Intangible Capital and Labor Income:
Firm-Level Evidence from India

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Abstract

The relationship between capital deepening and labor income shares is much studied. However, there is little evidence on how traditional forms of capital, such as machinery and equipment, and intangible 'knowledge-based' capital, such as software, research and development (R&D), organizational culture, and brand value, differentially affect labor income, particularly in developing economies. Using balance sheet data from over 30,000 companies in India between 2001 and 2021, this paper finds a significant positive relationship between both tangible and intangible capital, on the one hand, and labor income share, on the other hand. The positive relationship between intangible capital assets and labor income share can be attributed to the positive impact of intangibles on both labor productivity and employment, which is indicative of complementarities with jobs. Furthermore, the positive link between intangible capital assets and labor income share is stronger for firms operating in sectors with high skill, R&D, or ICT intensity, which is indicative of complementarities with skills.

Keywords: Intangible Capital, Firm, Labor Income, Labor Productivity, India.

JEL Classification Numbers: D24, E22, E24; J30.

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1. Introduction

The Kaldor facts, based on data from the United States during the first half of the 20th century, posited a stable labor share of income over time (Kaldor 1961). Since the mid-1970s, however, evidence has documented a decline in the labor share of income across both advanced and developing economies (Elsby, Hobijn, and Sahin 2013; Karabarbounis and Neiman 2014; Chen, Los, and Timmer 2018; Autor et al. 2020; Glover & Short 2020). These declining labor income shares are attributed, at least in part, to automation induced by technological progress that reduced the price of capital relative to labor (Goos, Manning, and Salomons, 2014).[2]

It is estimated that the reduction in the price of capital goods due to technological progress can explain roughly half of the observed decline in labor share, on average, across countries (Karabarbounis and Neiman 2014). Similarly, evidence from the United States shows that automation accounted for about 14 percent of the decline in labor share over the past few decades (Prettner 2019). Autor and Salomons (2018) further distinguish between the impact of automation on jobs and labor income shares. While job losses in industries directly affected by automation are offset by job gains in other industries, this is not the case with labor income shares. More recently, using firm-level data, Autor et al. (2020) attribute the decline in the U.S. labor income share to the rise of superstar firms with high markups.

This literature does not distinguish between traditional forms of capital, such as machinery and equipment, and intangible capital comprising 'knowledge-based' assets, such as software, research and development (R&D), organizational culture, brand value, and relationships with clients and suppliers (Corrado, Hulten, and Sichel, CHS 2005). And investments in intangible assets, as a share of GDP, have reached similar levels to tangible assets in many European countries, and have even exceeded tangible investments in the United States and the United Kingdom since the late 2000s (van Ark et al., 2009; Corrado et al., 2016).

Investments in intangible capital can affect the labor income share by affecting either jobs or wages. Intangible assets, such as R&D, are believed to complement skills, which can lead to an increased demand for skilled workers and higher wages (Corrado et al., 2009; Velic, 2025). Similarly, intangible assets such as economic competencies, which includes worker training (CHS 2005), may increase firms' reliance on workers when knowledge is tacit and embedded in human capital, improving employees' outside options through mobility and poaching opportunities (Bartelsman, Dobbelaere, and Mattioli, 2026). Because such knowledge is only partially contractible and can be carried across firms, workers may gain stronger bargaining positions and wages. At the same time, investment in intangible assets, such as software, may result in the automation of middle-skilled, routine jobs alongside the creation of high-skilled jobs (see, for instance, Acemoglu and Autor 2011; Autor 2015; Acemoglu and Restrepo 2019). Investing in intangible assets, such as brand value, may allow firms to raise productivity without necessarily creating more jobs or raising wages.

[2] Some studies, however, provide alternative explanations. For example, Glover and Short (2020) argue that the global decline in labor income share cannot be fully explained by capital deepening in response to declining investment prices. For a review of the recent literature on labor income shares, see Grossman and Oberfield (2022).

While the productivity effects of intangible assets are well documented, the relationship between investments in intangible capital and labor income shares is less understood, particularly in developing economies.[3] Industry-level data for advanced economies find a heterogeneous relationship between intangible capital intensity and the labor income share, which is positive in service-trade-oriented economies but negative in manufacturing-export-oriented economies (García-Lázaro and Pearce 2023). However, industry-level aggregates conceal the underlying mechanisms that operate at the firm level, where investment, technology adoption, and employment decisions are made. This is especially important in developing economies, where firms are highly heterogeneous and face sharply differing capital constraints.

To fill the gap in the literature, we use a unique firm-level dataset from India to estimate the relationship between intangible capital intensity and the labor income share.[4] In doing so, we measure investments and capital stocks in three types of intangible assets: computerized information, innovative properties, and economic competencies. Based on data from over 30,000 firms between 2001 and 2021, we find that, on average, a 1-percent increase in the intangible capital-to-value-added ratio (i.e., intangible capital intensity) is associated with an increase in the labor share of 0.1 percent. We also find that on average, a 1-percent increase in the tangible capital-to-value-added ratio is associated with an increase in the labor share of 0.5 percent. The results remain robust to the inclusion of firm fixed effects and are valid for all three types of intangible capital. Furthermore, we find that the positive link between intangible capital intensity and labor income share is stronger in sectors with high skill intensity or ICT intensity. We do not find similar results for tangible capital, which is indicative of a complementarity between intangible capital and the production process, where the use of skills and technology is more salient.

Finally, we explain the positive link between intangible capital stock and the labor income share by examining the effects of intangibles on labor productivity and total employment. Our analysis shows that both intangible and tangible stock per worker is significantly and positively associated with higher labor productivity. However, we find that intangible capital intensity is also positively and significantly associated with total employment, while tangible capital is negatively and significantly associated with total employment. The results suggest that intangible assets are more labor-augmenting than labor-displacing than tangible assets.

Our paper contributes to the literature on the economic impacts of intangible capital, which[5] is primarily focused on advanced economies. It adds to two previous studies on intangible assets among software firms in India (De and Dutta 2007; De 2009), as well as to a cross-sectional analysis of 3,200 corporate firms reporting a positive relationship between intangible assets and productivity (Goldar and Parida 2017). Closely related, Khanna and Sharma (2018) found that there is a complementarity between IT and R&D in generating labor productivity growth among firms in India's manufacturing sector.

[3] In terms of the productivity effects of intangible assets, please see, for instance, Corrado, Haskel, and Jona-Lasinio (2017), Corrado et al (2022), van Criekingen, Bloch, and Eklund (2022), and van Ark, de Vries, and Erumban (2024).
[4] ICT and complementary types of intangible investment (especially organizational capacity) have been shown in other country contexts to be essential to services sector growth (e.g., Bloom et al. 2012; Ilmakunnas and Piekkola 2014).
[5] See, for instance, CHS (2005), Corrado et al. (2022), Crouzet et al. (2022), van Criekingen, Bloch, and Eklund (2022), García-Lázaro and Pearce (2023), and Velic (2025).

Second, it contributes to the literature that explores the heterogeneity in the economic impacts of intangible assets across sectors and across various types of firms. Chen, Niebel, and Saam (2016) showed that output elasticity of intangibles is stronger in more ICT-intensive sectors for 10 European countries. Niebel, O'Mahony, and Saam (2016) reported that the contribution of intangibles to labor productivity growth is generally highest in the manufacturing and financial services sectors. Li and Wu (2020) found that China's ICT-intensive sectors grow more rapidly in regions with faster intangible capital development. Friesenbicher, Kugler, and Knobl (2025) showed intangibles, such as software and licenses, played a more important role in production for small and medium enterprises (SMEs). Hill and Rothaermel (2003) find weaker growth impacts of intangible capital among older, larger firms that may be related to challenges in managing innovative activities due to organizational inflexibility and inertia.

Third, it contributes to the literature that estimates investments in intangible capital. Studies measuring intangible investment at the macro level have been undertaken for a range of advanced economies: the United States (CHS 2009); the United Kingdom (Haskel and Marrano 2007); Germany (Crass et al. 2009; Crass and Peters 2014); France, Italy, and Spain (Hao, Manole, and van Ark 2009); Japan (Fukao et al. 2009); and South Korea (Chun and Nadiri 2016). However, the 2008 System of National Accounts (SNA) excludes several significant categories of intangible assets—such as branding, design, human capital and training, and organizational capital—which can lead to underinvestment in intangible capital (UN 2008; van Criekingen, Bloch, and Eklund 2022). We contribute to the literature by applying the approach of previous studies that use firm-level data to estimate intangible assets in advanced economies (Bontempi and Mairesse 2015; Di Ubaldo and Siedschlag 2021) to data from a developing economy.

The rest of the paper is structured as follows. Section 2 describes how intangible investments and capital stock are estimated using the firm-level data obtained from the Centre for Monitoring Indian Economy (CMIE) Prowess database and provides descriptive statistics. Section 3 presents the empirical strategy for analyzing the relationship between intangible capital stock and the labor income share, using a standard constant elasticity of substitution (CES) production function. Section 4 empirically assesses the link between intangible capital stock and labor income share at the firm level, followed by a series of robustness checks and heterogeneity analyses. Section 5 provides additional analyses of the underlying channels through which intangibles affect the labor income share (i.e., labor productivity and total employment). Section 6 concludes.

2. Data and Descriptive Statistics: Measuring intangible investment in India

The 2008 System of National Accounts (SNA), recognizes certain intangible assets as part of gross fixed capital formation, particularly intellectual property products (IPPs) such as software and R&D expenditures. However, coverage remains partial, as several major categories of intangible assets, such as branding, design, human capital, and training, remain excluded from official investment measures. Given this inadequate coverage of intangible assets in the official statistics, researchers have often relied on alternative methods to measure intangible investment (CHS 2005).

CHS (2005) proposed an expenditure approach in which any expenditure intended to increase future consumption is considered an investment, and intangible assets are defined as "knowledge-based." They identify three types of intangible assets: 1) computerized information (such as

software and databases), 2) innovative property (including research and development, mineral exploration, etc.), and 3) economic competencies (such as market research, branding, operational models, and employer-provided training). In this paper, we broadly follow the asset classification in CHS to measure intangible investment in India, using firm-level balance sheet data sourced from the CMIE's Prowess database (see Appendix for details).[6]

2.1. Estimating intangible investment and capital stock

The Prowess database contains data for over 30,000 firms since 1990, with the number of companies changing over time as its coverage improves. This paper focuses on the period from 2001 to 2021, during which the number of firms with sufficient data exceeded 5,000 in every year. These firms together represented 40 to 50 percent of the national value added reported by the India KLEMS database each year in the sample period (Das et al. 2021).

To estimate investment in different assets, we first convert gross fixed assets (GFA) reported by firms in their financial statements to investment flows by calculating the difference between the current and previous year's GFA values (see Appendix A2 for details). This approach works for all tangible and intangible assets capitalized by the firm (see Table 1). However, many expenses incurred by firms that should be capitalized as intangible assets are often not capitalized in these financial statements. Therefore, as the second step in the estimation process, we capitalize some of the expense categories reported in the balance sheets, following the definitions in CHS (2009) and the approaches from subsequent studies (such as Bontempi and Mairesse 2008 and Marrocu et al. 2011).[7]

We identify six expense categories under the intangible group, listed in the lower panel of Table 1. We treat the full reported values of the first four categories—royalties (technical know-how fees), license fees, research and development expenses, and staff training expenses—as intangible investments. For advertising and sales promotion expenditures, we follow CHS (2005) and treat 60 percent of these expenses as investments, reflecting their short-lived nature. Each individual asset and expense category from Prowess is linked to one of the three CHS intangible categories in Table 1. We then calculate total investment in each intangible asset type by summing the estimated investment flows from both gross fixed asset and expense categories.

Table 1: Asset groups and their sources in Prowess

Prowess Gross Fixed Assets (GFA) categories	**Tangible Assets**
Land and building	Land & Buildings
Plant & machinery, computers, and electrical installations	Machinery & Equipment
Transport & communication equipment and infrastructure	Machinery & Equipment
Furniture, social amenities, and other fixed assets	Machinery & Equipment
	Intangible Assets
Goodwill	Economic competencies

[6] See van Criekingen, Bloch, and Eklund (2021) for a review of approaches used to measure intangibles in the literature, including this macro-expenditure approach, as well as micro approaches using firm-balance sheet data either to estimate broad groups of intangibles or specific components such as advertising (Peters and Taylor 2017; Marrocu et al. 2012; Bontempi and Mairesse 2015; Belo et al. 2014; Dubin 2007).

[7] Given that the definition of intangible is less straightforward compared to tangible assets, the decision on capitalization of certain expenses is usually subject to the firms' discretion (Marrocu et al. 2011).

Brands & trademark	Economic competencies
Software	Computerized information
Mining rights	Innovative property
Licenses & trade-related rights	Innovative property
Patents & copyrights	Innovative property
Technical know-how, incl. product designs/formulae, etc.	Innovative property
Prowess Expenses categories, capitalized by this study	**Intangible Assets**
Royalties, technical know-how fees, etc.	Innovative property
License fees	Innovative property
Research & development expenses (capital account)	Innovative property
Staff training	Economic competencies
Advertising expenses (60%)*	Economic competencies
Sales promotion expenses (60%)*	Economic competencies

Notes: Given that the effects of advertising and sales promotion are short-lived, CHS (2005) assumes 60 percent of advertising and market research expenditures are treated as investments (CHS 2005, p.32).

The nominal tangible investment flows are converted to real volumes using investment price deflators for machinery and construction, and intangibles are deflated using output deflators from the business services sector. Data on both flows are obtained from the India KLEMS dataset (Das et al. 2021). Then we obtain capital stock for the two types of tangible assets – land & buildings and machinery – and three types of intangible assets – economic competencies, computerized information, and innovative property – using the standard perpetual inventory method (PIM).[8]

2.2. Trends and composition of intangibles

At the firm level, the composition of capital stock in India has shifted from tangible to intangible assets over the past two decades (see Figure 1A). This shift was broad-based, though it occurred at varying rates across the six major sectors in our sample.[9] For all firms, the share of intangible assets in total capital stock rose from about 5 percent in 2001 to over 10 percent in 2019, before declining slightly to 9 percent in 2021. This easing since the late-2010s is linked to a decrease in intangible investment rates after 2017, which is also reflected in the NAS estimates of IPP.[10] Although the precise causes of the decline in intangible intensity in 2017 remain unclear, events such as demonetization in November 2016 and the short-term disruptions from the introduction of the Goods and Services Tax (GST) in July 2017 may have played a role. These policy changes likely created short-term business uncertainty, tightened credit conditions, and temporarily slowed demand (Nagaraj 2025)—all factors that could have affected investment, including investment in intangibles (such as innovation and brand building).

[8] That is, $K_{i.j.t} = K_{i.j.t-1}(1-\delta_j) + I_{i.j.t.}$ where K is the real net capital stock, and I is the real investment flow, both for firm i, asset-type j, and year t. δ is the asset-specific economic depreciation rate, obtained from the India KLEMS for the tangible assets, and CHS (2005) for the intangible assets (see Appendix Table A2). To operationalize the PIM, we also assume a firm-level initial capital stock for each asset by converting the reported GFA in the earliest year at historical costs to the replacement cost of the asset value, following Srivastava (1996; see Appendix A2 for details).

[9] As shown in Appendix Figure A1, the share of intangibles in total capital stock and total investment increased across all six broad sectors (except mining and utilities) between 2001 and 2021.

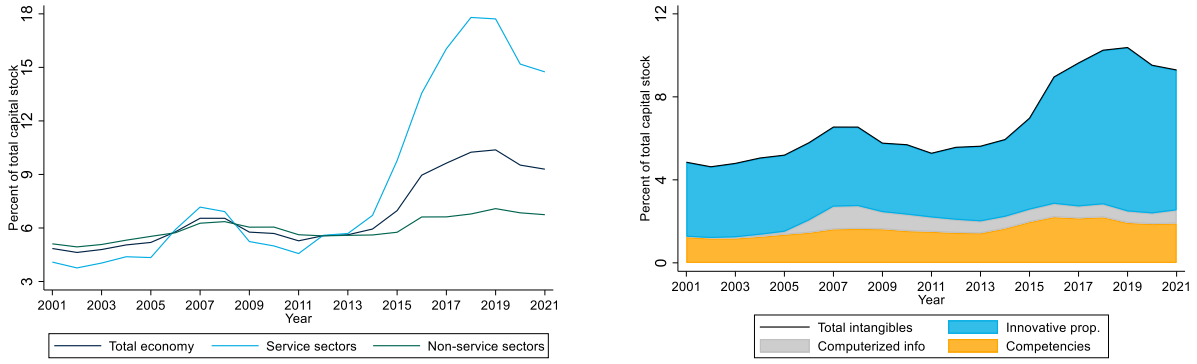
[10] The intangible investment to value-added ratio in our estimates increased from 2.3 percent in 2011 to 5.6 percent in 2016, whereas the IPP to value-added ratio in the NAS increased from 2.7 to 4.2. Both fell in 2017 to 4.4 percent and 3.6 percent, respectively, and have mostly remained flat since then. While the two are not entirely comparable due to differences in asset and industry coverage, the overall trend is aligned.

The rise in intangible assets between 2001 and 2019 was especially pronounced in the service sector, with the share increasing by about 14 percentage points—from 4 percent in 2001 to 18 percent in 2019 (Figure 1A). In contrast, other sectors saw an increase of only about 2 percentage points. Notably, the decline in intangible assets from 2019 to 2021 was also more pronounced in the service sector, by roughly 3 percentage points. In contrast, the share of intangibles in total capital stock remained nearly unchanged in other sectors.

Most of India's intangible capital stock is concentrated in innovative properties (Figure 1B). On average, approximately two-thirds of intangible capital stock consists of innovative property – such as mining rights, patents, copyrights, licenses, license fees, and R&D expenses. Around one-fourth is in economic competencies, which include goodwill, brands and trademarks, staff training, and parts of advertising and sales promotion. The share of capital stock in computerized information has grown since 2005, rising from 0.1 percent of total capital stock in 2005 to nearly 0.6 percent in 2017. Over the same period, the share of innovative property and economic competencies in total capital stock increased by 1.8 and 1.5 times, respectively. However, while innovative properties and computerized information maintained their relative contributions to the total capital stock, the share of competencies declined modestly by 2021, resulting in a relatively flat overall share of intangibles in the total capital stock.

Figure 1: Evolution of intangibles over time, 2001-2021

A. Intangible capital stock, by sector **B. Composition of intangible capital stock**



Source: Authors' calculations using CMIE Prowess Database.
Notes: A. The three lines show intangible capital stock as a share of total capital stock for each year from 2001 to 2021. The navy line represents the total economy, while the light blue (green) line represents service (non-service) sectors. The estimates are based on all the firms for which we had data on intangibles and are therefore a subset of the total firms reported in the Prowess Database.

3. Empirical strategy

Using a standard constant elasticity of substitution (CES) production function and some log-linearization (see Bentolila and Saint-Paul 2003; Garcia-Lazaro and Pearce 2023), we derive the following estimable equation that sets the foundation for the empirical analysis in the following section:[11]

$$\ln S_{L_{it}} = \beta_0 + \delta \ln z_{it} + \gamma \ln n_{it} + \boldsymbol{\beta_1 X_{it}} + f_i + yr_t + e_{it} \quad (1)$$

[11] See Appendix A3 for details on model derivations.

where $\ln S_{L_{it}}$ is the labor income share (in logs), defined as the compensation of labor as a share of the value-added of firm i in year t.[12] The tangible capital intensity, z_{it}, and the intangible capital intensity, n_{it} are defined as tangible and intangible capital stock (Z and N) as a ratio of real total value-added (Y), respectively. β_0 is a constant term, $\boldsymbol{X_{it}}$ is a set of time-varying controls, f_i is firm fixed effects, and yr_t is time-fixed effects. Lastly, e_{it} is the remaining error term. Since the Prowess reports financial data annually, the time-fixed effects are based on years. In addition to firm fixed effects, we control for firm age, defined as the number of years since incorporation (reported in Prowess; in logs). In the robustness check, we also consider other firm-level controls, such as the employment size (see Section 4 below for details).

Here, our main coefficients of interest are γ and δ. They are the partial elasticities of intangibles and tangibles to output ratios on the labor income share, respectively. If the estimated values for δ are positive (negative), tangible capital and labor behave as complements (substitutes). Likewise, if the estimated values for γ are positive (negative), intangible capital and labor act as complements (substitutes), within the CES production framework. To estimate our coefficient of interest, we start with the fixed effects (FE) estimator as our baseline. As a robustness check, we adopt the generalized method of moments (GMM) approach to eliminate unobservable firm fixed effects and address potential dynamic endogeneity issues when analyzing panel data.

In total, we have data on relevant variables from approximately 240,000 observations from 30,722 firms from 2001 to 2021. About 90 percent of the observations in our sample are from two broad sectors: manufacturing and market services (see Appendix Table A1). Value added (Y_{it}) in Equation (1) is calculated as the sum of sales and inventories (a measure of output), subtracting expenditure on intermediate inputs and fuel consumption, all at the firm level (Goldar and Parida, 2017). We augment these firm-level value-added measures by including expenses on our capitalized intangible assets and then deflate them using industry-specific value-added deflators from the India KLEMS database. Wage compensation is reported by Prowess, and thus, the dependent variable ($\ln S_{L_{it}}$) is the log of reported labor compensation as a percentage share of the augmented value-added. Since most firms lack employment data in Prowess, we estimate employment using firm-level labor compensation and industry wage rates from the Annual Survey of Industries and India KLEMS (see Appendix A2 for details).

A median firm in our sample hires about 510 employees, aged approximately 19 years, with a value-added per employee amounting to 1.1 million 2011 Indian Rupees. The tangible capital intensity, amounting to 104 percent of value-added, is noticeably higher than the intangible capital intensity at a median firm. About 60 percent of the tangible assets are in land and buildings, with the rest being in machinery and equipment. Meanwhile, in a medium firm, the total intangible capital stock only amounts to about 2 percent of value-added. When comparing across sectors, we find that tangible capital intensity is lowest in construction and market services, while intangible capital intensity differs little across sectors (with the highest being in market services). Moreover, the means of several variables under consideration differ notably from their medians. Therefore,

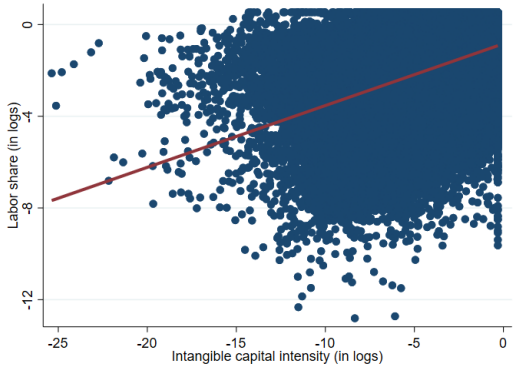
[12] Both labor compensation and value added are in nominal terms when computing the labor income share here.

in the following analyses, we winsorized the data to prevent extreme values from affecting our results.[13] The sample statistics (winsorized at the top 5 percent) are shown in Appendix Table A4.

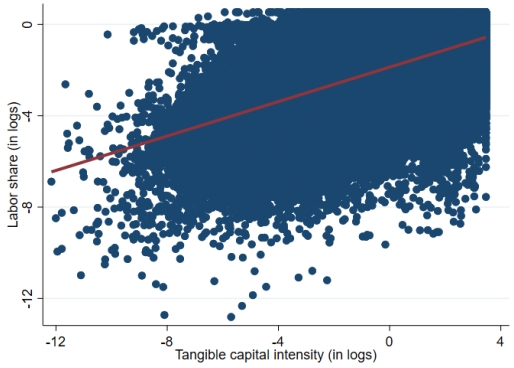
Figure 2 plots capital intensity against labor income share over our sample period 2001-2021. We do so for both tangible and intangible assets. In both plots, the fitted line exhibits a positive slope, indicating a positive relationship between capital intensity and the labor income share. Moreover, the slope does not noticeably differ between tangible and intangible capital intensity. Since various factors, such as sectoral features, can affect both capital intensity and the labor income share, we analyze their relationship more formally in the following section using Equation (1).

Figure 2: Capital intensity vs labor income share, 2001-2021

A. Intangible capital intensity
(percent of total value added, in logs)



B. Tangible capital intensity
(percent of total value added, in logs)



Source: Authors' calculations using CMIE Prowess Database.
Notes: The data covers the period 2001-2021 and is winsorized at the top 5 percent. The red line is the fitted line. The x-axis shows capital stock (intangible in A and tangible in B) as a ratio value-added (in logs), and the y-axis shows the labor income share (in logs).

4. Empirical results

4.1. Baseline results

Table 2 presents our baseline fixed-effects estimates from Equation (1), controlling for firm-specific effects. All regressions include a full set of year dummies and firm age as control variables. Capital stock measures are included at increasing levels of asset disaggregation across columns. The sample is winsorized at the top 5 percent to avoid the results being affected by extreme values.[14]

In Column [1], we include total capital intensity, which is the sum of total tangibles and total intangibles as a ratio of value-added (i.e., the total capital stock-to-value-added ratio). The estimated coefficient is positive and significant at the 1 percent level. This result implies that, on average, a 1 percent increase in the total capital stock-to-value-added ratio is associated with an increase in labor share by 0.5 percent. The positive coefficients indicate a low elasticity of

[13] It should be noted that almost all findings reported here and in the subsequent tables remain robust when using non-winsorized data. Results will be provided upon request.
[14] The results in Table 2 remain unchanged when trimming the top 5 percent of the sample to address extreme values or when using subsamples before or after 2013. See Online Appendix for details.

substitution or complementarity between capital and labor in the context of Indian firms.[15] Moreover, it seems to suggest that capital accumulation contributed to value-added in Indian firms, with the gains being partially allocated to employees.

To understand what types of capital assets are driving the results, we separate total tangible and total intangible capital stocks in Column [2]. We observe that both categories are significantly and positively associated with labor income share. Column [3] further investigates the relationship between various subcomponents of tangible and intangible assets and labor share. The positive association between capital intensity and labor income share is found to be significant for all types of tangible and intangible assets. Among the intangibles, competencies and computerized information seem to have a slightly larger impact than innovative property. Roth and Thum (2022) also observed that competencies have a relatively greater impact on productivity than innovative property and software in their EU industry-level sample. In contrast, firm-level evidence from Germany, which did not include competencies, suggests that R&D has a stronger effect than purchased software (Kaus, Slavtchev, and Zimmermann 2024). As argued by Crouzet et al. (2022), some intangible assets, such as computerized information and competencies, are stored in key (often skilled) employees and cannot enter the production process alone, while the same may not apply to innovative property. Therefore, it is possible that increasing investment in computerized information and competencies gives key employees greater bargaining power, leading to more rent-sharing and, in turn, a higher labor share (Bartelsman, Dobbelaere, and Mattioli, 2026). While the firm-level data we use in this study do not allow us to distinguish workers by skill, macroeconomic evidence points to a rapid increase in high-skilled employment and their compensation share in India over our sample period (see Appendix Figure A6).

The results from Columns [2] and [3] also show that the partial elasticities of tangible-to-value-added ratios with respect to the labor share are greater than those of the intangible-to-value-added ratios. This pattern is broadly consistent with earlier studies on the relative contributions of tangibles versus intangibles to labor productivity growth (for instance, Borgo et al. 2013 and van Ark et al. 2009 on the effects in the UK and some catching-up EU countries). More recent evidence, however, suggests a more nuanced picture: the effects of tangibles and intangibles are more balanced (e.g., Roth and Thum 2022), and the effect of intangibles is stronger for certain groups of firms (e.g., Kaus, Slavtchev, and Zimmermann 2024). As wage is a function of labor productivity, the larger contribution of tangibles to labor productivity may be reflected in a larger impact on the labor income share in our sample. To test this hypothesis, we run some additional analyses in Section 5.

Table 2. Baseline results (Fixed Effects)

Dep var: Labor income share	[1]	[2]	[3]
Total capital stock	0.535***		
	(0.005)		
Total tangibles		0.457***	
		(0.005)	

[15] Evidence on the elasticity of substitution between labor and capital in India is limited. Available studies focusing on the formal manufacturing sector from 1980 to 2008 suggest no evidence of strong substitutability between these factors (Goldar, Pradhan, and Sharma 2013).

─ Land & buildings			0.193***
			(0.017)
─ Machinery & equipment			0.245***
			(0.018)
Total intangibles		0.095***	
		(0.003)	
─ Economic competencies			0.035***
			(0.006)
─ Computerized information			0.031***
			(0.004)
─ Innovative property			0.016***
			(0.005)
Firm age	-0.253***	-0.263***	-0.149***
	(0.013)	(0.013)	(0.052)
Constant	-1.444***	-0.945***	-1.557***
	(0.031)	(0.034)	(0.204)
Obs	239989	239989	19651
Nr of firms	30722	30722	3701
R-sq.	0.426	0.441	0.478
Adj. R-sq.	0.425	0.441	0.477

Notes: Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. The labor income share (dependent variable), firm age, and the capital stock variables (measured as ratios to value added) are used in the regression in log form. The sample is winsorized at the top 5 percent to avoid results being affected by extreme values.

4.2. Robustness checks

In this subsection, we run a series of robustness checks to confirm our baseline findings. First, we apply the GMM estimator to the model specifications in Table 2 and report the results in Table 3. We find that the results remain largely the same. While tangible intensity is associated with a slightly smaller labor share at the firm level, the coefficient for intangible intensity is almost twice as large as the estimate in Table 2 (Column [2] in Table 3). Furthermore, the subcategories of intangibles in Column [3], economic competencies, and computerized information also have slightly higher coefficients. The coefficients before the three subcategories remain positive and significant at the 10 percent level when the GMM estimator is applied.

Table 3. The generalized method of moments (GMM) approach

Dep var: Labor income share	[1]	[2]	[3]
Total capital stock	0.543***		
	(0.010)		
Total tangibles		0.412***	
		(0.009)	
─ Land & buildings			0.111**
			(0.055)
─ Machinery & equipment			0.275***
			(0.057)
Total intangibles		0.185***	
		(0.007)	
─ Economic competencies			0.055***
			(0.017)
─ Computerized information			0.049***
			(0.015)

─ Innovative property			0.032*
			(0.018)
Firm age	-0.471***	-0.646***	-0.362**
	(0.033)	(0.038)	(0.144)
Constant	-0.843***	0.507***	-0.646
	(0.085)	(0.119)	(0.791)
Obs	239989	239989	19651
Nr of firms	30722	30722	3701
Sargan-Hansen p-val	0.000	0.070	0.322
Kleibergen-Paap p-val	0.000	0.000	0.000

Notes: Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. The labor income share (dependent variable), firm age, and the capital stock variables (measured as ratios to value added) are used in the regression in log form. The GMM estimator is applied here. The sample is winsorized at the top 5 percent to avoid results being affected by extreme values.

As employment size can affect both the labor income share and the capital intensity, we add it as an additional control in Table 4. As mentioned earlier, employment data is available only for some firms in the Prowess database. In Columns [1]-[3], we follow previous studies and use an indirect approach to impute employment for each firm to keep our sample unchanged from our baseline. Specifically, for firms with missing employment data, we construct an implicit employment estimate by dividing total labor compensation from Prowess by the industry's average wage rate (i.e., total emoluments per employee; see Appendix A2). Since the imputed employment measure assumes that the wage rates faced by each firm within a broadly defined industry are the same, it is not a precise measure of firm-level employment. Yet, it may be considered labor input measured in efficiency units (e.g., Balakrishnan, Pushpangadan, and Babu 2000). Then, we use the reported employment as the additional control in Columns [4]-[6]. While using the imputed employment numbers ensures that the sample size in Columns [1]-[3] does not differ from the baseline, using the reported employment numbers avoids the estimates being affected by the imputation method we apply.

The results, estimated using firm fixed effects, are strongly in line with the baseline.[16] Regardless of which type of employment estimate is added, the link between the labor income share and the capital intensity rate is found to be positive and significant for all types of tangible and intangible assets. The results seem to indicate that capital assets complement labor in India's firms. Moreover, in line with what we have found before, the positive effect is found to be bigger for tangible assets than for intangible assets. While the partial elasticity of the intangible intensity on the labor share amounts to 0.5, the partial elasticity of the tangible intensity is about 0.1. That is, on average, a 1 percent increase in the (in)tangible capital-to-value-added ratio is associated with a significant increase in the labor income share by (0.1) 0.5 percent.

Table 4. Robustness check: Additional controls

	Imputed employment			Reported employment		
Dep var: Labor income share	[1]	[2]	[3]	[4]	[5]	[6]
Total capital stock	0.605***			0.565***		
	(0.005)			(0.014)		
Total tangibles		0.528***			0.493***	
		(0.005)			(0.015)	

[16] It is worth noting that the fixed effects results in Tables 4-7 are largely robust to the use of the GMM estimator (see Online Appendix for details).

─ Land & buildings			0.288***			0.247***
			(0.020)			(0.039)
─ Machinery & equipment			0.241***			0.203***
			(0.018)			(0.034)
Total intangibles		0.084***			0.083***	
		(0.002)			(0.007)	
─ Economic competencies			0.027***			0.032***
			(0.005)			(0.009)
─ Computerized information			0.033***			0.027***
			(0.004)			(0.007)
─ Innovative property			0.025***			0.014**
			(0.005)			(0.006)
Employment	0.377***	0.366***	0.426***	0.119***	0.111***	0.063***
	(0.006)	(0.006)	(0.030)	(0.014)	(0.014)	(0.017)
Firm age	-0.506***	-0.515***	-0.319***	-0.062	-0.085*	-0.015
	(0.013)	(0.013)	(0.041)	(0.044)	(0.044)	(0.080)
Constant	-2.760***	-2.253***	-3.574***	-2.504***	-1.987***	-1.661***
	(0.037)	(0.039)	(0.211)	(0.144)	(0.154)	(0.299)
Obs	237766	237766	19651	30953	30953	5597
Nr of firms	30399	30399	3701	4833	4833	1037
R-sq.	0.554	0.561	0.601	0.519	0.526	0.560
Adj. R-sq.	0.554	0.561	0.600	0.519	0.526	0.558

Notes: Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. The fixed-effect estimator is used in all columns. The labor income share (dependent variable), firm age, and the capital stock variables (measured as ratios to value added) are used in the regression in log form. The sample is winsorized at the top 5 percent to avoid results being affected by extreme values.

Lastly, we test whether our results are robust to the treatment of extreme values. In Appendix Table A5, we first re-estimate the regressions in Table 2 using the raw data (unwinsorized) in Columns [1]-[3], and then re-estimate the regressions with data winsorized at the top 1, 3, and 10 percent, respectively. The results are strongly in line with the baseline results, with the coefficients before the intangible capital intensity remaining positive and significant throughout the table. As extreme values tend to concentrate in a few specific sectors, Appendix Table A6 addresses this issue by excluding observations from those sectors: that is, excluding the financial sector alone in Columns [1]-[3] and excluding both the financial and rental services sectors in Columns [4]-[6]. Lastly, Columns [7]-[9] show the results when observations with the labor income share exceeding 100 percent are excluded. The results remain strongly aligned with the baseline results presented in Table 2, indicating that our results are not notably affected by how we handle extreme values.

4.3. Heterogeneous effects

In this subsection, we test whether the relationship between the labor income share and (tangible and) intangible capital stocks varies across different types of firms. As shown in previous studies, the contribution from intangibles to output or labor productivity growth may vary across sectors and firm sizes.[17] We examine whether the relationship varies by sector (i.e., services vs non-services sectors; sectors with high vs low skill intensity / R&D intensity / ICT intensity), by firm age (in logs), and by firm size (captured by a dummy that equals one if the imputed number of employees is above 500 and 0 otherwise). To accomplish this goal, we extend the baseline model

[17] See, for instance, van Ark et al. (2009), Chen, Niebel, and Saam (2016), Niebel, O'Mahony, and Saam (2017), and Friesenbicher, Kugler, and Knobl (2023).

in Equation (1) to include interaction terms between various types of capital stock and the firm characteristics under consideration, respectively. The results are shown in Table 5.

Table 5. Heterogeneous effects on labor income share

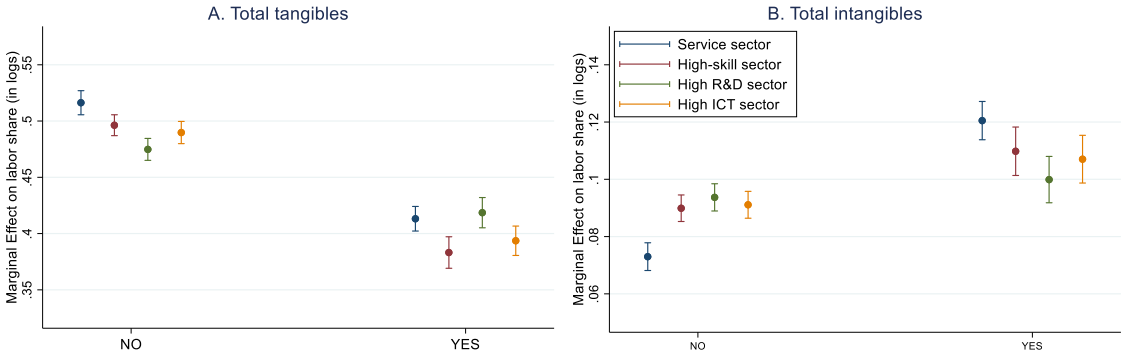
	(1)	(2)	(3)	(4)	(5)	(6)
	Services	High skill	High R&D	High ICT		
`Int var'=	sectors	sectors	sectors	sectors	Age	Emp.>500
Firm age	-0.261***	-0.263***	-0.264***	-0.263***	-0.343***	-0.295***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.018)	(0.013)
Total tangibles	0.516***	0.496***	0.475***	0.490***	0.245***	0.466***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.010)	(0.005)
Total intangibles	0.073***	0.090***	0.094***	0.091***	0.222***	0.108***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.003)
Interaction effects (* `Int var')						
- Total tangibles	-0.103***	-0.113***	-0.056***	-0.096***	0.079***	-0.038***
	(0.009)	(0.010)	(0.010)	(0.010)	(0.003)	(0.007)
- Total intangibles	0.048***	0.020***	0.006	0.016***	-0.044***	-0.054***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)
Constant	-0.972***	-0.940***	-0.935***	-0.933***	-0.665***	-0.878***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.048)	(0.034)
Obs	239989	239989	239989	239989	239989	239989
Nr of firms	30722	30722	30722	30722	30722	30722
R-sq.	0.444	0.444	0.442	0.443	0.451	0.450
Adj. R-sq.	0.444	0.444	0.441	0.443	0.451	0.450

Notes: Robust standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01. The fixed-effect estimator is used in all columns. The labor income share (dependent variable), firm age, and the capital stock variables (measured as ratios to value added) are used in the regression in log form. *`Int var'* refers to the interaction variables, which are dummy variables equal to 1 if a firm is in the service industry (Column [1]), is in a high skill–intensive sector (Column [2]), is in a high R&D–intensive sector (Column [3]), or is in a high ICT–intensive sector (Column [4]), and 0 otherwise. "High skill–intensive" sectors are defined as those in the top one-third proportion of highly skilled workers (education beyond the secondary level) within total employment, based on KLEMS and household labor force data. "High R&D–intensive" and "High ICT–intensive" sectors refer, respectively, to sectors in the top one-third of R&D expenditure relative to value added and of gross fixed assets in computer and IT equipment relative to value added; both measures are derived from aggregated Prowess firm-level data. The sample is winsorized at the top 5 percent to avoid results being affected by extreme values.

First, we add the interaction terms between various types of capital stock and the service-sector dummy to Column [1]. The service-sector dummy equals one if the firm is in the service sector and zero otherwise. Consistent with the baseline, the coefficients for both tangible and intangible capital stock are positive and significant, indicating that both types of capital intensities enhance labor income share in non-service sectors. Furthermore, the coefficient for the interaction term between total intangible capital intensity and the service sector dummy is positive and significant, suggesting that intangible capital complements labor more and thus raises the labor share more in the service sector than in the non-service sector (as depicted in Figure 3). Meanwhile, the coefficient for the interaction term between tangible capital intensity and the service sector dummy is negative and significant. This means that the positive effect of tangibles on labor income share is stronger in non-service sectors than in service sectors. Since most non-service firms in our sample are manufacturing firms, the significant difference in the effect between services and non-services sectors mainly captures the difference between manufacturing and service firms.[18]

[18] While the labor share in the service sectors, on average, benefits more from intangibles, not all service sectors invest heavily in intangible assets. In 2021, firms in the post and telecommunications, trade and transport, and business and financial services sectors

Figure 3. The marginal effect of tangibles and intangibles: sectoral characteristics



Notes: The charts are based on regression results shown in Table 5. The dots show the estimated marginal effects of the capital stock-to-value-added ratio in logs (tangible capital stock in A and intangible capital stock in B) on the labor share. The spikes indicate the corresponding 90 percent confidence intervals.

Second, we explore other dimensions of sector heterogeneity that might be related to the marginal effect of intangibles on the labor income share. In particular, in Columns [2]-[4], we include the interaction terms between tangible (and intangible) capital intensities and a set of dummy variables indicating whether firms are in sectors with high skill, R&D, and ICT intensity, respectively. Here, "high skill (intensity)" sectors are defined as those comprising the top one-third in the ratio of highly skilled workers (characterized by education beyond the secondary level) over the total employment, based on KLEMS data. The "High R&D (intensity)" sectors denote those with the highest one-third ratio of R&D expenditure relative to value-added, derived from aggregated Prowess firm-level data. Similarly, "High ICT (intensity)" sectors refer to those with the highest one-third ratio of gross fixed assets in computer and IT equipment to value-added, aggregated from Prowess firm-level data. As shown in Columns [2] and [4] (and Figure 3), the marginal effect of total intangible capital as a ratio to value-added on labor income share is significantly larger in firms operating in sectors with high skill and ICT intensity, respectively. Although the difference is not significant between sectors with high or low R&D, the coefficient for the interaction term remains positive in Column [3]. Meanwhile, the marginal effect of total tangible capital intensity on labor income share is significantly smaller in firms operating in sectors with high skill, R&D, and ICT intensity, respectively.

These results suggest intangibles play a stronger complementary role in labor and thus benefit workers more in those sectors. These findings are in line with the previous studies that find that intangibles contribute more to labor productivity growth in firms in ICT-intensive and other skill-intensive sectors (e.g., Chen, Niebel, and Saam 2016, Niebel, O'Mahony, and Saam 2017, Li and Wu 2020). This also supports the argument that certain intangible assets, such as computerized information and competencies, are housed within key (often skilled) employees and cannot be utilized in the production process independently (Crouzet et al. 2022). This phenomenon, which

collectively owned 49 percent of total intangible capital assets in our sample (see Appendix Figure A4 for details). Therefore, the extra labor income gains from intangibles in the service sectors may come from some specific service sectors. To test this hypothesis, we interact a set of sector dummies with various measures of capital intensity. We highlight sectors with more intangibles, which are "post and telecommunication," "trade and transport (and storage)," and "business and financial services," and compare them with non-services sectors. Results show that some of these specific service sectors indeed experience higher labor-income gains from intangibles than non-service sectors. The results are included in the Online Appendix.

can be more prominent in sectors with high skill and ICT intensity, can potentially lead to a higher labor share.

Third, we include the interaction terms between tangible and intangible capital intensities and a firm's age to test whether the positive link between various types of capital stocks and labor income share evolves as firms age. As shown in Column [5] (and Figure A5), the positive effect of intangible capital intensity on the labor income share declines significantly as firms age, as the coefficient for the interaction term between intangible capital intensity and age is negative and significant. However, the magnitude of the coefficient is relatively small. The marginal effect of intangible capital intensity on labor income share stays positive and significant for firms of all ages in our sample. Meanwhile, the marginal effect of tangible capital intensity on labor income increases with a firm's age, showing that the complementarity between capital and labor varies between tangible and intangible assets as firms age.

Fourth, we include interaction terms between capital intensity rates and a dummy variable (equal to 1 for firms with more than 500 employees) to test if the positive relationship between capital intensity and labor share varies by firm size. As shown in Column [6], the coefficient for the interaction term between intangible capital intensity and labor income is negative and significant. Meanwhile, the coefficient for the interaction term between tangible capital intensity and labor share is insignificant. This indicates that intangible assets are generally more advantageous for smaller firms (as depicted in Appendix Figure A5). The weaker effects seen in older, larger firms may result from organizational inflexibility and inertia, which hinder their ability to manage innovation (Hill and Rothaermel 2003).

5. Mechanism: labor productivity and employment

Here we attempt to explain the positive link between intangible capital stock and the labor income share by examining the effects of intangibles on labor productivity and employment, respectively. As shown in Appendix A3, labor productivity, measured as value-added per worker, is linked to the labor income share via its role in determining the optimal wage rate. Therefore, with some modification, we estimate the effect of intangibles on labor productivity at the firm level as follows.

$$Ln\frac{Y_{it}}{L_{it}} = \beta_2 + \alpha \,\mathrm{Ln}\left(\frac{Z_{it}}{L_{it}}\right) + \beta \,\mathrm{Ln}\left(\frac{N_{it}}{L_{it}}\right) + \boldsymbol{\beta_3 X_{it}} + f_i + yr_t + e_{it} \qquad (2)$$

where the estimated coefficients would be α, which is the shares of tangible capital, and β, which is the share of intangible capital, as defined in Appendix A3. Here labor productivity, measured as output per worker (in logs), is regressed against capital stock per worker (in logs), both in terms of tangible ($\frac{Z_{it}}{L_{it}}$) and intangible ($\frac{N_{it}}{L_{it}}$) ones. Same as before, the model specification includes time-varying controls ($\boldsymbol{X_{it}}$), firm fixed-effects(f_i), and time-fixed effects (i.e., yr_t).

Table 6 reports the regression results using imputed employment to match the baseline sample.[19] We find that increasing total capital stock per worker by 1 percent is associated with a significant

[19] The results are robust to using reported employment and a combination of reported (where available) and imputed employment. The results are included in the Online Appendix.

increase in labor productivity by about 0.3 percent. While the coefficients for tangibles and intangibles are both positive and significant, the one for intangibles is about half of the one for tangibles. When examining the subgroups of assets, we find that land and buildings, machinery and equipment, economic competencies, and innovative property are positively and significantly associated with a firm's labor productivity. In all, the results suggest that the positive link between intangible capital and the labor income share we found in Indian firms can be partly explained by the positive effect of intangibles on labor productivity.

Table 6. Intangibles and labor productivity

Dep var: Labor productivity	[1]	[2]	[3]
Total capital stock	0.262***		
	(0.007)		
Total tangibles		0.186***	
		(0.007)	
─ Land & buildings			0.037*
			(0.022)
─ Machinery & equipment			0.070***
			(0.024)
Total intangibles		0.094***	
		(0.003)	
─ Economic competencies			0.044***
			(0.007)
─ Computerized information			-0.002
			(0.006)
─ Innovative property			0.058***
			(0.007)
Firm age	0.098***	0.100***	0.123**
	(0.017)	(0.017)	(0.062)
Constant	-0.156***	0.276***	-0.073
	(0.041)	(0.043)	(0.198)
Obs	237766	237766	19651
Nr of firms	30399	30399	3701
R-sq.	0.051	0.060	0.067
Adj. R-sq.	0.051	0.060	0.066

Notes: Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Labor productivity, measured as real value added per worker using imputed employment (dependent variable), firm age, and the capital stock variables (measured in per worker terms) are used in the regression in log form . The sample is winsorized at the top 5 percent to avoid results being affected by extreme values.

While we have shown that intangibles positively affect labor productivity, it is possible that the gains are achieved at the expense of reduced employment. Therefore, we further estimate the association between capital intensity and the size of employment. The results are reported in Table 7, with the first columns using imputed employment to maintain sample size consistent with the baseline setup in Table 2 and columns [4]-[6] using reported employment. As shown below, the results do not change much when using reported rather than imputed employment.

First, in both Columns [1] and [4], we find that increasing total capital stock intensity (i.e., the ratio of total capital stock over value-added) by 1 percent is associated with a significant decrease in total employment by about 0.2 percent. The negative effect is mainly driven by the link between tangible capital intensity and employment. As shown in Column [2] and [5], total employment is negatively and significantly associated with tangible capital intensity, while it is positively and significantly linked with intangible capital intensity. This suggests that increasing investment in

tangible assets may lead to a reduction in employment, whereas accumulating intangible assets increases demand for employment. Second, the results in Columns [3] and [6] indicate that the negative effect of tangible capital intensity on total employment is mostly driven by land and buildings, whereas the complementarity between intangibles and employment primarily stems from economic competencies. It is also worth noting that the impact of innovative property on employment tends to be negative, implying that investment in innovative property may improve labor productivity by reducing employment.

Table 7. Intangibles and employment

	Imputed employment			Reported employment		
Dep var=	[1]	[2]	[3]	[4]	[5]	[6]
Total capital stock	-0.189***			-0.166***		
	(0.005)			(0.016)		
Total tangibles		-0.191***			-0.172***	
		(0.005)			(0.016)	
─ Land & buildings			-0.224***			-0.262***
			(0.021)			(0.048)
─ Machinery & equipment			0.009			0.083**
			(0.018)			(0.037)
Total intangibles		0.022***			0.019**	
		(0.003)			(0.008)	
─ Economic competencies			0.019***			0.015**
			(0.006)			(0.008)
─ Computerized information			-0.003			-0.004
			(0.005)			(0.012)
─ Innovative property			-0.022***			-0.016
			(0.007)			(0.010)
Firm age	0.685***	0.696***	0.399***	0.498***	0.496***	0.369**
	(0.018)	(0.018)	(0.064)	(0.077)	(0.077)	(0.147)
Constant	3.477***	3.525***	4.738***	4.581***	4.653***	5.610***
	(0.043)	(0.045)	(0.469)	(0.226)	(0.225)	(0.503)
Obs	237766	237766	19651	30953	30953	5597
Nr of firms	30399	30399	3701	4833	4833	1037
R-sq.	0.137	0.138	0.216	0.070	0.070	0.207
Adj. R-sq.	0.137	0.138	0.215	0.069	0.069	0.204

Notes: Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Employment (dependent variable), firm age, and capital stock variables (measured as ratios to value added) are used in the regression in log form. The sample is winsorized at the top 5 percent to avoid extreme values from affecting the results.

Furthermore, we test whether the relationship between intangibles and labor productivity and employment varies across firm types. In particular, we test whether the positive associations are driven by the rise in skilled workers in India, following the capital-skill complementarity hypothesis (e.g., Krusell et al. 2000).[20] We do so by adding various interaction terms, especially those sector dummies that single out industries that demand more skilled workers, to Column [2] in Table 6. The results are generated using imputed employment and reported in Table 8. In line with our findings in section 4.3, we find that labor productivity gains from increasing intangible capital stock per worker are significantly larger in firms that are younger, smaller, or operating in

[20] According to labor force survey data, the proportion of high-skilled workers—those with secondary education and above—in India's market economy more than doubled between 2000 and 2021 – rising from 16 percent to 32 percent in just two decades (Appendix Figure A6). During this period, labor productivity and labor income share for skilled workers also increased steadily.

services or sectors with high skill or high ICT intensity.[21] This result provides some support to the hypothesis that intangibles and skilled workers are complementary. Meanwhile, we find the reverse for total employment, reported in Appendix Table A7. While increasing intangible capital intensity is positively associated with total employment across all sectors, the effect is weaker in firms operating in services or sectors with high skill or high ICT intensity. It is possible that when firms with low skill or low ICT intensity invest more in intangibles, they also need to hire more skilled workers to benefit from such investment, while the hiring need is not present for firms with sufficient skilled workers.

Table 8. Heterogeneous effects on labor productivity (using imputed employment)

	(1)	(2)	(3)	(4)	(5)	(6)
	Services	High skill	High R&D	High ICT		
`Int var'=	sectors	sectors	sectors	sectors	Age	Emp.>500
Firm age	0.095***	0.099***	0.101***	0.099***	-0.041*	0.113***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.023)	(0.017)
Total tangibles	0.189***	0.191***	0.207***	0.192***	0.251***	0.177***
	(0.010)	(0.008)	(0.008)	(0.008)	(0.013)	(0.007)
Total intangibles	0.071***	0.087***	0.093***	0.084***	0.153***	0.090***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.010)	(0.003)
Interaction effects (* `Int var')						
- Total tangibles	-0.011	-0.016	-0.076***	-0.022	-0.027***	0.026***
	(0.013)	(0.014)	(0.016)	(0.014)	(0.005)	(0.008)
- Total intangibles	0.052***	0.026***	0.003	0.037***	-0.020***	0.012***
	(0.006)	(0.008)	(0.007)	(0.008)	(0.003)	(0.003)
Constant	0.284***	0.276***	0.282***	0.278***	0.639***	0.250***
	(0.044)	(0.044)	(0.043)	(0.044)	(0.060)	(0.044)
Obs	237766	237766	237766	237766	237766	237766
Nr of firms	30399	30399	30399	30399	30399	30399
R-sq.	0.061	0.060	0.061	0.060	0.061	0.060
Adj. R-sq.	0.061	0.060	0.060	0.060	0.061	0.060

Notes: Robust standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01. The fixed-effect estimator is used in all columns. Labor productivity, measured as real value added per worker using imputed employment (dependent variable), firm age, and the capital stock variables (measured in per-worker terms), is used in the regression in log form. *`Int var'* refers to the interaction variables, which are dummy variables equal to 1 if a firm is in the service industry (Column [1]), is in a high skill–intensive sector (Column [2]), is in a high R&D–intensive sector (Column [3]), or is in a high ICT–intensive sector (Column [4]), and 0 otherwise. "High skill–intensive" sectors are defined as those in the top one-third proportion of highly skilled workers (education beyond the secondary level) within total employment, based on KLEMS data. "High R&D–intensive" and "High ICT–intensive" sectors refer, respectively, to sectors in the top one-third of R&D expenditure relative to value added and of gross fixed assets in computer and IT equipment relative to value added; both measures are derived from aggregated Prowess firm-level data. The sample is winsorized at the top 5 percentiles to avoid results being affected by extreme values.

6. Conclusion

Using firm-level data from over 30,000 companies in India, we find that both tangible and intangible capital deepening are positively and significantly associated with the labor income share. Further, we find that when firms invest more in capital, whether machinery (tangible) or know-how (intangible), the increase in labor income share can be explained by productivity gains. However, we find an important difference. The stock of tangible capital, such as equipment and machinery, appears to reduce jobs, whereas intangible capital, including software, R&D, or brand value, tends to create more jobs. Lastly, we find that intangible assets—such as software, R&D, training, and competencies—boost labor income more significantly for smaller, younger firms that operate in services and in sectors with more intensive use of skilled workers and ICT. This suggests

[21] We also examined whether the differences in the effect on labor productivity between services and non-services sectors are driven by some specific service sectors. See Online Appendix for details.

that intangible capital investments are making jobs especially more valuable for people with higher skills.

Future research can directly investigate this link between capital intensity, skill intensity, jobs, and labor incomes. For instance, when firms are characterized by increasing investments in intangible capital, such as R&D or software, do they also adopt better technology and management practices that need more skilled employees, which can boost labor income overall? Similarly, does an increase in tangible capital intensity (e.g., machinery and automation) within firms reduce the need for (unskilled) workers, e.g., in routine or manual jobs? These differences between intangible and tangible capital deepening also have policy implications. For one, it is important to distinguish between types of capital when crafting policies that support inclusive economic growth, higher productivity, and a resilient workforce. For another, policymakers might want to focus on skill building alongside growing investments in intangible capital so that a large number of workers can benefit from digital technologies.

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Appendix: Data, Variables, Estimation Strategy, and Additional Tables and Figures

A1. The Prowess Data

The Prowess database records the financial performance of over 30,000 companies in India since 1990, collected from annual reports of companies, stock exchanges, and regulators. The database includes listed companies, unlisted public companies, and private companies of all sizes and ownership types. The number of companies included in the database changes over time as its coverage improves. While the Prowess is regarded as highly representative of the Indian corporate landscape, offering a comprehensive and standardized view of the financial performance of Indian businesses, it may not capture the smallest or most geographically dispersed firms well nor cover the sectors equally**.**

In Table 1 below, we aggregate the Prowess companies covered in this study into six broad sectors, matching each firm with its corresponding parent industry group under the 27 KLEMS industry categories. Over the period 2001-2021, on average, the largest two sectors in terms of coverage of firms are market service (45%) and manufacturing (44%). These two sectors, along with the mining and utilities sectors, also collectively captured the majority of sales, output, and value-added generated by the firms in our sample (construction of these variables are discussed in the subsequent sections of this appendix). The distribution of industries in Prowess differs from that in the National Accounts, partly because the National Accounts include the informal economy and public sector, while Prowess does not. The discrepancy is particularly noticeable in the agriculture and non-market services sectors[22]. Each of these sectors contributes approximately one-fifth of the total value added and more than 10 percent of output in the KLEMS framework, yet they represent only a small portion of the total value added or output recorded in Prowess.

Table A1. Industry distribution of select variables (averaged over the period 2001-2021)

	Prowess				KLEMS	
(in %)	Value added	Output	Sales	Obs.	Value added	Output
Agriculture	0.6	0.9	0.9	1.6	19.0	12.0
Construction	4.1	3.9	3.9	5.4	8.4	11.2
Manufacturing	45.1	58.2	58.4	44.7	17.0	34.2
Market Services	36.2	26.0	25.9	44.1	30.0	24.3
Mining & Utilities	13.6	10.7	10.6	2.4	5.3	5.6

[22] Note that the Prowess database focuses on the corporate sector and does not systematically cover agriculture, since most agricultural activity in India is not organized as formal companies. However, in practice, it includes corporate agribusiness and agricultural processing firms (e.g. plantations, corporate farms, seed and biotech companies etc.) which correspond to national industry classifications (NIC) like crop cultivation, seed propagation, dairy production, and so on. However, most primary farms and smaller producers are excluded, as they do not report formal audited financial statements.

Non-market Services	0.4	0.3	0.3	1.8	20.3	12.5
Total	100.0	100.0	100.0	100.0	100.0	100.0

Notes: Each cell shows the industry distribution of the corresponding variables (in %) averaged over the period 2001-2021. The last column shows the share of observations from each of the corresponding industries.

A2. Construction of variables using Prowess Data

A2.1 Investment and capital stock

The Prowess database covers profit and loss accounts and balance sheets and, therefore, includes information on sales, gross fixed assets (GFA), and various expenditure categories, including labor compensation.[23] These variables, either available in the asset or expenses category of the balance sheet, can be matched with the three types of intangible assets mentioned in the main text and used in estimating intangible investments (and capital stock). The GFA is the cumulative historical value of a company's fixed assets before accounting for any depreciation or amortization, presented in their original purchase price. Prowess provides information on GFA existing at the end of the financial year, along with total additions, deductions, and depreciation of assets during the year. From this, the gross capital formation can be approximated as the sum of total additions to fixed assets and the cost of depreciation net of all the deductions during the year.[24] However, not all firms report all the relevant variables required – additions, depreciation, and deductions. Therefore, we follow the previous firm-level studies and define investment in current prices in any given asset type *j* in year *t* (i.e., $P_{i.j.t}I_{i.j.t}$) as the difference between the values of the current and the previous year's GFA (i.e., $GFA_{i.j.t}$) reported by the firm i,[25] plus the (accounting) depreciation cost (i.e., $D_{i,j,t}$)[26]:

$$P_{i.j.t}I_{i.j.t} = GFA_{i.j.t} - GFA_{i.j.t-1} + D_{i,j,t} \qquad \text{(A2.1)}$$

where *P* is the investment price, *I* is the real investment, *GFA* is the nominal gross fixed asset, and D is the accounting depreciation cost, all for firm *i*, asset type *j*, and year *t.* This approach is used to estimate investment for all asset types, including both tangible and intangible assets, which are

[23] The availability of firm characteristics varies by variables. For example, only 13 percent of the sample has information on firm ownership, while all firms under our consideration report their year of incorporation.

[24] In the National Accounts, investment is measured by capital formation, which is defined as the value of net additions to capital goods. However, in financial accounts of firms, information on capital formation is not typically available.

[25] A few adjustments are carried out to deal with the missing and negative values in GFA data. First, we exclude all firms that reported negative GFA in any of the five GFA categories (i.e., land & buildings, machinery, competencies, computerized information, and innovative property). We also exclude all firms that had more than three consecutive years of missing value after 2000. For other firms, the missing GFA data is interpolated linearly, assuming that the total investment generated during the period with missing values is equally distributed across years.

[26] The Prowess does not report depreciation costs for all years for all firms, and such data is also missing for any firm with missing GFA data. Our approach is to use the reported depreciation values whenever available. For missing years, we estimate the depreciation cost using the average firm-level depreciation rate, based on the available data, for any given asset. Although we also attempted other alternatives, such as running fixed-effect regressions using available depreciation and GFA data to estimate depreciation rates or using the depreciation cost from a random year for the same firm, we opted to use the firm's average depreciation rate, as it ensures broader sample coverage and minimizes extreme volatility in investment.

capitalized in firms' financial statements (see the top two sections in Table 1 in the main text for the list of these assets). It gives the estimates of investment for each tangible asset type, while providing the estimates of the part of investment on intangibles captured by the firms.

Investment price deflators: For tangible assets, the aggregate investment deflators from the India KLEMS database are used. The deflators, though differing between the two types of tangible assets—machinery and construction—are applied to all firms.[27] There are no specific deflators for intangible assets available. Since many intangible assets (e.g., R&D, software, consulting, branding, etc.) are closely linked to the business services sector, we assume the output prices of these services to reflect the costs associated with intangible assets. Therefore, we use the value-added price deflators for the real estate and business services sector obtained from the KLEMS to deflate the intangible assets.[28]

Asset-specific depreciation rates: The asset-wide depreciation rates used here are based on Corrado, Hulten, and Sichel (2009) and Das et al. (2020). Corrado, Hulten, and Sichel (2009) assume an annual depreciation rate of 33 percent for computerized information (based on BEA's assumptions for own-account software), 20 percent for innovative property (encompassing both scientific and non-scientific R&D), 60 percent for brand equity, and 40 percent for firm-specific resources. We directly adopt the CHS estimates for computerized information and innovative property. For competencies, we consider the simple average of brand equity and firm-specific resources. For tangible assets, we take 2.5 percent depreciation for construction and 9 percent for machinery and equipment. The latter is the average of machinery and transportation equipment, as provided in the India KLEMS database (see Das et al. 2020).

Table A2: Asset categories and depreciation rates

Asset category	Depreciation rate (%)
Intangible assets	
Innovative property	20.0
Computerized information	33.0
Economic competencies	50.0
Tangible assets	
Land & Buildings	2.5
Machinery & Equipment	9.0

Source: Corrado, Hulten and Sichel (2009), Das et al (2021).

[27] Applying the same deflectors to all firms implicitly assumes a competitive capital market. Although this assumption is questionable, especially in developing countries, where imperfections are persistent in the factor market, it is hard to obtain industry-level deflators for investment. Moreover, given that the firms in our database are formal sector firms, the assumption is less problematic.

[28] A more appropriate deflator would be to use business services deflator, excluding real estate sector. However, the India KLEMS or India's national accounts does not report prices for business activities alone.

Initial capital stock: In addition to estimates on investment flows and depreciation rates, the application of the perpetual inventory method (discussed in the main text) to estimate capital stock requires us to estimate the initial capital stock. In the literature, industry- or aggregate-level initial capital stock is usually computed using a steady-state capital/output ratio assumption (see Harberger, 1978).[29] Given the short historical firm-level data we are dealing with, one can consider the gross fixed assets reported in the first year by Prowess as the initial capital stock. To convert the reported values that are at historical costs to the replacement cost of the asset value, we convert the reported gross fixed assets values to replacement costs by revaluing the base year capital. In particular, following Srivastava (1996), we estimate the revaluation factor (R_T) in year T, which is the ratio of the replacement cost (GFA_T^r) to historic value (GFA_T) as follows:[30]

$$\frac{GFA_T^r}{GFA_T} = R_T = \frac{[(1+g)(1+\pi)-(1-d)]}{[(g+\delta)(1+\pi)]} \times \frac{(1-d)}{(1-\delta)} \qquad \text{(A2.2)}$$

where GFA_T is the sum of past investment streams valued at the historic cost as reported by the firm in year *T*, i.e., $GFA_T = \sum_{t=S}^{T} P_t I_t$, where year *S* is the first vintage of investment. GFA_T^r is the gross fixed asset at replacement cost, which is defined as $GFA_T^r = P_T(\sum_{t=S}^{T} I_t)$. g and π are the growth rates of real investment and investment prices between *S* and *T*, respectively, which are assumed to be constant. d is the accounting depreciation rate, reported by the firm.[31] δ is the economic depreciation rate. Eq (A2) has often been used to estimate the revaluation factor, without accounting for economic depreciation, in which case it reduces to $\frac{(1+g)(1+\pi)-1}{g(1+\pi)}$ (see Balakrishnan et al., 2000).

Assuming *T* as the first year of available data on GFA and 1975 or the year of incorporation (whichever is the lowest) as *S*, it gives us on average more than twenty years of data on investment after the first vintage. π is computed as the compound growth rate of investment prices between the first vintage year (*S*) and the initial year of capital stock (*T*):

$$\pi_j = (P_{j.T}/P_{j.s})^{1/N} - 1 \qquad \text{(A2.3)}$$

Here *P*, the investment price deflators, are the implicit deflators for gross fixed capital formation (GFCF) taken from National Accounts Statistics. π is calculated separately for machinery (i.e., *j=1)* and equipment and construction assets (*i.e., j=2*). Similarly, following Balakrishnan et al (2000), we use the investment growth rate of the aggregate economy to proxy g, but separately for construction and equipment assets:

$$g_j = (I_{j.T}/I_{j.s})^{1/N} - 1 \qquad \text{(A2.4)}$$

[29] CHS (2009) assumes a zero initial stock in their macro data, considering years as early as 1928 for scientific R&D and brand equity, as well as 1945 and 1946 for non-scientific R&D and firm-specific resources, and 1958 for computerized information. However, these assumptions may be unrealistic in our case, given the limited time series data we have for India.

[30] Note that the subscript i and j are suppressed in the following equations for brevity.

[31] This is obtained as the ratio of the nominal value of accounting depreciation during the year and the value of gross fixed assets, calculated separately for machinery & equipment and construction assets and averaged over all reported years. Before, averaging across years, we remove any reported depreciation rate that is higher than 40 percent, or negative.

where *I*, the real investment, is taken from the National Accounts Statistics. Depending upon the *S* (either 1975 or the incorporation year), the parameters π and g will vary across firms. The estimated growth rate of investment (g) or investment prices (π) are negative for firms without longer-time data series, which can result in negative initial capital stock in *T*. In such cases, the pre-2001 period averages for g and π are used for the entire sample of firms.[32]

Table A3: Capital stock in tangible and intangible assets

(in percent of total assets, 2001-2021)

		Tangible assets			
		Land and building	**Machinery and equipment**		**Total**
Capitalized by firms	Average	25.5	67.7		93.2
	Median	25.7	68.6		94.2
		Intangible assets			
		Economic competencies	**Digitized information**	**Innovative properties**	**Total**
Capitalized by firms	Average	0.2	0.5	1.1	1.9
	Median	0.1	0.6	0.02	1.2
Capitalized by us	Average	1.4	0.0	3.5	4.9
	Median	1.5	0.0	3.5	4.9
Total	Average	1.6	0.5	4.6	6.8
	Median	1.6	0.6	3.7	5.8

Source: Author calculation using data from Prowess.

Notes: The shares are calculated in real terms. The averages and median values for total intangible assets correspond to the average and median of the total economy in Figure 1A and to those of the three intangible components in Figure 1B.

In Table A3, we show the distribution of estimated capital stock by asset types, using the perpetual inventory method. From 2001 to 2021, on average, 93-94 percent of all capital stocks were tangible, leaving just about 6 percent as intangible. Most of the intangible capital originates from assets that are not capitalized on the firm's balance sheet and are instead included in expense categories. While half of the digitized information is capitalized on the balance sheet, the other two categories of intangible assets are primarily reflected in expense categories and are capitalized here. This highlights the importance of our estimation approach for gaining a better understanding of intangibles.

A2.2. Output and value added*: Prowess* does not provide data on standard measures of value added and output, consistent with national account concepts. The closest variable available in Prowess that aligns with the concept of output is sales. Following previous literature (e.g. Goldar and Parida 2017), we define output as the sum of sales and inventories, which includes changes in the stock of finished goods and work-in-progress. Prowess also contains information on expenditures for intermediate raw materials and fuel consumption. To calculate value added, we

[32] The pre-2001 average growth rate of investment (investment price) for the asset land & buildings was 6 (8) percent, and for machinery & equipment was 8 (6) percent.

subtract the total intermediate consumption from the gross output value.[33] These firm-level estimates of value added are augmented to include the estimated intangible costs under the expense categories, as

$$Y_{it} = Y_{it}^{F} + INT_{i,t}^{X} \quad \text{(A2.5)}$$

where Y_{it}^{F} is the value added in current prices reported by the firm (calculated as the sum of sales and inventories minus material and fuel costs), and $INT_{i,t}^{X}$ is the intangibles under the expense categories of intangibles (see Table 1 for details). See Figure A2 for the scatterplots of reported sales and estimated value added.

The nominal value added is then deflated using industry value-added deflators from the India KLEMS database, with a base year of 2011, for the industry to which the firm belongs. For example, the value added of all firms in the broadly defined industry of "transport equipment" is deflated using the value-added deflator for the transport industry from the India KLEMS database.

A2.3. Employment: Prowess provides employment data only in about 10 percent of firms that report gross fixed asset data. Therefore, following the previous studies, we use an indirect approach to impute employment series for each firm. We combine firm-level data on total labor compensation available in Prowess with average wage rates obtained as total emoluments per employee for the industry in which the firm operates to construct an implicit employment estimate, i.e.

$$L_{i.t} = C_{i.t} \div \frac{C_{I.t}}{L_{I.t}} \quad \text{(A2.6)}$$

where $L_{i.t}$ is the employment and $C_{i.t}$ is the total labor compensation, both for firm i in year t (from the Prowess database). $C_{I.t}$ is the total compensation and $L_{I.t}$ is total employment for industry I (such that $i \in I$). The average wage rate for each industry I ($C_{I.t}/L_{I.t}$) is calculated using data on compensation and employment from the Annual Survey of Industries (ASI) for two-digit manufacturing industries. For the non-manufacturing sectors, they are obtained from the India KLEMS database.

A3. Deriving the estimation equation

Following Bentolila and Saint-Paul (2003) and Garcia-Lazaro and Pearce (2023), we use a standard constant elasticity of substitution (CES) production to examine the link between intangible capital intensity and labor income share.[34] Here, the value added of firm i in year t, Y_{it}, is produced as follows:

[33] By construction, this may still include intermediate service inputs, which is not the case with the KLEMS value added measure, potentially overstating the level of value added in Prowess.

[34] Bentolila and Sait-Paul (2003) showed that there is a stable relationship between the labor share and an observable variable, the capital-output ratio. They further show that the response of the labor share to the capital-output ratio is related to the elasticity of substitution in the production function between labor and capital.

$$Y_{it} = A_i * [\alpha(Z_{it})^{\sigma} + \beta(N_{it})^{\sigma} + (1-\alpha-\beta)(L_{it})^{\sigma}]^{\frac{1}{\sigma}}, \quad \text{(A3.1)}$$

where Z_{it} is tangible capital, N_{it} is intangible capital, and L_{it} is the number of employees. α and β are the shares of intangible and tangible capital, respectively, σ denotes the parameter of substitution between capital and labor,[35] and A_i captures the total factor productivity.

The labor income share, $S_{L_{it}}$, is defined as the compensation of labor over the value-added of firm i in year t, which equals one minus tangible and intangible shares:

$$S_{L_{it}} = \frac{w_{it}L_{it}}{Y_{it}} = 1 - r_{it}^{Z} * \frac{Z_{it}}{Y_{it}} - r_{it}^{N} * \frac{N_{it}}{Y_{it}}, \quad \text{(A3.2)}$$

where w_{it}, r_{it}^{Z}, and r_{it}^{N} are the real returns on labor, tangible capital, and intangible capital, respectively.[36] As firms maximize profits by using the production function shown in Eq(A3.1), they are subject to the following cost function: $C_{it} = w_{it}L_{it} + r_{it}^{T}T_{it} + r_{it}^{N}N_{it}$. The first-order condition of labor and capital inputs yields the following optimal rates:

$$w_{it} = (1-\alpha-\beta)(A_i)^{\sigma}\left(\frac{Y_{it}}{L_{it}}\right)^{1-\sigma} \quad \text{(A3.3)}$$

$$r_{it}^{Z} = \alpha(A_i)^{\sigma}\left(\frac{Z_{it}}{Y_{it}}\right)^{\sigma-1} \quad \text{(A3.4)}$$

$$r_{it}^{N} = \beta(A_i)^{\sigma}\left(\frac{N_{it}}{Y_{it}}\right)^{\sigma-1} \quad \text{(A3.5)}$$

Eq(A3.3) shows that the optimal wage rate can be expressed as a function of labor productivity, measured as value-added per worker, and total factor productivity at the firm level. Meanwhile, the optimal yields for capital inputs are expressed as functions of capital intensities, captured by $\frac{Z_{it}}{Y_{it}}$ and $\frac{N_{it}}{Y_{it}}$, respectively in Eq(A3.4) and Eq(A3.5).

Following Eq(A3.2), the labor income share can be further rewritten as

$$S_{L_{it}} = 1 - \alpha(A_i)^{\sigma}\left(\frac{Z_{it}}{Y_{it}}\right)^{\sigma} - \beta(A_i)^{\sigma}\left(\frac{N_{it}}{Y_{it}}\right)^{\sigma} \quad \text{(A3.6)}$$

$$= 1 - \alpha(A_i z_{it})^{\sigma} - \beta(A_i n_{it})^{\sigma}\,, \quad \text{(A3.7)}$$

where the tangible capital intensity is z_{it} and the intangible capital intensity is n_{it}. The equation here shows that the relationship between the intangible capital intensity and the labor share depends on two parameters, β and σ, with the former being greater than zero by definition and the latter determining the substitutability ($\sigma > 0$) or complementarity ($\sigma < 0$) between labour and each type of capital input. When $\sigma >$ (<)0, $S_{L_{it}}$ would be decreasing (increasing) in z_{it} and n_{it}.[37]

[35] In this notation, σ can be re-written as (ρ-1)/ρ, where ρ = elasticity of substitution. Here we use σ for brevity.

[36] Here we assume constant returns to scale and perfect competition.

[37] It is also worth noting that the labor share can also be expressed as $\frac{w_{it}L_{it}}{Y_{it}} = (1-\alpha-\beta)(A_i)^{\sigma}\left(\frac{Y_{it}}{L_{it}}\right)^{-\sigma}$. When $\sigma <$ (>)0, the labor income share would be increasing (decreasing) in labor productivity.

Log-linearizing Eq(A3.7), and extending to include time-varying firm-specific factors, and firm and time fixed effects, gives us the following estimable equation that sets the foundation for the empirical analysis in the following section: [38]

$$\ln S_{L_{it}} = \beta_0 + \delta \ln z_{it} + \gamma \ln n_{it} + \boldsymbol{\beta_1 X_{it}} + f_i + yr_t + e_{it} \quad \text{(A3.8, also Eq(1))}$$

where β_0 is a constant term, and $\boldsymbol{X_{it}}$ is a set of time-varying controls f_i is firm fixed effects, and yr_t is time-fixed effects. Here e_{it} is the remaining error term. Here, the main coefficients of interest are γ and δ. They are the partial elasticities of intangibles and tangibles to output ratios on the labor income share, respectively.[39]

[38] The log-linearization takes the following step. First, as $\mathrm{Ln}(1+x) \approx x$, when we logged equation (A3.7) on both sides, we get $\mathrm{Ln}(S_{L_{it}}) \approx -\alpha(A_i z_{it})^{\sigma} - \beta(A_i n_{it})^{\sigma} = -\alpha\left(e^{\sigma \ln(A_i z_{it})}\right) - \beta\left(e^{\sigma \ln(A_i n_{it})}\right)$. Then, using Taylor approximation, we can express $\mathrm{Ln}S_{L_{it}}$ as $\ln\left(S_{L_{it}}\right) \approx -\alpha\sigma * (\ln(A_i) + \ln(z_{it})) - \beta\sigma * (\ln(A_i) + \ln(n_{it})) = -\alpha\sigma * \ln(z_{it}) - \beta\sigma * \ln(n_{it}) - \sigma(\alpha+\beta)\ln(A_i)$. Here $-\sigma(\alpha+\beta)\ln(A_i)$ is absorbed into the constant term, controls and the fixed effects.

[39] Here δ captures $-\alpha\sigma$, while γ is approximately $-\beta\sigma$. As the share of either capital input is positive, the signs of δ and γ should be the same as "-σ".

A4. Additional tables and figures

Table A4. Summary statistics.

Variable	Description	Mean	Median	SD	Nr of obs
Labor income share	Labor compensation in percent of value-added (in logs)	2.8	2.8	1.6	239989
Firm age	Nr of years from the firm's establishment (in logs)	2.9	2.9	0.8	239989
Land & buildings	Land & building in percent of value-added (in logs)	3.7	3.7	2.0	202617
Machinery & equipment	Mach. & equipment in percent of value-added (in logs)	3.9	4.0	1.9	239455
Economic competencies	Economic comp. in percent of value-added (in logs)	0.0	0.2	2.2	223297
Computerized information	Comp. information in percent of value-added (in logs)	-0.6	-0.7	2.2	68301
Innovation property	Innovation prop. in percent of value-added (in logs)	0.7	0.9	2.2	62601
Total tangibles	Total tangibles in percent of value-added (in logs)	4.5	4.6	2.0	239989
Total intangibles	Total intangibles in percent of value-added (in logs)	0.6	0.7	2.2	239989
Total capital stock	Total capital stock in percent of value-added (in logs)	4.6	4.7	1.9	239989
Employment (imputed)	Employment (imputed) (in logs)	5.3	5.3	2.1	239989
Employment (reported)	Employment (reported) (in logs)	6.1	6.2	2.2	30953
Labor productivity (imputed)	Value-added per worker, using imputed employment (in logs)	0.1	0.1	1.5	237766

Notes: All variables are reported in log form. All variables (except firm age) have been winsorized at the top 5 percent to avoid results being affected by extreme values. The value added used to calculate the labor income share and the capital-related variables has been adjusted for the expenses used to compute the investment in intangibles.

Table A5. Robustness check: winsorizing extreme values

	Not winsorized			Winsorized (0, 99)			Winsorized (0, 97)			Winsorized (0, 90)		
Dep var: Labor income share	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**	**[9]**	**[10]**	**[11]**	**[12]**
Total capital stock	0.610***			0.596***			0.567***			0.511***		
	(0.005)			(0.005)			(0.005)			(0.005)		
Total tangibles		0.526***			0.513***			0.485***			0.436***	
		(0.005)			(0.005)			(0.005)			(0.005)	
─ Land & buildings			0.204***			0.205***			0.202***			0.178***
			(0.018)			(0.018)			(0.017)			(0.016)
─ Machinery & equipment			0.268***			0.268***			0.258***			0.231***
			(0.019)			(0.019)			(0.019)			(0.017)
Total intangibles		0.103***			0.103***			0.101***			0.092***	
		(0.003)			(0.003)			(0.003)			(0.002)	
─ Economic competencies			0.037***			0.037***			0.037***			0.034***
			(0.006)			(0.006)			(0.006)			(0.006)
─ Computerized information			0.031***			0.031***			0.032***			0.033***
			(0.005)			(0.005)			(0.005)			(0.004)
─ Innovative property			0.017***			0.017***			0.017***			0.015***
			(0.005)			(0.005)			(0.005)			(0.005)
Firm age	-0.301***	-0.317***	-0.171***	-0.299***	-0.314***	-0.171***	-0.281***	-0.292***	-0.164***	-0.219***	-0.229***	-0.130***
	(0.015)	(0.015)	(0.057)	(0.015)	(0.014)	(0.057)	(0.014)	(0.014)	(0.056)	(0.013)	(0.013)	(0.048)
Constant	0.552***	1.020***	0.584***	-1.267***	-0.715***	-1.449***	0.648***	1.094***	0.611***	0.703***	1.109***	0.759***
	(0.040)	(0.040)	(0.205)	(0.034)	(0.037)	(0.206)	(0.038)	(0.037)	(0.209)	(0.036)	(0.035)	(0.192)
Obs	239989	239989	19651	239989	239989	19651	239989	239989	19651	239989	239989	19651
Nr of firms	30722	30722	3701	30722	30722	3701	30722	30722	3701	30722	30722	3701
R-sq.	0.516	0.530	0.525	0.487	0.502	0.518	0.456	0.472	0.499	0.385	0.400	0.446
Adj. R-sq.	0.516	0.530	0.524	0.487	0.502	0.517	0.456	0.472	0.498	0.385	0.400	0.445

Notes: Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. The fixed-effect estimator is used in all columns. The labor income share (dependent variable), firm age, and the capital stock variables (measured as ratios to value added) are used in the regression in log form. The sample is winsorized at the top 3-percent in Columns [4]-[6] (5-percent in Columns [7]-[9]; 10 percent in Columns [10]-[12]) to avoid results being affected by extreme values.

Table A6. Robustness check: other approaches to deal with extreme values without winsorizing the data

	Excl. firms in finance			Excl. firms in finance or rental services			Excl. obs with the labor income share>100		
Dep var: Labor income share	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**	**[9]**
Total capital stock	0.574***			0.577***			0.587***		
	(0.006)			(0.006)			(0.005)		
Total tangibles		0.501***			0.504***			0.507***	
		(0.006)			(0.006)			(0.005)	
─ Land & buildings			0.203***			0.202***			0.202***
			(0.018)			(0.018)			(0.017)
─ Machinery & equipment			0.257***			0.257***			0.265***
			(0.019)			(0.019)			(0.019)
Total intangibles		0.093***			0.091***			0.099***	
		(0.003)			(0.003)			(0.003)	
─ Economic competencies			0.034***			0.034***			0.037***
			(0.006)			(0.006)			(0.006)
─ Computerized information			0.028***			0.028***			0.031***
			(0.005)			(0.005)			(0.005)
─ Innovative property			0.015***			0.015***			0.017***
			(0.005)			(0.005)			(0.005)
Firm age	-0.289***	-0.303***	-0.165***	-0.288***	-0.303***	-0.163***	-0.299***	-0.314***	-0.170***
	(0.015)	(0.015)	(0.057)	(0.015)	(0.015)	(0.057)	(0.015)	(0.015)	(0.056)
Constant	0.597***	1.017***	0.610***	0.597***	1.016***	0.610***	-1.287***	-0.750***	-1.466***
	(0.041)	(0.041)	(0.206)	(0.042)	(0.041)	(0.206)	(0.034)	(0.037)	(0.205)
Obs	220604	220604	19248	215380	215380	19195	238485	238485	19646
Nr of firms	27255	27255	3584	26451	26451	3563	30645	30645	3700
R-sq.	0.472	0.486	0.509	0.476	0.490	0.508	0.491	0.506	0.520
Adj. R-sq.	0.472	0.486	0.508	0.476	0.489	0.508	0.491	0.506	0.520

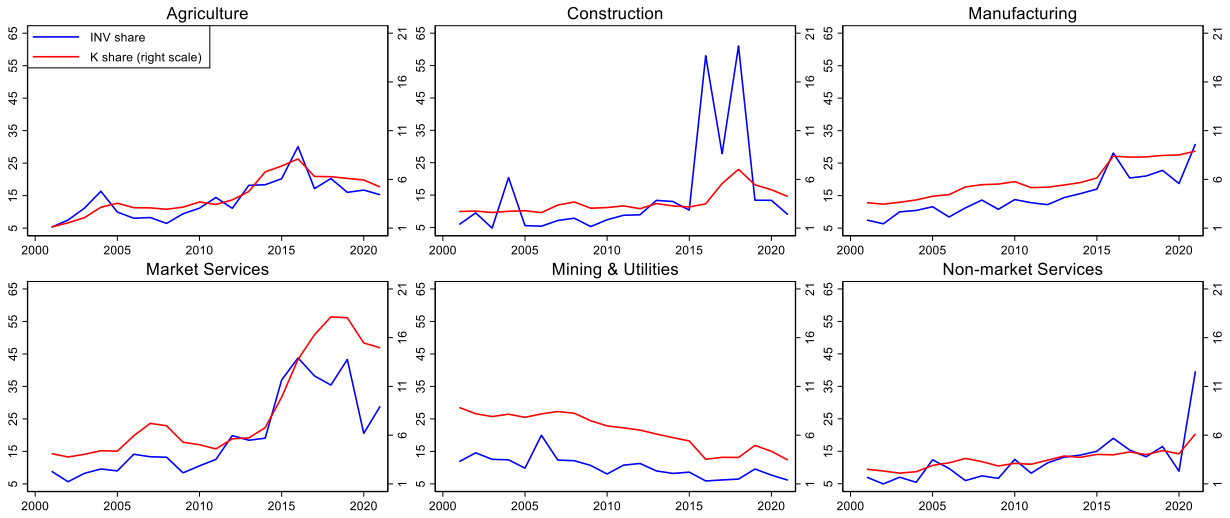
Notes: Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. The fixed-effect estimator is used in all columns. The labor income share (dependent variable), firm age, and capital stock variables (measured as ratios to value added) are used in the regression in log form. The sample is not winsorized.

Table A7. Heterogeneous effects on employment

	(1)	(2)	(3)	(4)	(5)	(6)
`Int var'=	Services sectors	High skill sectors	High R&D sectors	High ICT sectors	Age	Emp.>500
Firm age	0.699***	0.698***	0.696***	0.697***	0.658***	0.598***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.023)	(0.016)
Total tangibles	-0.159***	-0.176***	-0.188***	-0.170***	-0.066***	-0.197***
	(0.008)	(0.006)	(0.006)	(0.006)	(0.012)	(0.005)
Total intangibles	0.030***	0.031***	0.022***	0.029***	0.002	0.070***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.010)	(0.003)
Interaction effects (* `Int var')						
- Total tangibles	-0.050***	-0.038***	-0.009	-0.058***	-0.047***	0.082***
	(0.010)	(0.011)	(0.011)	(0.011)	(0.004)	(0.007)
- Total intangibles	-0.019***	-0.033***	-0.002	-0.026***	0.007**	-0.199***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.003)	(0.003)
Constant	3.519***	3.535***	3.527***	3.538***	3.600***	3.725***
	(0.045)	(0.045)	(0.045)	(0.045)	(0.060)	(0.040)
Obs	237766	237766	237766	237766	237766	237766
Nr of firms	30399	30399	30399	30399	30399	30399
R-sq.	0.140	0.140	0.138	0.140	0.142	0.244
Adj. R-sq.	0.139	0.140	0.138	0.140	0.142	0.243

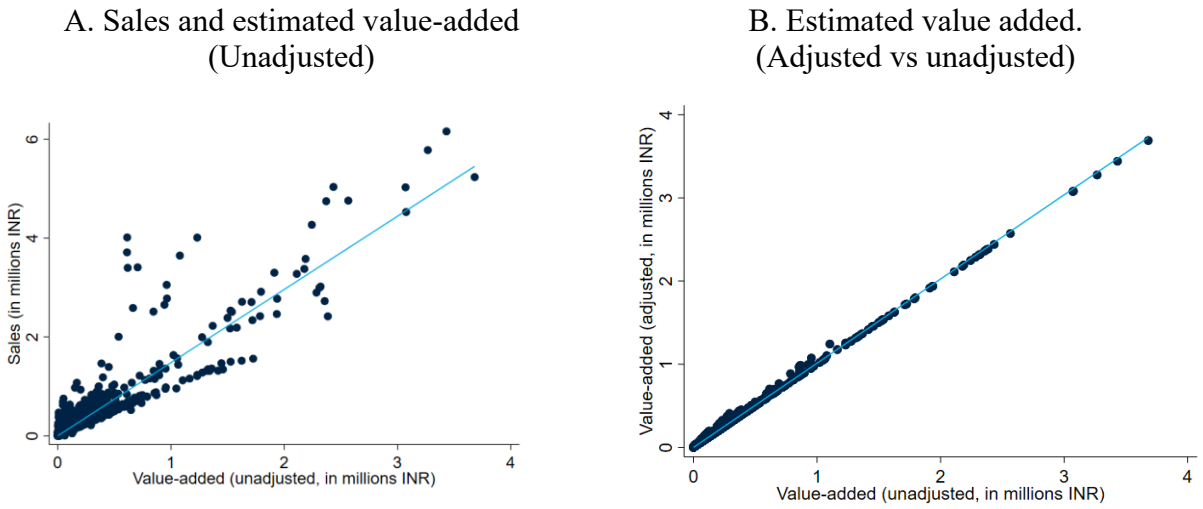
Notes: Robust standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01. The fixed-effect estimator is used in all columns. Imputed (dependent variable), firm age, and capital stock variables (measured in % value-added terms) are used in the regression in log form. *`Int var'* refers to the interaction variables, which are dummy variables equal to 1 if a firm is in the service industry (Column [1]), is in a high skill–intensive sector (Column [2]), is in a high R&D–intensive sector (Column [3]), or is in a high ICT–intensive sector (Column [4]), and 0 otherwise. "High skill–intensive" sectors are defined as those in the top one-third proportion of highly skilled workers (education beyond the secondary level) within total employment, based on KLEMS and household labor force data. "High R&D–intensive" and "High ICT–intensive" sectors refer, respectively, to sectors in the top one-third of R&D expenditure relative to value added and of gross fixed assets in computer and IT equipment relative to value added; both measures are derived from aggregated Prowess firm-level data. The sample is winsorized at the top 5 percentiles to avoid results being affected by extreme values.

Figure A1. Intangible investment (capital stock) in percent of total investment (capital stock), by broad sector



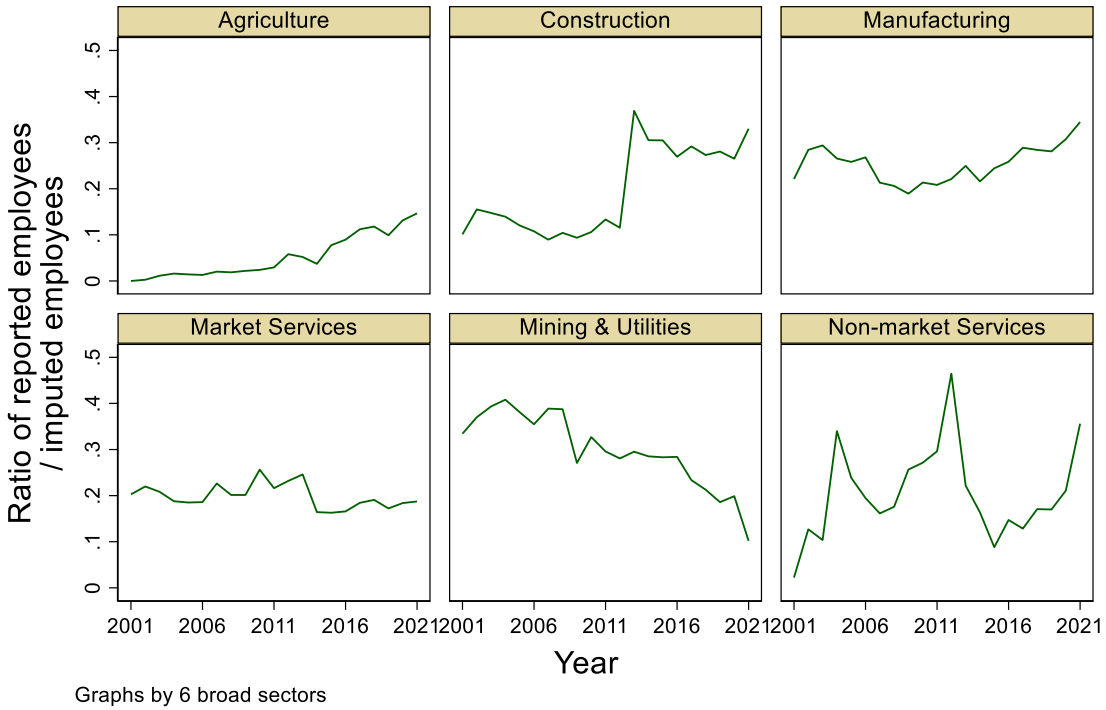
Notes: The red lines show intangible capital stock in percent of capital stock(right-hand side) for the six broad sectors, while the blue lines show the intangible investment in percent of total investment (left-hand side).

Figure A2: Scatter plot of reported sales and estimated value added



Notes. The light blue lines are fitted lines in both panels. In both A and B, the x-axis shows estimated value-added not adjusted for intangible investment under the expense category. It is the value added (in millions INR) measured as output minus intermediate and fuel expenses. In A, the y-axis shows the reported **sales** (in millions INR). In B, the y-axis shows the estimated value added augmented to account for intangible investment under the expense category.

Figure A3. The ratio of reported employment / imputed employment (by sector)



Notes: The lines show the ratios of the number of reported employees over the number of imputed employees by sector and by year.

Figure A4. Sectoral distribution of intangible capital stock (Year 2021)

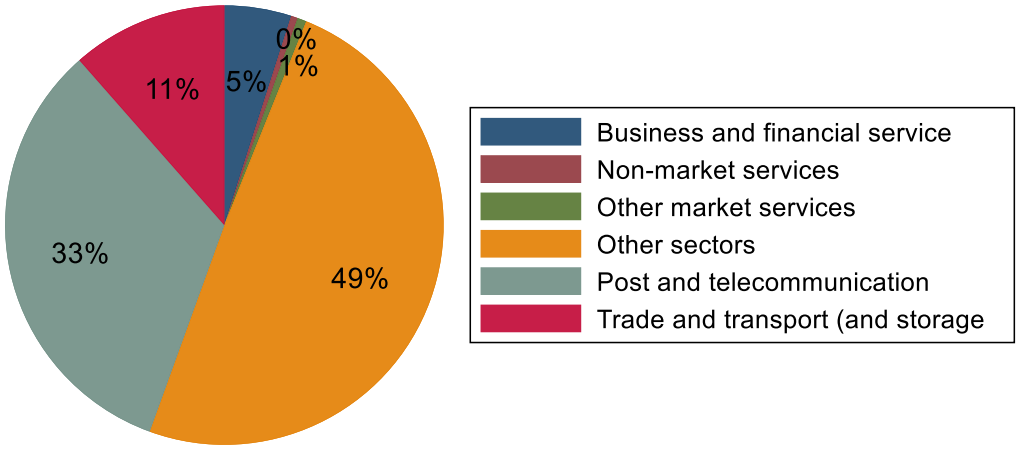
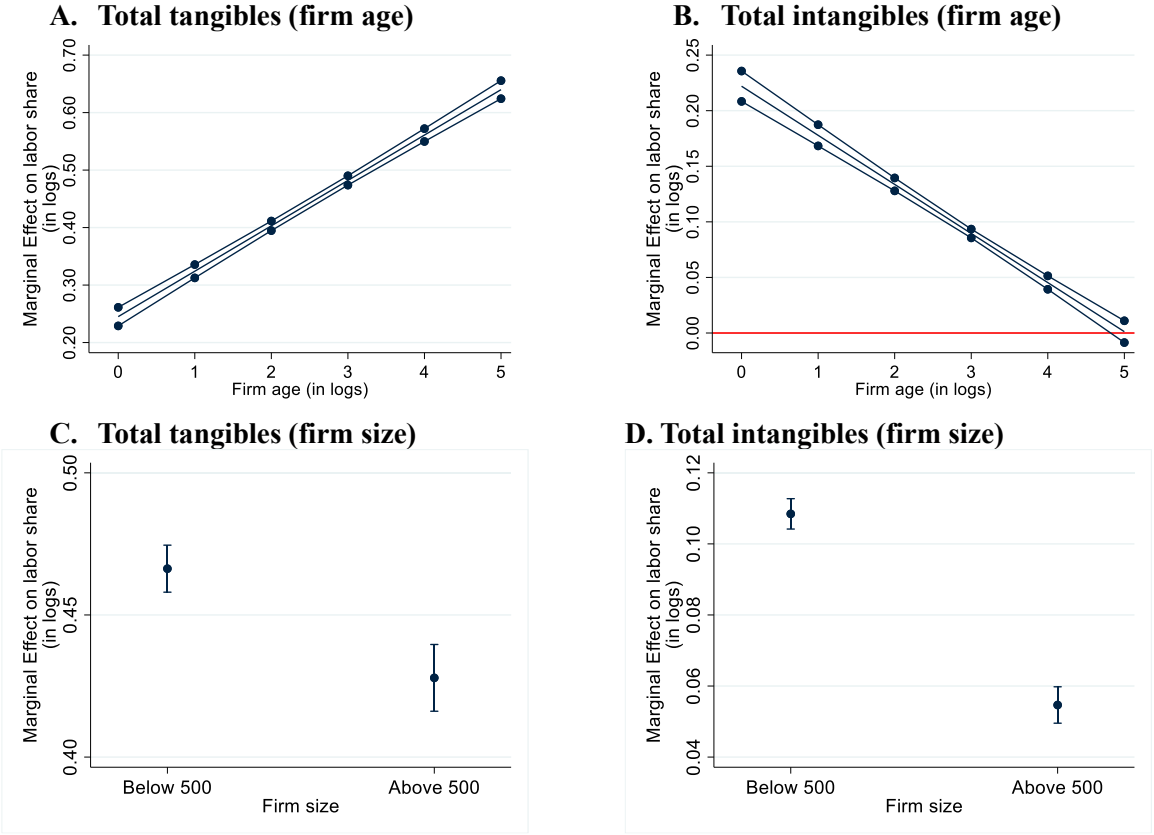
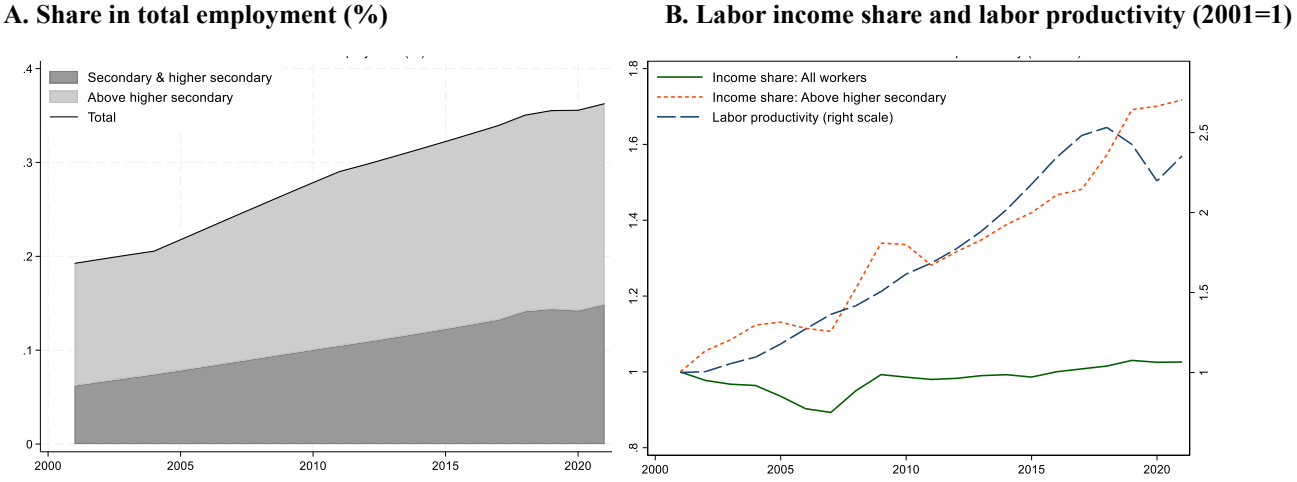


Figure A5. The marginal effect on labor income share (other firm characteristics)



Notes: The charts are based on regression results shown in Table 5, Columns [2]-[4]. The dots show the estimated marginal effects of total intangible assets per employee in logs on labor productivity. The spikes show the corresponding 90 percent confidence intervals.

Figure A6. Employment and labor income share of high-skilled workers and labor productivity (aggregate economy)



Sources: Household labor force data from the Employment and Unemployment Surveys and the Periodic Labour Force Surveys (PLFS); India KLEMS database.
Notes: High-skilled workers are defined as those with education above the higher secondary level. Labor income share is measured as total compensation to all workers (or to high-skilled workers specifically) relative to nominal value added in the aggregate economy.