*} = \frac{\alpha}{\beta_i} \frac{W_i}{R_i}, \qquad \frac{M_i^*}{L_i^*} = \frac{\sigma_i}{\beta_i} W_i. \tag{7}$$

The observed capital per worker and research expenditure per worker can therefore be interpreted as realized equilibrium intensities. Defining $k_i \equiv K_i/L_i$ and $m_i \equiv M_i/L_i$, substituting into (2), and using the constant-returns restriction in (4), gives the intensive-form productivity equation

$$\frac{Y_i}{L_i} = A_0 \Phi_j \exp(\psi h_i) k_i^{\alpha} m_i^{\sigma_0 + \sigma_1 h_i}. \tag{8}$$

Taking logs yields the equation that motivates the empirical work:

$$\ln\left(\frac{Y_i}{L_i}\right) = \ln A_0 + \ln \Phi_j + \alpha \ln k_i + \psi h_i + \sigma_0 \ln m_i + \sigma_1 h_i \ln m_i. \tag{9}$$

Proposition 1 (Absorptive capacity and the research-productivity gradient)**.** *Under* (2)–(4)*, the elasticity of labor productivity with respect to research expenditure per worker is increasing in human capital:*

$$\frac{\partial \ln(Y_i/L_i)}{\partial \ln m_i} = \sigma_0 + \sigma_1 h_i, \qquad \frac{\partial^2 \ln(Y_i/L_i)}{\partial h_i \, \partial \ln m_i} = \sigma_1 > 0. \tag{10}$$

The regression specification follows from (9). Industry fixed effects absorb $\ln \Phi_j$. The estimating equation is

$$\ln\left(\frac{Y_i}{L_i}\right) = c + \alpha \ln\left(\frac{K_i}{L_i}\right) + \theta h_i + \beta_R \ln m_i + \beta_{Rh} \, h_i \ln m_i + \delta_j + \varepsilon_i, \tag{11}$$

with the structural mapping

$$\theta = \psi, \qquad \beta_R = \sigma_0, \qquad \beta_{Rh} = \sigma_1, \qquad \delta_j = \ln \Phi_j. \tag{12}$$

The interaction coefficient is therefore the empirical counterpart of the absorptive-capacity parameter. A positive estimate of β_{Rh} means that firms with stronger human capital obtain a larger productivity payoff from research expenditure, exactly the mechanism emphasized in the firm-level literature on R&D, training, and productivity (Aw et al., 2007; Yang et al., 2010; Yasar, 2013; Griffith et al., 2004).

Remark 1 (Why the empirical equation keeps m_i)**.** *The equilibrium ratios in* (7) *imply that* m_i *is an optimal research intensity. One could substitute the second ratio into* (8) *and write labor productivity entirely in terms of factor prices and parameters. That fully substituted equation is theoretically useful, but it would eliminate the observed research-intensity variable from the empirical specification. The paper therefore estimates the conditional intensive-form equation* (11)*, using the realized* m_i *observed in the census. This keeps the estimating equation aligned with the data while still grounding* m_i *in the firm's equilibrium input choice.*

3.1 Expected signs and benchmark magnitudes

Table 1 summarizes the expected signs and plausible magnitudes for the key coefficients. The benchmark ranges are not priors or mechanical acceptance bands. They are intended as discipline for interpretation. Capital elasticities around one third are standard in the broader income-share literature (Gollin, 2002). Positive direct effects of education and training on productivity are well established in firm-level and aggregate work (Black and Lynch, 1996; de la Fuente, 2011). Surveys of R&D returns generally find positive but modest private-productivity elasticities, with many estimates clustering in the low decimals (Hall et al., 2010). Absorptive-capacity arguments suggest that the interaction between research expenditure and skill should also be positive, and small relative to the direct capital coefficient (Cohen and Levinthal, 1990; Aw et al., 2007; Yang et al., 2010; Yasar, 2013).

4 Data and empirical method

4.1 Economic Census data and estimation sample

The analysis uses establishment-level microdata from Egypt's Fifth Economic Census (2017/2018), compiled by the Central Agency for Public Mobilization and Statistics (CAPMAS) and dis-

Table 1: Expected signs and indicative benchmark ranges

Parameter	Economic meaning	Sign	Indicative range	Selected basis in the literature
α	Elasticity of productivity with respect to capital per worker	+	0.20 to 0.40	Capital-share benchmarks and productivity regressions typically place the coefficient near one third (Gollin, 2002).
θ	Direct effect of the human-capital proxy	+	0.05 to 0.25	Education and training tend to raise firm productivity, though magnitudes vary with the skill measure and sector (Black and Lynch, 1996; de la Fuente, 2011).
β_R	Direct research-productivity association at $h_i = 0$	+	0.01 to 0.12	Firm-level private returns to R&D are usually positive and often modest in size (Hall et al., 2010).
β_{Rh}	Complementarity between research expenditure and workforce skill	+	0.005 to 0.05	Absorptive-capacity arguments and firm-level evidence suggest a positive but comparatively small interaction term (Cohen and Levinthal, 1990; Aw et al., 2007; Yang et al., 2010; Yasar, 2013).

The ranges are interpretive guides rather than structural restrictions. Because the empirical human-capital variable is a workforce share, the coefficients on skill and the interaction term should be read as magnitudes that are plausible in firm-level productivity regressions, not as factor shares.

tributed through the Economic Research Forum's Open Access Micro Data Initiative (OAMDI, 2022). The unit of observation is the establishment. The census records information on employment, value added, output, fixed assets, selected expenditure items including research and experimental spending, and the educational composition of the workforce, all classified at the two-digit ISIC Rev. 4 level. That breadth is essential here because the question is inherently comparative: whether establishments operating within the same broad industry exhibit different productivity outcomes depending on research expenditure and workforce composition.

The baseline estimation sample contains roughly 166,000 establishments after dropping observations with missing values or with the nonpositive entries that the logged specification cannot accommodate. The exact number varies slightly across columns because the alternative human-capital and outcome measures are not observed for exactly the same firms. The sample is cross-sectional, so the empirical design emphasizes comparison across firms rather than within-firm change over time. Appendix B provides further details on data construction, sectoral coverage, and the full list of two-digit industries entering the regressions.

4.2 Variable construction

Net value added per worker is the main productivity measure. That choice is deliberate. Value-added-based outcomes are less sensitive than gross output to cross-firm differences in

intermediate-input intensity and are closer to the productivity concept implied by the framework. Gross value added per worker and gross output per worker are retained as alternative outcomes precisely so that the reader can see whether the result strengthens or weakens as the measurement basis becomes broader.

Research expenditure is measured by research and experimental spending per worker. Capital intensity is measured by fixed (invested) capital per worker. Human capital is proxied in two ways: a baseline measure equal to the share of workers with above-intermediate or university education, and a tighter alternative equal to the share of workers with university education only. Both are intended to capture the internal capability needed to interpret and implement new knowledge, but the university-share proxy places more weight on the upper tail of the formal-education distribution.

All monetary variables enter the regressions in logarithms with a one-unit shift, $\ln(1 + x)$. The shift is necessary because research expenditure includes many zero observations; without it, those firms would drop out and the sample would be selected on a strictly positive R&D outlay. The one-unit shift is small relative to the typical scale of the underlying variables and is applied uniformly across the productivity, capital and research measures, so it does not bias the comparative-statics interpretation of the coefficients.

Table 2: Variables used in the empirical analysis

Object in the paper	Definition used in estimation
Net value added per worker	Baseline productivity outcome; logged monetary measure.
Gross value added per worker	Alternative value-added productivity outcome; logged monetary measure.
Output per worker	Alternative gross-output productivity outcome; logged monetary measure.
Research expenditure per worker	Research and experimental expenditure per worker; logged with a unit shift to retain zero outlays.
Capital per worker	Fixed (invested) capital per worker; logged monetary measure.
Skilled share	Share of workers with above-intermediate or university education.
University share	Share of workers with university education.
Industry fixed effects	Two-digit economic-activity indicators (ISIC Rev. 4).

4.3 Descriptive patterns

Table 3 reports summary statistics for the main regression variables. Three features stand out. First, productivity dispersion is wide, which is typical of firm-level census data and consistent with the well-documented persistence of within-industry productivity heterogeneity (Syverson,

2011). Second, research expenditure is highly skewed: the mean logged value is small relative to the upper tail, consistent with a large mass of firms reporting little or no formal research activity and a much smaller group undertaking substantial spending. Third, human capital is unevenly distributed, with both the skilled and university shares ranging from zero to one and pronounced mass at both extremes.

These features matter for interpretation. In data like these, research expenditure is unlikely to capture only frontier innovation; it is more likely to combine formal R&D with applied problem-solving and various forms of incremental upgrading. Far from weakening the exercise, this makes it more relevant for a middle-income economy where productivity growth often comes through adoption, adaptation, and organizational improvement rather than patented invention alone.

Table 3: Summary statistics

Variable	N	Mean	SD	Min	Max
Net value added per worker (log)	166,691	10.786	0.987	0.000	19.709
Gross value added per worker (log)	167,412	10.824	0.989	0.000	19.713
Output per worker (log)	170,292	11.016	1.505	0.000	19.910
Research expenditure per worker	170,330	0.066	0.650	0.000	16.242
Skilled share	169,777	0.266	0.351	0.000	1.000
University share	170,011	0.208	0.317	0.000	1.000
Capital per worker	169,897	10.343	1.364	0.115	21.627
Employment	170,330	15.517	184.339	1.000	24,432.000

Summary statistics are reported for the working variables used in the regression analysis. Monetary variables are expressed per worker and logged with a one-unit shift where described in the text.

4.4 Empirical specification

The estimating equation follows directly from the intensive-form expression derived in Section 3. Let i index establishments and let $j(i)$ denote the two-digit industry in which establishment i operates. The baseline specification is

$$\ln y_i = c + \alpha \ln k_i + \theta h_i + \beta_R \ln m_i + \beta_{Rh}\, h_i \ln m_i + \delta_{j(i)} + \varepsilon_i, \tag{13}$$

where y_i is labor productivity, k_i is capital per worker, m_i is research expenditure per worker, h_i is the human-capital share, and $\delta_{j(i)}$ is a full set of two-digit industry fixed effects. The baseline outcome is net value added per worker; gross value added per worker and gross output per worker are used as alternative productivity measures, and the specification is re-estimated with the university-share proxy replacing the broader skilled-share measure.

The specification is estimated by ordinary least squares with heteroskedasticity-robust standard errors. The fixed effects are cross-sectional industry indicators rather than establishment

fixed effects over time. They absorb all additive differences across two-digit industries, including broad differences in production technology, input intensity, demand conditions, accounting conventions, and average research opportunities. Equivalently, the coefficients are estimated from within-industry variation after deducting industry means: if $\tilde{x}_i$ denotes the residual from projecting a variable x_i on the industry indicators, then the coefficient vector is the OLS coefficient from the residualized regression

$$\widetilde{\ln y_i} = \alpha \widetilde{\ln k_i} + \theta \widetilde{h_i} + \beta_R \widetilde{\ln m_i} + \beta_{Rh} \widetilde{h_i \ln m_i} + \widetilde{\varepsilon_i}. \tag{14}$$

The identifying comparison is therefore not between firms in different sectors. It is between firms operating within the same two-digit industry, conditional on capital intensity, research intensity, workforce composition, and the interaction between research intensity and human capital.

The coefficient of interest is β_{Rh}. The model predicts that the productivity gradient with respect to research expenditure depends on human capital:

$$\frac{\partial \, \mathrm{E}[\ln y_i \mid \ln k_i, h_i, \ln m_i, \delta_{j(i)}]}{\partial \ln m_i} = \beta_R + \beta_{Rh} h_i. \tag{15}$$

Thus, β_R is the research-productivity gradient when $h_i = 0$, while β_{Rh} measures how that gradient changes with the human-capital share. A positive β_{Rh} means that research expenditure is more strongly associated with productivity in firms with more educated workers. In the language of the theoretical framework, β_{Rh} is the empirical counterpart of the absorptive-capacity parameter σ_1.

4.5 Identification, threats to inference, and what the cross-section can credibly show

The maintained identifying restriction is a conditional mean restriction:

$$\mathrm{E}\big[\varepsilon_i \mid \ln k_i,\ h_i,\ \ln m_i,\ h_i \ln m_i,\ \delta_{j(i)}\big] = 0. \tag{16}$$

Under this condition, OLS coefficients recover conditional productivity gradients within industries. The assumption is transparent and demanding, and it is worth being explicit about exactly what could violate it and how the design pushes back.

(i) Selection on observed firm characteristics. The two-digit industry fixed effects absorb broad differences in production technology, input intensity, accounting practice, and product market structure. Within an industry cell, the residualized comparison in (14) is between

firms that share these underlying conditions. Capital per worker is held constant in the same regression, and human capital enters separately so that the interaction term is identified from variation in the joint distribution of $h_i \ln m_i$ that is orthogonal to either margin alone. This is a meaningful amount of conditioning even before any unobservable enters the discussion.

(ii) Selection on unobservables: managerial quality and access to finance. Establishments choose research expenditure and workforce composition jointly with managerial quality, access to credit, and product-market position, none of which is directly observed in the census. If unobserved managerial quality raises both productivity and reported research, the OLS coefficient on $\ln m_i$ will be biased upward, and the same logic could in principle apply to the interaction term if managerial quality also correlates with the workforce skill share. Two features mitigate this concern. First, the existing Egyptian evidence shows that finance and business conditions matter for innovation effort (Saadi et al., 2024; Giovanis and Ozdamar, 2018), but those studies do not find that finance fully *accounts for* innovation–productivity links once observable controls are included. Second, the structural prediction being tested is not the level of β_R but the sign and direction of the cross-derivative β_{Rh}. For unobserved managerial quality to mechanically generate a positive β_{Rh}, it would have to correlate positively and disproportionately with the joint occurrence of high research spending and a skilled workforce, beyond what its correlation with each margin separately implies. This is a stricter requirement than an upward bias on β_R alone.

(iii) Simultaneity in input choices. Following the standard production-function literature (Griliches and Mairesse, 1995; Levinsohn and Petrin, 2003; Ackerberg et al., 2015), simultaneity between productivity and contemporaneous input choices typically biases the labor and capital coefficients more than the R&D coefficient, and the cross-section here cannot apply the within-firm timing strategies that those papers exploit. The interpretation is therefore deliberately reduced-form: the estimates are conditional associations from a large cross-section, disciplined by the production framework and by within-industry comparisons. They are not interpreted as structural treatment effects.

(iv) Measurement of R&D. Reported research expenditure in a census is a noisy measure of underlying technology effort. Some firms classify applied problem-solving as research; some genuine innovators do not record it as a separate line item. Classical measurement error in $\ln m_i$ would attenuate β_R toward zero and complicate interpretation of β_{Rh}. The robustness section therefore looks at whether the qualitative pattern survives across alternative outcome

measures (net value added, gross value added, gross output) and across alternative human-capital definitions (broad skill share versus university-only share). The pattern survives, with the strongest evidence appearing in the value-added specifications, where measurement is more defensible.

(v) What the design *does not* claim. The cross-section does not identify causal effects of R&D on productivity, does not account for selection into reporting positive research expenditure, and does not separate within-firm dynamics from across-firm composition. The contribution of equation (13) is therefore not to claim quasi-experimental variation. It is to test the model's central prediction in the available census data: the association between research expenditure and productivity is stronger when establishments have greater human-capital capacity. The reduced-form orientation is consistent with the broader productivity literature, which routinely emphasizes that large differences across firms remain even within narrowly defined industries and that R&D-return estimates are sensitive to measurement, simultaneity, and the specification of production relationships (Syverson, 2011; Hall et al., 2010).

5 Results

5.1 Net value added per worker: the main specification

Table 4 keeps the focus on the paper's main outcome, net value added per worker. Column (1) uses the broader skilled-share proxy; column (2) replaces it with the university share. The pattern is stable across the two measures.

Research expenditure enters positively in both columns. The direct coefficient is 0.034 with the broad skill-share proxy and 0.039 with the university-share proxy. These are modest but precisely estimated gradients, economically sensible for census data in which formal research spending is uncommon and often reflects incremental technological improvement. Human capital also enters positively. A ten-percentage-point increase in the broad skilled share is associated with about 1.5% higher net value added per worker, while the corresponding figure is about 1.6% for the university share.

The central result is the interaction term. It is positive in both columns, statistically significant at the 5% level in the skilled-share specification and at the 10% level in the university-share specification. In the broad skilled-share specification, the estimated semi-elasticity of productivity with respect to research expenditure is 0.034 for an establishment with no skilled workers and about 0.044 at the sample mean skilled share of 0.266. With the university-share proxy, the corresponding semi-elasticity rises from 0.039 to about 0.046 at the sample mean university

share of 0.208. The implication is not that research spending is irrelevant in low-skill settings: it is that the same increase in research effort is associated with a meaningfully larger productivity payoff when the workforce is better equipped to absorb it.

Table 4: Net value added per worker: main results

Dependent variable: net value added per worker (log)	(1) Skilled share	(2) University share
Research expenditure per worker	0.034***	0.039***
	(0.008)	(0.008)
Human capital	0.150***	0.162***
	(0.007)	(0.008)
Research expenditure × human capital	0.037**	0.032*
	(0.015)	(0.017)
Capital per worker	0.318***	0.319***
	(0.002)	(0.002)
Constant	7.203***	7.203***
	(0.033)	(0.033)
Observations	165,794	166,011
R^2	0.272	0.271
Industry fixed effects	Yes	Yes

Heteroskedasticity-robust standard errors are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Human capital is the broad post-secondary skill share in column (1) and the university-educated share in column (2). All monetary variables are entered in logarithms; research expenditure is unit-shifted before logging to retain zero observations.

5.2 Robustness across alternative productivity measures

Tables 5 and 6 ask whether the main result depends on how productivity is measured. It does not in any broad qualitative sense, but the strength of the complementarity result is clearly sharper for value-added measures than for gross output, which is exactly the ranking the framework predicts.

With the broad skill-share proxy, research expenditure is positively associated with all three outcomes. The interaction term is positive and statistically significant for net value added and gross value added, but smaller and statistically insignificant for output per worker. The same pattern appears when the university share is used, although the interaction in the net-value-added specification is estimated somewhat less precisely. This ranking is informative: gross output is a noisier productivity proxy because it loads on intermediate-input use and product mix as well as on efficiency, while value added is closer to the underlying concept in the framework. It is therefore reassuring that the clearest evidence of complementarity appears exactly where measurement is more defensible. The direct human-capital coefficients tell a similar story: they

are larger in the value-added specifications than in the gross-output specification, especially when the university-share proxy is used. That is also plausible, since more highly educated workers are likely to be especially important for design, coordination, and problem-solving, margins that are more tightly linked to value added than to gross sales or production volume.

Table 5: Alternative productivity measures: broad skilled-share proxy

	(1) Net value added	(2) Gross value added	(3) Output
Research expenditure per worker	0.034***	0.028***	0.080***
	(0.008)	(0.008)	(0.011)
Skilled share	0.150***	0.145***	0.117***
	(0.007)	(0.007)	(0.010)
Research expenditure × skilled share	0.037**	0.040***	0.017
	(0.015)	(0.015)	(0.020)
Capital per worker	0.318***	0.331***	0.365***
	(0.002)	(0.002)	(0.003)
Constant	7.203***	7.054***	7.432***
	(0.033)	(0.033)	(0.047)
Observations	165,794	166,486	169,306
R^2	0.272	0.300	0.372
Industry fixed effects	Yes	Yes	Yes

Heteroskedasticity-robust standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.3 Economic magnitudes and structural mapping

The coefficients are economically coherent and broadly aligned with the benchmark discussion. Capital per worker enters with elasticities between 0.318 and 0.366, close to conventional capital-share benchmarks. The direct human-capital coefficients sit in the low tenths. The research coefficients are modest, but that is not surprising in a setting where reported research expenditure is limited and likely to capture applied problem-solving as much as formal laboratory-style R&D.

The framework provides a direct structural mapping from the reduced-form coefficients to the underlying theoretical parameters. Under the model in Section 3, the direct human-capital coefficient maps into ψ, the coefficient on research expenditure maps into σ_0, and the interaction term maps into σ_1. Table 7 reports the benchmark ranges together with the main Egyptian estimates under that mapping. Using the net-value-added specification with the broad skill-share proxy, the capital elasticity is 0.318, the direct skill effect is 0.150, the research elasticity is 0.034, and the absorptive-capacity term is 0.037. With the university-share proxy, the corresponding coefficients are 0.319, 0.162, 0.039, and 0.032. Every coefficient lies within or close to the indicative range from the reference literature, and the absorptive-capacity term has the predicted

Table 6: Alternative productivity measures: university-share proxy

	(1) Net value added	(2) Gross value added	(3) Output
Research expenditure per worker	0.039***	0.032***	0.084***
	(0.008)	(0.008)	(0.010)
University share	0.162***	0.160***	0.122***
	(0.008)	(0.007)	(0.011)
Research expenditure × university share	0.032*	0.036**	0.009
	(0.017)	(0.017)	(0.023)
Capital per worker	0.319***	0.331***	0.366***
	(0.002)	(0.002)	(0.003)
Constant	7.203***	7.056***	7.433***
	(0.033)	(0.033)	(0.047)
Observations	166,011	166,708	169,540
R^2	0.271	0.300	0.372
Industry fixed effects	Yes	Yes	Yes

Heteroskedasticity-robust standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

positive sign in both specifications. These magnitudes support the same substantive conclusion: firms with stronger internal capabilities obtain larger productivity payoffs from research expenditure.

Table 7: Benchmark comparison and structural mapping

Parameter	Benchmark range	Net value added: skilled share	Net value added: university share
Capital elasticity, α	0.20 to 0.40	0.318	0.319
Direct skill effect, $\theta = \psi$	0.05 to 0.25	0.150	0.162
Research elasticity, $\beta_R = \sigma_0$	0.01 to 0.12	0.034	0.039
Absorptive-capacity term, $\beta_{Rh} = \sigma_1$	0.005 to 0.05	0.037	0.032

Benchmark ranges are interpretive guides from the literature discussed in the text. The structural mapping follows the model in which the elasticity of productivity with respect to research expenditure is $\sigma_0 + \sigma_1 h_i$.

The results are consistent with absorptive capacity. They line up across human-capital measures, are strongest for the value-added outcomes one would most trust, and the magnitudes are reasonable when compared with the broader literature. Taken together, the results support a measured substantive claim: in Egypt's establishment population, research expenditure is more strongly associated with productivity when firms have a more educated workforce. That pattern is difficult to reconcile with a view of technology investment as independent of internal

capability, and it motivates the policy discussion that follows.

6 Policy discussion

The evidence points to a narrow but important policy lesson: the productivity return to technology support depends on the capabilities of the firms receiving it. Research expenditure is positively associated with productivity, but the association is significantly stronger among firms with more educated workers. That pattern matters because innovation policy is often designed around the input side of the problem—grants, tax incentives, research subsidies, digital-upgrading programs, or other instruments that encourage firms to spend on technology. The estimates suggest that such instruments are unlikely to reach their full payoff when they are disconnected from the internal capabilities needed to use that technology effectively.

This has direct implications for the design of firm-level support programs. A policy that subsidizes research or technology adoption should not treat capability building as an optional add-on. The empirical interaction between research expenditure and human capital indicates that the same research intensity is associated with higher productivity where the workforce is better prepared to absorb it. In practical terms, innovation incentives, matching grants, and co-financing schemes are likely to be more effective when paired with training, technician certification, managerial upgrading, applied engineering support, or structured links with universities and technical institutes. The point is not simply to raise reported research expenditure. It is to raise the probability that such expenditure will alter production practices, product quality, process efficiency, or the establishment's ability to solve technical problems.

The results also speak to targeting. The estimates are identified within two-digit industries, so the policy-relevant comparison is not between sectors with very different production technologies, but between establishments facing broadly similar sectoral conditions. Even within industries, the productivity gradient with respect to research expenditure is steeper where human capital is stronger. This suggests that a uniform technology-subsidy program may underperform if it ignores firm readiness. Some establishments may need direct support for research or digital adoption; others may first need workforce upgrading, technical assistance, or organizational support before technology spending can translate into productivity. A more effective policy design would therefore screen not only for project quality or financial need, but also for absorptive capacity.

This does not imply that support should be restricted only to already skilled firms. Such a rule would risk reinforcing existing productivity gaps. The better interpretation is sequential. Firms with stronger capabilities may be ready for research grants, digital investment, or

applied-innovation support. Firms with weaker capabilities may benefit more from earlier-stage interventions: worker training, basic process upgrading, quality-control systems, managerial practices, and assistance in identifying usable technologies. The empirical result is consistent with this approach. It suggests that technology and skills policies are complements, but it does not imply that only one type of firm deserves policy attention.

The sectoral dimension is also important. The census covers establishments across manufacturing, trade, services, transport, professional activities, education, health, and other sectors. Research expenditure in this setting should not be interpreted narrowly as cutting-edge laboratory R&D. In many firms, it is more likely to capture applied problem-solving, adaptation, process improvement, and small-scale technology upgrading. That is precisely why the complementarity with human capital is informative. The policy dimension in Egypt is not only the creation of frontier innovators; it is also the diffusion of productive practices across a broad establishment base. Programs that help firms adapt existing technologies may therefore be as relevant as programs that support formal R&D.

The broader lesson is therefore not that Egypt should choose between innovation policy and skills policy. The evidence suggests the opposite. Technology support is more likely to raise productivity when firms have the human capital needed to absorb and implement new knowledge. For an economy seeking productivity growth through upgrading rather than factor accumulation alone, policy should be designed around that complementarity.

7 Conclusion

This paper studies how technology investment and internal firm capability interact in shaping firm productivity. The question is central for economies such as Egypt, where policy increasingly emphasizes innovation, digital upgrading, and private-sector productivity growth, but firm-level technology effort remains uneven and difficult to translate into broad productivity gains. The evidence in this paper suggests that the relevant margin is not research expenditure alone. What matters is whether firms have the human capital needed to absorb, adapt, and implement what that expenditure is meant to produce.

The empirical analysis uses establishment-level microdata from Egypt's Fifth Economic Census to relate productivity to research expenditure, capital intensity, workforce education, and their interaction within two-digit industries. The main outcome is net value added per worker, with gross value added and gross output per worker used as alternative productivity measures. Across specifications, research expenditure is positively associated with productivity, and the association is significantly stronger in firms with higher shares of educated workers. The inter-

action is not large, which is exactly what a cross-section dominated by small firms with limited formal R&D would predict. It is nevertheless visible in value-added outcomes and stable across alternative human-capital measures.

The theoretical framework gives this pattern a direct economic interpretation. Research expenditure enters as a productive input, while human capital raises the elasticity of productivity with respect to that input. The interaction term in the regression is therefore not an auxiliary control: it is the empirical counterpart of the absorptive-capacity parameter σ_1. In that sense, the paper moves the discussion away from the average return to technology spending and toward the conditions under which such spending is more productive. This distinction is important. A policy that raises reported research expenditure may have limited impact if firms lack the skills, processes, and technical capacity needed to turn expenditure into usable knowledge.

The policy implication is straightforward but often missed. Supporting innovation and developing skills should not be treated as separate instruments. Matching grants, tax incentives, innovation vouchers, digital-upgrading programs, and applied research support are more likely to raise productivity when paired with capability-building measures inside firms. These may include technician training, managerial support, links with universities and technical institutes, and programs that help firms adapt technologies to their own production constraints. The point is not that every firm should become a formal R&D participant. For many Egyptian firms, productivity growth is more likely to come from diffusion, adaptation, and incremental process improvement, and those margins still require human capital.

The paper also points to a measurement and design agenda. Better firm-level data on research expenditure, technology adoption, training, and innovation outputs would make it possible to distinguish more clearly between spending that reflects genuine upgrading and spending that merely records routine activity. Linking future census or survey rounds over time, ideally with administrative tax or social-security registers, would also allow researchers to separate selection from productivity effects more convincingly and to apply the within-firm control-function methods that the cross-section here cannot. For now, the evidence points to a clear and policy-relevant conclusion: in Egypt's establishment population, research expenditure is more strongly associated with productivity when firms have a more educated workforce. Technology investment and human capital are complements, and that complementarity should be built into the design of productivity policy.

Data availability

The analysis uses licensed establishment-level microdata from the Egypt Economic Census 2017/2018, distributed by the Economic Research Forum through OAMDI and originally collected by CAPMAS. Access to the underlying data is subject to the provider's licensing terms. The raw establishment-level microdata are therefore not redistributed by the author. Researchers seeking access should apply directly through the Economic Research Forum data portal.

Code availability

Stata do-files, output logs, table files, and replication documentation are available with the submission materials. The code reproduces the analysis once the licensed data have been obtained from the data provider.

Declarations

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A Full theoretical framework

This appendix derives the productivity equation used in the empirical analysis and provides full proofs. The central departure from a standard Cobb-Douglas production function is that research expenditure is treated as a productive input whose elasticity depends on human capital. This gives a theoretical basis for the interaction between research expenditure and the human-capital share in the estimating equation.

A.1 Production technology and constant returns

Establishment i operates in industry j. Output is the numeraire, so the output price is normalized to one. The establishment uses physical capital K_i, labor L_i, and research expenditure M_i. Human capital, denoted $h_i \in [0, 1]$, is treated as a predetermined establishment characteristic. It reflects the existing composition of the workforce and is taken as given at the production stage, rather than being chosen jointly with input and research decisions.[4] The production function is

$$Y_i = A_0 \Phi_j \exp(\psi h_i) K_i^{\alpha} L_i^{\beta_i} M_i^{\sigma_i}, \tag{17}$$

where

$$\sigma_i \equiv \sigma(h_i) = \sigma_0 + \sigma_1 h_i, \qquad \sigma_0 > 0, \qquad \sigma_1 > 0. \tag{18}$$

The term Φ_j is an industry productivity shifter and A_0 is common baseline technology. The research block follows the view in Aghion and Howitt (2008) that research effort is costly and increases productive technology, while the dependence of σ_i on h_i formalizes absorptive capacity in the spirit of Cohen and Levinthal (1990). One may equivalently write

$$Y_i = A_i K_i^{\alpha} L_i^{\beta_i}, \qquad A_i = A_0 \mu_i, \qquad \mu_i = \Phi_j \exp(\psi h_i) M_i^{\sigma_i}. \tag{19}$$

Remark 2 (Why total research expenditure enters before normalization)**.** *The empirical variable is research expenditure per worker, $m_i = M_i/L_i$. The production technology, however, must be written first in terms of total research expenditure M_i if one wants a meaningful constant-returns restriction. If one were to put the already normalized variable m_i directly into the production function and hold it fixed when scaling K_i and L_i, the constant-returns restriction would be $\alpha + \beta_i = 1$, not $\alpha + \beta_i + \sigma_i = 1$. The rigorous route is therefore to write the technology in terms*

[4] Treating human capital as predetermined simplifies the production-stage problem and isolates the mechanism of interest. Workforce composition typically adjusts slowly relative to input and research decisions, reflecting past hiring, training, and institutional constraints. Modeling h_i as given at the time of production therefore avoids introducing a joint optimization problem over skills and research effort, and allows the interaction term to be interpreted as capturing how existing capabilities condition the productivity payoff to research expenditure.

of total research expenditure M_i and then derive the intensive equation in terms of m_i.

Because research expenditure is part of the productive technology, the labor exponent is $1-\alpha-\sigma_i$. Constant returns to scale in reproducible inputs require

$$\alpha+\beta_i+\sigma_i=1. \tag{20}$$

Since σ_i varies with human capital, the labor exponent is establishment-specific:

$$\beta_i=1-\alpha-\sigma_i=1-\alpha-\sigma_0-\sigma_1 h_i. \tag{21}$$

The maintained parameter restrictions are

$$0<\alpha<1, \qquad 0<\sigma_i<1-\alpha, \qquad \beta_i>0. \tag{22}$$

These restrictions ensure positive exponents and diminishing returns in each input, while preserving constant returns in (K_i, L_i, M_i) for a given level of human capital.

Proposition 2 (Constant returns to scale)**.** *For a given (h_i, j), production in* (17) *is constant returns to scale in (K_i, L_i, M_i) if and only if* (20) *holds.*

Proof. Scale all reproducible inputs by a positive scalar $t>0$. Then

$$\begin{aligned} Y_i(tK_i, tL_i, tM_i) &= A_0\Phi_j \exp(\psi h_i)(tK_i)^{\alpha}(tL_i)^{\beta_i}(tM_i)^{\sigma_i} \\ &= t^{\alpha+\beta_i+\sigma_i} A_0\Phi_j \exp(\psi h_i) K_i^{\alpha} L_i^{\beta_i} M_i^{\sigma_i} \\ &= t^{\alpha+\beta_i+\sigma_i} Y_i(K_i, L_i, M_i). \end{aligned} \tag{23}$$

For output to scale one-for-one with inputs, we need $Y_i(tK_i, tL_i, tM_i) = tY_i(K_i, L_i, M_i)$ for all $t>0$. This holds if and only if $\alpha+\beta_i+\sigma_i=1$. □

A.2 Competitive equilibrium and optimal input intensities

The establishment takes the wage rate W_i, the rental rate of capital R_i, and the unit price of research expenditure as given. One unit of research expenditure costs one unit of output. The production-stage profit is

$$\Pi_i = A_0\Phi_j \exp(\psi h_i) K_i^{\alpha} L_i^{\beta_i} M_i^{\sigma_i} - R_i K_i - W_i L_i - M_i. \tag{24}$$

An interior competitive optimum satisfies the first-order conditions

$$\frac{\partial \Pi_i}{\partial K_i} = 0 \quad \Longrightarrow \quad \alpha A_0 \Phi_j \exp(\psi h_i) K_i^{\alpha-1} L_i^{\beta_i} M_i^{\sigma_i} = R_i, \tag{25}$$

$$\frac{\partial \Pi_i}{\partial L_i} = 0 \quad \Longrightarrow \quad \beta_i A_0 \Phi_j \exp(\psi h_i) K_i^{\alpha} L_i^{\beta_i-1} M_i^{\sigma_i} = W_i, \tag{26}$$

$$\frac{\partial \Pi_i}{\partial M_i} = 0 \quad \Longrightarrow \quad \sigma_i A_0 \Phi_j \exp(\psi h_i) K_i^{\alpha} L_i^{\beta_i} M_i^{\sigma_i-1} = 1. \tag{27}$$

Equivalently, since $Y_i = A_0 \Phi_j \exp(\psi h_i) K_i^{\alpha} L_i^{\beta_i} M_i^{\sigma_i}$,

$$R_i = \alpha \frac{Y_i}{K_i}, \qquad W_i = \beta_i \frac{Y_i}{L_i}, \qquad 1 = \sigma_i \frac{Y_i}{M_i}. \tag{28}$$

Proposition 3 (Equilibrium input ratios)**.** *At an interior competitive equilibrium, the optimal capital intensity and research intensity are*

$$\frac{K_i^*}{L_i^*} = \frac{\alpha}{\beta_i} \frac{W_i}{R_i}, \qquad \frac{M_i^*}{L_i^*} = \frac{\sigma_i}{\beta_i} W_i. \tag{29}$$

Proof. Dividing (25) by (26) gives $R_i/W_i = (\alpha/\beta_i)(L_i/K_i)$, hence $K_i/L_i = (\alpha/\beta_i)(W_i/R_i)$. Dividing (27) by (26) gives $1/W_i = (\sigma_i/\beta_i)(L_i/M_i)$, hence $M_i/L_i = (\sigma_i/\beta_i)W_i$. The same result follows directly from (28). □

A.3 Intensive-form productivity equation

Define capital per worker and research expenditure per worker as $k_i \equiv K_i/L_i$ and $m_i \equiv M_i/L_i$. Substitute $K_i = k_i L_i$ and $M_i = m_i L_i$ into (17):

$$\begin{aligned} Y_i &= A_0 \Phi_j \exp(\psi h_i)(k_i L_i)^{\alpha} L_i^{\beta_i} (m_i L_i)^{\sigma_i} \\ &= A_0 \Phi_j \exp(\psi h_i) k_i^{\alpha} m_i^{\sigma_i} L_i^{\alpha+\beta_i+\sigma_i}. \end{aligned} \tag{30}$$

Using $\alpha + \beta_i + \sigma_i = 1$ gives $Y_i = A_0 \Phi_j \exp(\psi h_i) k_i^{\alpha} m_i^{\sigma_i} L_i$. Dividing both sides by L_i:

$$y_i \equiv \frac{Y_i}{L_i} = A_0 \Phi_j \exp(\psi h_i) k_i^{\alpha} m_i^{\sigma_i}. \tag{31}$$

Substituting $\sigma_i = \sigma_0 + \sigma_1 h_i$:

$$\frac{Y_i}{L_i} = A_0 \Phi_j \exp(\psi h_i) \left(\frac{K_i}{L_i}\right)^{\alpha} \left(\frac{M_i}{L_i}\right)^{\sigma_0+\sigma_1 h_i}. \tag{32}$$

Taking natural logs yields

$$\ln\left(\frac{Y_i}{L_i}\right) = \ln A_0 + \ln \Phi_j + \psi h_i + \alpha \ln k_i + (\sigma_0 + \sigma_1 h_i) \ln m_i$$
$$= \ln A_0 + \ln \Phi_j + \alpha \ln k_i + \psi h_i + \sigma_0 \ln m_i + \sigma_1 h_i \ln m_i. \tag{33}$$

Proposition 4 (Estimated equation)**.** *The constant-returns technology in* (17)*, combined with the research elasticity in* (18)*, implies the regression equation*

$$\ln\left(\frac{Y_i}{L_i}\right) = c + \alpha \ln\left(\frac{K_i}{L_i}\right) + \theta h_i + \beta_R \ln m_i + \beta_{Rh} h_i \ln m_i + \delta_j + \varepsilon_i, \tag{34}$$

with structural mapping $\theta = \psi$*,* $\beta_R = \sigma_0$*,* $\beta_{Rh} = \sigma_1$*, and* δ_j *absorbing* $\ln \Phi_j$*.*

Proof. Equation (33) contains $\ln A_0$ and $\ln \Phi_j$. In estimation, $\ln A_0$ is part of the constant c, while $\ln \Phi_j$ is absorbed by the two-digit industry fixed effects δ_j. Two-digit industry indicators absorb broad differences in technology, input intensity, accounting practice, and market structure across activities. The remaining coefficients correspond directly to α, ψ, σ_0, and σ_1. □

A.4 Absorptive capacity and comparative statics

Proposition 5 (Human capital raises the return to research)**.** *Labor productivity is more elastic with respect to research expenditure per worker when human capital is higher:*

$$\frac{\partial \ln(Y_i/L_i)}{\partial \ln m_i} = \sigma_0 + \sigma_1 h_i, \qquad \frac{\partial^2 \ln(Y_i/L_i)}{\partial h_i \, \partial \ln m_i} = \sigma_1 > 0. \tag{35}$$

Proof. Differentiating (33) with respect to $\ln m_i$ gives $\sigma_0 + \sigma_1 h_i$. Differentiating this expression with respect to h_i gives σ_1, which is positive by (18). □

The derivative with respect to human capital is also informative:

$$\frac{\partial \ln(Y_i/L_i)}{\partial h_i} = \psi + \sigma_1 \ln m_i. \tag{36}$$

Human capital has a direct productivity effect through ψ and an indirect effect through the productivity of research expenditure. When research intensity is larger, the indirect channel is stronger. This is the theoretical basis for interpreting the empirical interaction term as absorptive capacity.

A.5 Summary of restrictions and empirical interpretation

Object	Restriction / mapping	Interpretation
Capital exponent	$0 < \alpha < 1$	Elasticity of output with respect to capital
Research elasticity	$\sigma_i = \sigma_0 + \sigma_1 h_i$	R&D payoff rises with human capital
CRS restriction	$\alpha + \beta_i + \sigma_i = 1$	Constant returns in K, L, M
Labor exponent	$\beta_i = 1 - \alpha - \sigma_i > 0$	Residual exponent required by CRS
Empirical R&D coefficient	$\beta_R = \sigma_0$	Baseline research-productivity coefficient
Empirical interaction	$\beta_{Rh} = \sigma_1$	Absorptive-capacity effect
Human-capital coefficient	$\theta = \psi$	Direct skill/productivity channel

The theory therefore gives the paper a sharp foundation. It explains why research expenditure per worker belongs in the productivity equation, why the interaction with human capital is central, and why the coefficient on capital per worker can be interpreted as a production elasticity. The key identifying prediction is not merely that research expenditure is positively associated with productivity. It is that the elasticity of productivity with respect to research expenditure is larger in firms with more human capital.

B Data

B.1 Data source, scope, and empirical use

The analysis uses establishment-level microdata from Egypt's Fifth Economic Census (2017/2018), collected by the Central Agency for Public Mobilization and Statistics (CAPMAS) and distributed through the Economic Research Forum's Open Access Micro Data Initiative (OAMDI, 2022). The census frame covers active and temporarily closed non-government establishments in the public sector, the public business sector, and the private sector. CAPMAS reports a frame of 4,119,716 firms, of which 3,858,342 were active and 261,374 were temporarily closed.

Three features make the census especially useful for this paper. First, it records *research and experimental expenditure* as a separate cost item rather than forcing innovation to be proxied by technology dummies or qualitative survey questions. Second, it records the educational composition of the workforce in enough detail to construct skill shares that are directly relevant to absorptive capacity. Third, the census is classified by two-digit ISIC Rev. 4 economic activity and covers a broad range of sectors, which makes within-industry comparisons both feasible and economically meaningful.

The working sample used in the paper is smaller than the full census frame because the regressions require positive employment and non-missing values for the variables entering each specification. The baseline net-value-added specification with the broad skill-share proxy uses 165,794 establishments. The industry tables below are computed on that baseline estimation sample and are therefore aligned with the fixed effects used in the main regressions.

B.2 Variable definitions and economic rationale

Table 8 summarizes the construction of the paper's main variables and the logic for each choice.

For ease of reference, the main transformations can be written compactly as

$$y_i^{NVA} = \ln\left(1 + \frac{NVA_i}{L_i}\right), \qquad y_i^{GVA} = \ln\left(1 + \frac{GVA_i}{L_i}\right), \qquad y_i^{Y} = \ln\left(1 + \frac{Y_i}{L_i}\right),$$

$$m_i = \ln\left(1 + \frac{RD_i}{L_i}\right), \qquad k_i = \ln\left(1 + \frac{K_i}{L_i}\right), \qquad h_i^B = \frac{PostSec_i + Univ_i}{L_i}, \qquad h_i^U = \frac{Univ_i}{L_i}.$$

Here NVA_i denotes net value added, GVA_i gross value added, Y_i total production, RD_i research and experimental expenditure, K_i invested capital, $PostSec_i$ workers with above-intermediate education, and $Univ_i$ workers with university-or-higher education.

Table 8: Variable construction and economic rationale

Variable in the paper	Construction used in the analysis	Economic rationale
Total workers, L_i	Total workers in the establishment, including paid and unpaid workers.	Using total workers keeps the labor input consistent with the establishment production concept and avoids overstating productivity in owner-managed and family establishments where unpaid labor is economically active.
Net value added per worker (main outcome)	Log of one plus net value added per worker.	The main productivity outcome is based on value added rather than gross output because value-added measures are less sensitive to differences in intermediate-input intensity across firms. The net concept is preferred because it is closer to the resource surplus generated by the establishment.
Gross value added per worker (robustness)	Log of one plus gross value added per worker.	This measure checks whether the results depend on the treatment of depreciation. It remains a value-added concept and is therefore a useful robustness outcome.
Output per worker (robustness)	Log of one plus total production per worker.	Output per worker is retained as a broader robustness measure. It is more exposed than value added to variation in materials intensity and product mix, so it is informative precisely when it yields weaker complementarity estimates.

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Variable in the paper	Construction used in the analysis	Economic rationale
Research expenditure per worker	Log of one plus research and experimental expenditure per worker.	This is the paper's direct measure of targeted technology effort. Using expenditure intensity rather than a binary innovation indicator preserves variation in the scale of research activity. The one-unit shift retains firms with zero reported formal research outlays.
Capital per worker	Log of one plus invested capital per worker.	The paper uses invested capital as the cross-sectional proxy for capital intensity. The census also reports gross fixed capital formation, but that variable is a flow of additions during the year rather than a stock-like measure. Invested capital is therefore the more appropriate control for the intensive-form production equation.
Broad skill share (baseline human-capital proxy)	Share of workers with above-intermediate or university or higher education.	The baseline human-capital measure captures the internal capabilities most likely to strengthen absorptive capacity: technical and post-secondary skills that help firms understand, adapt, and implement new technology.
University share (alternative human capital proxy)	Share of workers with university or higher education only.	This tighter proxy isolates the upper tail of formal education and asks whether the complementarity result is driven specifically by university-level human capital rather than by the broader skilled workforce.

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Variable in the paper	Construction used in the analysis	Economic rationale
Two-digit industry fixed effects	Indicator variables for the establishment's two-digit economic activity under ISIC Rev. 4.	Industry fixed effects absorb broad activity-level differences in technology, input intensity, accounting practice, and market structure. In a census spanning dozens of activities, they are essential for making the comparison within rather than across industries.

Notes: All logarithmic variables use a one-unit shift before logging so that firms with zero reported values remain in the working sample.

A few additional choices deserve emphasis. The preferred labor denominator is *total workers*, not paid workers only. This matters in Egypt because many small firms rely on owners and unpaid family workers. Excluding that labor would overstate productivity and distort skill shares in exactly the segment of the economy where informality and family management are most common.

The capital proxy is *invested capital per worker*. The census also reports gross fixed capital formation, but CAPMAS defines that variable as additions to fixed assets net of exclusions plus inventory changes, which makes it a flow concept rather than a stock-like measure. For a cross-sectional production equation, invested capital is the more appropriate control for capital intensity.

The research measure is based on *research and experimental expenditure per worker*. CAPMAS includes this item among service expenses in the establishment questionnaire, which is unusually helpful for a middle-income country dataset because it provides a direct monetary measure of deliberate technology effort. Firm-level evidence generally finds that private returns to R&D are positive but modest, and that their payoff depends on complementary organizational and skill conditions (Hall et al., 2010; Aw et al., 2007; Yang et al., 2010). This is exactly the margin the paper studies.

B.3 Industry coverage and the role of industry fixed effects

Industry fixed effects are central in this dataset. CAPMAS classifies firms by two-digit ISIC Rev. 4 activity, and the sample design itself is organized around economic activity and employment size. The baseline estimation sample spans 18 one-digit sectors and 82 two-digit industries.

That breadth is economically valuable, but it also means that firms differ systematically in technology, materials intensity, and market environment. Two-digit industry fixed effects therefore serve a clear purpose: they ensure that the interaction between research expenditure and human capital is identified from comparisons among firms operating in similar activity cells rather than from comparisons across fundamentally different sectors.

Table 9 reports the one-digit sector composition of the baseline estimation sample. Wholesale and retail trade and manufacturing account for most firms, but the data also include agriculture, construction, transport, finance, education, health, professional services, and a range of personal and business services. Table 10 then lists the full set of two-digit industries represented in the working sample.

Table 9: Broad sector composition of the baseline estimation sample

Code	Broad sector	Firms	Share (%)
1	Agriculture, forestry and fishing	4,988	3.01
2	Mining and quarrying	447	0.27
3	Manufacturing	35,665	21.51
4	Electricity, gas, steam and air conditioning supply	147	0.09
5	Water supply; sewerage, waste management and remediation activities	751	0.45
6	Construction	2,003	1.21
7	Wholesale and retail trade; repair of motor vehicles and motorcycles	74,603	45.00
8	Transportation and storage	2,158	1.30
9	Accommodation and food service activities	11,108	6.70
10	Information and communication	621	0.37
11	Financial and insurance activities	1,048	0.63
12	Real estate activities	1,447	0.87
13	Professional, scientific and technical activities	4,469	2.70
14	Administrative and support service activities	3,263	1.97
16	Education	1,992	1.20
17	Human health and social work activities	10,299	6.21
18	Arts, entertainment and recreation	1,580	0.95
19	Other service activities	9,205	5.55

Notes: Unweighted counts from the baseline net-value-added/broad-skill regression sample ($N = 165{,}794$). The sector labels correspond to the one-digit ISIC Rev. 4 categories represented in the estimation sample.

Table 10: Two-digit industries represented in the baseline estimation sample

Code	Two-digit industry	Firms
Agriculture, forestry and fishing		
01	Crop and animal production, hunting and related service activities	4,849
02	Forestry and logging and related service activities	60

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Code	Two-digit industry	Firms
03	Fishing and aquaculture	79
Mining and quarrying		
06	Extraction of crude petroleum and natural gas	32
07	Mining of metal ores	9
08	Other mining and quarrying	376
09	Mining support service activities	30
Manufacturing		
10	Manufacture of food products	9,814
11	Manufacture of beverages	42
12	Manufacture of tobacco products	57
13	Manufacture of textiles	1,929
14	Manufacture of wearing apparel	3,685
15	Manufacture of leather and related products	726
16	Manufacture of wood and of products of wood and cork, except furniture	3,023
17	Manufacture of paper and paper products	493
18	Printing and reproduction of recorded media	772
19	Manufacture of coke and refined petroleum products	37
20	Manufacture of chemicals and chemical products	575
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	133
22	Manufacture of rubber and plastics products	1,233
23	Manufacture of other non-metallic mineral products	1,858
24	Manufacture of basic metals	224
25	Manufacture of fabricated metal products, except machinery and equipment	3,675
26	Manufacture of computer, electronic and optical products	84
27	Manufacture of electrical equipment	400
28	Manufacture of machinery and equipment n.e.c.	278
29	Manufacture of motor vehicles, trailers and semi-trailers	132
30	Manufacture of other transport equipment	52
31	Manufacture of furniture and wood products n.e.c.	5,580
32	Other manufacturing industries	258
33	Repair and installation of machinery and equipment	605
Electricity, gas, steam and air conditioning supply		
35	Electricity, gas, steam and air conditioning supply	147

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Code	Two-digit industry	Firms
Water supply; sewerage, waste management and remediation activities		
36	Water collection, treatment and supply	110
37	Sewerage and Sanitation networks	16
38	Waste collection, treatment and disposal activities; materials recovery	625
Construction		
41	Construction of buildings	1,215
42	Civil engineering	445
43	Specialized construction activities	343
Wholesale and retail trade; repair of motor vehicles and motorcycles		
45	Wholesale and retail trade and repair of motor vehicles and motorcycles	8,335
46	Wholesale trade, except of motor vehicles and motorcycles	5,158
47	Retail trade, except of motor vehicles and motorcycles	61,110
Transportation and storage		
49	Land transport and transport via pipelines	398
50	Water transport	264
51	Air transport	17
52	Warehousing and support activities for transportation	1,317
53	Postal and courier activities	162
Accommodation and food service activities		
55	Accommodation services activities	642
56	Food and beverage service activities	10,466
Information and communication		
58	Publishing activities	84
59	Motion picture, video and television programme production, sound recording and music publishing activities	116
60	Programming and broadcasting activities	21
61	Telecommunications	251
62	Computer programming, consultancy and related activities	140
63	Information service activities	9
Financial and insurance activities		
64	Financial service activities, except insurance and pension funding	601
65	Insurance, reinsurance and pension funding, except compulsory social security	86
66	Activities auxiliary to financial service and insurance activities	361
Real estate activities		

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Code	Two-digit industry	Firms
68	Real estate activities	1,447
Professional, scientific and technical activities		
69	Legal and accounting activities	2,056
70	Activities of head offices; management consultancy activities	322
71	Architectural and engineering activities; technical testing and analysis	605
72	Scientific research and development	39
73	Advertising and market research	596
74	Other professional, scientific and technical activities	705
75	Veterinary activities	146
Administrative and support service activities		
77	Rental and leasing activities	1,031
78	Employment activities	187
79	Travel agency, tour operator, reservation service and related activities	1,124
80	Security and investigation activities	44
81	Services to buildings	171
82	Executive office service activities and special office support activities	706
Education		
85	Education	1,992
Human health and social work activities		
86	Human health activities	5,823
87	Residential care activities	179
88	Social work activities without accommodation	4,297
Arts, entertainment and recreation		
90	Creative, arts and entertainment activities	62
91	Libraries, archives, museums and other cultural activities	25
92	Gambling and betting activities	2
93	Sports activities and amusement and recreation activities	1,491
Other service activities		
94	Activities of membership organizations	559
95	Repair of computers and personal and household goods	2,741
96	Other personal service activities	5,905

Notes: Unweighted counts from the baseline net-value-added/broad-skill regression sample. The codes reported here are standard two-digit ISIC Rev. 4 industry identifiers used for the fixed effects.