Capital & Labor Substitution Patterns: Recent Deviations From The Literature

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Abstract

This paper investigates recent trends in capital-labor substitution across industries, extending previous research. By utilizing updated country and industry-level panel data, we examine how firms adapt to technological advancements and shifts in labor dynamics. A key contribution of this study is the incorporation of patents and R&D expenditures as measures of technological enhancement, allowing for a more nuanced analysis of their role in improving capital productivity.

We hypothesize that manufacturing industries are likely experiencing the highest levels of labor substitution, given the inherent ease of automating processes and the accelerated rate of technological progression driven by AI. Through a fixed-effects estimation strategy, we control for unobserved heterogeneity across countries and time, providing robust empirical insights into industry-specific substitution patterns. Ultimately, we arrive at a disproved hypothesis as other other industries have exhibited more dramatic trends in labor substitution in recent years.

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1 Introduction

Technological advancements have historically influenced the balance between capital and labor, with automation increasingly shaping production processes. Traditional economic theories suggest that as capital investment in technology grows, labor demand shifts, often favoring high-skilled workers. However, the rise of artificial intelligence (AI) presents new challenges to these established models, as it enables automation of not only routine tasks but also cognitive functions. As Acemoglu and Restrepo (2019) note the creation of new labor-intensive tasks can offset the displacement of labor by automation, but the net effect is theoretically ambiguous. 'Similarly, Brynjolfsson and Mitchell (2017) have found that 'AI-driven automation is fundamentally different from past technological changes, as it can substitute for cognitive as well as manual tasks.' Studies like these highlight the need for a deeper examination of how AI is impacting the dynamics of capital and labor substitution.

This study conducts a cross-country analysis utilizing data from the EUKLEMS National Accounts, which provides economic indicators on production, labor, and capital across multiple countries. WIPO patent data is incorporated to capture the level and direction of technological advancement, particularly in AI/computer-related investments. We highlight little distinction between the two terms as increasing computational capabilites and AI are simply forms of task automation. These datasets can't distinguish traditional IT from AI investment however allow for an assessment of how overall automation is influencing capital-labor dynamics at both the national and sectoral levels in order to justify our new empirically supported framework for handling innovative capabilities.

The empirical approach relies on regression analysis using a fixed-effects panel data framework to examine variations across industries while controlling for country-specific and sector-specific heterogeneity. Our model expresses output (gross value added) as a function of total factor productivity (TFP), technology capital (such as AI-related investments), physical capital (machinery and equipment), and labor input, measured as total hours worked. To establish a baseline understanding, an Ordinary Least Squares (OLS) regression is first conducted to test whether the data behaves as expected based on findings in the existing literature. This is followed by fixed-effects estimations, refining the analysis by accounting for unobserved heterogeneity at the industry and national levels, ensuring a more precise measurement of AI's role in capital-labor substitution patterns.

By incorporating a cross-country and cross-sectoral perspective, this study aims to determine whether traditional economic models adequately capture the effects of AI-driven automation on labor market dynamics. The findings will provide empirical insights into whether recent AI and technology capital investment leads to anticipated significant manufacturing labor displacement, skill-biased technological change, or the emergence of new labor-intensive tasks, contributing to the ongoing debate on automation's impact on employment and productivity.

2 Literature Review

The relationship between technological innovation and capital-labor substitution has been widely studied in economic literature. Classical economic models suggest that as technology advances, firms adjust production by reallocating inputs between capital and labor to maximize efficiency. Historically, automation has replaced routine manual tasks while increasing the demand for high-skilled labor, leading to shifts in wage structures and employment patterns. However, recent developments in artificial intelligence (AI) and machine learning introduce complexities beyond traditional automation, as AI can substitute both manual and cognitive tasks. This shift challenges long-standing assumptions about capital-labor substitution, raising important questions about whether AI follows previous industry trends or represents a fundamental deviation in labor market dynamics (Agrawal et al., 2019);(Brynjolfsson & Mitchell, 2017).

The classical understanding of capital-labor substitution is rooted in foundational economic theories that describe how firms optimize inputs based on technological progress. Early models, such as the Cobb-Douglas production function, assume a constant elasticity of substitution (CES) between capital and labor, meaning that automation enhances productivity but does not necessarily displace labor in the long run. Other theories, such as the Solow Growth Model (1956), emphasize the role of technological progress in driving long-term economic growth, positing that increases in capital investment lead to productivity improvements that benefit labor. These models traditionally assume that technological advancements complement human labor rather than replace it entirely.

However, more recent theories, such as Skill-Biased Technological Change (SBTC), suggest that technological innovation disproportionately benefits high-skilled workers while reducing demand for low-skilled labor (Autor, Katz & Krueger, 1998). Similarly, the Routine-Biased Technological Change (RBTC) hypothesis posits that automation primarily replaces routine, middle-skill jobs while increasing demand for both high-skilled cognitive work and low-skilled manual labor (Goos et al., 2014). These frameworks have historically guided discussions on labor market transformations.

The emergence of AI, however, introduces new dimensions to capital-labor substitution that these models may not fully capture. Unlike past waves of automation, AI has the potential to automate non-routine cognitive tasks, such as decision-making, problem-solving, and strategic planning—domains that were previously thought to be exclusive to human labor. The Task-Based Model of Automation (Acemoğlu & Restrepo, 2019) expands on these insights by proposing that AI-driven automation can both displace existing jobs and create new labor-intensive tasks. This model introduces a critical ambiguity: while automation reduces labor demand in some sectors, it may also generate new employment opportunities in emerging industries, making its net effect on labor markets uncertain.

The impact of technological progress on labor markets has been a defining feature of economic history. Each industrial revolution has introduced new production technologies that altered the balance between capital and labor, leading to shifts in employment structures, productivity, and wage distribution. By examining past technological transformations, we can better understand whether AI-driven automation follows historical patterns or represents a structural break in capital-labor substitution.

The First Industrial Revolution introduced mechanized production through steam engines and textile machinery, fundamentally shifting employment from agriculture to industry. While early mechanization displaced artisans and manual laborers, it also created new demand for factory workers, resulting in net employment growth over time (Mokyr, 1990). This period demonstrated that automation, despite causing short-term disruptions, ultimately led to higher productivity and job creation in emerging sectors.

The Second Industrial Revolution accelerated capital-intensive production through electrification, assembly lines, and mechanized transportation. While these innovations significantly increased productivity, they also replaced many low-skilled industrial jobs with capital-intensive machinery. However, this transition spurred the expansion of white-collar employment, as demand for managerial, administrative, and engineering roles increased (Goldin & Katz, 2008). This shift reinforced the Skill-Biased Technological Change (SBTC) hypothesis, as technological progress benefited high-skilled workers while reducing opportunities for low-skilled labor.

The Digital Revolution of the late 20th century introduced computers, robotics, and information technology, leading to Routine-Biased Technological Change (RBTC). This era was characterized by the automation of repetitive, routine tasks, such as clerical work, manufacturing, and customer service. While digitalization increased demand for high-skilled knowledge workers, it also hollowed out middle-skill jobs, leading to greater wage inequality (Autor, Levy & Murnane, 2003). This period marked the first major instance where automation contributed to labor market polarization, benefiting the highly skilled while reducing opportunities for routine-task workers.

Unlike past waves of automation that primarily replaced physical labor and routine tasks, AI-driven automation introduces cognitive automation, allowing machines to perform tasks that were previously exclusive to human intelligence, such as decision-making, language processing, and strategic analysis. Studies suggest that AI's ability to substitute for both manual and cognitive labor could lead to fundamentally different labor market dynamics (Brynjolfsson & McAfee, 2017).

Acemoglu & Restrepo (2019) argue that AI-driven automation could either mirror past trends—creating new labor-intensive tasks—or represent a structural break, where AI permanently reduces labor demand. The uncertainty surrounding AI's labor market effects necessitates empirical examination to determine whether existing economic models still apply.

The adoption of AI-driven automation has led to mixed labor market effects, with empirical studies revealing both job displacement and job augmentation, depending on industry, skill level, and national economic structure. While past technological revolutions primarily replaced physical labor, AI introduces the capability to automate cognitive functions, raising concerns about its broader impact on employment structures (Brynjolfsson & McAfee, 2017).

A growing body of research suggests that AI does not uniformly eliminate jobs but instead transforms job structures. Acemoglu & Restrepo (2020) argue that while AI-driven automation reduces labor demand in some industries, it also creates new labor-intensive tasks, particularly in sectors requiring human oversight and decision-making. Similarly, Autor (2019) emphasizes that AI augments high-skilled jobs in knowledge-based industries while displacing middle-skilled workers who perform routine tasks, such as clerical work, bookkeeping, and administrative support.

However, the extent of AI-driven labor displacement varies across sectors and skill levels. Bessen (2019) found that AI adoption is highest in cognitive-intensive industries, such as finance, medicine, and law, where it serves as a complementary tool rather than a full substitute. In contrast, industries with high routine-task intensity, such as manufacturing, customer service, and data processing, face higher risks of labor replacement. Frey & Osborne (2017) estimate that nearly 47% of U.S. jobs are at risk of automation, with administrative support, transportation, and manufacturing being the most vulnerable.

Despite concerns over job displacement, some researchers argue that AI may not significantly reduce net employment but instead contribute to labor market polarization. Goos, Manning & Salomons (2014) link automation to wage inequality, suggesting that AI-driven productivity gains primarily benefit high-skilled professionals while low-skilled and routine workers experience job losses or stagnant wages. This polarization is particularly evident in advanced economies, where AI-driven technologies enable capital deepening, leading to higher productivity but greater wage disparities. Rodrik (2018) further notes that in emerging economies, where labor costs remain relatively low, AI adoption is slower, reducing immediate displacement risks but potentially delaying long-term productivity gains.

These findings suggest that AI-driven automation does not operate as a uniform force across labor markets. Its impact is highly dependent on task composition, industry structure, and national economic policies. The next section explores how AI's effects differ across countries and industries, providing a comparative analysis of capital-labor substitution patterns in AI-intensive economies.

Innovation Measurement: Measuring innovation accurately is crucial for understanding the dynamics of technological progress and its economic implications. While traditional metrics like R&D expenditure provide valuable insights, there are important limitations for assessing a country's innovation capacity and the value they bring to technological progression. Utilizing Patent data offers a complementary and more nuanced perspective on innovation, especially in the leading industry of Artificial Intelligence. Patents represent inventions deemed novel and commercially valuable enough to warrant legal protection, thus signaling both inventive capacity and potential economic impact. Analyzing patent trends, as done by Leusin et al. (Leusin et al., 2020) in the context of Artificial Intelligence, allows for a deeper understanding of technological development trajectories and the geographic distribution of innovative activity. Specifically, the identification of "national breeding grounds" where there exists a disproportionate level of AI-related patents activity which foreign inventors turn to certain countries for protecting their intellectual property. This signifies higher importance that these patents are expected to contribute to the market and innovation. Leusin et al.'s (Leusin et al., 2020) research concludes that there's a potential bifurcation in global AI development, with China primarily focused on protecting AI innovation domestically, while the US operates within a more international framework. This difference highlights the varying approaches countries take in fostering and protecting their AI advancements.

Cross Country Variation in AI's Impact on Labor Markets:

The effects of AI-driven automation on labor markets vary significantly across countries, shaped by differences in economic development, technological adoption rates, labor market policies, and industry composition. While advanced economies experience rapid AI integration, leading to labor polarization and wage inequality, emerging economies face slower AI diffusion, reducing immediate displacement risks but potentially limiting long-term productivity gains. These disparities highlight the importance of institutional factors in shaping AI's impact on employment and capital allocation.

In advanced economies such as the United States, Germany, and Japan, AI adoption has accelerated due to extensive investments in automation technologies, machine learning, and robotics. The impact of AI on these economies has been characterized by labor market polarization, where high-skilled professionals benefit from AI-driven productivity gains, while workers in routine-based occupations experience job displacement. Research by Frey and Osborne (2017) estimates that nearly 47% of U.S. jobs are at risk of automation, with occupations in transportation, administrative support, and manufacturing being the most vulnerable. Similarly, Acemoglu and Restrepo (2020) highlight that AI disproportionately displaces routine cognitive and manual labor, as firms substitute capital for labor in process-driven jobs. The extent of labor displacement, however, varies depending on the institutional framework. Countries with strong worker protections and retraining programs, such as Germany and Scandinavian nations, experience less severe employment shocks as displaced workers transition into new roles. In contrast, economies with more flexible labor markets but weaker social safety nets, such as the United States and the United Kingdom, exhibit higher rates of job displacement and wage inequality (Goos, Manning & Salomons, 2014).

Emerging economies such as Brazil, India, and Eastern European nations have experienced a slower pace of AI adoption, primarily due to differences in economic structure, labor costs, and technological investment. Unlike in advanced economies, where automation replaces costly labor, many emerging markets rely on low-wage workers, making AI-driven automation less economically viable. The slower adoption of AI in these economies has led to fewer immediate job losses, as firms retain a labor-intensive production model. Automation investments often require significant upfront capital, and in regions where wages remain low, businesses have little incentive to replace human workers with AI-driven systems. While this reduces the short-term impact of AI-induced job displacement, it also delays the productivity benefits associated with technological progress. Research by Rodrik (2018) suggests that while automation improves efficiency, its economic impact in developing nations remains constrained by weaker digital infrastructure and workforce skill gaps.

Beyond technological readiness, the degree to which AI affects labor markets across countries is influenced by government policies and economic structures. Nations with highly flexible labor markets, such as the United States and the United Kingdom, experience faster AI adoption but also higher worker displacement, as firms face fewer regulatory barriers to replacing employees with AI-driven systems. By contrast, countries with rigid labor protections, such as France and Italy, exhibit lower automation adoption rates, as businesses must navigate restrictive employment laws before implementing AI-driven changes. The role of government intervention is also crucial in shaping the long-term effects of AI. Nations that actively invest in AI adoption, digital infrastructure, and workforce retraining, such as South Korea and Germany, have managed to reduce the negative consequences of AI by facilitating labor force transitions into emerging industries (Autor, 2019).

These cross-country variations suggest that AI's labor market effects are not uniform but rather depend on the interaction between economic policies, workforce adaptability, and technological investments. As AI continues to shape global employment trends, understanding these institutional differences is crucial for forecasting the long-term implications of automation. While advanced economies experience higher AI adoption and labor market polarization, emerging economies face a slower transition, delaying both displacement risks and productivity gains. The following section presents a comparative analysis of cross-country labor substitution patterns, examining how AI-driven automation influences capital and labor across different economic contexts.

3 Theoretical Model

Our analysis employs a Cobb-Douglas production function to model the relationship between capital and labor inputs and output. Building upon the insights of Kromann et al. (2019) regarding the impact of automation on productivity, we incorporate distinct types of capital to reflect the potentially differential contributions of technological and physical capital. This distinction allows us to assess whether AI-driven technological investments complement or substitute labor differently than traditional physical capital investments.

$$Y_{itj} = A \cdot (PC_{itj})^{\alpha} \cdot (TC_{itj})^{\beta} \cdot (H_{itj})^{\gamma}$$

(1)

Our model is structured such that output (Y_{itj}) represents gross value added (GVA) for industry j, in country i, at time t. The term A captures total factor productivity (TFP), while PC and TC denote technology capital (e.g., AI-related investments) and physical capital (e.g., machinery and equipment), respectively. Labor input, denoted as H, measures total hours worked. For simplicity, our model is then expressed in logarithmic form, allowing for easy interpretation of returns to scale, elasticities (α, β, γ) and ensuring comparability across industries and countries.

3.1 OLS Specifications

$$\log(Y_{itj}) = a_{itj} + \alpha log(PC_{itj}) + \beta log(TC_{itj}) + \gamma \log(H_{itj}) + \epsilon_{itj}$$

(2)

Where α_{itj} the total factor productivity for the given country, year, and industry combinations and ϵ_{itj} being the year. In order to show data reliability and justify the usefulness of patents as an innovation proxy and its significance to productivity overall, we'll initially create a subset of the total data to recreate the findings of Kromann et al. Alternatively, from using robot intensity as a measure of quality of physical capital, we'll use patent intensity as a proxy of country specific technology capital quality.

$$PI_{itj} = P_{it}/TC_{itj} \tag{3}$$

Where PI_{itj} is patent intensity, and P_{it} is the total number of technology-related patents in a given country over time. We also want to note that industry variation isn't collected on the same level, so taking a total sum of relevant patents for the country and relating it to the total amount of technology capital. This is the way where we choose to proxy industries' ability to absorb country wide innovation over time and relates to industries incorporating technological advances into efficient means of production.

$$\log(Y_{itj}) = a_{itj} + \alpha log(PC_{itj}) + \beta log(TC_{itj}) + \gamma \log(H_{itj}) + \delta(PI_{itj}) + \epsilon_{itj} \tag{4}$$

Alternatively, we hope to justify the types of capital behavior and interaction with productivity and the profit maximizing behavior of firms differently. Capital is then grouped (with patent intensity introduced later in Table 3) to demonstrate whether or not different types of capital should be treated separately especially important when discussing the influence of patent intensity.

$$\log(Y_{itj}) = a_{itj} + \alpha log(TotCap_{itj}) + \gamma \log(H_{itj}) + \epsilon_{itj}$$

(5)

Where $TotCap$ is the combination of physical and technological capital. The next models help account for unobserved differences by incorporating country, year, and industry-fixed effects. Using various specifications of the following general fixed effects equation, we attempt to control for unobserved heterogeneity biasing our OLS models.

3.2 Fixed Effect Specifications

$$\log(Y_{itj}) = \alpha\log(TC_{itj})+\beta\log(PC_{itj})+\gamma\log(H_{itj})+\delta\log(PI_{itj})+\rho_i+\omega_t+\lambda_j+\epsilon_{itj} \tag{6}$$

In this fixed-effect model, all the terms remain the same but with additional ρ_i , ω_t , and λ_j , representing country, time, and industry fixed effect, respectfully. This is essential to account for structural differences (explained further below). Introducing the patent intensity term adds a measure of technological capital quality, leading to the final fixed-effects model.

Country fixed-effects control for unobservable factors specific to each country that could influence productivity outcomes. These factors may include macro-level policies such as taxation, trade regulations, and government investment in infrastructure or innovation. Institutional differences, including labor laws, education systems, regulatory environments, and cultural factors, also play a role in shaping how labor and capital are utilized in production.

Year fixed-effects account for temporal shocks and global trends that affect all countries and industries within a given year. Incorporating year-fixed effects also allows us to control for economic cycles, including major recessions that occurred within our dataset's time frame and general technological advancements.

Industry fixed-effects address variations in production processes, capital usage, and labor dynamics across industries, ensuring that structural differences between industries do not bias results.

Ideally, we expect to observe differences and diminishing marginal returns within the fixed-effects models. However, in later discussions, returns to labor and different types of capital are analyzed individually by industry, and their directional effects may not always be consistent. Moving forward, we now discuss the dataset followed by the overall research strategy.

4 Data Description

The dataset incorporates key economic variables that help assess the relationship between AI technological innovation and labor substitution. These variables include capital investment, labor market dynamics, and productivity, allowing quantification of the impact of AI and automation on firm decisions such as employment and allocation of capital. An IQR filter was applied to technology capital and hours worked to address potential measurement errors indicated by repeated, unusually high year-over-year values. A data anomaly was identified in the 2018 labor hours for all countries, showing values 100 times greater than in 2017 and 2019. This was interpreted as a measurement error, and the affected data points were removed to avoid skewing the results. Other variables appeared unaffected.

4.1 Technology Capital

The Technology Capital variable (TC) captures the total investment in computing power-related assets, including computing equipment, communication technology, and software/database capital, all indexed to the 2020 country and industry values. For example, the currencies in the data set are all in national currencies, indexing the values by putting them all over the country and industry's 2020 value allows for cross country comparison. Summing these components forms the backbone of AI- and computer-driven transformation in industries, enabling automation, machine learning applications, and enhanced computational capabilities. For example, a rising $TechnologyCap$ coefficient alongside a negative labor coefficient suggests a growing reliance on technology capital, potentially indicating labor substitution, particularly in industries where automation displaces human tasks. Conversely, if employment remains stable or increases concurrently with technology capital, it implies that capital complements rather than substitutes for labor.

4.2 Labor

Hours worked by persons engaged in production (H) were chosen instead of total hours worked by all employees, as the latter includes administrative roles that act as overhead labor rather than direct production labor. Our focus is on actual labor trends in the production of final goods, justifying this variable choice. Additionally, we use hours worked rather than total employees, as employee counts alone may not account for trends in reduced working hours, potentially biasing our estimates.

4.3 Physical Capital

The Physical Capital variable (PC) captures traditional investments in machinery and equipment, including transport equipment and other machinery, again indexed in the same way to express investment in real terms. Again, if $PhysicalCap$ increases over time while employment remains steady, this suggests that capital is enhancing labor productivity. However, if employment declines as physical capital rises, this suggests that physical capital investment is displacing human workers, all else constant.

4.4 Total Capital

A broader perspective on capital accumulation is provided by Total Capital ($TotC$), which aggregates both technology ($TechnologyCap$) and physical ($PhysicalCap$) capital investments and is simply the sum of both variables. The variable total capital is particularly important for assessing whether increasing capital investment overall is substituting labor/complementing it and whether or not the data suggests different rates of substitution between the types of capital.

4.5 Output-Dependent Variable

Output (Y) is measured by gross value added at 2020 levels, a fundamental measure of economic productivity. While the EUKLEMS variable list indicates a 2015 index, the actual values reflect a 2020 index for this and all other indexed variables. Since AI's economic impact is often assessed through its ability to enhance productivity, a sharp increase in output following an increase in technology capital adoption suggests higher productivity and efficiency gains all else constant, potentially compensating for job losses in certain industries. As mentioned by Acemoglu and Restrepo (2017) this doesn't necessarily mean people being explicitly fired and replaced by a machine/computer, but a job that would've been some form of capital now does a human's. This distinction is essential in understanding what we mean by labor substitution.

4.6 Patent Intensity

Patent intensity (PI) measures AI-technology-related patents collected from WIPO. We filtered patents based on technologies that are linked to computer automation capabilities in some way, including electrical machinery, audio-visual technology, digital communication, computer technology, telecommunications, and semiconductors (WIPO, 2025). These figures were summed for each country to proxy the quality of new technology. This measure is then divided by total technology-related capital to create a ratio. This figure is normalized to a 0-1 scale based on the maximum number of patents for each country-industry combination. The intuition behind this approach is that patents increase relatively to the size and innovative nature of the country, so showing the relative changes of the countries innovation (technology patents). The lag duration for this indicator requires careful consideration, as the full integration of new technologies into production processes and the realization of increased technology capital returns can take several years. However, the data reveals a relatively consistent growth in patent intensity. Countries with high innovation rates tend to incrementally increase their patenting activity each year, roughly proportional to the growth of their capital stock. Countries with lower innovation rates tend to have smaller capital stocks and exhibit similar patterns in overall patenting activity. Therefore, lagging the patent variable may reveal stronger relationships with realized productivity gains. This preliminary analysis underscores the importance of patents as an innovation proxy. Subsequent analysis will employ country clusters based on patenting behavior (described below) to address these differences.

4.7 Patent and Innovation Measurement

Accurately capturing a country's innovation capacity is a central challenge in this study, given the multifaceted nature of innovation and the inherent limitations of patent data. Although patents are frequently used as a proxy for technological progress (Leusin et al., 2020), it is widely acknowledged that not all patents represent equally significant breakthroughs (Zeebroeck, 2010). To address this, prior research has advocated for patent quality indicators such as forward citations, patent family size, and renewal status. However, given the data constraints in this study—especially in cross-country comparisons—we focus on the number of patents related to AI and automation and utilize a new metric to differentiate high-innovation from low-innovation countries.

4.8 Summary Statistics

The key variables on the entire dataset over the years 1995-2021, across 29 countries and 55 industries while omitting for blank cells. *Output is in mil-

Table 1:

	Output	TechnologyCap	PhysicalCap	H_EMPE	Patent_Int_indexed
Mean	92.14	105.56	164.38	101.92	0.42
SD	258.41	212.48	74.52	135.48	0.29
Min	0.05	0.00	2.01	0.19	0.00
Max	15010.31	6151.32	5015.93	9146.67	1.00

lions of national currency indexed to the country and industry's 2020 value = 100 . $TechnologyCap$ is done in the same way however is the sum of chained linked volumes then price indexed to 2020 as the types of technology capital accounts being summed should be treated independently. $PhysicalCap$ was done slightly different and was the sum of price indexed accounts, weighing the forms of physical capital equally. Changing these methods of indexing alters the interpretations of coefficients; however, no significant differences were noted. $HEMPE$ is defined as thousands of hours worked indexing to keep comparability. Patent intensity (PI) is a number 0-1 based on the maximum PI value the country takes on.

We later run a modified Kromann et al. 2019 dataset with far reduced observations, as explained below, however here's this one:

Table 2:

	Output	TechnologyCap	PhysicalCap	H_EMPE	Patent_Int_indexed
Mean	96.54	144.16	170.84	129.28	0.48
SD	33.87	196.55	18.99	31.36	0.27
Min	58.36	4.08	91.99	84.46	0.01
Max	314.91	1118.91	200.51	249.41	1.00

5 Results

5.1 Initial Findings

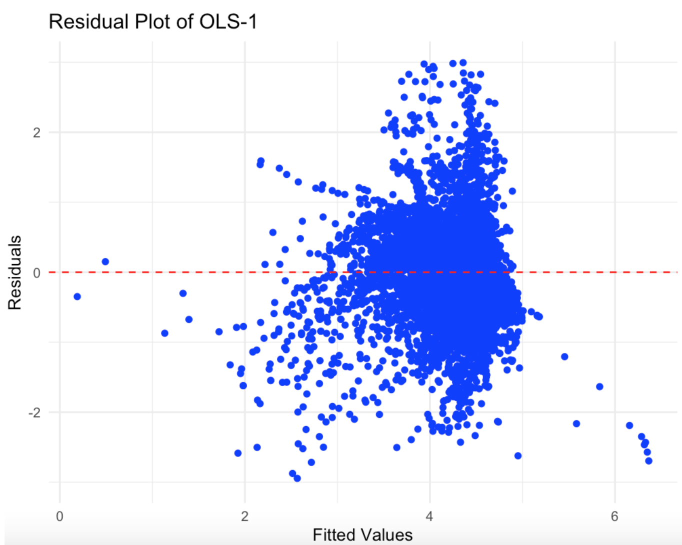
Using the entire dataset without further filtering for industries or countries produces intuitive and promising coefficients for the variables of interest (table 3). The results suggest diminishing and almost constant returns to scale. However, since OLS does not account for unobserved heterogeneity across countries, industries, and time periods, its estimates may be biased due to systematic differences. Given the presence of missing data, we removed blank and outlier entries rather than using imputation methods to avoid potential biases. The dataset's substantial size ensures that removing this subset of data does not significantly compromise the robustness of our results.

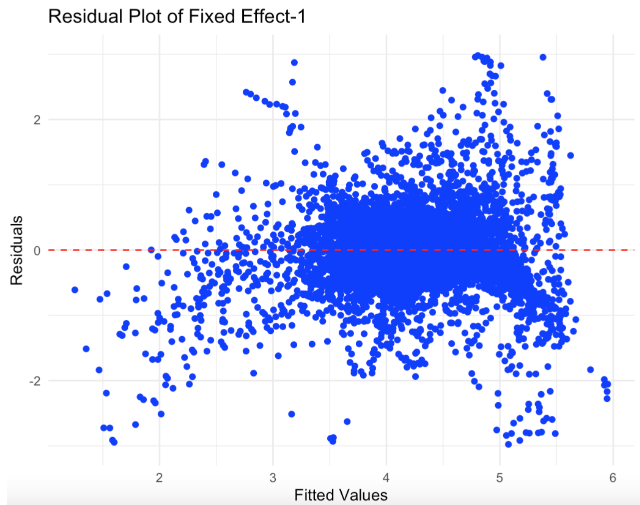
The first point here is that we are seeing reasonable returns to scale as the coefficient sum to around almost one indicating decreasing returns to scale (doubling of inputs leads to less than doubling of output). Additionally, technology capital has a proportionately lower coefficient than physical capital, consistent with the findings of Stiroh, K. J. (2005) and Kroman et al. (2019). While the R-squared value is modest (above 0.2), this is to be expected as using the whole data set for all countries and industries that receive different returns to technological progression and physical capital. The residual plot for this initial regression yields distinct clustering.

To counter some of this, we then utilized the basic fixed-effects regression on our two types of capital and labor with the same data set giving convincing results.

Table 3:

	Dependent variable:
	log_Output
log_TechnologyCap	0.113***
	(0.003)
log_PhysicalCap	0.600***
	(0.008)
log_H_EMPE	0.215***
	(0.010)
Constant	−0.135**
	(0.057)
Observations	27,485
R^2	0.271
Adjusted R^2	0.271
Residual Std. Error	0.446 (df = 27481)
F Statistic	3,400.747*** (df = 3; 27481)
Note:	*p<0.1; **p<0.05; ***p<0.01





	FE Model 1
log_TechnologyCap	0.05 (0.02)**
log_PhysicalCap	0.58 (0.24)*
log_H_EMPE	0.17 (0.06)**
Num. obs.	27488
Num. groups: country	29
Num. groups: industry	55
Num. groups: year	27
R^2 (full model)	0.49
R^2 (proj model)	0.15
Adj. R^2 (full model)	0.49
Adj. R^2 (proj model)	0.15

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

FE Model 1 Whole Dataset

The full model's R-squared increases substantially, which is intuitive. Different industries utilize technology capital differently; labor-intensive industries, such as construction, are less likely to experience the same efficiency gains from technology investments as, for instance, insurance companies. Demeaning the data for countries' specific technological progression and for time as well helps account for these cross-sectional differences. The first FE model shows that accounting for cross-country, industry, and time differences leads to a more accurate way of predicting productivity gains. Next, we highlight the relatively similar physical capital and labor coefficients while technology dramatically changes suggesting the anticipated omitted variable bias. The residual plot now generates more randomness suggesting the removal of some unobserved heterogeneity.

This removes some of the root problems however, we then applied additional filtering to focus on more distinct industry categories initially, ensuring clearer interpretation in hopes of recreating similar results found by Kromann

	OLS-1	OLS-2	OLS-3	OLS-4	FE-1	FE-2	FE-3	FE-4
(Intercept)	-0.005	0.064	0.910+	0.999*				
	(0.712)	(0.715)	(0.471)	(0.496)				
log_TechnologyCap	0.131***	0.110**			0.016		0.011	
	(0.037)	(0.035)			(0.012)		(0.006)	
log_PhysicalCap	0.429***	0.452***			0.081*		0.083*	
	(0.120)	(0.120)			(0.020)		(0.020)	
log_H_EMPE	0.362***	0.347***	0.318***	0.286***	0.063+	0.057+	0.065+	0.057+
	(0.068)	(0.068)	(0.066)	(0.061)	(0.024)	(0.023)	(0.025)	(0.023)
Patent_Int_indexed	0.219*			0.210+			-0.058	0.000
	(0.111)			(0.110)			(0.090)	(0.102)
log_TotalCapital			0.379***	0.380***		0.056*		0.057**
			(0.073)	(0.074)		(0.017)		(0.006)
Num.Obs.	272	272	272	272	272	272	272	272
R2	0.205	0.194	0.181	0.164	0.707	0.707	0.707	0.707
R2 Adj.	0.193	0.185	0.175	0.154	0.682	0.683	0.681	0.682

et al. (2019) and highlighting even sub-industry differences. The following eight sub-industries for manufacturing were selected: Manufacturing of basic metals and fabricated metal products except machinery and equipment, chemicals, computer, electronic and optical products, electrical equipment, machinery and equipment, motor vehicles, trailers, semi-trailers and of other transport equipment, textiles, wearing apparel, leather and related products, wood, paper, printing and reproduction, food products; beverages and tobacco products, rubber and plastic products and other non-metallic mineral products and finally coke and refined petroleum products. These groupings are not exactly the industries chosen by Kromann et al. (2019) , variables were constructed with slightly different independent variables as it was ambiguous to their actual choices. The following countries were analyzed using various OLS and fixed-effect specifications for the period 2004-2007: Denmark, France, UK, Italy, Germany, Sweden, Spain, Japan, and Finland again for no particular reason besides comparing to Kromann et al. 2019. This isn't our final dataset to analyze cross-industry differences but merely to show that for even sub-industry differences (within manufacturing as a whole), there still exists the need for country-industry specific controls relating to technological progression that we later accomplish through clustering countries and all industries again.

The low OLS R-squared in some cases suggests an issue that requires further consideration. The anchor's approach of using variables scaled by labor leads to co-linearity and likely the higher R-squared. Additionally, the larger number of observations also allows the model to better fit the data.

However, we note several key similarities and differences that are crucial to developing our hypothesis. Kromann et al. (2019) observes that when introducing a metric of capital quality, such as robot intensity, the coefficient of the related capital type increases while the coefficient for physical capital decreases. This finding points to the potential for omitted variable bias in studies that neglect the quality of capital inputs. We acknowledge this issue and propose methods to control for it, enabling more reliable conclusions.

Furthermore, the observation that total capital is not simply the sum of the two capital coefficients contradicts findings, suggesting that different types of capital are utilized in distinct ways. This idea deserves further exploration through statistical tests which determine when utilizing the fixed effect models (FE-1) the two types of capital being different to each other is statistically significant in our case.

The reduced statistical significance of variables in the fixed-effects models may be attributed to the similarity between industries and countries particularly regarding technology capital. However, physical capital and labor remain statistically significant, albeit with smaller coefficients compared to the OLS results. This continued significance of physical capital supports previous findings, reinforcing the notion that capital should be treated separately.

The R-squared for the FE models all dramatically increase from their OLS counterparts. This shows that controlling for country and industry structural differences while accounting for technological advancement, global shocks, etc. through a time fixed effect term leads to clearer estimates of the independent variables.

Patent intensity indicates a differential impact of innovation on the types of capital, highlighting the importance of incorporating additional patent-based controls. The varying elasticity of the different capital types between specifications points towards the need to treat them separately while interpreting their coefficients with appropriate caution.

Ultimately, it becomes evident that the current model may not be able to capture meaningful cross-industry variation without accounting for how nations innovate in productivity-enhancing technologies. This consideration is particularly relevant as extracting and comparing industry estimates using the small dataset of Kromann et al. (2019) would prove difficult as there are too few observations for each sub-industry. Alternatively, we propose that poorer countries, which tend to innovate less, may not benefit from the same advancement as knowledge-based economies (richer). Accounting for this through utilizing patents and RD expenditure figures we suggest a new method of analyzing nation's industries' ability to incorporate innovation into means of production.

5.2 Methods and Additional Proposed Controls

As mentioned, patents are suspected to affect capital returns in developed vs. developing countries differently, and even sub-industry differences exist. Hence the need for comparing not only industries to each other but industries in developed vs developing countries as well due to whether or not they'll be able to use the more current period AI-related innovations. This then influences technology capital returns to be comparatively greater than physical capital in developed economies.

We restrict our attention to patents associated specifically with AI and automation, drawing on the WIPO patent database to identify relevant patent families. We then derive a measure of $Patents\_per\_Innov$ by combining patent counts with indicators of national R&D and innovation inputs. Formally, we compute:

$$\text{Patents\_per\_Innov} = \frac{\text{Total\_Patents}^2}{\text{InnovProp} + \text{RD} + \text{Software\_DB}}$$

total_patents is the total number of AI- and automation-related patents filed by a given country in a given year

InnovProp, **RD**, and **Software_DB** capture various dimensions of innovation input (e.g., proprietary innovation indices, R&D expenditure measures, or software development benchmarks).

By squaring the $Total\_Patents$ term, we assign additional weight to countries that exhibit a disproportionately large volume of patenting activity relative to their R&D indicators, thus helping to differentiate truly innovation-intensive economies from those with moderate but not leading-edge patent portfolios. This transformed ratio allows us to cluster countries into high- and low-innovation groups, ensuring that extreme patenting outliers are given due emphasis in the dataset.

The figure above illustrates the results of our clustering, plotting each country's **mean** (x-axis) and **standard deviation** (y-axis) of $Patents\_per\_Innov$. The color-coded clusters separate countries with high average patenting intensity and higher variance from those with lower averages and more stable (or uniformly low) patent activity. For instance, countries such as the United States, Germany, and France appear on the higher end of the x-axis, reflecting both a large volume of AI-related patents and lower variability. Conversely, smaller economies or those with less AI-driven R&D, such as Romania or Bulgaria, tend to cluster toward the lower-left portion of the chart, indicating more modest patenting activity and higher volatility.

To validate these groupings, we cross-check them against the Global Innovation Index (GII). The GII provides an internationally recognized benchmark of innovation performance, incorporating both input measures (e.g., R&D spending, human capital, and institutional frameworks) and output measures (e.g., patents, publications, and technology diffusion). We find that our clustering based on the $Patents\_per\_Innov$ metric aligns closely with the **GII** rankings, lending credibility to our classification approach. Specifically, countries

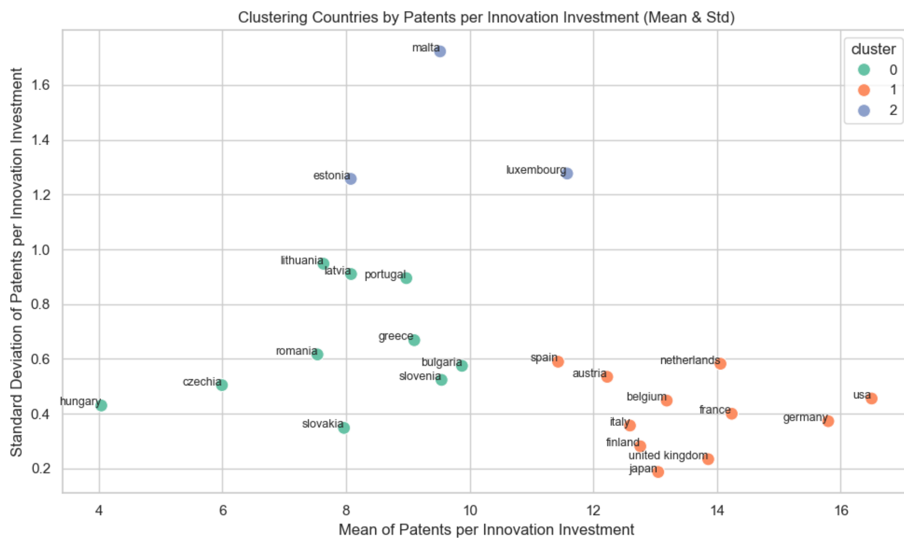


Figure 1: Proposed Clustering Method

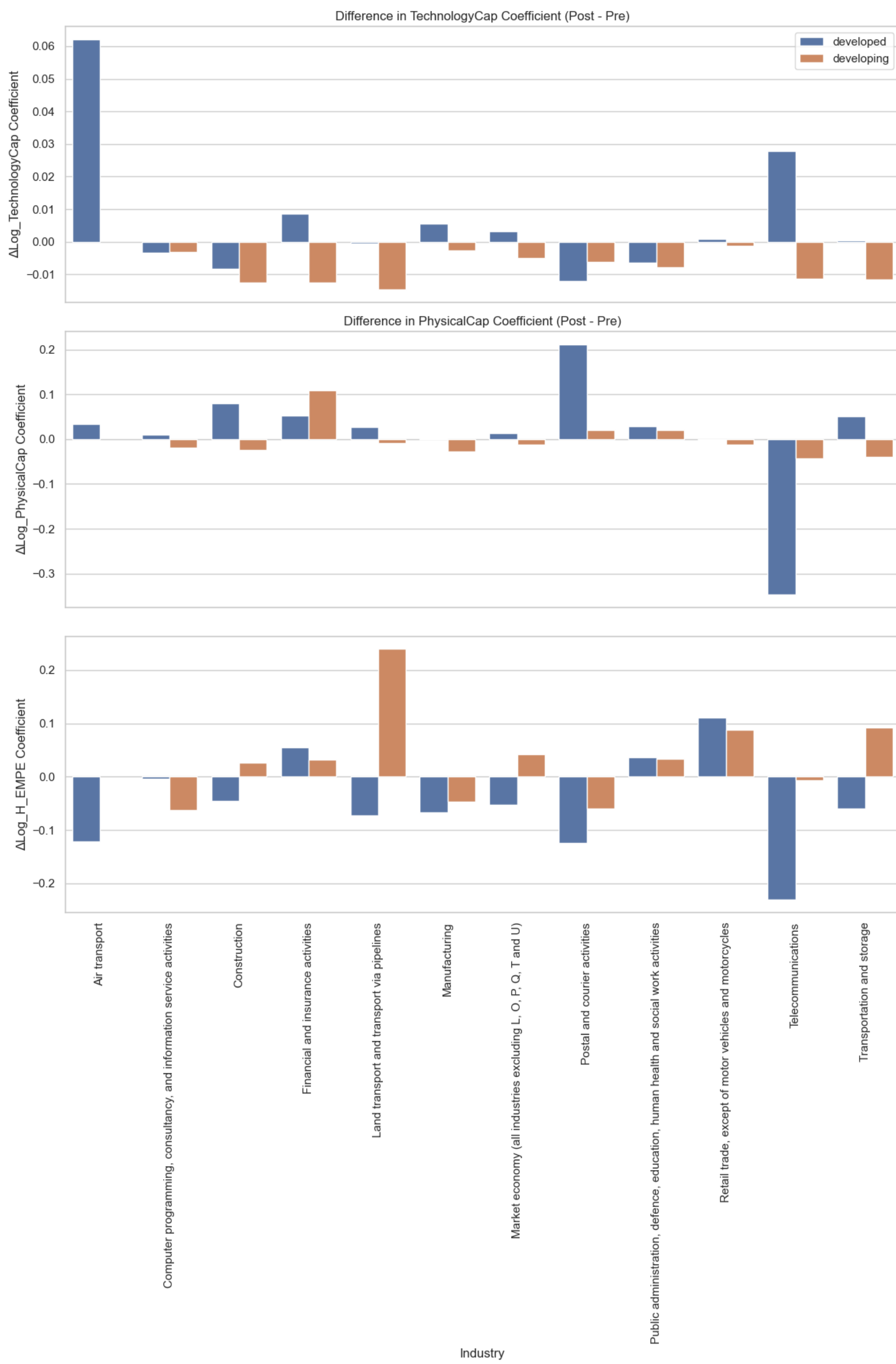
known for robust innovation ecosystems—such as those with strong AI research hubs—consistently appear in the high-innovation cluster, whereas economies with more modest R&D infrastructure or fewer AI patent filings tend to fall into the low-innovation category. Moving forward we will be utilizing only cluster 'zero' as 'Developing', and 'one' as 'Developed' countries and will not be considering cluster two since these aren't clearly defined and we already have sufficient observations.

To extract industry-specific coefficient estimates, separate fixed-effects regressions were run for developed and developing countries, incorporating dummy variables and examining pre-2008 and post-2009 outcomes. We anticipate greater adoption of AI and technology capital in more recent periods. The period around 2008-2009, encompassing the Global Financial Crisis, was excluded due to its differential impacts on various industries.

$$\log(Y_{itj}) = \sum_j \alpha_j D_j \log(TC_{itj}) + \sum_j \beta_j D_j \log(PC_{itj}) + \sum_j \gamma_j D_j \log(H_{itj}) + \alpha_i + \delta_t + \epsilon_{itj}$$

Running this a similar FE model for pre- and post- period industry estimations. We then see the difference between the coefficient estimates for each period grouping and for the clusters. These differences displayed in the table below show the general direction of the change in input elasticities over time.

Coefficient Changes by Country Grouping


Difference in TechnologyCap Coefficient (Post - Pre)
developed
developing
ΔLog_TechnologyCap Coefficient
0.06
0.05
0.04
0.03
0.02
0.01
0.00
-0.01
Difference in PhysicalCap Coefficient (Post - Pre)
ΔLog_PhysicalCap Coefficient
0.2
0.1
0.0
-0.1
-0.2
-0.3
ΔLog_H_EMPE Coefficient
0.2
0.1
0.0
-0.1
-0.2
Air transport
Computer programming, consultancy, and information service activities
Construction
Financial and insurance activities
Land transport and transport via pipelines
Manufacturing
Market economy (all industries excluding L, O, P, Q, T and U)
Postal and courier activities
Public administration, defence, education, human health and social work activities
Retail trade, except of motor vehicles and motorcycles
Telecommunications
Transportation and storage
Industry

This section presents a comparative analysis of coefficient shifts across selected industries that demonstrated statistical significance in all core explanatory variables: technology capital, physical capital, and employment. We see a variety of results across industries; however, only the ones with all statistically significant explanatory variables are displayed above. The developed vs. developing country classification is derived from our prior unsupervised clustering approach, which was cross-validated against GII.

Figure X visualizes the changes in regression coefficients between the pre-2008 and post-2009 to 2020 periods. This time division was selected to mitigate potential bias arising from the 2008 financial crisis and COVID-19 shocks. For each industry and country group, the chart displays the difference in coefficient estimates ($\beta_{post}\beta_{pre}$). Regressions were run using a country fixed-effects specification, allowing us to isolate industry-level patterns while accounting for unobserved national heterogeneity.

Several trends are immediately observable. In developed countries, industries such as **Air Transport** and **Telecommunication** exhibit a notable increase in the coefficient for technology capital, coupled with a decline in the employment coefficient. This pattern is consistent with capital deepening, as firms in these sectors increasingly adopt automation and advanced technological solutions. These findings align with existing literature suggesting that automation is more prevalent and effective in advanced economies (Kromann et al., 2019; Acemoglu & Restrepo, 2019). The reduction in labor's marginal contribution may signal labor substitution or productivity gains enabled by technology.

Secondly, developing countries display more heterogeneous patterns. In many cases, a negative change in the Technology Capital coefficient is observed, potentially reflecting lagged adoption of new technologies or constraints in capital investment. Notably, **Financial and Insurance Activities** and **Human Health Activities** in developing countries show consistent directional changes across all coefficients, with rising Physical Capital playing a larger role. The divergent responses in labor coefficients, particularly in Human Health Activities, suggest that sector-specific characteristics and institutional factors mediate how technology translates into productivity gains.

These results align with findings from (Li et al., 2021) and the (WHO, 2020), which emphasize that in many low- and middle-income countries, health system improvements in the 2010s were achieved primarily through increases in healthcare personnel and basic infrastructure rather than through high-tech innovation. Additionally, donor funding and development programs during this period often prioritized expanding physical clinics, hospitals, and access to primary care services, especially in rural and underfunded regions. The increased productivity of labor may therefore reflect more effective deployment of healthcare workers within newly built or upgraded facilities, rather than automation or AI-based efficiency gains.

This sector's trajectory underscores the importance of context-specific development dynamics. While developed economies may be leveraging technology to substitute labor in healthcare, developing economies appear to be expanding service delivery by investing in labor and physical capital, driven by demographic pressures, public health goals, and institutional constraints on digital adoption. These contrasting pathways highlight the need for industry- and region-specific interpretations when analyzing capital-labor substitution patterns.

The **Postal and Courier Activities** sector is another area of interest, showing distinct shifts across both country groups. In developed countries, this may be driven by scale effects and logistical automation, while in developing countries, transitional inefficiencies may explain mixed results. Overall, the observed coefficient changes highlight technological advancement's non-uniform impact across industries and country income groups. These results underscore the importance of accounting for technological readiness and institutional capacity when interpreting labor-capital substitution patterns across economies.

In the **air transport** sector, the regression reveals a significant increase in the Technology Capital coefficient and a simultaneous decline in the Employment coefficient after 2009. This trend reflects the industry's widespread adoption of automation and digital infrastructure, including automated customer service systems, real-time route optimization, predictive maintenance, and fleet management technologies. As these innovations scaled, the marginal contribution of labor—particularly in administrative, scheduling, and ground operations—declined, illustrating a clear case of labor substitution through capital deepening in a globalized and cost-sensitive industry(Acemoğlu & Restrepo, 2019).

Notably, the increase in the TechCap coefficient for air transport is comparatively large, indicating that this sector is an outlier in terms of how strongly technological capital has contributed to post-2009 productivity. This suggests a structural transformation rather than a marginal shift, driven by factors such as post-crisis restructuring, the rise of low-cost carriers leveraging tech to minimize labor inputs, and regulatory shifts accelerating digital adoption.(Boussemart et al., 2019) The outlier status of air transport also highlights the potential for non-linear or accelerating returns to tech investment in this industry, where fixed technological costs can be distributed across high output levels. This increase underscores the importance of accounting for sector-specific dynamics when analyzing capital-labor substitution patterns and may warrant further investigation through robustness checks or interaction terms in the regression specification.

In the **Land transport and transport via pipelines** sector, our analysis reveals notable differences between developed and developing economies. In developed countries, the reduced employment coefficient indicates that as these economies further integrate automation—through advanced routing systems, semi-autonomous vehicles, and other digital logistics solutions—the marginal contribution of labor declines. This is consistent with OECD findings, which note that increased automation in transport services tends to streamline operations and reduce labor dependency (OECD, Transport Bridging Divides, 2025). While the physical capital coefficient sees only minor changes, suggesting that ongoing investment in fleet upgrades and infrastructure are largely incremental and do not dramatically shift the production function, the technology capital coefficient remains largely unchanged. This implies that the level of technological integration in developed economies has already reached a plateau where additional investments yield diminishing marginal returns.

In contrast, developing countries exhibit a significantly increased employment coefficient in this sector. This surge reflects the continued reliance on labor-intensive transport services in these regions, where advanced automation technologies have been adopted at a slower pace. Reports from the World Bank emphasize that many developing nations rely more heavily on manual labor in transportation due to limited access to high-tech investments and infrastructure upgrades (World Bank Group, 2025). The lack of significant change in the physical capital coefficient in these economies further indicates that investments in equipment and infrastructure are modest and gradual, constrained by financial limitations. Additionally, the observed reduction in the technology capital coefficient underscores a lower level of tech adoption, potentially due to infrastructural barriers, limited R&D spending, and a strategic preference for expanding labor capacity rather than investing in advanced technological solutions, as highlighted by the International Transport Forum under the OECD ("ITF Transport Outlook 2021," 2021).

The divergence in technology adoption between developed and developing economies is evident. Developed countries leverage automation and technology to enhance productivity and, in some cases, substitute labor. Conversely, developing economies, often constrained by capital and infrastructure limitations, maintain a greater reliance on manual labor. This contrast underscores the critical role of technology and infrastructure investments in driving economic development and shaping labor market dynamics (How Technology Adoption Affects Global Economies, 2012).

Financial and insurance activities also suggest complementary effects of AI adoption, aligning with findings in Feng et al. (2022). In developed economies, the increase in the technology estimate and the subsequent negative labor coefficient indicate a shift from easily automated, clerical tasks to more complex roles requiring a 'human touch.' Developing economies exhibit a similar pattern, likely driven by changes in physical capital stock, such as optimizing the number of bank branches. Firms in these countries may experience higher returns to physical capital than to technology until an optimal allocation is reached, at which point diminishing marginal returns become more pronounced.

Finally, **Manufacturing** shows declining labor coefficients for both developed and developing countries, while the technology coefficient is positive for developed countries and negative for developing countries. This aligns with our hypothesis: developing economies are not yet fully utilizing recent AI-related investments and likely prioritize improvements in physical capital, which remain relatively constant between periods, and labor efficiencies. In contrast, the developed country cluster can leverage AI's automation capabilities in production processes. However, telecommunications and air transportation demonstrate a greater capacity for this over the period, also exhibiting larger decreases in labor returns. The ambiguous nature of changes in physical capital returns suggests the need to consider sub-industry differences, given the varying nature of manufacturing and the wide range of equipment used. While some industries use similar equipment and production processes, assembly-line manufacturing employs highly sub-industry-specific physical capital.

In summary, while the data exhibit similarities to our initial hypothesis, the less pronounced labor substitution in manufacturing, especially within developed economies, suggests a more nuanced interpretation. This may be due to the unrealized returns of technology capital, as successful integration of innovations into large-scale assembly lines often requires considerable time. Alternatively, it could be attributed to a combination of lagged returns and sub-industry differences, as the nature of manufacturing processes varies significantly, influencing technology capital decisions.

5.3 Limitations and Recommendations For Future Work

While our pre- and post- analysis by industry and the comparison between developed and developing countries yield some valuable insights, several limitations must be acknowledged.

Our division of the sample into pre-2008 and post-2009 periods, though designed to mitigate the confounding effects of the financial crisis and later COVID biases, might oversimplify gradual or nonlinear trends in technology adoption and labor dynamics. Economic shifts do not occur abruptly, and important transitional dynamics may be obscured by this binary time split. Additional periods could be used and is a recommendation for future research; however, it is at the expense of reduced observations.

Secondly, the classification into developed and developing countries is based on our clustering methodology cross-referenced with the Global Innovation Index. However, these categorizations are inherently coarse and may mask significant intra-group heterogeneity. For instance, some developing countries might exhibit characteristics more similar to developed economies in certain industries, while variations within developed countries may influence the observed coefficients.

Another limitation arises from the industry-level analysis itself. Although focusing on the profit-maximizing behavior of firms in these industries enhances the robustness of our results, it narrows the scope of inference. Industries with less pronounced profit-maximizing behavior or those that are undergoing structural transitions might follow different dynamics that our analysis does not capture. Moreover, the aggregation of data at the industry level might conceal firm-specific strategies and regional nuances that are critical for understanding the complete picture of capital-labor substitution.

Finally, our empirical strategy—relying on OLS regressions with fixed effects—may not fully address potential endogeneity issues. Unobserved variables, measurement errors, or omitted factors that affect both the dependent variable and our predictors could bias our estimates. Future research might consider alternative econometric techniques, such as instrumental variable approaches or dynamic panel data models, to better account for these challenges. Combining studies using quality of human capital metrics and technology spillovers are the main issue however, industry variation is not easily accessible and reliable.

Another important limitation of our analysis relates to the measurement of technological capital. As technology continues to improve, each dollar spent on tech investments yields more output than in previous periods. However, our measure is based solely on nominal spending and does not adjust for improvements in the quality or efficiency of technology over time. Combined with the declining costs of computing power over this time (Tupy and Bailey, 2023) leads to even more bias of coefficient estimates.

Together, these limitations suggest that while our findings offer insight into the differential impact of technological, physical, and labor inputs across industries and country groups, generalizing these results leads to obvious bias. As confirmed by Acemoglu and Restrepo, our analysis confirms that labor tech substitute is ambiguous. Further investigation incorporating more granular data and alternative methodologies could provide deeper insights into the complex dynamics underlying capital-labor substitution.

6 Conclusion

This research examined recent trends in capital-labor substitution across various industries, utilizing a fixed-effects model and incorporating patents and R&D expenditures as measures of technological advancement. While the initial hypothesis suggested that manufacturing industries would experience the highest levels of substitution due to automation and rapid technological progress, the findings revealed a more nuanced picture. Contrary to expectations, other industries demonstrated more significant substitution trends. This challenges conventional assumptions and highlights the complex interplay between technological advancements, capital investment, and labor dynamics in the modern economy. Further research could explore the specific factors driving substitution in these unanticipated sectors, potentially delving into the role of AI and other emerging technologies in reshaping labor markets and production processes. The evolving nature of capital-labor substitution underscores the need for ongoing investigation and analysis to understand the long-term implications for economic growth, employment patterns, and income distribution.

However, this analysis still provides a framework useful in generating meaningful implications regarding shorter-term firm and governmental policy decisions. Industry optimal capital allocation can be used at the firm level. Additionally, nations' education systems can adjust accordingly to enforce skills in demand for the future job market. Finally, it may lead to conclusions about nations' innovative capabilities and whether or not a country should be investing in more RD or gain higher returns by importing technology from more advanced economies.

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