Financial Development, Technology Adoption, and Sectoral Productivity Convergence*

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Abstract

This paper documents differences in productivity convergence patterns across key economic sectors and introduces an endogenous growth model to explain how both financial development and a country's income level drive sectoral convergence. The model predicts that sectors with higher technological frontier growth, such as agriculture, will experience slower and delayed convergence compared to sectors with lower frontier growth, like services. It also demonstrates that aggregate divergence may eventually transition into convergence as sectors catch up. As income continues to rise, financial constraints gradually ease, enabling lagging sectors to adopt technologies more intensively and accelerate productivity growth. Even if the country diverges from the technological frontier, this process strengthens aggregate wealth and establishes a positive feedback loop.

KEYWORDS: Productivity Convergence, Technology Adoption, Financial Development, Sectoral Productivity Gap, Technological Frontier.

JEL classification: O14, O33, O41, O47, G28

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1 Introduction

One of the central questions in development economics is whether developing countries can achieve faster economic growth to catch up with more advanced economies. A consensus view in the literature is that differences in income across countries are primarily due to variations in total factor productivity[1]. Likewise, differences in productivity growth stem from disparities in technology usage (see Jerzmanowski (2007) and Aghion et al. (2005)). Since technology adoption occurs at the industry level, analyzing sectoral productivity is essential for understanding overall GDP per capita convergence[2]. Thus, Rodrik (2013) examined convergence within the manufacturing sector and its subsectors, finding evidence of unconditional convergence in manufacturing labor productivity, while Kinfemichael & Morshed (2019) identified similar patterns within the services sector.

In this paper, I explore the variation in convergence patterns across sectors and explain the link between aggregate-level convergence and sector-level dynamics, highlighting the mechanisms by which countries transition from a phase of divergence to convergence in their income. First, I analyze sectoral productivity convergence between 1991 and 2019 and find that while manufacturing and services sectors exhibit a significant trend toward narrowing productivity gaps, the agricultural sector demonstrates less pronounced convergence dynamics with persistent disparities across countries. Second, I document a positive correlation between financial development and the intensity of use of technologies, which disappears once financial development reaches a technology-specific threshold, expanding on Comin & Nanda (2019), who showed that financial development enhances technology adoption but did not account for this threshold effect.

The objective of this paper is to develop a technology adoption model consistent with the aforementioned correlation, capable of explaining productivity convergence patterns among countries in different sectors. Therefore, I consider a multisector growth model with financing

[1]See Klenow & Rodrìguez-Clare (1997), Prescott (1998), Caselli (2005), and Jones (2016), for example.

[2]If convergence is observed across major sectors–such as agriculture, manufacturing, and services–it suggests that overall GDP per capita is likely to converge as well. This has prompted researchers to focus on sectoral productivity convergence.

frictions that builds on Aghion et al. (2005). The basic framework of the paper is expanded to account for differences in productivity between less and more advanced technologies. The specificity of each sector in the technology adoption process is also incorporated. Sectors with more advanced technologies typically require greater investments and specialized skills to ensure successful adoption. Another important and novel aspect of the model is that a country may successfully adopt technology but still fail to catch up with the frontier productivity. The level of productivity a country achieves after adopting new technology depends not only on the frontier sector's productivity but also on how intensively the new technology is utilized. Comin & Mestieri (2018) has documented that, even when technologies are available everywhere, their intensity of use varies significantly across countries.

To simplify the analysis, I assume that in the absence of credit constraints, countries can borrow without limit and adopt technologies at the same intensity as those at the technological frontier. However, a country's financial development is strongly correlated with its governance indicators, including government effectiveness, control of corruption, voice and accountability, political stability, and the rule of law (Porta et al. (1998)). Thus, in the absence of institutional weaknesses, such as weak creditor protections or market imperfections that create credit constraints, it is expected that countries' technology adoption would align with that of developed countries.

The model's predictions align with the observations discussed earlier, demonstrating that financial constraints hinder technology adoption more in industries further from the technological frontier. Consequently, these industries experience slower convergence to the frontier, leading to varying cross-country productivity convergence patterns at the industry or sectoral level. A notable example is the use of tractors in agriculture. Although tractors represent well-established technology, their adoption is less widespread in less developed countries and even more limited in nations with lower levels of financial development. Thus, industries with high investment requirements for technology adoption, particularly in countries with low initial incomes, face substantial delays due to financial constraints, which widens the gap between these industries and the technological frontier, leading to divergence.

However, even when these industries lag behind, they continue to achieve productivity growth[3]. As a result, overall economic growth can still take place, gradually easing financial constraints as the country's financing capacity improves with rising income. This improved financing capacity allows these lagging sectors to adopt technologies more effectively and at a greater scale than before, accelerating their growth and contributing to overall income growth, thereby creating a reinforcing feedback loop. A key implication is that even industries initially diverging from the technology frontier can eventually shift to a convergence path, leading overall income to transition from divergence to convergence.

Financial development plays a crucial role in this process by facilitating quicker transitions from divergence to convergence. Indeed, countries with higher initial levels of financial development and income are likely to converge earlier and more rapidly due to their stronger financing capacity, which accelerates technology adoption and productivity growth. However, the transition from divergence to convergence is possible, even if the degree of financial development remains unchanged over time, simply because income levels continue to grow. Even so, the divergence phase will last longer, meaning the transition will occur later than if the financial system experienced an improvement.

The empirical analysis is drawn from the World Development Indicators (WDI) dataset, which covers over 110 countries from 1991 to 2019 and demonstrates a significant positive relationship between financial development, GDP per capita, and the rate of convergence. The cross-country regression results indicate that a country like India, with a product of the financial development index and the logarithm of GDP per capita equal to 1.9 and starting with approximately the same relative sectoral productivity across its three sectors compared to France (a ratio of 0.15 in agriculture, 0.17 in manufacturing, and 0.12 in services in 1991) will take around 81 years to catch up with France in services, 185 years in manufacturing, and 305 years in agriculture. However, by increasing India's initial financing capacity from 1.9 to France's level of 4.52 in 1991, the convergence rate significantly improves, reducing the time needed to catch up with France to 37 years in services, 45 years in manufacturing, and 74 years in agriculture.

[3] Even if a sector diverges, technology adoption still occurs, albeit at a slower pace, leading to reduced productivity growth compared to the technological frontier in that sector.

The services sector exhibits the fastest rate of productivity convergence, followed by manufacturing and then agriculture, reflecting differences in productivity growth across these sectors at the frontier. Interestingly, between 1991 and 2019, the top ten most developed countries[4] experienced the highest average annual growth rate in agriculture, at 3.06%, compared to 1.97% in manufacturing and 0.86% in services. This inverse relationship confirms that sectors with higher growth rates at the frontier tend to have slower convergence rates, while those with lower growth rates at the frontier converge more rapidly.

While it may appear intuitive that faster frontier technology progress in a sector would slow convergence, it also creates greater potential for growth in developing countries through catch-up effects (by increasing the productivity gap). This paper reveals that in agriculture, the higher productivity gap does not translate into higher relative productivity growth for developing countries. Instead, their higher productivity growth in agriculture, relative to the frontier agricultural productivity growth, remains lower than in manufacturing and services relative to their respective frontiers. This is primarily due to more severe financial constraints in sectors with a larger productivity gap, which hinder technology adoption and slow convergence.

Related Literature. My paper contributes to the broad literature analyzing the channels driving productivity differences across countries. Specifically, it addresses the literature examining the dynamics of sectoral productivity gaps across countries (Rodrik (2013), Kinfemichael & Morshed (2019), and Herrendorf et al. (2022)). Another strand of this literature explores why poorer countries do not efficiently adopt and utilize the advanced technologies available in developed countries, which could help them grow faster and achieve similar levels of wealth. This strand includes studies that focus on the role of distortions or barriers to technology adoption (e.g., Parente & Prescott (1999), Hsieh & Klenow (2014), Bento & Restuccia (2017), Cole et al. (2016), and Comin & Nanda (2019)). From this perspective, policies that address misallocation, particularly in the financial system, are seen as contributing to improved technology adoption. The four papers most closely related to my work are Aghion et al. (2005), Rodrik

[4]These top ten countries, with higher levels of financial development and GDP per capita in 1991 and available data, are France, Switzerland, Germany, the United Kingdom, Australia, the Netherlands, Austria, Denmark, Cyprus, and Singapore.

(2013), Kinfemichael & Morshed (2019), and Herrendorf et al. (2022).

While Aghion et al. (2005) used a Schumpeterian growth model to argue that credit constraints play a crucial role in explaining cross-country differences in technology adoption, their model does not address how some sectors within the same country may face greater financial constraints in adopting technologies. Indeed, in their paper, the framework is such that all innovators in the same country adopt the same average technology of the frontier without taking into account the specificity of each sector. As they pointed out in the conclusion of their working paper, financial development should be especially favorable to innovation in R&D-intensive sectors, where technology transfer requires much external finance. This paper addresses this gap by demonstrating that, within a given country, the intensity of new technology adoption and utilization can vary across industries, even when the overall level of financial development is identical.

This variation in technology adoption is driven by differing productivity gaps across sectors. Sectors with smaller productivity gaps are more likely to adopt and utilize new technologies to a greater extent, as higher-productivity sectors typically possess a larger pool of knowledge and expertise. This enables their workforce to better understand and integrate new technologies into their operations, facilitating smoother adoption processes. Furthermore, contrary to Aghion et al. (2005), the model predicts that the threshold level beyond which financial development no longer affects productivity growth is sector-specific. Sectors closer to the technology frontier become financially unconstrained earlier than those further from the frontier.

In addition, Aghion et al. (2005) analyze convergence of at aggregate level, where countries are locked into specific country categories. This means that countries that diverge remain divergent. However, recent literature has shown that while some countries that experienced divergence in terms of economic development in the 1960s, they appear to embark on convergence path some 30 years later, as highlighted in the concept of "converging to convergence" by Kremer et al. (2022). My work provides a framework to rationalize such development paths through a collateral-based financial constraint mechanism. The key insight is that industry-specific technology adoption costs are proportional to the gap between an industry's current technology level and its frontier. However, the economy's financing capacity scales with income levels, which continue to rise even in the case of divergence. As a result, the increase in financing capacity positively influences industry-level technology adoption and overall economic growth.

Taking into account endogenous industry-specific intensity of technology adoption thus allows to explain transitions between different convergence paths, something that Aghion et al. (2005) struggled with where countries are locked in the specific convergence pattern forever if their level of financial development does not change.

Moreover, the model's predictions on the convergence of sectoral productivity are noteworthy, especially when compared to the findings of Rodrik (2013), Kinfemichael & Morshed (2019), and Herrendorf et al. (2022). Specifically, Rodrik (2013) demonstrates that unconditional convergence in manufacturing labor productivity occurs across 118 countries, regardless of geography, policies, or other country-level factors. Similarly, Kinfemichael & Morshed (2019) provides evidence of unconditional convergence in services across 95 countries.

In contrast, Herrendorf et al. (2022) construct new cross-country comparable data and find no evidence of unconditional convergence in manufacturing labor productivity among 64 countries with varying levels of financial development and GDP per capita. This paper underscores the significance of a country's initial wealth and financial development levels in determining whether it experiences convergence or divergence in sectoral productivity. Thus, my results may help to rationalize the inconclusive and somewhat contradictory evidence on productivity convergence from these earlier studies.

The subsequent sections are structured as follows. Section 2 provides a concise overview of the evidence concerning sectoral productivity convergence, technology adoption, and financial development. Following this, Section 3 elaborates on the theoretical model, outlining its key components. The model's predictions regarding convergence are explored in Section 4, while Section 5 analyzes these predictions in relation to the data. Finally, Section 6 concludes the paper by summarizing the key findings and highlighting their implications.

2 Sectoral Productivity Convergence, Financial Development, and Technology Adoption

In this section, I analyze sectoral productivity trends from 1991 to 2019, focusing on how the distribution of productivity has evolved across agriculture, manufacturing, and services. Since technological advancement is the primary driver of productivity growth, I also examine the relationship between technology adoption and financial development. This analysis motivates the development of the model.

2.1 Sectoral Productivity Convergence

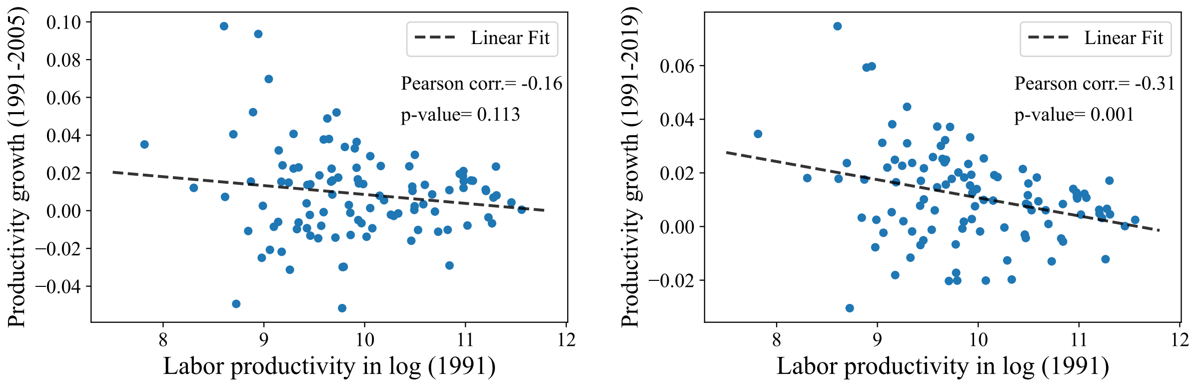
In the literature on cross-country convergence, recent studies have shown varying results regarding the convergence of labor productivity across different sectors. For instance, Rodrik (2013) demonstrated that unconditional convergence in manufacturing labor productivity occurs regardless of geography, policies, or country-specific factors. Similarly, Kinfemichael & Morshed (2019) found evidence of unconditional convergence in the services sector. However, the agricultural sector does not exhibit clear evidence of such convergence, indicating a different dynamic compared to manufacturing and services. Using sectoral labor productivity data from WDI (2022), measured as value added per worker in constant 2015 international US\$[5], I document a shift in convergence patterns across all three sectors over time.

First, I conduct β–convergence analysis of sectoral productivities across countries which occurs when less productive countries grow faster than more productive ones, serving as a necessary but not sufficient condition for developing countries to catch up with developed countries. Figures I-III present scatter plots with linear fit lines for each sector across two distinct periods: 1991-2005 and 1991–2019. The linear fit lines are derived from the regression specified in equation (5.3), computed for each sector without including fixed effects or country characteristics. On the vertical axis, I plot the average annual growth in log of labor productiv-

[5] I convert value added per worker in 2015 US\$ prices into constant 2015 international US\$ using purchasing power parities (PPPs) to ensure comparability across countries and over time. For a detailed explanation, refer to Subsection 5.1.

ity in agriculture, manufacturing, and services.

In the services sector, the correlation for 1991-2019 is -0.31 (p-value = 0.001), indicating β-convergence, as shown by Kinfemichael & Morshed (2019). This suggests that countries with lower initial productivity in services have experienced relatively higher growth, thereby narrowing the productivity gap. In contrast, the earlier period from 1991-2005 shows a correlation of -0.16 (p-value = 0.100), reflecting a less pronounced convergence trend. This implies that some countries which were not converging between 1991-2005 began to do so during the period 1991-2019.



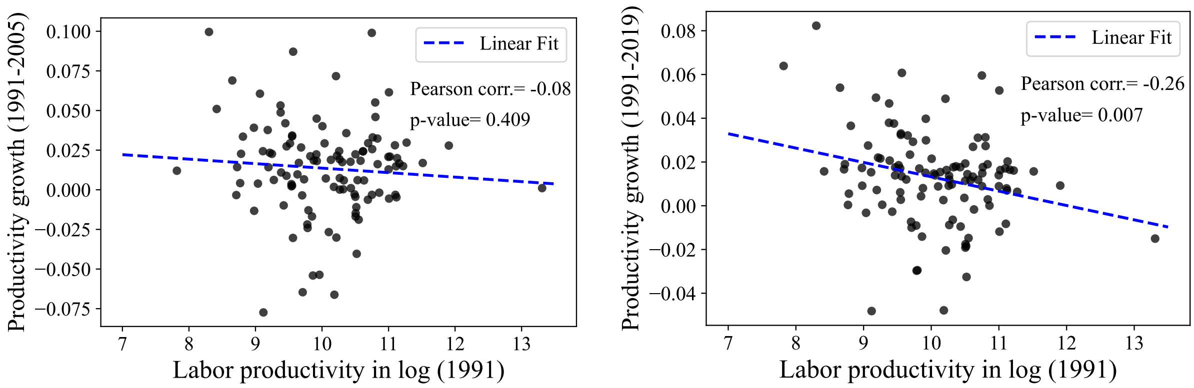
(a) 1991–2005

(b) 1991–2019

FIGURE I: Services Labour Productivity Convergence by Periods

In the manufacturing sector, the Pearson correlation between initial labor productivity and subsequent growth is -0.26 (p-value = 0.005) for the period 1991-2019, indicating significant convergence during this period. In contrast, the earlier period of 1991-2005 shows a much weaker and non-significant correlation of -0.08 (p-value = 0.375), suggesting an absence of convergence. This finding contrasts with Rodrik (2013), who showed unconditional convergence in manufacturing for 1995-2005. The observed difference may be attributed to my use of comparable data from the World Development Indicators (2022), following a similar approach to Herrendorf et al. (2022), who used comparable data from the Expanded Economic Transformation Database (EETD) and also found no evidence of unconditional convergence in manufacturing between 1995 and 2005.

In contrast, Rodrik (2013) relied on value-added per worker data in nominal US dollars from UNIDO, which might not adequately account for differences across countries and time periods. This suggests that convergence in manufacturing has strengthened over time, with the trend becoming more pronounced in the period 1991-2019 compared to the lack of convergence observed from 1991-2005. This is further evidenced by the steeper slope in the trend line for 1991-2019, as shown in Figure IIb.



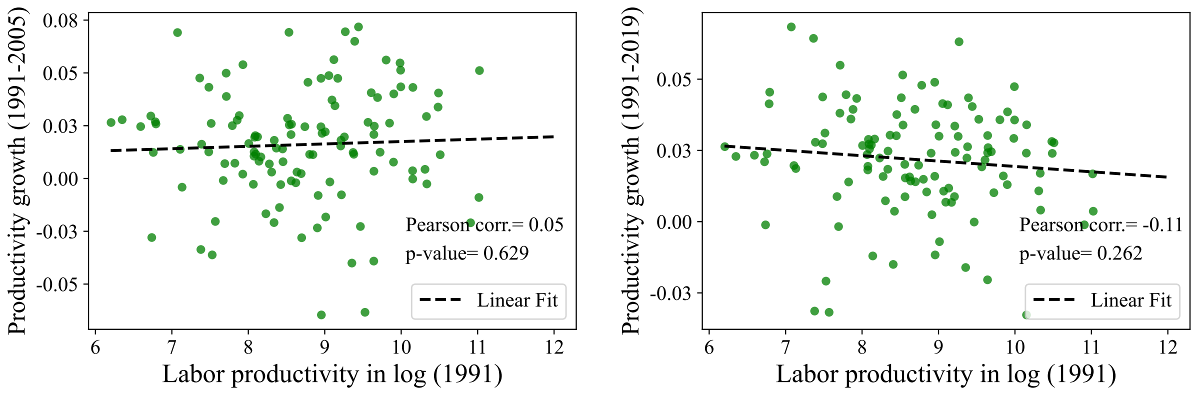
(a) 1991–2005 **(b)** 1991–2019

FIGURE II: Manufacturing Labour Productivity Convergence by Periods

In the agriculture sector, the findings indicate a weak and non-significant correlation between initial labor productivity and subsequent average growth for the period 1991-2005, with a slope of 0.02 (p-value = 0.806), reflecting an absence of convergence. By 2019, although the correlation slope has shifted to -0.10 (p-value = 0.299), this change does not signify the onset of convergence, as it remains non-significant. These results suggest that, despite a slight shift in the direction of the correlation, the agriculture sector had not yet embarked on a convergence path by the end of 2019.

This lack of convergence in agriculture may be attributed to the sector's unique growth dynamics across countries. The agricultural sector is characterized by rapid productivity increases at the technological frontier compared to other sectors. Between 1991 and 2019, the average productivity in agriculture among the top ten most developed countries grew by 3.06% per year, which is about 55% faster than the growth seen in manufacturing (1.97%) and nearly four times the growth rate in services (0.86%).

This significant difference in growth can help explain why convergence is less evident in agriculture compared to manufacturing and services, even as some countries shift from divergence to convergence across all sectors. The disparity in productivity growth implies that rapid advancements in agriculture at the frontier may create challenges for less developed countries to



(a) 1991–2005 **(b)** 1991–2019

FIGURE III: Agriculture Labour Productivity Convergence by Periods

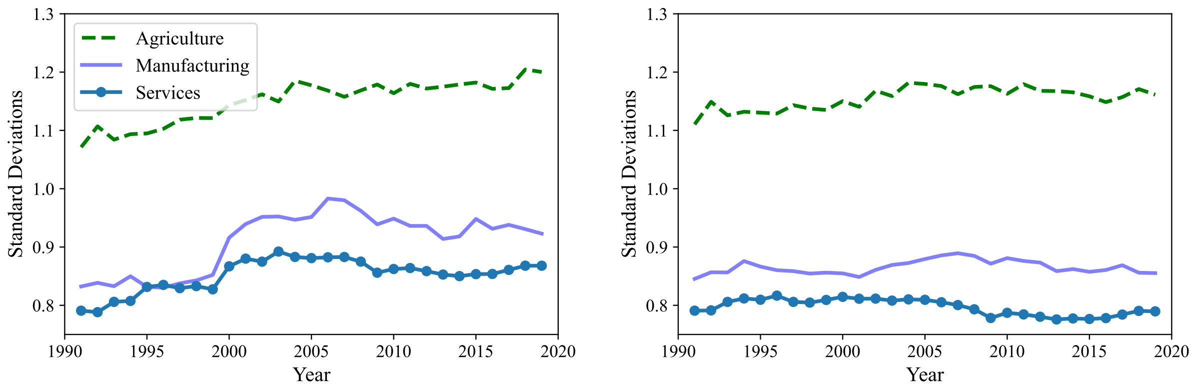
catch up, thereby widening the productivity gap. Conversely, the comparatively slower growth rates in manufacturing and services enable these countries to narrow the gap more effectively, fostering greater convergence in these sectors.

Next, I examine σ-convergence[6] in agriculture, manufacturing and services for two panels of countries: *Panel A* which contains all of the 180 countries for which data are available over the period 1991-2019 and *Panel B* which is limited to countries with no missing data in 1991[7]. The Panel B is restricted then to take into account a sample with data at both the beginning and the end of the period to determine whether the dispersion of productivity has decreased over the years for the same countries. σ-convergence occurs when the cross-sectional standard deviation of log productivity decreases over time. It is important to note that while β-convergence is a necessary condition for σ-convergence, it is not sufficient on its own. Consequently, β-convergence does not necessarily guarantee σ-convergence. This distinction is exemplified by Young et al. (2008), who identified β-convergence in GDP per capita among U.S. counties while failing to find evidence of σ-convergence. This suggests that various shocks or conditions can differentially impact convergence outcomes across different contexts.

Figure IV plots the measure of standard deviation over the period 1991-2019 for both *Panel A and B*. It shows that the productivity gaps are largest in agriculture, smallest in services, and intermediate in manufacturing. Data encompassing a broader range of developing and

[6] σ-convergence refers to the reduction in the dispersion of productivity levels across countries over time.

[7] Countries that have data for earlier years generally have non missing data for late years in World Bank database.



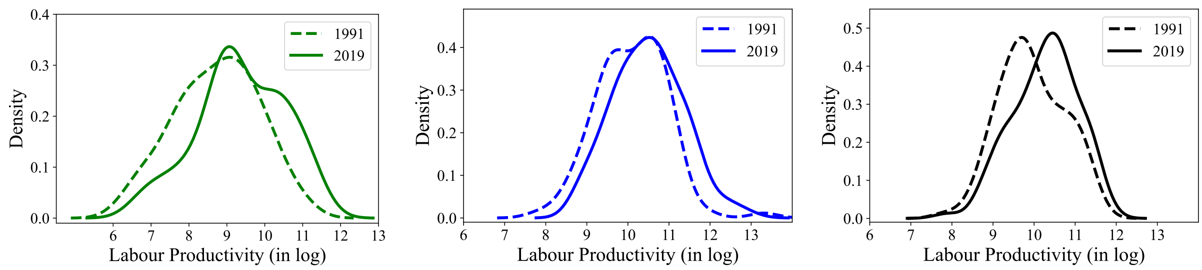
(a) *Panel A* : 180 countries of unbalanced panel **(b)** *Panel B* : 110 countries of balanced panel

FIGURE IV: σ-Convergence in Agriculture, Manufacturing, and Services

developed countries, in comparison to Herrendorf et al. (2022), indicates that there has been no divergence in sectoral productivity since 2005. The graphs reveal a modest decline in the productivity gap for both services and manufacturing sectors following this year. In contrast, the agriculture sector experienced a slight divergence during the 1990s; however, since 2005, it has exhibited stability in the standard deviation of productivity.

Likewise, when comparing the distributions of sectoral productivities between 1991 and 2019 for 110 countries, we can see how sectoral productivities distribution has shifted, whether the distribution has become more equal or more skewed, and how many countries have moved into different productivities brackets. An analysis of the density curves, as depicted in Figure V, reveals that the distribution of productivity in the services sector has become slightly more concentrated over time, with the minor peak that existed on the right side of the distribution in 1991–characterized by a slight elevation–having disappeared by 2019. This indicates a trend toward σ-convergence, as countries gradually catch up with the most productive ones. In manufacturing, the distribution, which was bimodal in 1991, has evolved into a unimodal shape, providing evidence of a certain level of convergence among countries.

Conversely, while the density curve for productivity in the agricultural sector exhibits a more elongated peak in 2019, it also features a noticeable hump extending toward the right. This indicates that some developed countries have experienced even greater growth in agricultural productivity between 1991 and 2019. Thus, while progress in agricultural productivity is evident in some countries, significant heterogeneity in productivity levels persists across coun-



(a) Agriculture **(b)** Manufacturing **(c)** Services

FIGURE V: Sectoral Productivity Distribution Over Time

tries within the agricultural sector.

In summary, the analysis of productivity trends across sectors reveals distinct patterns of convergence and divergence that correlate with the growth rates of sectoral productivity among the top ten most developed countries from 1991 to 2019. While manufacturing and services exhibit a stronger trend toward convergence over time, characterized by lower growth rates at the frontier, the agricultural sector displays significant growth rates in developed countries and less evidence of convergence. These findings underscore the importance of exploring the drivers behind productivity growth at sector level, particularly focusing on the role of technology adoption and financial development.[8]

2.2 Financial Development and Technology Adoption

Previous work, such as King & Levine (1993), Rajan & Zingales (1998), Levine (1997), Beck et al. (2000), and Aghion et al. (2005), demonstrated that financial development has a significant positive impact on both capital accumulation and total factor productivity growth. While Comin & Nanda (2019) focused on the role of financial development in advanced technology adoption across developed economies, I extend this analysis by showing that, beyond a certain threshold specific to each technology, financial development no longer influences technology adoption.

I combine three types of data. First, I use measures of technology diffusion from the HC-

[8]For example, Madsen & Timol (2011) highlighted the crucial role of research and development (R&D) and financial development in driving productivity convergence in OECD manufacturing sectors. This raises the question of whether similar dynamics apply to all countries.

CTA[9] dataset introduced in Comin & Hobijn (2004), since relevant data for technology adoption are not available. This dataset contains historical data on the adoption of several major technologies over the last 200 years across a large set of countries. I then construct panel data at the technology-country-year level, measuring the quantity adopted of each technology in each country over time.

As shown in Table I, the set of technologies covers the three economic sectors (agriculture, industry and services). The heterogeneous nature of the technologies explored is also reflected in their measures. Some technologies are measured by the number of units in operation (e.g., cars, computers, Radio) and some that capture the ability to produce something (electric arc steel, electricity, telegraphic services) are measured by the total production or by the number of users (e.g., cellphones). Following Comin & Nanda (2019), this metric will serve as a measure of the intensity of technology adoption and utilization.

TABLE I: Summary of Technology Data

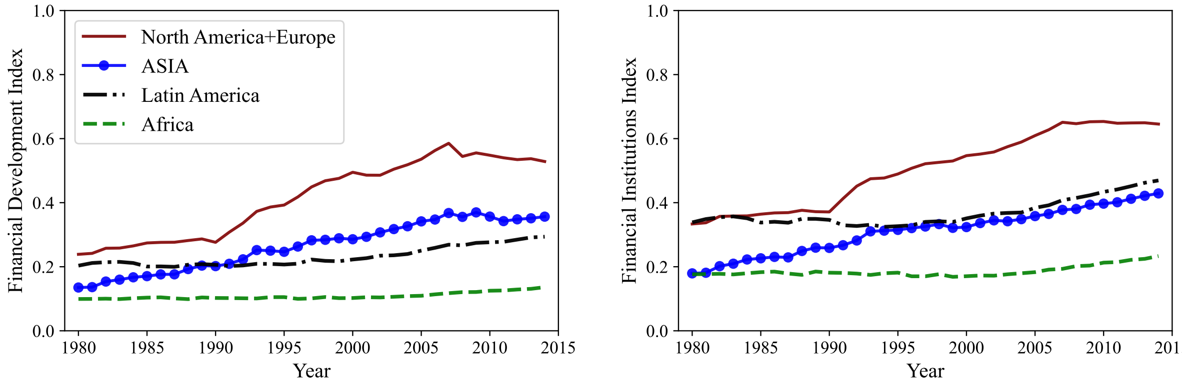
Technology	**Measure**	**Sector**	**Countries**
Tractors	Number in operation	Agriculture	130
Electric production	KwHr produced	Industry	120
Aviation pkm	Million passenger kilometers	Services	70
Commercial vehicles	Number in operation	Services	78
Internet users	Number of individuals	Services	128
Radio	Number in operation	Services	120
Telephone	Number connected	Services	84
Private vehicles	Number owned	Services	103
Television	Number in operation	Services	123

Second, I use the Financial Development Index[10] developed by International Monetary Fund (IMF) as a measure of financial development. It summarizes how developed financial institutions and financial markets are in terms of their depth (size and liquidity), access (ability of individuals and companies to access financial services), and efficiency (ability of institutions

[9] HCCTA: Historical Cross-Country Technology Adoption

[10] A vast body of literature estimates the impact of financial development on economic growth, inequality, and stability. A typical empirical study proxies financial development with either one of two measures of financial depth: the ratio of private credit to GDP or stock market capitalization to GDP. However these indicators do not take into account the complex multidimensional nature of financial development and number of countries included in note.

to provide financial services at low cost and with sustainable revenues and the level of activity of capital markets). The index is normalized between 0 and 1 and is provided for over 180 countries with annual frequency from 1980 to 2014. More details on the index construction are discusssed in the Data Appendix A.



(a) Financial Development **(b)** Financial Institutions

FIGURE VI: Average Regional Levels of Financial Development Indexes Over Time

Note: The graph illustrates the average level of financial development over time across different regions. The data includes 40 countries from Asia, 33 from Latin America, 43 from North America and Europe combined, and 46 from Sub-Saharan Africa.

Figure VI shows the evolution over time of the financial institution and financial development indices, highlighting significant regional divergence. The financial development index varies considerably across regions–North America and Europe, Asia, Latin America, and Sub-Saharan Africa–revealing distinct growth patterns. North America and Europe exhibit the highest levels of financial development, with a sharp acceleration beginning in 1990. This increase reflects substantial improvements in financial infrastructure, the introduction of new financial technologies, and strengthened regulatory frameworks, making these regions global leaders in financial development.

In contrast, Asia shows steady and consistent growth in its financial development index. Although starting at a lower level than Latin America in 1980, Asian countries gradually strengthened their financial systems, surpassing Latin America by 1990. Despite these gains, Asia's financial development remains lower than that of North America and Europe, although continuous reforms and expanded market access have driven substantial improvements. Latin America displays low but positive growth, with most gains occurring after 2000, yet the region's progress lags due to persistent economic and political challenges. Sub-Saharan Africa, meanwhile, shows little to no growth in financial development, with advances in mobile banking having minimal impact on the overall financial system, which continues to face deep structural challenges.

Observation : *The intensity of use of adopted technologies is positively correlated with financial development, but this correlation weakens once financial development reaches a sector-specific threshold.*

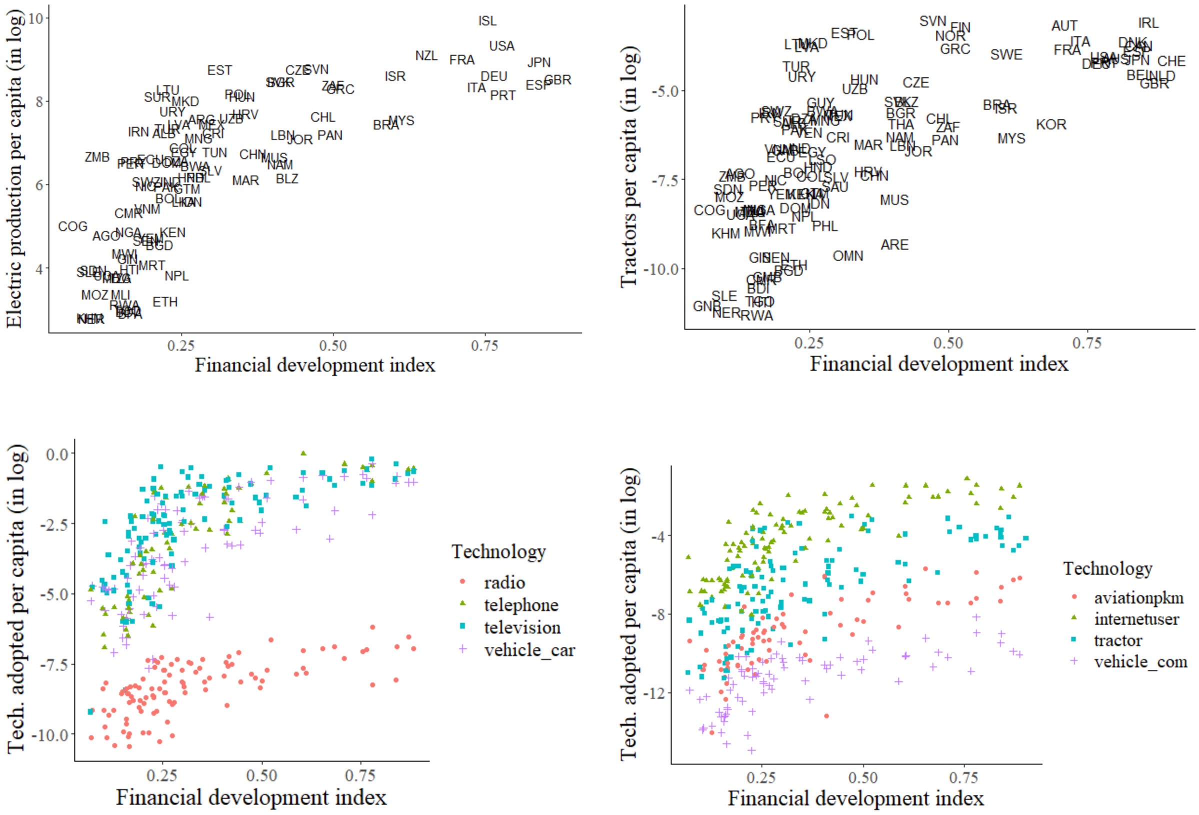


FIGURE VII: Average Levels of Financial Development and Log Technology Adoption per Capita (1980–2003)

Figure VII plots the average log of total electricity production per capita and the number of tractors adopted per capita across countries from 1980 to 2003 against the average level of the financial development index. The figure shows a positive correlation between financial development and technology adoption, which diminishes once financial development reaches a certain threshold. Additionally, Figure VII includes scatter plots for other technologies, revealing a consistent pattern across various technologies. However, the threshold at which the correlation becomes insignificant varies across different technologies.

For instance, the threshold at which financial development is no longer correlated with technology adoption ranges from 0.4 to 0.5 for tractors and electricity production, while it falls between 0.25 and 0.3 for televisions and commercial vehicles. This suggests that financial development plays a relatively more significant role in driving the adoption of tractors compared to commercial vehicles. Moreover, within the same country, even at a similar level of financial development, certain technologies may face greater constraints than others.

This relationship between financial development and technology adoption suggests that better credit access may initially drive cross-sector differences in adoption rates. However, as financial systems improve, their influence on technology adoption diminishes. While countries with higher levels of financial development experience faster initial growth, the role of finance in explaining long-term cross-country productivity growth could become less significant. In the following section, I present an endogenous growth model that captures these dynamics, highlighting how sectoral productivity convergence between countries are shaped by financial constraints through technology adoption.

3 Theoretical Model

The model economy is based on Aghion et al. (2005), where economic activity takes place in countries that do not trade goods or factors of production but do share technological ideas. Each individual lives for two periods. In the first period, they are endowed with two units of labor, and in the second period, they have none. At the end of the first period, households acquire skills and invest their savings in a technology adoption project as entrepreneurs.[11] The saving rate $s \in (0,1)$ is exogenous, and the utility function is assumed to be linear, such that $U(c_1, c_2) = c_1 + \beta c_2$, where c_1 is consumption in the first period of life, c_2 is consumption in the second period, and $\beta \in (0,1)$ represents the discount rate applied to second-period consumption

[11]Technology adoption involves an uncertain process of adapting ideas from the world technology frontier to the domestic economy. Innovation is required because technology and expertise often have tacit, country-specific qualities.

relative to the first.

3.1 Goods Production Sectors

Final Good. There is a unique final good in the economy that is also used as an input to produce intermediate goods. This good is taken as the numeraire. The final good is produced competitively using labor and a continuum of intermediate goods as inputs, with the aggregate production function given by:

$$Y_t = L_t^{1-\alpha} \int_0^1 A_{jt}^{1-\alpha} x_{jt}^{\alpha} dj, \tag{3.1}$$

where $0 < \alpha < 1$, A_{jt} is the productivity in sector j at time t, and x_{jt} is the input of the latest version of intermediate good j used in final good production at time t. L_t represents the population and the number of production workers at time t. Since the final sector is competitive, the representative firm takes the prices of its output and inputs as given, then chooses the quantity of intermediate goods from each sector j to use in order to maximize its profit as follows:

$$\begin{cases} p_{jt} = \alpha x_{jt}^{\alpha-1} A_{jt}^{1-\alpha} L_t^{1-\alpha} & \forall j \in [0,1] \\ w_t = (1-\alpha) L_t^{-\alpha} \int_0^1 A_{jt}^{1-\alpha} x_{jt}^{\alpha} dj. \end{cases}$$

The demand function for intermediate goods of variety j for the firm in the final sector is then given by :

$$x_{jt} = \alpha^{\frac{1}{1-\alpha}} p_{jt}^{-\frac{1}{1-\alpha}} A_{jt} L_t, \tag{3.2}$$

Intermediate Goods Production. In each intermediate sector, there is a monopoly whose production technology consists of using one unit of the final good to produce one unit of the intermediate good. Given that the intermediate producer operates in a monopoly, it charges the highest price that the final sector producer is willing to pay for variety j, under the assumption of a drastic innovation[12]. The monopolist maximizes profit as follows:

$$\max_{\{x_{jt}\}} p_{jt}x_{jt} - x_{jt} \tag{3.3}$$

$$\text{subject to} \qquad p_{jt} = \alpha x_{jt}^{\alpha-1} A_{jt}^{1-\alpha} L_t^{1-\alpha}.$$

Thus, the equilibrium[13] profit of the intermediate goods producer in sector j is given by:

$$\pi_{jt} = \pi A_{jt} L_t, \tag{3.4}$$

where $\pi := (1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}}$. Thus, the profits generated by each sector depend positively on its productivity. The wage rate w_t and the gross domestic product GDP_t are then expressed as:

$$w_t = \omega A_t, \tag{3.5}$$

$$GDP_t = (1+\alpha) w_t L_t, \tag{3.6}$$

where $\omega := (1-\alpha)\alpha^{\frac{2\alpha}{1-\alpha}}$, and $A_t := \int_0^1 A_{jt}\, dj$ represents the aggregate productivity in the economy at time t.

3.2 Credit Constraints

At the end of their first life period, households allocate resources to an innovation project. In sector j at time t, the investment made by an innovator for technology adoption is denoted as z_{jt}. The amount borrowed is represented by $z_{jt} - sw_t$, where w_t is the real wage and s indicates the saving rate. The interest rate is denoted by r, making the total repayment cost of the loan $(1+r)(z_{jt} - sw_t)$. Due to imperfections in the financial system, there are constraints on the total amount that can be borrowed for technology adoption projects[14], which limits the entrepreneur to borrowing no more than a finite multiple of her accumulated wealth:

$$z_{jt} \leq \kappa w_t, \tag{3.7}$$

[12]The innovator is not forced into price competition.

[13]Further details on the calculations are provided in Appendix B.

[14]See Appendix C for more details.

A highly developed financial system, indicated by a higher κ, is closely linked to effective governance, law enforcement, and the rule of law, which enhance creditor protection and build confidence in financial transactions. Strong legal frameworks ensure fair contract enforcement and encourage lending by safeguarding creditor rights, while effective law enforcement deters fraud, reducing lending risks. This transparency fosters investor trust, leading to increased credit availability and investment.

In an economy characterized by credit constraints, an entrepreneur's investment capacity is fundamentally limited by the maximum loan amount available, denoted as κw_t. This constraint implies that, irrespective of the sector in which the entrepreneur operates, their ability to invest is uniformly tied to the prevailing real wealth w_t. Consequently, this situation imposes significant restrictions on the potential for technological advancement.

The constancy of κw_t across various sectors highlights a significant inefficiency: entrepreneurs may face challenges in financing the adoption of advanced or more productive technologies that necessitate investments exceeding this threshold. When the required investment for technology adoption surpasses this limit, entrepreneurs lack viable avenues to secure the necessary funds, resulting in underinvestment in these technologies. This underinvestment is particularly detrimental in sectors where the technology gap is more pronounced.

3.3 Technological Progress and Productivity Growth

Technology adoption drives productivity growth, enabling monopolists to access the technology frontier. In each period t, one individual per sector j produces innovation for the next period. If successful, this individual becomes the monopolist in period $t+1$, with productivity given by:

$$A_{jt+1} = \theta_{jt+1}\bar{A}_{jt} + (1-\theta_{jt+1})A_{jt}, \tag{3.8}$$

where $\bar{A}_{jt}$ represents the frontier productivity[15] in the same sector at time t, and $\theta_{jt+1} \in [0,1]$ denotes the intensity[16] with which new technologies are utilized in the host country at period

[15] I assume that the frontier in sector j expands at a constant growth rate $\bar{g}_j$ due to innovation.

[16] $\theta_{jt+1} = 0$ means the entrepreneur did not succeed in the adoption project, while $\theta_{jt+1} = 1$ indicates successful adoption and utilization at the same intensity level as the world technology frontier.

$t+1$. Consequently, the productivity of the innovator does not immediately leap to the world frontier. Indeed, a country can successfully adopt a technology yet not utilize it intensively as the technological frontier. Comin & Mestieri (2018) documented that while adoption lags between poor and rich countries have converged, the intensity of use of adopted technologies in poor countries relative to rich countries has diverged.

Unlike Aghion et al. (2005) and standard Schumpeterian models, which assume that innovators achieve average frontier productivity irrespective of the sector, I argue that technology transfer is sector-specific. Within a country, certain sectors may be less advanced at the technological frontier, facilitating the adoption of new technologies in those sectors compared to others. Consequently, in equilibrium, the intensity of technology use and productivity levels may vary significantly across different sectors.

As in Aghion et al. (2005), I assume that local firms can access the frontier technology at a cost that increases with the level of productivity targeted, $\bar{A}_{jt}$. This suggests that the further ahead the frontier is in sector j, the more challenging it becomes to adopt the corresponding technology in that sector. The intensity of technology use, θ_{jt+1}, also increases with the amount of resources z_{jt} allocated by entrepreneurs. Consequently, the cost of an innovation is given by:

$$\frac{\lambda_{jt} z_{jt}}{\bar{A}_{jt}} = F\left(\theta_{jt+1}\right), \tag{3.9}$$

where F is a convex, increasing cost function with respect to the intensity of using new technologies. For simplicity, this function is defined as:

$$F(\theta_{jt}) = \eta \theta_{jt} + \frac{\psi}{2} \theta_{jt}^2, \tag{3.10}$$

with $\eta, \psi > 0$. The parameter λ_{jt} denotes the knowledge of the entrepreneur in the sector j. Indeed, technology adoption projects can be affected by the lack of competent resources (engineers, technicians) during the implementation phase. One of the internal factors contributing to the success of innovation projects is the presence of engineers and qualified scientists within the company, along with the leadership provided by a leader with a high level of academic training in the field of activity. Foster & Rosenzweig (1996) and Griffith et al. (2004) provide evidence that skills are an important determinant of a country's absorptive capacity. By learning from previous technologies, an entrepreneur becomes more likely to adopt new technologies.

The knowledge and expertise that a country possesses in a particular industry can help to reduce the cost of adopting new technologies in that industry by improving understanding of the technology, reducing training costs, facilitating integration with existing systems, and enhancing implementation. Following Howitt & Mayer-Foulkes (2005)[17], I model this "learning by doing" effect through the entrepreneurial skills λ_{jt}, which are assumed to be proportional to the productivity A_{jt}, reflecting knowledge spillover[18]:

$$\lambda_{jt} = \lambda A_{jt}. \tag{3.11}$$

Scotchmer (1991) also modeled innovation as a cumulative process, whereby existing knowledge acts as an input in the production of new technologies. By including absorptive capacity, the model captures the sectoral productivity proximity to the technological frontier and its impact on the intensity of technology use.

From equation (3.9), the adoption cost z_{jt} is then a function of the intensity of technology use θ_{jt+1} and the sectoral productivity proximity to the frontier $a_{jt} := \frac{A_{jt}}{\bar{A}_{jt}}$:

$$z_{jt} = \frac{\frac{\psi}{2}\theta_{jt+1}^2 + \eta\theta_{jt+1}}{\lambda a_{jt}}. \tag{3.12}$$

In equilibrium, the innovator chooses θ_{jt+1} (or z_{jt}) in order to maximize the expected net payoff

[17] With the difference that Howitt & Mayer-Foulkes (2005) assumed $\lambda_{jt} = \lambda A_t$ without considering the specificity of each entrepreneur in the sector in which they want to invest.

[18] This assumption is based on the idea that a country's productivity reflects its accumulated knowledge base, technical expertise, and absorptive capacity. However, technological advancement varies across sectors due to differences in resources and infrastructure. Assuming λ_{jt} proportional to sector productivity captures sectoral heterogeneity and reflects differences in technological progress and innovation intensity across sectors.

given by (3.13):

$$\max_{0 \le \theta_{jt+1} \le 1} \beta\pi \left[\theta_{jt+1}\bar{A}_{jt} + (1-\theta_{jt+1})A_{jt}\right] - z_{jt} \tag{3.13}$$

$$\text{subject to } \; z_{jt} \le \kappa w_t \; \text{ and equation (3.12).}$$

Assuming that, under perfect credit markets, each innovator can borrow an unlimited amount at the interest rate $r = \beta^{-1} - 1$ subject to a binding commitment to repay if the project succeeds, the problem of an innovator under perfect credit markets can be written as follows:

$$\max_{0 \le \theta_{jt+1} \le 1} \beta\pi \left[\theta_{jt+1}\bar{A}_{jt} + \left(1-\theta_{jt+1}\right)A_{jt}\right] - \left(\lambda a_{jt}\right)^{-1}\left(\frac{\psi}{2}\theta_{jt+1}^2 + \eta\theta_{jt+1}\right). \tag{3.14}$$

The intensity of use of adopted technologies at equilibrium under perfect credit markets is then given by:

$$\theta_{jt+1}^* = \begin{cases} 0 & \text{if} \quad A_{jt}(1-a_{jt}) \le \eta(\lambda\beta\pi)^{-1} \\ \psi^{-1}(\lambda\beta\pi A_{jt}(1-a_{jt}) - \eta) & \text{if} \quad \eta(\lambda\beta\pi)^{-1} < A_{jt}(1-a_{jt}) < (\lambda\beta\pi)^{-1}(\eta+\psi) \\ 1 & \text{if} \quad A_{jt}(1-a_{jt}) \ge (\lambda\beta\pi)^{-1}(\eta+\psi) \end{cases}$$

In the remainder of this paper, I assume that the parameters λ, ψ, and η are such that $A_{jt}(1-a_{jt})$ is greater than $(\lambda\beta\pi)^{-1}(\eta+\psi)$. Under this assumption, in a setting without credit constraints, all entrepreneurs within the same country would have the capacity to utilize technologies with an intensity comparable to that of the global frontier, allowing them to fully harness the productivity potential embedded in the latest technologies.

However, in the presence of credit constraints, the reality is quite different. Even when an entrepreneur successfully adopts a technology, the lack of sufficient funding can hinder their ability to invest the optimal amount of resources needed to use the technology at its full potential. Since the cost of technology adoption (z_{jt}) depends on the amount of resources available, entrepreneurs facing credit constraints may be forced to adopt suboptimal levels of technology intensity, thereby failing to reach the productivity levels achievable at the frontier. This means that they might not be able to afford the necessary training, infrastructure, or complementary inputs required for efficient technology implementation.

3.4 Equilibrium Technology Under Credit Constraints

Under credit constraints, the problem (3.13) of the innovator can be rewritten as follows:

$$\max_{0\leq\theta_{jt+1}\leq 1} \beta\pi\left[\theta_{jt+1}\bar{A}_{jt} + \left(1-\theta_{jt+1}\right)A_{jt}\right] - \left(\lambda a_{jt}\right)^{-1}\left(\frac{\psi}{2}\theta_{jt+1}^2 + \eta\theta_{jt+1}\right)$$
$$\text{s.t.}\ \ \theta_{jt+1} \leq -\frac{\eta}{\psi} + \left[\left(\frac{\eta}{\psi}\right)^2 + \frac{2\lambda\kappa w_t a_{jt}}{\psi}\right]^{\frac{1}{2}}$$

In equilibrium, the intensity of use of adopted technologies is given by :

$$\theta^*_{jt+1} = \begin{cases} 1 & \text{if } a_{jt} > \bar{a}_t(\kappa) \\ -\frac{\eta}{\psi} + \left[\left(\frac{\eta}{\psi}\right)^2 + \frac{2\lambda\kappa w_t a_{jt}}{\psi}\right]^{\frac{1}{2}} & \text{if } a_{jt} \leq \bar{a}_t(\kappa) \end{cases}$$

where $\bar{a}_t(\kappa) = \frac{\psi+2\eta}{2\lambda\kappa w_t}$ is decreasing in κ. The level of technology adoption, denoted by θ^*_{jt+1}, increases with the sectoral productivity proximity to the frontier technology, represented by a_{jt}. Consequently, when two countries with the same level of financial development adopt identical technologies, the country that is closer to the frontier will exhibit a higher level of technology usage. As a sector approaches the technological frontier, its productivity potential rises, enabling it to leverage advanced technologies more effectively.

A country with higher productivity in industry j (i.e., a higher a_{jt}) possesses more knowledge and expertise in that industry, which significantly impacts the cost associated with adopting new technologies (see Nelson & Phelps (1966)). Higher productivity typically translates into greater efficiency and a more skilled workforce, factors that contribute to lowering the cost of technology adoption. In contrast, countries with lower productivity in a given sector encounter higher adoption costs and face more severe credit constraints, particularly concerning training, integration with existing systems, and other implementation challenges.

Figure XI in Appendix D illustrates that as financial development increases, the intensity of technology adoption also rises. However, this positive effect diminishes beyond a certain threshold level of sectoral productivity proximity to the frontier or a specified level of financial development. This finding aligns with Proposition I, which posits that the impact of financial development on technology use becomes negligible beyond this threshold, consistent with the correlation illustrated in Figure VII.

Initially, in environments with low financial development, entrepreneurs encounter significant barriers to accessing funding for technology adoption, which restricts their ability to integrate new technologies. As financial development improves, these constraints are gradually alleviated, allowing entrepreneurs to secure the capital necessary for adopting advanced technologies.

Once these financial constraints are no longer binding, the relationship between financial development and technology adoption becomes negligible. This indicates that the primary role of financial development is to overcome the initial financial barriers faced by entrepreneurs. However, beyond a certain threshold of financial development, where these constraints are effectively mitigated, the influence of financial development on technology adoption disappears entirely.

Proposition I. *Financial development enhances the intensity of technology use up to a certain threshold. Below this threshold, improved access to finance helps entrepreneurs overcome adoption barriers. Beyond this point, the influence of financial development on technology adoption vanishes, as initial constraints are no longer binding.*

Proof. See Appendix D. ■

The threshold level, $\underline{\kappa}_{jt}$, beyond which financial development no longer affects the intensity of use of technology in sector j, is given by:

$$\underline{\kappa}_{jt} = \frac{2\eta + \psi}{2\lambda w_t a_{jt}}, \tag{3.15}$$

This threshold is sector-specific and evolves over time. In a given country, sectors closer to the technological frontier (with higher a_{jt}) will reach unconstrained status more rapidly than those further away. For instance, if a country's productivity gap with the frontier is larger in agriculture than in services or manufacturing, agricultural technology adoption will be more constrained compared to the other sectors.

Next, I examine how financial development interacts with a sector's productivity proximity to the frontier in influencing the intensity of use of adopted technologies. Specifically, I investigate whether the effect of financial development on the intensity of technology use is stronger in sectors that are closer to the frontier. To do so, I take the derivative (when $a_{jt} \leq \bar{a}_t(\kappa)$) of the intensity of technology use first with respect to financial development, and then with respect to sectoral productivity proximity to the frontier:

$$\frac{\partial^2 \theta^*_{jt+1}}{\partial a_{jt} \partial \kappa} = \frac{\partial^2 \theta^*_{jt+1}}{\partial \kappa \partial a_{jt}} = \frac{\lambda w_t}{\psi} \left[\left(\frac{\eta}{\psi} \right)^2 + \frac{\lambda \kappa w_t a_{jt}}{\psi} \right] \left[\left(\frac{\eta}{\psi} \right)^2 + \frac{2\lambda \kappa w_t a_{jt}}{\psi} \right]^{-\frac{3}{2}} > 0 \qquad (3.16)$$

The positive cross partial derivative indicates that before reaching certain threshold levels of financial development and sectoral proximity to the frontier, the two factors work together to increase the intensity of technology use[19]. In other words, when financial development is relatively low and a sector is still some distance from the frontier, improvements in either financial conditions or proximity will amplify the effect of the other on technology adoption. This reflects a complementary relationship between financial development and technological proximity in the early stages of sectoral advancement.

However, once a sector reaches a threshold level of proximity to the frontier and financial development has advanced sufficiently, the cross partial derivative becomes null. This implies that after these thresholds are reached, further increases in financial development or sectoral productivity proximity to the frontier do not reinforce each other in enhancing technology use. At this point, sectors have already realized most of the potential gains from these factors, and additional improvements in either variable no longer have the same multiplicative effect on technology adoption.

In the following section, I analyze the long-run effects of financial development on the dynamics of the sectoral productivity gap and the interplay between aggregate and sectoral

[19] The positive interaction between financial development and sectoral proximity is represented in Figure XI by the dashed red lines.

productivity convergence. This analysis will provide insights into how varying levels of financial development can influence not only individual sector growth but also the overall economic trajectory within countries. By understanding these dynamics, one can better assess the process of converging to convergence at the aggregate level, as introduced by Kremer et al. (2022).

4 Productivity Gap Dynamics and Financial Development

In this section, I will examine the dynamics of sectoral proximity to the frontier and study the convergence of sectoral productivity, as well as the impact of initial levels of financial development and income on sectoral convergence.

4.1 Dynamics of Sectoral Productivity Gap

In order to examine how sectors move closer to the frontier over time, it is essential to formulate recurrence relation between a_{jt} and a_{jt+1} based on the following equation that describes changes in productivity:

$$A_{jt+1} = \theta_{jt+1}\bar{A}_{jt} + (1-\theta_{jt+1})A_{jt}. \tag{4.1}$$

By dividing equation (4.1) by the frontier sectoral productivity $\bar{A}_{jt+1}$, the dynamics of the sectoral technology proximity can be written as follows:

$$a_{jt+1} = \frac{\theta_{jt+1}\left(1-a_{jt}\right)+a_{jt}}{1+\bar{g}_j}, \tag{4.2}$$

where $\bar{g}_j$ is the exogenous frontier productivity growth in sector j. Then the sectoral proximity to the frontier a_{jt} will evolve according to the unconstrained dynamical equation (4.3b): $a_{jt+1} = h_j(a_{jt})$ when $a_{jt} \geq \bar{a}_t$ and according to the constrained system (4.3a) : $a_{jt+1} = f_{jt}(a_{jt})$ when

$a_{jt} < \bar{a}_t$ such that :

$$\begin{cases} f_{jt}(a_{jt}) = \dfrac{a_{jt} + \theta_{jt+1}(1-a_{jt})}{1+\bar{g}_j} & \text{if} \quad a_{jt} \leq \bar{a}_t(\kappa) \qquad (4.3a) \\ h_j(a_{jt}) = \dfrac{1}{1+\bar{g}_j} & \text{if} \quad a_{jt} > \bar{a}_t(\kappa) \qquad (4.3b) \end{cases}$$

Thus $a_{jt+1} = \min\left\{\frac{1}{1+\bar{g}_j}, f_{jt}(a_{jt})\right\}$ for all $a_{jt} \in [0,1]$. Note that $f_{jt}(a_{jt})$ is a concave[20] function in a_{jt} with $f_{jt}(0) = 0$ and $f_{jt}(1) = \frac{1}{1+\bar{g}_j}$. I will now use the first derivative test to analyze the convergence behavior of the sequence generated by the function f_{jt}, $t = 0,1,2...$, on the interval $[0,1]$. If $f'_{jt}(0) < 1$ then $f'_{jt}(a_{jt})$ will be less than the the slope of the first bisector for all a_{jt} in $[0,1]$ because f'_{jt} is decreasing, and the function f_{jt} is a contraction mapping on $[0,1]$, and the sequence generated by the function f_{jt} will converge to 0 meaning the sectoral productivity is diverging. If $f'_{jt}(0) > 1$ then the sequence generated by the function f_{jt} will intersect the first bisector on the interval $[0,1]$ since $f_{jt}(1)$ is also less than 1. This will imply a convergence towards a non-zero point. After taking the derivative of the function f_{jt} and evaluating it at 0 and 1, I obtain the following system of equations:

$$\begin{cases} (1+\bar{g}_j)f'_{jt}(0) = 1 + \dfrac{\lambda \kappa w_t}{\eta} \\ (1+\bar{g}_j)f'_{jt}(1) = 1 + \dfrac{\eta}{\psi} - \left(\left(\dfrac{\eta}{\psi}\right)^2 + \dfrac{2\lambda \kappa w_t}{\psi}\right)^{1/2} \end{cases}$$

From where, I can get a relationship between the derivative of the function f_{jt} at 0 (respectively at 1) and the slope of the first bisector (respectively the slope of function h_j at 1) :

$$\begin{cases} f'_{jt}(0) \leq 1 & \text{if} \quad \kappa w_t \leq \dfrac{\eta \bar{g}_j}{\lambda} \\ f'_{jt}(0) > 1 & \text{if} \quad \kappa w_t > \dfrac{\eta \bar{g}_j}{\lambda} \end{cases} \quad \text{and} \quad \begin{cases} f'_{jt}(1) < 0 & \text{if} \quad \kappa w_t > \dfrac{\psi + 2\eta}{2\lambda} \\ f'_{jt}(1) \geq 0 & \text{if} \quad \kappa w_t \leq \dfrac{\psi + 2\eta}{2\lambda} \end{cases}$$

[20]See Appendix E for calculations of the first and second derivative functions of f_{jt}.

Since $\frac{\psi+2\eta}{2\lambda} > \frac{\eta\bar{g}_j}{\lambda}$[21] countries can be grouped into three categories based on income and financial development. The first category consists of high-income countries with advanced financial systems, which experience convergence across various economic sectors. The second category includes emerging economies with moderate levels of financial development and income, which initially achieve conditional convergence to a lower level before progressing toward unconditional convergence as their income grows over time. The third category encompasses countries that initially diverge but eventually shift into the second category (see Appendix F).

Contrary to the findings of Aghion et al. (2005), it is important to underscore that countries are not confined to a singular category. The model here introduces sector-level absorptive capacity and considers sectoral characteristics during the technology adoption process, focusing on sectoral frontier productivity rather than an aggregate frontier productivity targeted by entrepreneurs. This approach elucidates the influence of aggregate country income on the dynamics of sectoral productivities. In the study by Aghion et al. (2005), a country that begins to diverge continues on this path as long as its financial development remains unchanged. However, a recent study by Kremer et al. (2022) highlights the "converging to convergence" phenomenon, indicating that several countries initially diverging in the 1960s began to show signs of convergence approximately thirty years. My model demonstrates how a country that initially diverges at the sectoral level may commence convergence at a later stage.

Indeed, in a country that diverges in a given sector j, its financing capacity for technology adoption κw_t is below a minimum threshold of $\lambda^{-1}\eta\bar{g}_j$. This threshold represents the investment level that would ensure an intensity of use of adopted technologies, allowing sector j to achieve a productivity growth rate exceeding that of the frontier $\bar{g}_j$. Even as the gap with the frontier widens, the sector still witnesses positive productivity growth, as does the GDP per capita[22]. This results in an increasing financing capacity over time, implying that there exists a time from which κw_t surpasses $\lambda^{-1}\eta\bar{g}_j$. Consequently, the sector can experience faster growth

[21] $\frac{\eta\bar{g}_j}{\lambda} / \frac{\psi+2\eta}{2\lambda} = \frac{2\eta\bar{g}_j}{2\eta+\psi}$. As $2\eta\bar{g}_j \leq 2\eta$ and $\psi > 0$ then $\frac{\eta\bar{g}_j}{\lambda} / \frac{\psi+2\eta}{2\lambda} < 1$.

[22] As demonstrated by Comin & Mestieri (2018), while technology proliferated globally, its intensity of use varied among countries. In my model, this intensity of use of technologies is contingent upon the country's financial development and wealth. Provided the country's initial income are non-zero, the intensity of use of adopted technologies remains non-zero, thereby guaranteeing a growth in productivities.

than the frontier and begin to converge, as its wealth level provides sufficient financing capacity and investment, enabling a higher intensity of technology adoption.

For a country with a financing capacity κw_t that exceeds the threshold $\lambda^{-1}\eta\bar{g}_j$, allowing it to grow faster than the frontier, but remains below the efficient level $\lambda^{-1}(\eta+\psi/2)$, it cannot fully leverage technologies at the same level as developed frontier countries. However, it steadily closes the gap with the frontier, leading to an increase in a_{jt} over time. This growth advantage continues until a point T_j, from which the sectoral proximity to the frontier surpasses $\bar{a}_{T_j}(\kappa) = \frac{\psi+2\eta}{\lambda\kappa w_{T_j}}$. At this juncture, the financing capacity surpasses the financing need[23] $\bar{z}_{jt} = \frac{2\eta+\psi}{2\lambda a_{jt}}$, allowing the country to fully adopt frontier technologies and use them with equal intensity. It is noteworthy that the borrowing constraints faced by entrepreneurs are alleviated by the country's wealth. As the borrowing constraint becomes non-binding in a particular sector, the role of financial development in determining sectoral productivity convergence diminishes in significance, though it remains relevant in influencing the country's speed of convergence.

As shown in Figure XII in Appendix F, sectoral productivity gap converges asymptotically to the unconstrained steady state, $a_j^* = \frac{1}{1+\bar{g}_j}$, where T_j denotes the convergence time in sector j. As proven in Proposition II below, countries with higher levels of financial development converge faster than those with lower financial development. Likewise, sectors that grow more slowly at the frontier (lower $\bar{g}_j$) will experience faster convergence, meaning that T_j increases with $\bar{g}_j$.

While it may appear intuitive that faster frontier technology progress in a particular sector could lead to a relative lag in developing countries within that sector, the dynamics are more complex than they initially seem. Higher frontier productivity growth increases the productivity gap between developed and developing countries, thereby creating greater potential for catch-up growth. In theory, this positive correlation between the productivity gap and growth suggests that sectors with rapidly advancing frontiers, such as agriculture, could experience

[23] The financing need, $\bar{z}_{jt}$, required for the country to use technology at the same level as the frontier decreases with sectoral proximity. Since the financing capacity, κw_t, also increases over time, there exists a time T_j such that $\bar{z}_{jt} = \kappa w_t$. Beyond this time T_j, the constraint is lifted.

higher growth rates in developing countries.

However, two key challenges limit this catch-up potential. First, even if these sectors achieve higher growth in developing countries, the growth relative to the frontier often remains modest compared to other sectors. Second, financial constraints, which are typically uniform across sectors, disproportionately impact sectors with higher frontier growth. The slower rate of adoption of technology in these sectors exacerbates the lag, as these industries face greater barriers to closing the productivity gap compared to sectors with lower frontier growth.

Proposition II. *(i) Countries with higher financial development and higher income will converge faster than countries with lower financial development and lower income.*
(ii) Sectors that grow faster at the frontier will experience slower convergence compared to those with a slower growth rate at the frontier.

Proof. See Appendix G. ■

Sectors will then converge with lags to their respective steady-state productivity. Countries with a higher initial financing capacity level are expected to experience faster convergence within each sector. The second group of countries, characterized by moderate initial levels of financial development and income, is anticipated to converge after the first group, albeit at a slower rate. The third group, consisting of countries with low initial financing capacity levels, may initially experience a period of divergence before eventually converging toward more developed countries.

This observation suggests that the speed of convergence within each sector is positively correlated with a country's initial level of financial development and income. Additionally, some countries might undergo an initial phase of divergence, particularly in sectors that exhibit higher growth rates at the frontier, before gradually catching up with developed countries.

Next, I will conduct a comprehensive exploration of the connections between convergence at the aggregate level and the dynamics of convergence at the sector level.

4.2 Sectoral Productivity Convergence and Aggregate Behavior

The interaction between sectoral productivity growth and aggregate economic outcomes is central to understanding how economies evolve over time. Sectoral productivity growth, influenced by factors such as financial development and technology adoption, plays a pivotal role in shaping a country's overall growth trajectory. In this subsection, I will explore how sectoral productivity growth (g_{jt}) translates into aggregate productivity growth (g_t), taking into account the role of financial development, credit constraints, and proximity to the technological frontier.

From equation (3.8), sectoral productivity growth g_{jt} in sector j at time t can be derived as follows:

$$g_{jt} = \theta^*_{jt}\left(a^{-1}_{jt-1} - 1\right). \tag{4.4}$$

Sectors in countries that intensively employ adopted technologies will experience faster productivity growth. For sectors j with productivity close to the frontier such that $a_{jt} \geq \bar{a}_t(\kappa)$, the growth rate will be $a^{-1}_{jt} - 1$. This growth rate decreases with a_{jt}, indicating convergence, as sectors further from the frontier will experience higher growth rates.

Let $a_t := A_t/\bar{A}_t$ be the inverse measure of the country's distance to the world technology frontier at aggregate level. Then the growth rate g_t of GDP per capita at time t is given by :

$$g_t = \frac{1}{A_{t-1}} \int_0^1 \theta^*_{jt}(\bar{A}_{jt-1} - A_{jt-1})\, dj. \tag{4.5}$$

It follows that the economic growth rate g_t under the presence of credit constraints is less than the growth rate under perfect credit markets $a^{-1}_{t-1} - 1$ as follows:

$$g_t = a^{-1}_{t-1} - 1 \qquad \text{if} \quad a_{jt-1} \geq \bar{a}_{t-1} \quad \forall j \tag{4.6a}$$

$$g_t < a^{-1}_{t-1} - 1 \qquad \text{if} \quad \exists j \text{ such that } a_{jt-1} < \bar{a}_{t-1}. \tag{4.6b}$$

The growth rate in an economy with perfect credit markets is inversely related to the country's distance from the technological frontier. This relationship implies that countries with lower GDP per capita will experience more substantial growth, enabling them to catch up with more developed countries.

Equation (4.6a) proves that if all sectors of the economy converge towards their respective technological frontiers, then the overall economic will also converge. This indicates that improvements in technology within individual sectors contribute to the overall economic performance. Therefore, fostering technological advancement in each sector is essential for promoting broader economic convergence and development, as progress in one sector facilitates growth in others, ultimately leading to a more integrated and robust economy.

In a country, different sectors may be at varying distances from their respective technology frontier. Some sectors, closer to their frontier, may begin to converge, while others, more distant and constrained by limited financial development, may initially diverge. When financial development κ and income are below the level required for a sector to grow at the same rate as its frontier, this sector acts as a drag on aggregate convergence, slowing down the overall process. This creates a scenario where aggregate convergence is hindered by sectors that maintain a significant gap with their world technology frontier.

However, the aggregate convergence path is not fixed. A country diverging at the aggregate level may begin to converge as sectors transition from divergence to convergence. As the country's income grows, even amid aggregate-level divergence, it enhances overall financing capacity, alleviating financial constraints in sectors previously unable to adopt more intensively technologies. This increased financing capacity allows these sectors to accelerate their productivity growth, which, in turn, reinforces aggregate wealth and generates a positive feedback loop. Financial development plays a crucial role in this process. As financing capacity also expands with the deepening of financial development, previously lagging sectors gain access to the resources needed for convergence, further driving aggregate convergence.

Within a country, the impact of financial development on productivity growth varies across sectors. Some sectors may experience notable increases in productivity due to improvements in financial infrastructure and access to capital, while others may not benefit as much. Next, I define the critical threshold level of financial development for the whole economy beyond which finance does not affect economic growth, denoted as $\underline{\kappa}_t$, which is given by:

$$\underline{\kappa}_t = \max_j \left\{ \frac{2\eta + \psi}{2\lambda w_t a_{jt}} \right\}, \tag{4.7}$$

where $\underline{\kappa}_{jt} := \frac{2\eta+\psi}{2\lambda w_t a_{jt}}$ represents the sector j-specific threshold level of financial development below which finance affects technology adoption, as defined by equation (3.15). The critical financial development level $\underline{\kappa}_t$ for the entire economy is thus determined by the sector with the highest productivity gap (lowest proximity) to the frontier across all sectors. For countries where the level of financial development κ is below this threshold $\underline{\kappa}_t$, financial development positively influences technology adoption in some sectors, thereby enhancing overall economic growth. However, once a country exceeds the threshold $\underline{\kappa}_t$, the effect of financial development on technology adoption across all sectors disappears.

5 Testing Model Predictions

In this section, I assess how the model's predictions align with empirical findings. After outlining the data, I test Proposition II using cross-country and panel regressions, incorporating an interaction term between initial sectoral productivity and the product of the initial GDP per capita in log and financial development. The results support the model, showing that a country's sectoral convergence speed is influenced by its financial development, income, and varies across sectors.

5.1 Data Description

I use data from WDI (2022)[24] which provides sectoral value added per worker in constant 2015 US$ and has good coverage of countries (for up to 157 countries) from 1991 to 2019. I then construct sectoral productivity[25] levels in constant 2015 international US$ comparable across countries in the same year and over time. To do this, first, I calculate international prices in 2015 by dividing the GDP per capita in current international US$ by GDP per capita in constant US$. Second, I use the PPPs calculated to convert the sectoral productivities in constant 2015

[24] WDI : World Development Indicators from the World Bank Group.

[25] Productivity here refers to labour producitivity which is considered to be the value added per worker.

US$ into sectoral productivities in constant 2015 international US$ as follows:

$$PPP_{2015} = \frac{GDP_{2015}^{\text{current int. \$}}}{GDP_{2015}^{\text{constant \$}}}, \tag{5.1}$$

$$A_{jt}^{PPP_{2015}} = PPP_{2015} \times A_{jt}^{\text{constant \$}}. \tag{5.2}$$

κ is calibrated to the country's financial development index provided by IMF for several countries between 1980 and 2014[26].

Figures XVI-XVIII in Appendix H depict the convergence patterns from 1991 to 2019 for countries in the 1st and 4th quartiles of financing capacity, defined as the product of financial development and the logarithm of GDP per capita in 1991. The graphs reveal that countries in the 4th quartile exhibit a significantly steeper negative slope compared to those in the 1st quartile, which have lower levels of financing capacity. This suggests that countries with higher financing capacity are able to close the productivity gap more rapidly as predicted by the model in Proposition II-(i).

5.2 Econometric Specification

In this subsection, I examine β-convergence in agriculture, manufacturing, and services for 97 to 157 countries using the World Development Indicators (WDI) data. Following the standard approach in the literature, I regress the average annual growth in log productivity[27], g_{j0}^c, for each sector $j \in \{a, m, s\}$ on the initial level of log productivity for country $c = 1, 2, \ldots, N$ as follows:

$$g_{j0}^c = \alpha_j + \beta_j \log(A_{j0}^c) + \rho_j \kappa_0^c \log(A_0^c) + \gamma_j \log(A_{j0}^c) \times \kappa_0^c \log(A_0^c) + \varepsilon_j^c, \tag{5.3}$$

where, A_{j0}^c denotes the initial productivity of sector j in country c, κ_0^c indicates the initial level of financial development in country c, A_0^c stands for the initial GDP per capita of country c, and ε_j^c is the error term.

β-convergence, which refers to the process by which less productive economies grow faster

[26] More details on financial data are presented in Appendix A

[27] The average growth rate, g_{j0}^c, from date 0 to T is defined as:

$$g_{j0}^c = \frac{1}{T} \Delta_T \log(A_{j0}^c) = \frac{1}{T} \left[\log(A_{jT}^c) - \log(A_{j0}^c)\right].$$

and close the gap with more developed economies, is obtained by the partial derivative of g^c_{j0} with respect to $\log(A^c_{j0})$ as follows:

$$\frac{\partial g^c_{j0}}{\partial \log(A^c_{j0})} = \beta_j + \gamma_j \times \kappa^c_0 \log(A^c_0). \tag{5.4}$$

The coefficient β_j then measures the conditional speed of convergence. If β_j is negative, then each country converges towards a productivity trajectory that is determined by its financial conditions, and income level. If $\beta_j < 0$ and $\gamma_j < 0$ then the convergence of productivity across countries in sector j will be faster for countries with higher levels of financial development κ^c_t or income $\log(A^c_t)$. According to the predictions of the theoretical model in Proposition II-*(i)*, γ_j is expected to be negative.

In order to find the threshold value of the financing capacity beyond which countries would start converging in sector j meaning the marginal effect given in equation (5.4) is significant, I proceed to the following test on coefficients after regressions :

$$H_0 : \frac{\partial g^c_{j0}}{\partial \log(A^c_{j0})} = 0 \qquad \text{vs.} \qquad H_1 : \frac{\partial g^c_{j0}}{\partial \log(A^c_{j0})} \neq 0. \tag{5.5}$$

Thus, countries would converge in a sector j as long as the level of financing capacity $\kappa_0 \log(A_0)$ exceeds the threshold level x_0 solution of the equation $\phi_j(x) = 0$.[28]

To study the effect of the initial GDP per capita and initial financial development level on speed of sectoral productivity convergence, I take the difference between the average annual growth rates of country c and the technological frontier from equation (5.3), and deduce the convergence speed $S^c_j := \frac{1}{T^c_j}$[29] in sector j for country c as follow:

$$S^c_j = -\hat{\beta}_j - \hat{\rho}_j \frac{\left[\bar{\kappa}_0 \log(\bar{A}_0) - \kappa^c_0 \log(A^c_0)\right]}{\log(\bar{A}_{j0}) - \log(A^c_{j0})} - \hat{\gamma}_j \frac{\left[\bar{\kappa}_0 \log(\bar{A}_0) \log(\bar{A}_{j0}) - \kappa^c_0 \log(A^c_0) \log(A^c_{j0})\right]}{\log(\bar{A}_{j0}) - \log(A^c_{j0})} \tag{5.7}$$

[28] Demonstration is given in Appendix I. ϕ_j is a real function defined on the interval $[0, +\infty[$ by :

$$\phi_j(x) = (\hat{\beta}_j + \hat{\gamma}_j x)^2 - z^2_{\frac{\alpha}{2}} \left[\text{var}(\hat{\beta}_j) + \text{var}(\hat{\gamma}_j) x^2 + 2\text{cov}(\hat{\beta}_j, \hat{\gamma}_j) x\right]. \tag{5.6}$$

[29] T^c_j is the necessary time of the country c to catch-up with the technological frontier in sector j with initial GDP per capita $\log(\bar{A}_0)$, initial financial development $\bar{\kappa}_0$, and initial sectoral productivity $\log(\bar{A}_{j0})$.

If $\hat{\beta}_j < 0$ and $\hat{\gamma}_j < 0$, then the speed of convergence S_j^c increases with the absolute values of $\hat{\beta}_j$ and $\hat{\gamma}_j$ but decreases with $\hat{\rho}_j$ so that countries with higher initial income and higher initial level of financial development will converge more quickly. To see this, we can analyze in data, the effect of the country's initial level of financing capacity on its sectoral productivity convergence speed by calculating the partial derivative of S_j^c with respect to $\kappa_0^c \log(A_0^c)$ from equation (5.7) as following:

$$\frac{\partial S_j^c}{\partial \left[\kappa_0^c \log(A_0^c)\right]} = \frac{\hat{\rho}_j + \hat{\gamma}_j \log(A_{j0}^c)}{\log(\bar{A}_{j0}) - \log(A_{j0}^c)}. \tag{5.8}$$

Thus, we can see that the marginal effect of GDP per capita and the level of financial development on sectoral productivity convergence speed is positive as long as the level of the sectoral log productivity $\log(A_{j0}^c)$ is less than $-\frac{\hat{\rho}_j}{\hat{\gamma}_j}$ (which is the case in data).

In addition, I can calculate and compare the speeds of convergence across sectors for the same country, using the estimated parameters $\hat{\beta}_j$, $\hat{\rho}_j$, and $\hat{\gamma}_j$, alongside the initial levels of financing capacity and sectoral productivities of the country and the technological frontier, as specified in equation (5.7). The results of these estimations are discussed in the following subsection.

5.3 Empirical Results on Beta-Convergence

For each sector $j \in \{a, m, s\}$, I estimate cross-country regression models both with and without including initial financial development and income levels. A negative and statistically significant coefficient on initial labor productivity in the model without these variables suggests unconditional convergence. In contrast, a similar coefficient in the model that incorporates financial development and income levels indicates conditional convergence. In all estimations, I employ robust standard errors to address potential heteroscedasticity.

Table II presents the results of these cross-sectional regressions, corresponding to the scatter plots displayed in Figures Ib–IIIb. The cross-country specifications do not include time periods or any other fixed effects and cover a sample of 97 to 174 countries. The unconditional convergence estimates in columns (1), (3), and (5) of Table II indicate that the manufacturing and services sectors exhibit similar coefficients of -0.007, which are statistically significant at the 1% level over the entire period from 1991 to 2019. In contrast, the coefficient for the agriculture sector is -0.002 and is not statistically significant. For the overall period 1991-2019, the results in columns (2), (4), and (6) of Table II show that the coefficient associated with the interaction between financial development and GDP per capita is positive, being 0.028 for agriculture (significant at 5%), 0.041 for manufacturing (significant at 10%), and 0.048 for services (also significant at 5%).

TABLE II: Cross-Countries Regression Results : Dependant Variable: Average Growth in Productivity Between 1991 and 2019

	Agriculture		**Manufacturing**		**Services**	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{j0})$	-0.002	-0.002	-0.007***	-0.008**	-0.007***	-0.009**
	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)
$\hat{\rho}_j : \kappa_0 \log(A_0)$		0.028**		0.041*		0.048**
		(0.013)		(0.021)		(0.021)
$\hat{\gamma}_j : \kappa_0 \log(A_0)$		-0.003*		-0.003*		-0.004**
$\times \log(A_{j0})$		(0.001)		(0.002)		(0.002)
Countries	121	107	116	103	110	97
R-squared	0.01	0.10	0.07	0.27	0.10	0.27

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

This indicates that higher financial development and GDP per capita facilitate greater productivity growth across the three sectors during this period. Additionally, the coefficients $\hat{\gamma}_j$ for the interaction between a country's initial sectoral productivity and its financing capacity are negative: -0.003 (significant at 10%) for both agriculture and manufacturing, and -0.004 (significant the 5%) for services. This implies that between two countries with the same level of financing capacity, the country with a lower initial sectoral productivity will experience faster productivity growth, indicating convergence within countries with similar financing capacity (GDP per capita times financial development level). Moreover, if two countries have the same initial sectoral productivity, the one with a higher initial level of financing capacity, will experience a more rapid convergence process.

The cross-sectional model estimates in Table II, columns (2), (4), and (6), were used to determine the threshold levels of sectoral productivity in 1991, below which the marginal effects of financial development and GDP per capita on the speed of convergence are positive. The results show that the threshold levels are 11.01 for agriculture, 12.82 for manufacturing, and 12.14 for services. However, the maximum levels of sectoral productivity in 1991 in the data used for the estimations are 11.02 for agriculture, 11.91 for manufacturing, and 11.56 for services. These findings provide evidence that the marginal impact of financial development and income levels on the rate of sectoral productivity convergence is positive, as the observed productivity levels are below the respective thresholds.

Moreover, the data indicate that countries with financing capacity below a certain threshold are likely to experience divergence in the agricultural sector[30]. The marginal effect of initial productivity in 1991 on subsequent agricultural productivity growth, as derived from equation (5.4), is negative and significant only for countries with a level of financial development times log GDP per capita above 0.69, which corresponds to just above the 25th percentile of countries in 1991.

I now analyze the differences in convergence speed across various sectors and countries. By considering initial sectoral productivity levels, GDP per capita, and financial development, I can calculate the rate of convergence in a specific sector for a given country. Table II, specifically columns (2), (4), and (6), presents estimates indicating that a country like India, which has approximately the same relative productivity levels in the three major sectors compared to France (0.15 in agriculture, 0.17 in manufacturing, and 0.12 in services) will require different amounts of time across different sectors to catch up with France. Starting from an initial financing capacity level of $\kappa_0 \log(A_0) = 1.9$ in 1991, the estimates[31] suggest that it will take India approximately 81 years to catch up with France in the services sector, 185 years in manufacturing, and 305 years in agriculture.

However, if India's initial financial development were raised to match France's level of 4.52 in 1991, the convergence rates across sectors would improve significantly. In this case, the

[30]Unlike in the agricultural sector, Table II reports significant $\hat{\beta}_j$ coefficients for services and manufacturing, indicating a negative relationship between initial sectoral productivity and subsequent growth in both sectors.

[31]I use equation (5.7) to calculate the speed of convergence for India in the three sectors, allowing me to deduce the time required for India to catch up with France in each sector.

time needed to catch up with France would shorten to roughly 37 years in services, 45 years in manufacturing, and 74 years in agriculture. These estimates indicate that a country's initial levels of financial development and income play a crucial role in determining its convergence rate across different sectors. The higher the initial financial development and GDP per capita, the faster the country will achieve a comparable level of sectoral productivity relative to the frontier in each sector.

Additionally, the estimates underscore the significant variation in the time required for a country to reach the frontier across sectors. For example, convergence occurs most rapidly in the services sector, followed by manufacturing, and lastly agriculture. This variation reflects the differences in the inherent characteristics of these sectors, particularly their average annual productivity growth rates at the frontier, which between 1991 and 2019 were 3.06% in agriculture, 1.97% in manufacturing, and 0.85% in services for the top ten most developed countries.

5.4 Robustness Checks

In this subsection, I conduct robustness checks to ensure the reliability and validity of the baseline estimations in two ways: (1) by using an alternative data source for sectoral productivity, and (2) by conducting a panel data analysis, which accounts for unobserved heterogeneity and temporal dynamics that may influence the results. Additionally, I employ alternative measures of financial development, specifically the financial institutions index and the financial market index, to assess whether the conclusions hold true across different indicators of financial development.

Alternative Data. I use data from the Economic Transformation Database (ETD) of the Groningen Growth and Development Centre (GGDC). The ETD provides consistent annual data on employment and both real and nominal value added for 12 sectors across 51 economies for the period 1990–2018 (see Kruse et al. (2023) for more details). The nominal sectoral value added is expressed in local currency units (LCU) as VA_{jt}, while the real value added is reported in 2015 LCU prices as $VA\_Q_{jt}^{2015}$. Sectoral productivity is calculated as value added per worker.

To ensure comparability of productivity across countries and over time, I convert the data to international constant US dollars. Since the Productivity Level Database (PLD) from GGDC provides sectoral purchasing power parities (PPP) for value added in 2017 prices (expressed in LCU per USD), I first adjust the real value added to 2017 prices. This is done by multiplying the real value added in 2015 prices by the ratio of 2017 price to 2015 price, calculated from the ratio of nominal value added in 2017 to real value added in 2015 prices in 2017, as follows:

$$VA\_Q_{jt}^{2017} = VA\_Q_{jt}^{2015} \times \frac{VA_{j2017}}{VA\_Q_{j2017}^{2015}}. \tag{5.9}$$

Next, I calculate sectoral productivities that are comparable across countries and over time by dividing the real value added in 2017 prices by the 2017 sectoral PPP (PPP_{j2017}) and employment for each sector (EMP_{jt}), as follows:

$$A_{jt}^{PPP_{2017}} = \frac{VA\_Q_{jt}^{2017}}{EMP_{jt} \times PPP_{j2017}}. \tag{5.10}$$

I then run the cross-country regressions for agriculture, manufacturing, and services[32] from equation (5.3). The results based on GGDC data, presented in Table III, exhibit coefficients

TABLE III: Cross-Countries Regression Results Using GGDC data: Dependant Variable: Average Growth in Productivity Between 1990 and 2018

	Agriculture		**Manufacturing**		**Services**	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{j0})$	-0.003	0.004	-0.011**	-0.013**	-0.011***	-0.015***
	(0.002)	(0.003)	(0.004)	(0.006)	(0.003)	(0.004)
$\hat{\rho}_j : \kappa_0 \log(A_0)$		0.022*		0.033		0.045*
		(0.011)		(0.040)		(0.024)
$\hat{\gamma}_j : \kappa_0 \log(A_0)$		-0.003**		-0.002		-0.004
$\times \log(A_{j0})$		(0.001)		(0.004)		(0.002)
Countries	48	47	48	47	48	47
R-squared	0.05	0.23	0.18	0.34	0.22	0.49

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

comparable to those obtained using WDI data, with the exception of the $\hat{\beta}_j$ values. Notably, the $\hat{\beta}_j$ coefficients are slightly higher for the manufacturing and services sectors in the GGDC data

[32]Employment and value added in 2017 PPP are aggregated into three sectors (see Appendix A.2).

compared to the WDI data. It is also worth noting that the number of countries in the GGDC dataset is significantly reduced.

Panel Regressions. I now extend the cross-country estimation by conducting a panel data analysis, which accounts for unobserved heterogeneity and temporal dynamics that may influence the results. By controlling for country-specific unobserved heterogeneity and incorporating time variation, panel data models help mitigate potential confounding factors that could bias the estimates. o implement this approach, I estimate the following equation for each sector using both WDI and GGDC datasets:

$$g_{jt}^{c} = \alpha_j + \beta_j \log(A_{jt}^{c}) + \rho_j \kappa_t^{c} \log(A_t^{c}) + \gamma_j \log(A_{jt}) \times \kappa_t^{c} \log(A_t^{c}) + D_j^{c} + D_{jt} + \varepsilon_{jt}^{c} \tag{5.11}$$

where g_{jt}^{c} represents the average annual growth rate[33] of sector j labor productivity A_{jt}^{c} in constant international prices for country c between periods t and $t+\Delta t$. The terms D_j^c and D_{jt} represent country and time fixed effects, respectively. The inclusion of D_j^c accounts for country-specific characteristics, while D_{jt} captures time-specific shocks common across countries. ε_{jt}^{c} denotes the error term, and $\kappa_t^c \log(A_t^c)$ reflects the level of financial development, κ_t^c, alongside GDP per capita, $\log(A_t^c)$. By including both D_j^c and D_{jt}, the model corrects for omitted-variable bias by capturing unobserved heterogeneity across countries and time.

For each sector $j \in \{a, m, s\}$, I estimate panel regression equations with and without country fixed effects. Standard errors are clustered at the country level in all specifications. Table IV presents the results based on GGDC data. The dependent variable is the average growth rate of the 5 years average of log productivity, and the explanatory variables are the the initial 5-year average levels of labor productivity in log, the average financing capacity level $\kappa_t \log(A_t)$ over the previous 5 years, and the interaction of these two variables, with the fixed effects for each period, and country. The unconditional coefficients are consistent with Herrendorf et al. (2022), yielding values of -0.007 for manufacturing and services, and -0.002 for agriculture. This indicates that, after controlling for time shocks, the GGDC data do not exhibit unconditional convergence across the 48 countries. However, the estimates in columns (2), (4), and (6) reveal that the conditional coefficients for $\hat{\beta}_j$ are negative and significant, $\hat{\rho}_j$ is positive and significant

[33]
$$g_{jt}^{c} = \frac{1}{\Delta t}\left[\log(A_{jt+\Delta t}^{c}) - \log(A_{jt}^{c})\right]$$

TABLE IV: 5-Year Panel Regression Results Using GGDC dataset, Dependent Variable: Average Annual Growth in Productivity

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{jt})$	-0.002	-0.041***	-0.007	-0.066***	-0.007	-0.031*
	(0.002)	(0.012)	(0.005)	(0.018)	(0.005)	(0.017)
$\hat{\rho}_j : \kappa_t \log(A_t)$		0.027		0.023		0.063*
		(0.020)		(0.045)		(0.033)
$\hat{\gamma}_j : \kappa_t \log(A_t)$		-0.004*		-0.002		-0.006*
$\times \log(A_{jt})$		(0.002)		(0.004)		(0.003)
Country FE	No	Yes	No	Yes	No	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	47	48	47	48	47	48
Observations	240	235	240	235	240	235
R-squared	0.01	0.46	0.04	0.53	0.08	0.60

All data are aggregated to 5-year time periods spanning 1990-2018.
Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

for the services sector, and $\hat{\gamma}_j$ is negative and significant for both agriculture and services.

Table V presents the regression results for the 5-year panel estimations covering 146 to 170 countries from the 1991–2019 period, using data from the WDI dataset. The unconditional convergence results in columns (1), (3), and (5) are significant for manufacturing and services at the 1% level, but not significant for agriculture. The estimated coefficients of unconditional convergence are of a similar magnitude to those in Herrendorf et al. (2022) for their estimation with more countries (64 countries).

I also estimate the panel model using 10-year intervals with the financial institutions index and the financial markets index (see results[34] in Appendix L), instead of the financial development index. Table XII presents the results of equation (5.11), using 10-year intervals from 1991 to 2019. The findings indicate that the conditional convergence estimates are significant at the 1% level across all three sectors.

[34]Estimations using different financial indicators remain similar to those obtained with the financial development index.

TABLE V: 5-Year Panel Regression Results using WDI dataset, Dependent Variable: Average Annual Growth in Productivity

	Agriculture		**Manufacturing**		**Services**	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{jt})$	0.001	-0.042***	-0.005**	-0.063***	-0.003***	-0.056***
	(0.001)	(0.011)	(0.002)	(0.015)	(0.001)	(0.011)
$\hat{\rho}_j : \kappa_t \log(A_t)$		0.064***		0.004		0.087***
		(0.013)		(0.025)		(0.018)
$\hat{\gamma}_j : \kappa_t \log(A_t)$		-0.006***		-0.001		-0.008***
$\times \log(A_{jt})$		(0.001)		(0.002)		(0.002)
Country FE	No	Yes	No	Yes	No	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	170	159	166	155	157	146
Observations	796	744	786	734	769	717
R-squared	0.01	0.50	0.03	0.54	0.06	0.59

All data are aggregated to 5-year time periods spanning 1991-2019.
Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

6 Conclusion

This paper begins by documenting distinct patterns of productivity convergence between agriculture, manufacturing, and services. It then develops an endogenous growth model to explain the observed discrepancies between economic sectors. The model extends the framework of Aghion et al. (2005), incorporating three novel features. First, entrepreneurs adopt sector-specific technologies from the frontier. Second, the model accounts for a country's pre-existing knowledge of a specific technology before adoption. Third, it considers the intensity of use of adopted technologies as a key factor determining productivity growth, acknowledging that even if two countries successfully adopt the same technology, they may utilize it at different intensities, as documented by Comin & Mestieri (2018).

The model shows that countries with low income and financial development levels may initially experience temporary sectoral productivity divergence, particularly in industries with high investment requirements. However, as income grows and financing capacity improves, these industries can shift to a path of convergence, even if at a slower and less efficient pace than in the absence of credit constraints. This sectoral transition drives aggregate convergence, enabling the overall economy to move from divergence to convergence as lagging sectors close productivity gaps and contribute more significantly to economic growth.

Both the theoretical model and empirical findings predict that financial development and income positively influence the speed of sectoral productivity convergence. Sectors with higher productivity growth at the technological frontier (e.g., agriculture) not only converge more slowly but also begin their convergence later, lagging behind sectors with lower technological frontier growth rates (e.g., services).

There are several avenues for extending this analysis. For instance, this study assumes that if all countries had the same levels of income and financial development, they would adopt technologies with similar intensity. However, other factors, such as sectoral linkages, can amplify the dynamics between sectoral and aggregate convergence. Future research could explore how sectoral linkages affect the convergence process across countries. Another step would be to examine how financial development and technology adoption contribute to the divergent structural transformation paths and rates observed between developing and developed countries.

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Appendix

A Data Appendix

A.1 Financial Data

Financial Development Index (FD) is a relative ranking of countries on the depth, access, and efficiency of their financial institutions and financial markets. It is an aggregate of the **Financial Institutions Index (FI)** and the **Financial Markets Index (FM)**.

- *Financial Institutions Index (FI)* is an aggregate of :
  - Financial Institutions Depth Index (FID), which compiles data on bank credit to the private sector in percent of GDP, pension fund assets to GDP, mutual fund assets to GDP, and insurance premiums, life and non-life to GDP.
  - Financial Institutions Access Index (FIA), which compiles data on bank branches per 100, 000 adults and ATMs per 100, 000 adults.
  - Financial Institutions Efficiency Index (FIE), which compiles data on banking sector net interest margin, lending-deposits spread, non-interest income to total income, overhead costs to total assets, return on assets, and return on equity.
- *Financial Markets Index (FM)* is an aggregate of :
  - Financial Markets Depth Index (FMD), which compiles data on stock market capitalization to GDP, stocks traded to GDP, international debt securities of government to GDP, and total debt securities of financial and nonfinancial corporations to GDP.
  - Financial Markets Access Index (FMA), which compiles data on percent of market capitalization outside of the top 10 largest companies and total number of issuers of debt (domestic and external, non financial and financial corporations) per 100, 000 adults.
  - Financial Markets Efficiency Index (FME), which compiles data on stock market turnover ratio (stocks traded to capitalization).

Figure VIII illustrates the global distribution of financial development and financial institutions across countries in 2014. The map provides a comparative view of the financial landscape, highlighting variations in the depth, access, and efficiency of financial institutions. Each country is color-coded based on its level of financial development. Countries in red have the lowest levels of financial development, with values below 0.133, predominantly representing Sub-Saharan Africa (SSA). Orange indicates financial development between 0.133 and 0.242, also concentrated in SSA countries. Yellow represents countries with financial development between 0.242 and 0.357, covering parts of the Middle East and some Latin American nations. Gray includes countries with values between 0.357 and 0.479, encompassing most of Latin America, such as Argentina and Mexico, as well as India. Light blue denotes financial development between 0.479 and 0.674, covering countries like Brazil, South Africa, Saudi Arabia, and China. Finally, countries shaded in blue show the highest levels of financial development, above 0.674, representing the USA, Canada, Europe, Taiwan, and Australia.

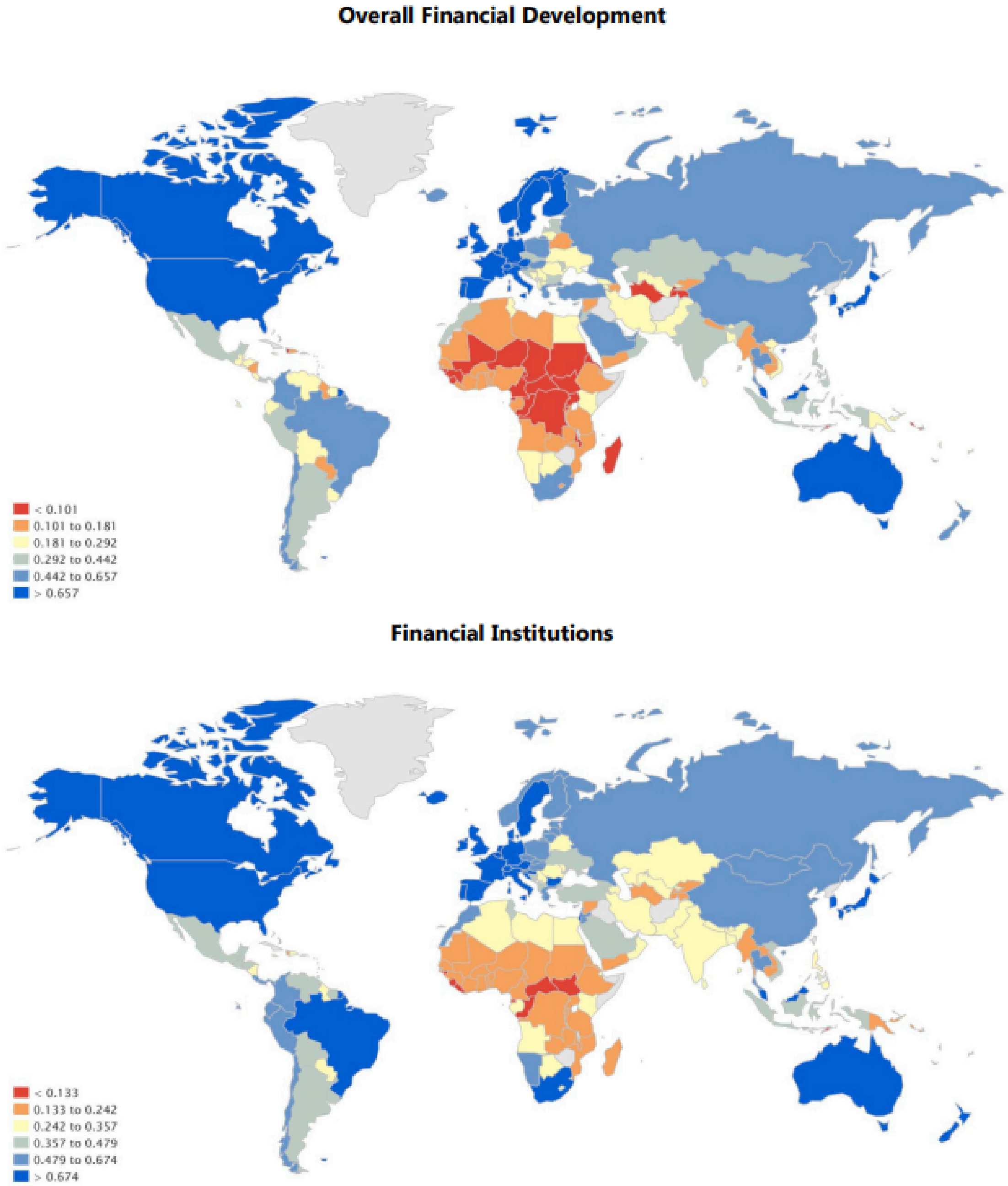
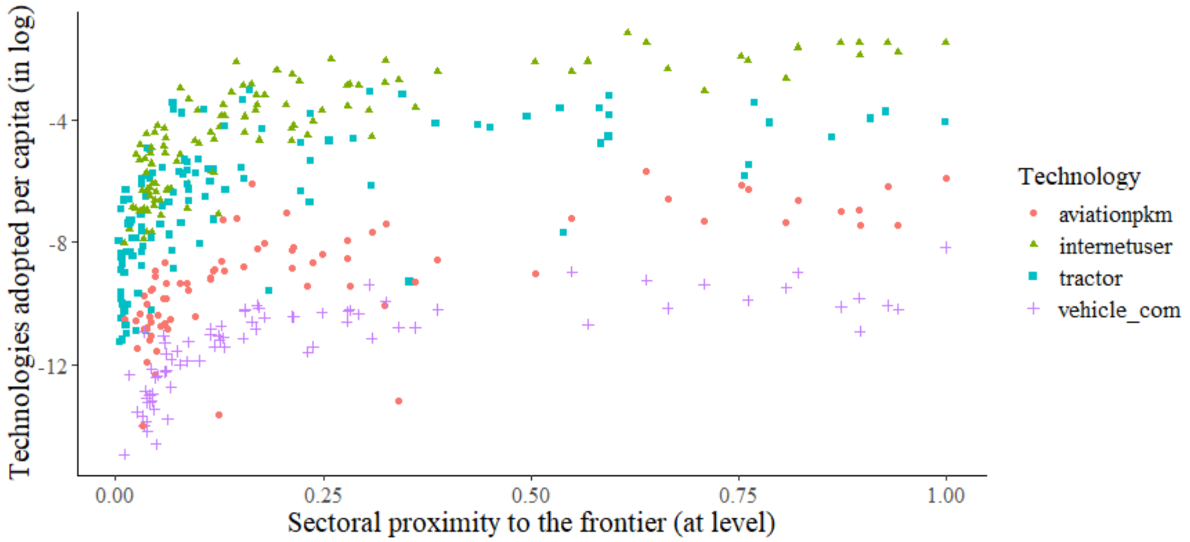


FIGURE VIII: Global Financial Development and Institutions Map (2014)

Next, I present the average intensity of technology use (in log) relative to sectoral proximity. As shown in Figure IX, the correlation with sectoral proximity (in levels) is positive up to a threshold, consistent with the model's predictions.



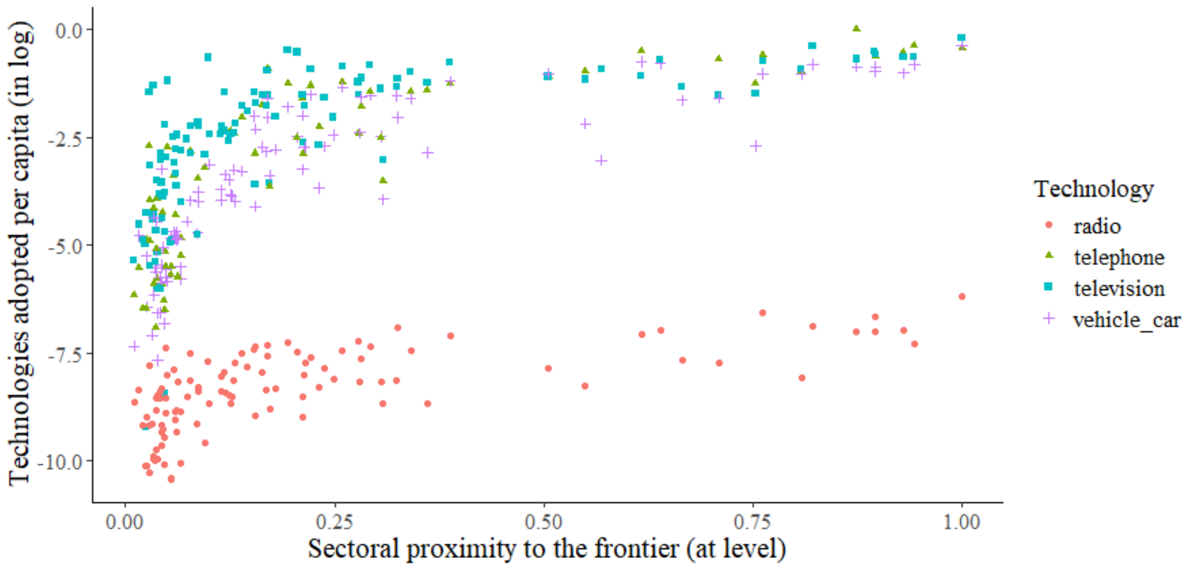
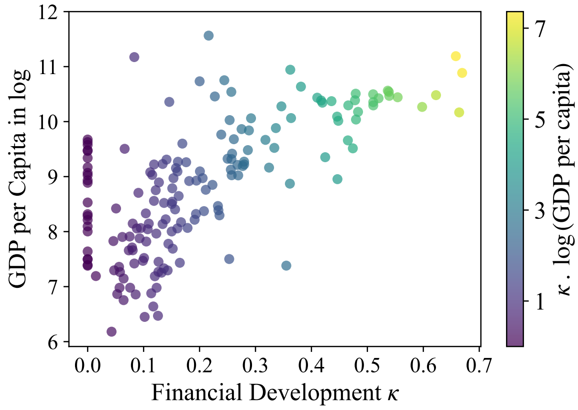
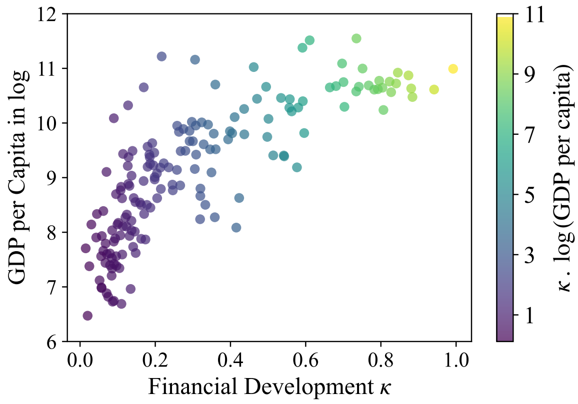


FIGURE IX: Average Levels of Sectoral Proximity at Level and Log Technology Adoption per Capita (1991–2003)

The scatter plot in Figure X shows the distribution of data points for different observations in 1991 and 2005. Each point represents a country, defined by its combination of κ (financial development) and $\log(A_0)$ (log GDP per capita). The points are color-coded from violet to yellow, indicating the level of development, with violet representing the lowest and yellow the highest. As shown in Figure X, the movement of countries along the financial development and GDP per capita spectrum highlights significant shifts that can influence the dynamics of convergence.



(a) 1991



(b) 2005

FIGURE X: Countries' Financial Development and GDP per capita Distribution Over Time

A.2 Sector Classification

- Agriculture corresponds to the International Standard Industrial Classification (ISIC) tabulation categories A and B (revision 3) or tabulation category A (revision 4), and includes forestry, hunting, and fishing as well as cultivation of crops and livestock production.

- Manufacturing corresponds to the International Standard Industrial Classification (ISIC) tabulation categories C-F (revision 3) or tabulation categories B-F (revision 4), and includes mining and quarrying (including oil production), manufacturing, construction, and public utilities (electricity, gas, and water).

- Services corresponds to the International Standard Industrial Classification (ISIC) tabulation categories G-P (revision 3) or tabulation categories G-U (revision 4), and includes wholesale and retail trade and restaurants and hotels; transport, storage, and communications; financing, insurance, real estate, and business services; and community, social and personal services.

B Goods Production

The monopolist maximizes profit as follows:

$$\max_{\{x_{jt}\}} p_{jt}x_{jt} - x_{jt}$$

$$\text{subject to} \qquad p_{jt} = \alpha x_{jt}^{\alpha-1} A_{jt}^{1-\alpha} L_t^{1-\alpha}$$

Hence, the equilibrium condition for the firm in the intermediate sector is given by:

$$x_{jt} = \alpha^{\frac{2}{1-\alpha}} A_{jt} L_t \tag{B.1}$$

The equilibrium price for variety j is then calculated by substituting (B.1) into the inverse demand function:

$$p_{jt} = \alpha^{-1} \tag{B.2}$$

which is identical for all sectors $j \in [0,1]$ and remains constant over time. The profit made by the intermediate monopoly in sector j is therefore given in equilibrium by:

$$\begin{aligned} \pi_{jt} &= \left(p_{jt} - 1\right) x_{jt} \\ &= \pi A_{jt} L_t \end{aligned} \tag{B.3}$$

where $\pi := (1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}}$. Thus, the profits generated by each sector depend positively on the productivity of that sector. The production of the final good in equilibrium is obtained by substituting (B.1) into (3.1):

$$Y_t = \alpha^{\frac{2\alpha}{1-\alpha}} A_t L_t \tag{B.4}$$

The wage rate w_t and the Gross Domestic Product GDP_t are then given by:

$$w_t = \omega A_t \tag{B.5}$$

$$GDP_t = \zeta A_t L_t \tag{B.6}$$

where $\omega := (1-\alpha)\alpha^{\frac{2\alpha}{1-\alpha}}$ and ζ is defined as $\zeta := (1-\alpha^2)\alpha^{\frac{2\alpha}{1-\alpha}}$. The term $A_t := \int_0^1 A_{jt}\,dj$ represents the aggregate productivity in the economy at time t and can also be interpreted as GDP per capita in the economy.

C Credit Constraints

At the end of their first period of life, households invest in an innovation project. The amount invested by an innovator in sector j at date t for technology adoption is z_{jt}, and the amount borrowed is $z_{jt} - sw_t$, where w_t is the real wage and s represents the saving rate. The interest rate is denoted by r, and therefore, the cost of repaying the loan is $(1+r)(z_{jt} - sw_t)$.

I introduce imperfections in the credit market into the model as in Aghion et al. (2005). This imperfection arises from the presence of moral hazard, meaning there is a possibility that the borrower may choose not to repay the loan by concealing the profits made. The borrower can pay a cost hz_{jt}, which is proportional to the amount invested, to avoid repaying her creditors when successful. This cost serves as an indicator of the degree of creditor protection. However, there is a probability q that the borrower will be caught by the lender, thereby obliging her to repay the loan. The total cost of being dishonest[35] is then: $hz_{jt} + q(1+r)(z_{jt} - sw_t)$. The borrower is prompted to choose honesty if:

$$hz_{jt} + q(1+r)(z_{jt} - sw_t) \geq (1+r)(z_{jt} - sw_t). \tag{C.1}$$

This implies the following condition on the amount z_{jt} that the innovator can invest in the

[35] I assume that the borrower's earnings π_{jt+1} will be sufficient to cover the cost of being dishonest hz_{jt} as well as the repayment of the loan and interest if caught, $(1+r)(z_{jt} - sw_t)$.

technology adoption project:

$$z_{jt} \leq \frac{(1-q)(1+r)}{(1-q)(1+r)-h} s w_t. \tag{C.2}$$

The maximum amount that the lender would agree to lend, ensuring that the borrower chooses to be honest, is given by:

$$l_t(q,h) = \frac{h s w_t}{(1-q)(1+r)-h}. \tag{C.3}$$

The function $l_t(q,h)$ is proportional and increasing with the real wage w_t, increasing with the cost of being dishonest h and the probability of being caught q, while it decreases with the interest rate r. Therefore, if the financial system is underdeveloped to the point that borrowers can easily cheat (low h) or it is difficult to get caught (low q), then projects in more productive sectors at the frontier, which require higher levels of investment, can become constrained.

I assume that the lender can make efforts[36] to influence the probability q by spending a unit cost $C(q)$ per loan amount. The convex cost function $C(q)$ is defined such that it increases with the probability q:

$$C(q) := c \ln\left(\frac{1}{1-q}\right) \tag{C.4}$$

with $c > h$ and $c > 1+r$. To do this, the lender solves the problem below:

$$\max_{\{q\}} \left[q(1+r) + c\ln(1-q)\right](z_{jt} - s w_t). \tag{C.5}$$

The first-order condition is:

$$q = 1 - \frac{c}{1+r}. \tag{C.6}$$

[36] For example, the cost of settling a financial dispute, or the cost to have access to financial information, etc.

Then, the condition (C.2) becomes:

$$z_{jt} \leq \kappa w_t, \tag{C.7}$$

where $\kappa := \dfrac{s}{1-\hbar}$ is the level of financial development which is increasing with $\hbar = h/c$. The parameter $\hbar$ provides information on the quality of financial institutions. The more expensive it is for borrowers to cheat (high h) and/or the easier it is for lenders to catch bad borrowers (low c), the higher κ will be. Strong financial institutions, corresponding here to a higher κ, allow for more efficient control by reducing c and increasing h, which relaxes the credit constraint. A highly developed financial system protects creditors by making it hard to defraud them.

While this paper does not delve into the implications of Foreign Direct Investment as a potential alternative source of financing, it is noteworthy that previous studies, such as those by Alfaro et al. (2004) and Suliman & Elian (2014), indicate that Foreign Direct Investment can positively influence economic activity, but only in contexts where the financial system is efficient. This suggests that enhancing domestic financial capabilities could be a crucial step in fostering an environment conducive to both local and foreign investments, ultimately paving the way for more robust economic development.

D Proof for Proposition I

Proof. Let's assume that $\kappa_1 < \kappa_2$ and $\theta_{jt}^{(1)}$ $\left(\text{respectively } \theta_{jt}^{(2)}\right)$ the equilibrium intensity of use of adopted technologies associated with the financial development level κ_1 (respectively κ_2). Then $\bar{a}_t(\kappa_1)$ is greater than $\bar{a}_t(\kappa_2)$. Then, we have :

$$\theta_{jt+1}^{(1)} = \begin{cases} 1 & \text{if } a_{jt} > \bar{a}_t(\kappa_1) \\ -\dfrac{\eta}{\psi} + \left[\left(\dfrac{\eta}{\psi}\right)^2 + \dfrac{2\lambda\kappa_1 w_t a_{jt}}{\psi}\right]^{\frac{1}{2}} & \text{if } \bar{a}_t(\kappa_2) \leq a_{jt} \leq \bar{a}_t(\kappa_1) \\ -\dfrac{\eta}{\psi} + \left[\left(\dfrac{\eta}{\psi}\right)^2 + \dfrac{2\lambda\kappa_1 w_t a_{jt}}{\psi}\right]^{\frac{1}{2}} & \text{if } a_{jt} \leq \bar{a}_t(\kappa_2) \end{cases}$$

and

$$\theta^{(2)}_{jt+1} = \begin{cases} 1 & \text{if } a_{jt} > \bar{a}_t(\kappa_1) \\ 1 & \text{if } \bar{a}_t(\kappa_2) \leq a_{jt} \leq \bar{a}_t(\kappa_1) \\ -\dfrac{\eta}{\psi} + \left[\left(\dfrac{\eta}{\psi}\right)^2 + \dfrac{2\lambda \kappa_2 w_t a_{jt}}{\psi} \right]^{\frac{1}{2}} & \text{if } a_{jt} \leq \bar{a}_t(\kappa_2) \end{cases}$$

Since θ^*_{jt+1} is strictly less than 1 when a_{jt} is less than $\bar{a}_t(\kappa)$, $\kappa_1 < \kappa_2$, then :

$$\begin{cases} \theta^{(1)}_{jt+1} = \theta^{(2)}_{jt+1} & \text{if} \quad a_{jt} \geq \bar{a}_t(\kappa_1) \\ \theta^{(1)}_{jt+1} < \theta^{(2)}_{jt+1} & \text{if} \quad \bar{a}_t(\kappa_2) \leq a_{jt} < \bar{a}_t(\kappa_1) \\ \theta^{(1)}_{jt+1} < \theta^{(2)}_{jt+1} & \text{if} \quad a_{jt} < \bar{a}_t(\kappa_2) \end{cases}$$

And finally,

$$\begin{cases} \theta^{(1)}_{jt+1} = \theta^{(2)}_{jt+1} & \text{if} \quad a_{jt} \geq \bar{a}_t(\kappa_1) \\ \theta^{(1)}_{jt+1} < \theta^{(2)}_{jt+1} & \text{if} \quad a_{jt} < \bar{a}_t(\kappa_1) \end{cases}$$

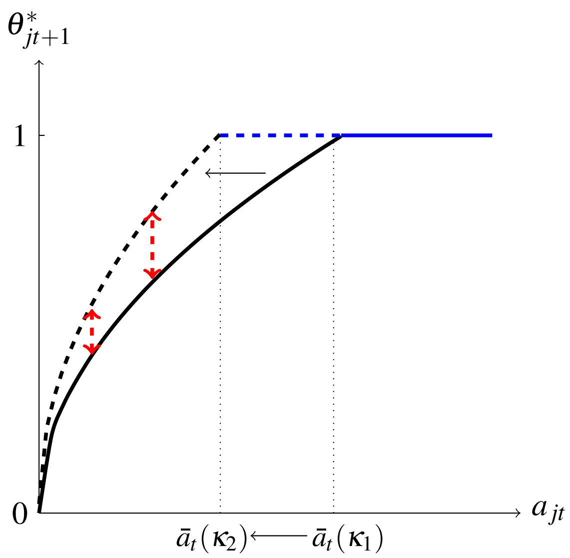


FIGURE XI: Effect of Financial Development on the Intensity of Use of Technologies ($\kappa_1 < \kappa_2$)

Beyond the threshold level of sectoral proximity, denoted as $\bar{a}_t(\kappa_1)$, financial development ceases to influence the intensity of technology use. Specifically, increasing the level of financial development from κ_1 to κ_2 does not result in a higher intensity of technology adoption for countries that have already surpassed this threshold. In other words, countries that are already close to the productivity frontier (such that $a_{jt} \geq \bar{a}_t(\kappa_1)$) do not benefit further in terms of technology use from additional financial development. However, for countries that are below this proximity threshold, an increase in financial development–moving from κ_1 to κ_2–will lead to greater intensity in technology adoption. This implies that financial development plays a crucial role in driving technological progress, but its effects are concentrated in countries that are still catching up with the frontier, whereas for more advanced economies, other factors might become more significant in driving further productivity growth. ■

E Variation study of f_{jt}

$$(1+\bar{g}_j)f_{jt}(a) = a + (1-a)\left[-\frac{\eta}{\psi} + \left(\left(\frac{\eta}{\psi}\right)^2 + \frac{2\lambda\kappa w_t a}{\psi}\right)^{\frac{1}{2}}\right]$$

By differentiating the function f_{jt} with respect to a, we obtain:

$$(1+\bar{g}_j)f'_{jt}(a) = 1 + \frac{\eta}{\psi} - \left(\left(\frac{\eta}{\psi}\right)^2 + \frac{2\lambda\kappa w_t a}{\psi}\right)^{\frac{1}{2}} + (1-a)\times\frac{\lambda\kappa w_t}{\psi}\left(\left(\frac{\eta}{\psi}\right)^2 + \frac{2\lambda\kappa w_t a}{\psi}\right)^{-\frac{1}{2}} \tag{E.1}$$

The second derivative f''_{jt} gives:

$$(1+\bar{g}_j)f''_{jt}(a) = -\frac{2\lambda\kappa w_t}{\psi}\left(\left(\frac{\eta}{\psi}\right)^2 + \frac{2\lambda\kappa w_t a}{\psi}\right)^{-\frac{1}{2}} - \frac{(1-a)(\lambda\kappa w_t)^2}{\psi^2}\left(\left(\frac{\eta}{\psi}\right)^2 + \frac{2\lambda\kappa w_t a}{\psi}\right)^{-\frac{3}{2}} \tag{E.2}$$

$f''_{jt} < 0 \Longrightarrow f_{jt}$ is concave in a. Also

$$\begin{cases} (1+\bar{g}_j)f'_{jt}(0) = 1 + \dfrac{\lambda\kappa w_t}{\eta} \\ (1+\bar{g}_j)f'_{jt}(1) = 1 + \dfrac{\eta}{\psi} - \left(\left(\dfrac{\eta}{\psi}\right)^2 + \dfrac{2\lambda\kappa w_t}{\psi}\right)^{1/2} \end{cases}$$

with $w_t = \omega A_t$ ($\omega = \alpha^{-1}\pi$.)

F Dynamics of Sectoral Productivity

- ***Case 1:** Sectoral productivity convergence for high financial developed and high income countries.*

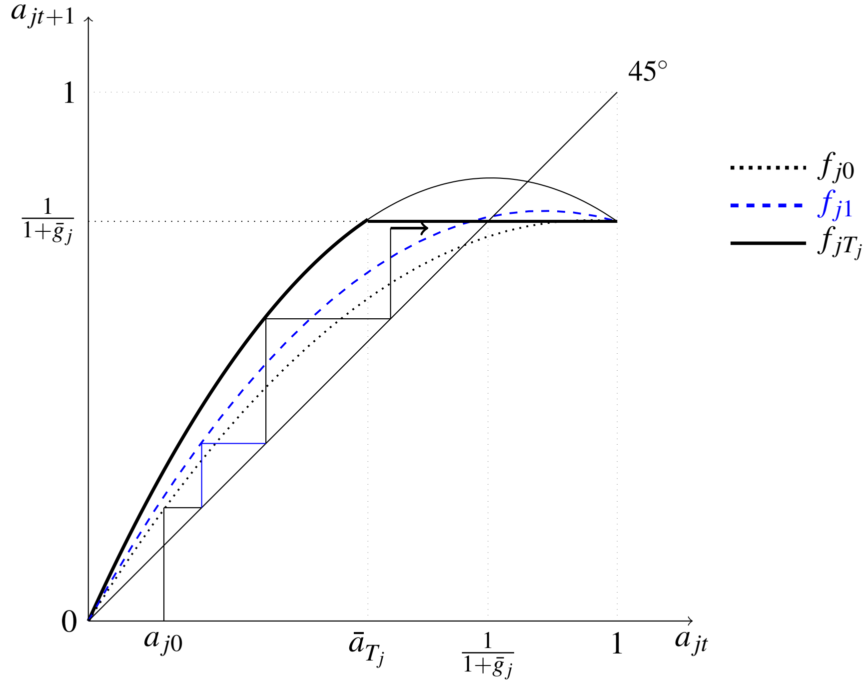


FIGURE XII: Sectoral productivity gap dynamic when $\kappa w_0 > \frac{\psi+2\eta}{2\lambda}$

When financial development or the level of initial income per capita are sufficiently high such that $\kappa w_0 > \frac{\psi+2\eta}{2\lambda}$, the evolution of the sectoral productivity gap is illustrated in Figure XII below. Since $f_{jt} \leq f_{jt+1}$ and $\bar{a}_t$ is decreasing with t, while a_{jt} is increasing with t as long as f_{jt} is above the first bisector, there exists a date T_j such that $a_{jt} \geq \bar{a}_{T_j}$ and $a_{jt+1} = h_j(a_{jt})$ for all $t \geq T_j$. The sectoral productivity proximity to the frontier a_{jt} for $j \in [0,1]$ will therefore converge to the steady state $a_j^* = \frac{1}{1+\bar{g}_j}$, where T_j represents the date of convergence.

- ***Case 2:** Countries with moderate levels of financial development and income per capita that are neither exceptionally high nor low will experience conditional convergence toward a lower level of sectoral productivity.*

When financial development and initial income are neither too high nor too low so that $\frac{\eta\bar{g}_j}{\lambda} < \kappa w_0 < \frac{\psi+2\eta}{2\lambda}$, then $f_{jt}(a_{jt}) < \frac{1}{1+\bar{g}_j}$ for all $0 \leq a_{jt} < 1$. Let us define $\hat{a}_{jt}$ such that

$\hat{a}_{jt} = f_{jt}(\hat{a}_{jt}) \quad \forall t \geq 0.$

If $a_{j0} < \hat{a}_{j0}$, the sectoral productivity proximity will increase to reach the fixed point $\hat{a}_j$ of the function $f_{jT_j'}$ given by: $\hat{a}_j = f_{jT_j'}(\hat{a}_j)$, where T_j' is the switching date to unconditional convergence such that $\kappa w_{T_j'} > \frac{\psi+2\eta}{2\lambda}$.

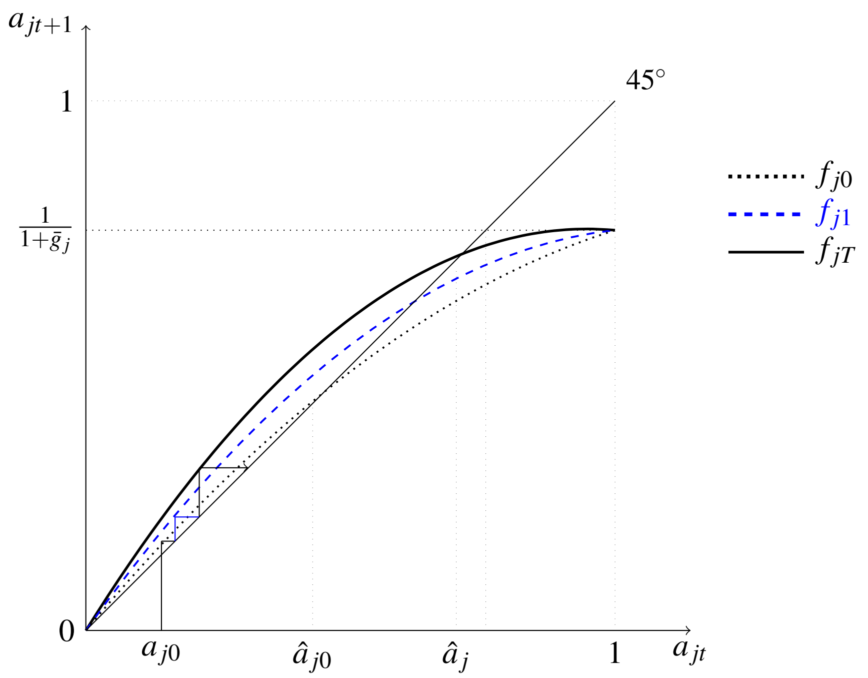


FIGURE XIII: Sectoral productivity gap dynamic when $\frac{\eta \bar{g}_j}{\lambda} < \kappa w_0 < \frac{\psi+2\eta}{2\lambda}$

If $a_{j0} > \hat{a}_{j0}$, then a_{jt} will decrease until a date T_0 from which $a_{jT_0} < \hat{a}_{jT_0}$ and will begin to grow again to converge towards $\hat{a}_j$. The dynamics of the sectoral productivity proximity is illustrated in Figure XIII below for the case where $a_{j0} < \hat{a}_{j0}$. Thus, countries in sector j will, in the long run, conditionally converge to $\hat{a}_j$, which is less than the unconditional sectoral productivity proximity steady state $a_j^* = \frac{1}{1+\bar{g}_j}$.

- ***Case 3:*** *Transient divergence in sectoral productivity occurs in countries with low financial development and low income per capita, or in cases where sectors at the frontier experience exceptionally high productivity growth.*

When the level of financial development and aggregate income are sufficiently low, or when the sector j productivity growth $\bar{g}_j$ is high such that $\kappa w_0 < \frac{\eta \bar{g}_j}{\lambda}$, then a_{jt} will decrease over time. The dynamics of the sectoral productivity gap are illustrated in Figure

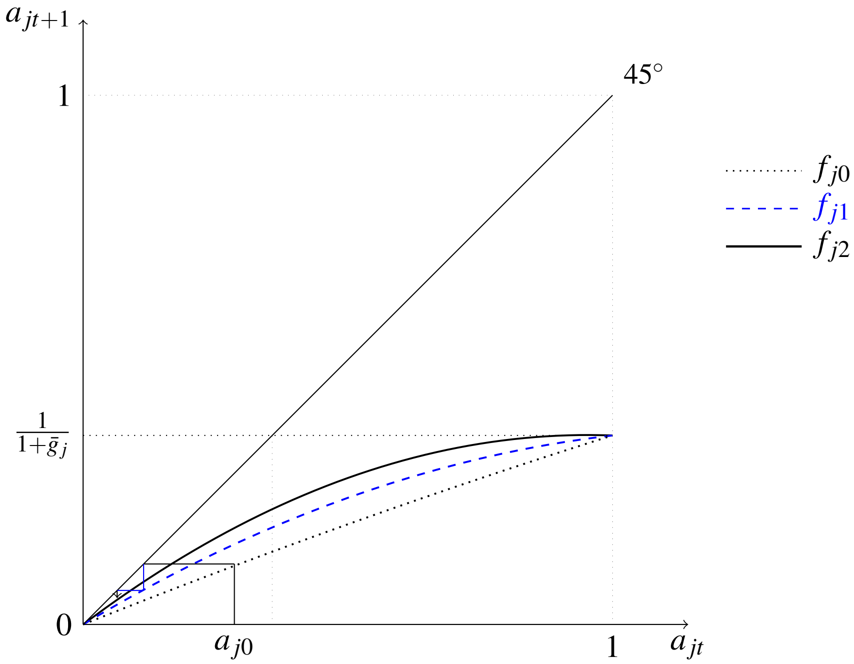


FIGURE XIV: Sectoral productivity gap dynamic when $\kappa w_0 < \frac{\eta \bar{g}_j}{\lambda}$

XIV. Under conditions of low income and low financial development, the sectoral productivity gap will continue to widen until a time τ_j where the level of income reaches a certain threshold such that $\kappa w_{\tau_j} > \frac{\eta \bar{g}_j}{\lambda}$.

To sum up, there are three categories of countries. The first category comprises countries with high income and high financial development, which will experience convergence across various economic sectors. The second category includes emerging countries with a moderate level of financial development and income, which will conditionally converge toward a lower level before eventually moving toward unconditional convergence as income continues to increase over time. The third category comprises countries that initially diverge but ultimately transition into the second category.

G Demonstration of Proposition II.

Proof: Financial development and income level positively impact the speed of convergence across countries because $\bar{a}_t(\kappa) = \frac{\psi+2\eta}{2\lambda\kappa w_t}$, and $f'_{jt}(1)$ decreases with κ (respectively with A_t), while $f'_{jt}(0)$ increases with κ (respectively with A_t). Therefore, countries with higher κ (or higher w_t) will become unconstrained more quickly, as illustrated in Figure XV, where τ is a given date. If $\kappa_1 < \kappa_2$, then $f_{j\tau,\kappa_1} < f_{j\tau,\kappa_2}$ and $\bar{a}_\tau(\kappa_2) < \bar{a}_\tau(\kappa_1)$.

Knowing that the unconstrained date and, therefore, the convergence time T_j^κ is given by:

$$T_j^\kappa = \min\left\{t \geq 0 \quad \text{such that } a_{jt} > \bar{a}_t(\kappa)\right\},$$

we can conclude that $T_j^{\kappa_2} \leq T_j^{\kappa_1}$. Given that the function f_{jt} has the same properties with respect to financial development κ and aggregate productivity A_0, one can similarly prove that countries with higher income will converge faster.

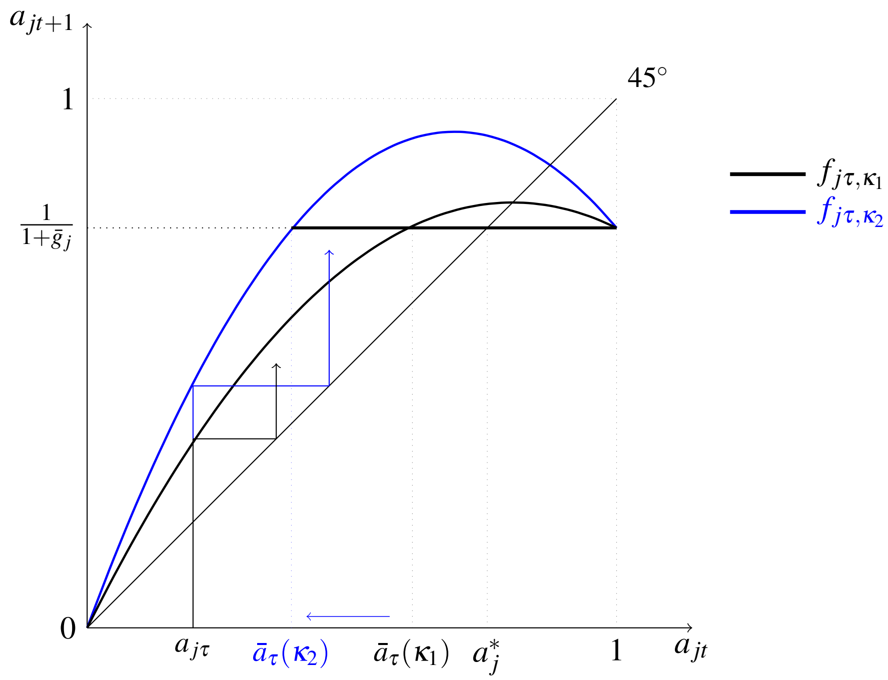


FIGURE XV: Financial development and convergence speed : $\kappa_1 < \kappa_2$

Now, let j_1 and j_2 be two sectors such that $\bar{g}_{j_1} < \bar{g}_{j_2}$. Define B_j as the set of all dates at which the sectoral proximity has reached its steady-state value a_j^*, given by:

$$B_j = \left\{t \geq 0 \quad \text{such that } a_{jt+1} = \frac{1}{1+\bar{g}_j}\right\}.$$

The convergence times T_{j_1} and T_{j_2} for sectors j_1 and j_2 are given by $T_{j_1} = \min\left(B_{j_1}\right)$ and $T_{j_2} = \min\left(B_{j_2}\right)$. To prove that T_{j_1} is less than T_{j_2}, note that since f_{jt} decreases with $\bar{g}_j$, if these two sectors start with the same proximity to the frontier a_0, then $a_{j_1t} > a_{j_2t}$ for all t. I begin by assuming that $\tau \in B_{j_2}$, which implies:

$$a_{j_2,\tau+1} = \frac{1}{1+\bar{g}_{j_2}}.$$

From this assumption, it follows that:

$$a_{j_2,\tau} \geq \bar{a}_\tau.$$

Since we know that $\bar{g}_{j_1} < \bar{g}_{j_2}$, it follows that $a_{j_1,t} > a_{j_2,t}$ for all t, and thus for τ, we have:

$$a_{j_1,\tau} > \bar{a}_\tau.$$

Therefore, at time τ, the value of $a_{j_1,\tau}$ exceeds the threshold $\bar{a}_\tau$, which leads us to conclude that:

$$a_{j_1,\tau+1} = \frac{1}{1+\bar{g}_{j_1}}.$$

Since $a_{j_1,\tau+1} = \dfrac{1}{1+\bar{g}_{j_1}}$, we have $\tau \in B_{j_1}$. Thus, if $\tau \in B_{j_2}$, then $\tau \in B_{j_1}$, which proves that:

$$B_{j_2} \subset B_{j_1}.$$

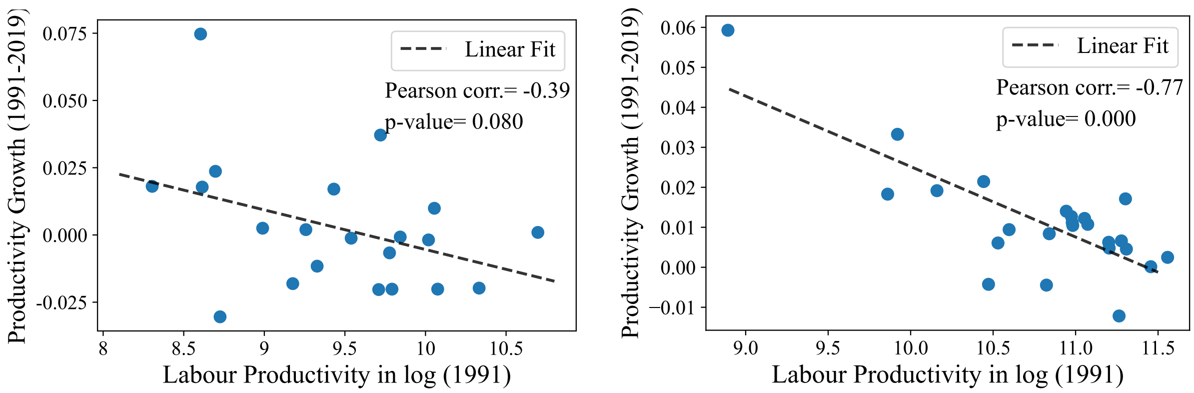
Furthermore, since $B_{j_2} \subset B_{j_1}$, it follows that:

$$\min(B_{j_2}) \geq \min(B_{j_1}).$$

This completes the proof.

H Convergence Across Development Quartiles

Figures XVI-XVIII illustrate the convergence over the period 1991-2019 for the 1st and 4th quartiles of financing capacity levels, measured as the financial development level multiplied by the log of GDP per capita in 1991. The analysis of the graphs indicates that countries in the 4th quartile–those with the highest levels of financial development and GDP per capita–exhibit a much steeper negative slope compared to countries in the 1st quartile, which have lower levels of financing capacity. For the services sector, the Pearson correlation for the 4th



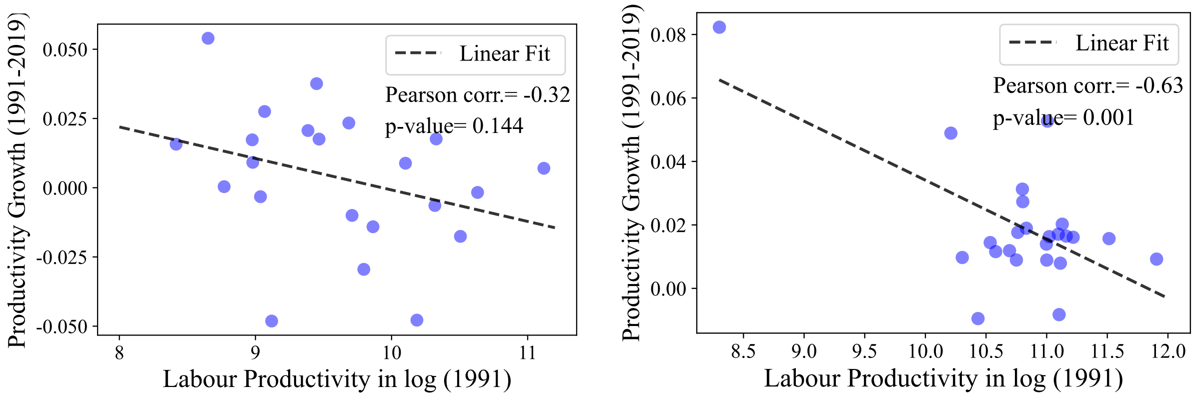
(a) First Quartile of $\kappa \times \log(\text{GDP per capita})$ in 1991 **(b)** Fourth Quartile of $\kappa \times \log(\text{GDP per capita})$ in 1991

FIGURE XVI: Convergence of Services Labour Productivity Across Financing Capacity Quartiles

quartile countries (Figure XVIb) is -0.77 (p-value = 0.000), demonstrating a significant and strong convergence, meaning that more advanced countries in this group are catching up with the productivity frontier at a faster rate. In contrast, the 1st quartile countries (Figure XVIa) exhibit a weaker and statistically insignificant (at the 5% level) correlation of -0.39 (p-value = 0.080), indicating a slower convergence trend.

In the manufacturing sector, the 4th quartile countries (see Figure XVIIb) also display a significant negative correlation of -0.63 (p-value = 0.001), indicating substantial convergence. Meanwhile, the 1st quartile countries (Figure XVIIa) exhibit a much weaker correlation of -0.32 (p-value = 0.144), which is not statistically significant. This comparison highlights that manufacturing convergence is more pronounced among countries with higher levels of financial development and income, likely due to their ability to adopt advanced technologies and improve productivity more efficiently.

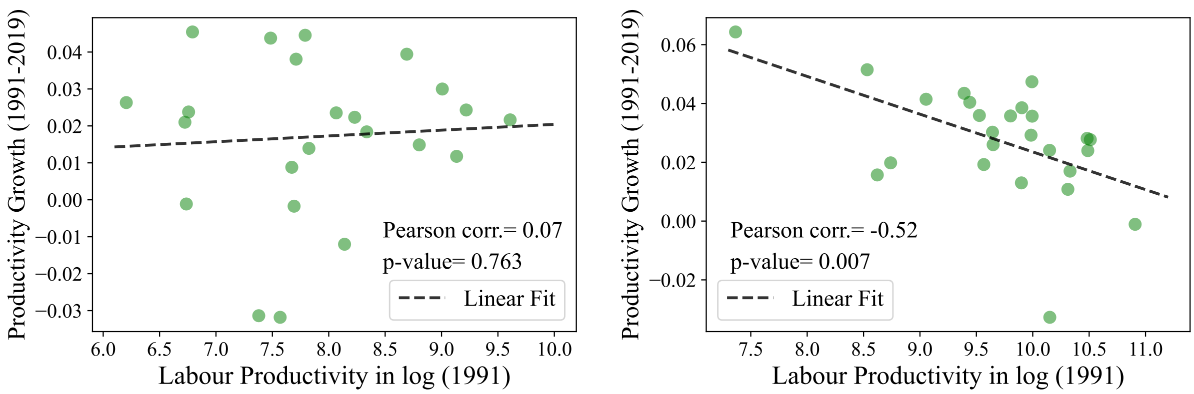
Lastly, in the agriculture sector, the trend is particularly revealing. The correlation for the 4th quartile group (Figure XVIIIb) is -0.52 (p-value = 0.007), indicating a significant convergence among countries with high level of financing capacity, even though the overall analysis suggests no clear convergence in the agricultural sector. In contrast, the 1st quartile countries (Figure XVIIIa) exhibit a nearly flat correlation of 0.07 (p-value = 0.763), indicating a



(a) First Quartile of $\kappa \times \log(\text{GDP per capita})$ in 1991 **(b)** Fourth Quartile of $\kappa \times \log(\text{GDP per capita})$ in 1991

FIGURE XVII: Convergence of Manufacturing Productivity Across Development Quartiles

lack of convergence in the agricultural sector among countries with the lowest level of financing capacity.



(a) First Quartile of $\kappa \times \log(\text{GDP per capita})$ in 1991 **(b)** Fourth Quartile of $\kappa \times \log(\text{GDP per capita})$ in 1991

FIGURE XVIII: Convergence of Agriculture Labour Productivity Across Financing Capacity Quartiles

I Test of significance

To test the significance of the marginal effect of sectoral initial productivity on sectoral productivity growth, I perform the following test:

$H_0 : \beta_j + \gamma_j * \kappa_t A_t = 0 \qquad \text{vs} \qquad H_1 : \beta_j + \gamma_j * \kappa_t A_t \neq 0$

The Student's test statistic is given by:

$$Z = \frac{\hat{\beta}_j + \hat{\gamma}_j * \kappa_t A_t - (\beta_j + \gamma_j * \kappa_t A_t)}{\sqrt{var(\hat{\beta}_j) + (\kappa_t A_t)^2 * var(\hat{\gamma}_j) + 2\kappa_t A_t * cov(\hat{\beta}_j, \hat{\gamma}_j)}}$$

Since the data size is large enough, under the null hypothesis, the Z statistic follows a centered and reduced normal distribution. Thus the null hypothesis is rejected if and only if:

$$(\hat{\beta}_j + \hat{\gamma}_j \kappa_t A_t)^2 > z^2_{\frac{\alpha}{2}} \left[\mathrm{var}(\hat{\beta}_j) + \mathrm{var}(\hat{\gamma}_j)\,(\kappa_t A_t)^2 + 2\mathrm{cov}(\hat{\beta}_j, \hat{\gamma}_j)\,\kappa_t A_t \right] \tag{I.1}$$

where $z_{\alpha/2} = F^{-1}\left(1 - \frac{\alpha}{2}\right)$ and F is the cumulative function of a standard normal distribution and T is the number of observations.

J Zeros of ϕ_j

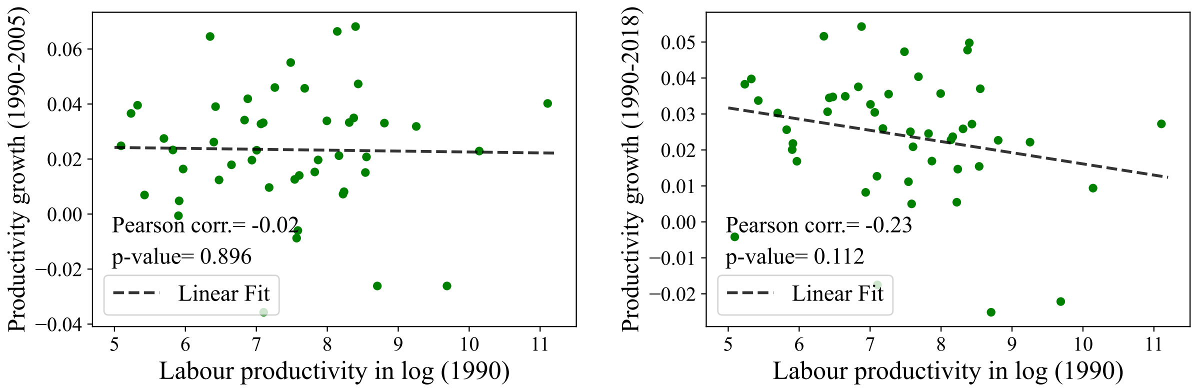
I used Newton-Raphson method to find the zero of the functions ϕ_j. The algorithm is described as below :

1. *Step 1.* Choose an initial estimate x_0 for the root.
2. *Step 2.* Calculate the function value $\phi_j(x_0)$ and its derivative $\phi_j'(x_0)$ at x_0.
3. *Step 3.* Calculate the next estimate $x_1 = x_0 - \dfrac{\phi_j(x_0)}{\phi_j'(x_0)}$.
4. *Step 4.* Repeat steps 2 and 3 until the desired level of accuracy is reached i.e $|x_1 - x_0| \leq 10^{-6}$.

K Sectoral Productivity Convergence in GGDC Data

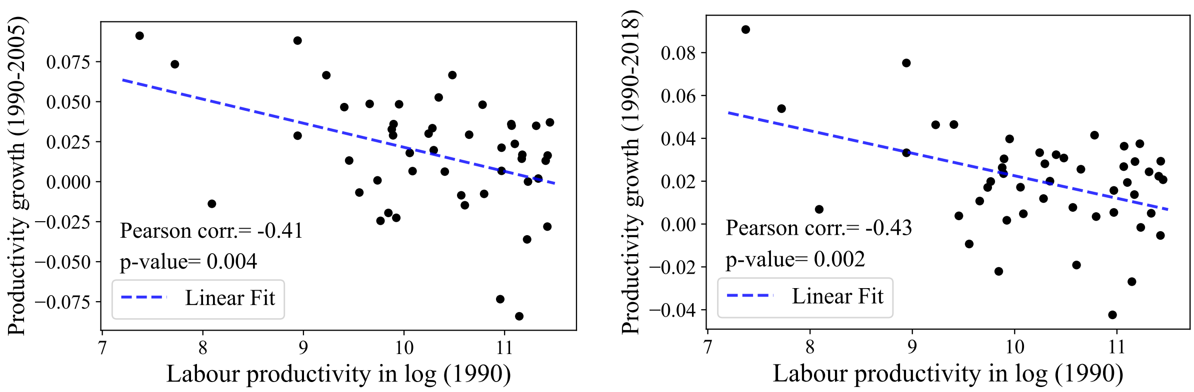
Here I examine the correlations between initial productivity levels in 1990 and average productivity growth from 1990 to 2018 across three sectors–agriculture, manufacturing, and services–using data from the Economic Transformation Database (ETD) of the GGDC. The analysis reveals a weak inverse relationship in agriculture, with a Pearson correlation coefficient of -0.23 and a p-value of 0.112, indicating that this correlation is not statistically significant. In contrast, the manufacturing sector exhibits a moderate negative correlation of -0.43 with a significant p-value of 0.002, suggesting that higher initial productivity levels are associated with lower subsequent growth rates.

Similarly, the services sector shows an even stronger negative correlation of -0.47 and a p-value of 0.001, indicating a statistically significant relationship. When comparing these correlations to those found in the World Development Indicators (WDI) dataset with more countries, we observe that the negative correlations for manufacturing and services in the GGDC data are more pronounced, emphasizing a stronger convergence pattern in these sectors than what was previously identified using WDI data.



(a) 1990–2005 **(b)** 1990–2018

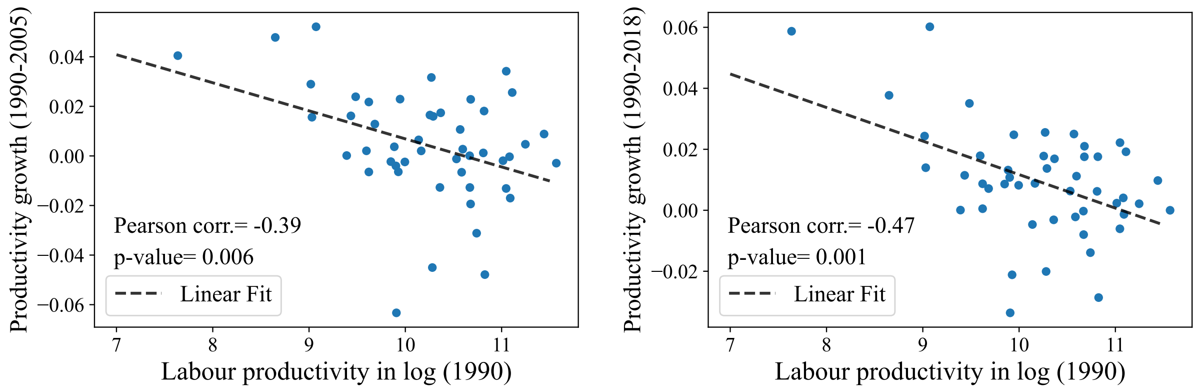
FIGURE XIX: Agriculture Labour Productivity Convergence in GGDC data



(a) 1990–2005 **(b)** 1990–2018

FIGURE XX: Manufacturing Labour Productivity Convergence in GGDC data

Between 1990 and 2005, the correlations between initial productivity levels and subsequent growth exhibit a weaker pattern of convergence compared to the 1990–2018 period. In agriculture, the correlation is almost nonexistent at -0.02 with a p-value of 0.896, showing no relationship between initial productivity and growth. Both manufacturing and services also display weaker correlations during this earlier period, with Pearson coefficients of -0.41 and



(a) 1990–2005 **(b)** 1990–2018

FIGURE XXI: Services Labour Productivity Convergence in GGDC data

-0.39, respectively, though still statistically significant. This indicates that while productivity convergence was already present in these sectors by 2005 in GGDC data, it became more pronounced in the following years.

L Regression Outputs

TABLE VI: Cross-Countries Regression Results Using WDI data and Financial Market Index: 1991–2019

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{j0})$	-0.002	-0.003	-0.007**	-0.010***	-0.007***	-0.010***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
$\hat{\rho}_j : \kappa_0 \log(A_0)$		0.027*		0.043**		0.049***
		(0.015)		(0.019)		(0.014)
$\hat{\gamma}_j : \kappa_0 \log(A_0)$		-0.002		-0.003*		-0.004***
$\times \log(A_{j0})$		(0.002)		(0.002)		(0.001)
Countries	115	107	111	103	105	97
R-squared	0.01	0.11	0.07	0.27	0.10	0.24

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

TABLE VII: Cross-Countries Regression Results Using GGDC data and Financial Institutions Index : 1990–2018

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{j0})$	-0.003	0.004	-0.011**	-0.012*	-0.011***	-0.013***
	(0.002)	(0.003)	(0.004)	(0.007)	(0.003)	(0.004)
$\hat{\rho}_j : \kappa_0 \log(A_0)$		0.021*		0.023		0.042*
		(0.011)		(0.035)		(0.022)
$\hat{\gamma}_j : \kappa_0 \log(A_0)$		-0.003**		-0.002		-0.003*
$\times \log(A_{j0})$		(0.001)		(0.003)		(0.002)
Countries	48	47	48	47	48	47
R-squared	0.05	0.21	0.18	0.29	0.22	0.45

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

TABLE VIII: Cross-Countries Regression Results Using GGDC data and Financial Market Index : 1990-2018

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{j0})$	-0.003	0.004	-0.011**	-0.013**	-0.011***	-0.015***
	(0.002)	(0.003)	(0.004)	(0.006)	(0.003)	(0.004)
$\hat{\rho}_j : \kappa_0 \log(A_0)$		0.022*		0.033		0.045*
		(0.011)		(0.040)		(0.024)
$\hat{\gamma}_j : \kappa_0 \log(A_0)$		-0.003**		-0.002		-0.004
$\times \log(A_{j0})$		(0.001)		(0.004)		(0.002)
Countries	48	47	48	47	48	47
R-squared	0.05	0.23	0.18	0.34	0.22	0.49

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

TABLE IX: 5-Year Panel Regression Results Using WDI data and Financial Market Index1991–2019

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{jt})$	0.001	-0.053***	-0.005*	-0.067***	-0.004**	-0.064***
	(0.001)	(0.009)	(0.002)	(0.012)	(0.001)	(0.011)
$\hat{\rho}_j : \kappa_t \log(A_t)$		0.044***		-0.013		0.059***
		(0.013)		(0.022)		(0.017)
$\hat{\gamma}_j : \kappa_t \log(A_t)$		-0.004***		0.001		-0.005***
$\times \log(A_{jt})$		(0.001)		(0.002)		(0.002)
Country FE	No	Yes	No	Yes	No	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	170	159	166	155	157	146
Obs.	796	744	786	734	769	717
R-squared	0.01	0.48	0.03	0.54	0.06	0.58

All data are aggregated to 5-year time periods spanning 1991-2019.
Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

TABLE X: 5-Year Panel Regression Results Using WDI data and Financial Institutions Index1991–2019

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{jt})$	0.001	-0.045***	-0.005*	-0.065***	-0.004**	-0.059***
	(0.001)	(0.010)	(0.002)	(0.013)	(0.001)	(0.011)
$\hat{\rho}_j : \kappa_t \log(A_t)$		0.073***		-0.010		0.100***
		(0.014)		(0.026)		(0.020)
$\hat{\gamma}_j : \kappa_t \log(A_t)$		-0.007***		0.001		-0.009***
$\times \log(A_{jt})$		(0.001)		(0.002)		(0.002)
Country FE	No	Yes	No	Yes	No	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	170	159	166	155	157	146
Obs.	796	744	786	734	769	717
R-squared	0.01	0.49	0.03	0.54	0.06	0.59

All data are aggregated to 5-year time periods spanning 1991-2019.
Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

TABLE XI: 5-Year Period Panel Regression Results Using GGDC data and Financial Institutions Index

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{jt})$	-0.002	-0.035***	-0.007	-0.060***	-0.007	-0.024
	(0.002)	(0.012)	(0.005)	(0.018)	(0.005)	(0.018)
$\hat{\rho}_j : \kappa_t \log(A_t)$		0.031*		0.040		0.099***
		(0.018)		(0.033)		(0.034)
$\hat{\gamma}_j : \kappa_t \log(A_t)$		-0.005**		-0.004		-0.009***
$\times \log(A_{jt})$		(0.002)		(0.003)		(0.003)
Country FE	No	Yes	No	Yes	No	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	48	48	47	48	48	47
Observations	240	235	240	235	240	235
R-squared	0.01	0.48	0.04	0.54	0.08	0.61

All data are aggregated to 5-year time periods spanning 1990-2018.
Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

TABLE XII: 10-Year Period Panel Regression Results, Dependent Variable: Average Growth in log Productivity

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{jt})$	0.000	-0.050***	-0.006**	-0.071***	-0.004***	-0.042***
	(0.001)	(0.009)	(0.002)	(0.012)	(0.001)	(0.008)
$\hat{\rho}_j : \kappa_t \log(A_t)$		0.081***		-0.023		0.071***
		(0.019)		(0.022)		(0.019)
$\hat{\gamma}_j : \kappa_t \log(A_t)$		-0.007***		0.002		-0.006***
$\times \log(A_{jt})$		(0.002)		(0.002)		(0.002)
Country FE	No	Yes	No	Yes	No	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	170	159	169	158	169	158
Obs.	323	302	319	298	312	291
R-squared	0.01	0.82	0.05	0.81	0.04	0.87

All data are aggregated to 10-year time periods spanning 1991-2019.
Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

TABLE XIII: 10-Year Panel regression results with Financial Institutions Index, Dependent Variable: Average Growth in log Productivity

	Agriculture		**Manufacturing**		**Services**	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{jt})$	0.000	-0.050***	-0.006**	-0.071***	-0.004***	-0.037***
	(0.001)	(0.011)	(0.002)	(0.014)	(0.001)	(0.008)
$\hat{\rho}_j : \kappa_t \log(A_t)$		0.059***		-0.014		0.057***
		(0.013)		(0.019)		(0.015)
$\hat{\gamma}_j : \kappa_t \log(A_t)$		-0.006***		0.001		-0.006***
$\times \log(A_{jt})$		(0.001)		(0.002)		(0.001)
Country FE	No	Yes	No	Yes	No	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	170	159	169	158	169	158
Obs.	323	302	319	298	312	291
R-squared	0.01	0.82	0.05	0.81	0.04	0.88

All data are aggregated to 5-year time periods spanning 1991-2019.
Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

TABLE XIV: 10-Year Panel regression results with Financial Market Index, Dependent Variable: Average Growth in log Productivity

	Agriculture		**Manufacturing**		**Services**	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{jt})$	0.000	-0.053***	-0.006**	-0.070***	-0.004***	-0.046***
	(0.001)	(0.014)	(0.002)	(0.017)	(0.001)	(0.011)
$\hat{\rho}_j : \kappa_t \log(A_t)$		0.063**		-0.011		0.074***
		(0.028)		(0.028)		(0.026)
$\hat{\gamma}_j : \kappa_t \log(A_t)$		-0.006**		0.001		-0.007***
$\times \log(A_{jt})$		(0.003)		(0.002)		(0.002)
Country FE	No	Yes	No	Yes	No	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	170	159	169	158	169	158
Obs.	323	302	319	298	312	291
R-squared	0.01	0.82	0.05	0.81	0.04	0.87

All data are aggregated to 5-year time periods spanning 1991-2019.
Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1