

Financial Development, Technology Adoption, and Sectoral Productivity Convergence*

Komla Avoumatsodo[†]

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Abstract

This paper documents productivity convergence patterns across key economic sectors and introduces an endogenous growth model to explain how financial development and income levels affect sectoral productivity convergence. The model predicts that sectors with higher technological frontier growth, such as agriculture, will experience slower and delayed convergence. It also shows that even sectors initially diverging from the global technological frontier ultimately shift toward a convergence path, driven by rising income per capita. Consequently, aggregate divergence eventually transitions into convergence as lagging sectors catch up. As income rises, financial constraints ease, allowing these sectors to adopt technologies more intensively and accelerate productivity growth. Even when a country diverges from the technological frontier, this process reinforces income growth and creates a positive feedback loop. Financial development strengthens this transition by reducing financing frictions, thereby accelerating the shift from divergence to convergence.

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

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

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[†]University of Northern British Columbia, komla.avoumatsodo@unbc.ca

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 productivity¹. 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 convergence². 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.

Therefore, 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. To this, I consider a multisector growth model with financing 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. Consequently, in the absence of institutional weaknesses—such as weak creditor protections or market imperfections that create credit constraints³—it is expected that countries' technology adoption would align with that of developed countries. This assumption allows the model to generate a correlation between

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

²If 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.

³A 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. \(1998\)](#)).

financial development and technology adoption that vanishes once financial development reaches a time-varying threshold level.

The model demonstrates 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. 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 growth⁴. 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 100 countries from 1991 to 2019 and demonstrates a significant positive relationship between financial development, GDP per capita, and the rate of convergence. The 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 77 years to catch up with France in services, 140 years in manufacturing, and 200 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, 44 years in manufacturing, and 60 years in agriculture.

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 countries⁵ 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.

⁴Even 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.

⁵These 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.

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. This 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 \(2013\)](#), [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 technologies⁶. 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. How-

⁶According to [Comin & Nanda \(2019\)](#), the level of financial development impacts technology adoption unevenly: deeper financial markets speed up the diffusion of capital-intensive technologies—particularly shortly after their invention—but have less influence on the spread of technologies that don't require substantial capital investment.

ever, 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 Facts on Finance, Technology, and Sectoral Convergence

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 : Evidence

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\$⁷, 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 productivity 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 = 0.113), 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.

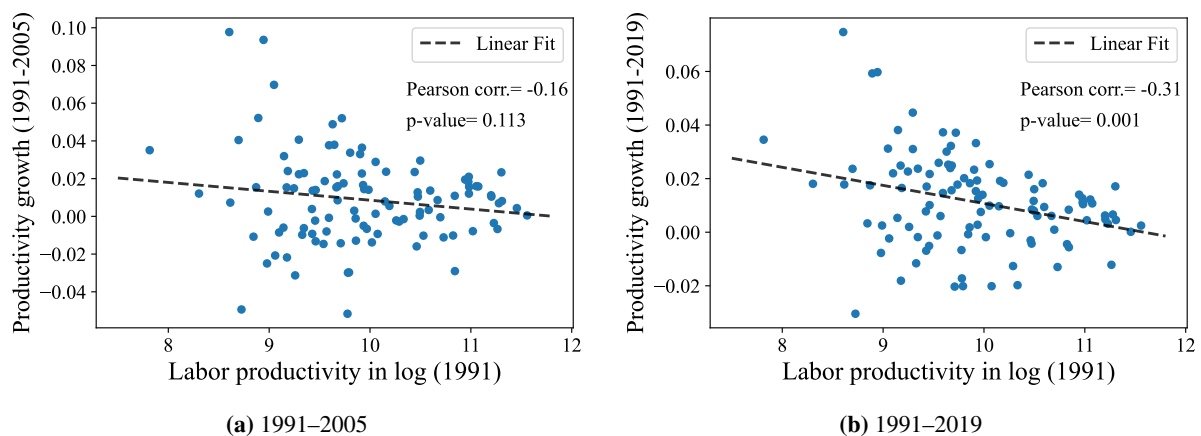


FIGURE I: Services Labor Productivity Convergence by Periods

Note: This figure shows average annual growth in service sector productivity over 1991–2005 and 1991–2019, plotted against initial productivity in 1991 using WDI data.

In the manufacturing sector, the Pearson correlation between initial labor productivity and subsequent growth is -0.26 (p-value = 0.007) 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 = 0.409), 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

⁷I 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.

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.

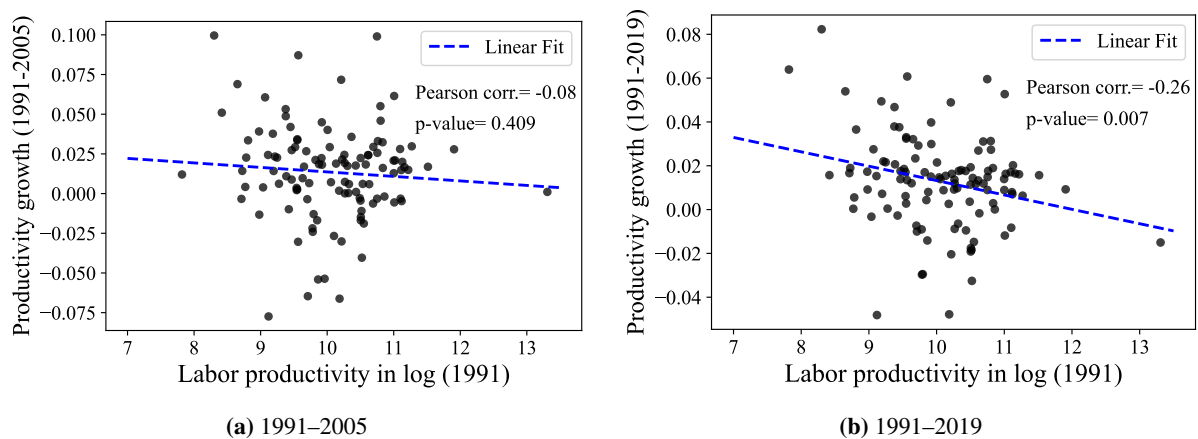


FIGURE II: Manufacturing Labor Productivity Convergence by Periods

Note: This figure shows average annual growth in manufacturing productivity over 1991–2005 and 1991–2019, plotted against initial productivity in 1991 using WDI data.

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 0.05 (p-value = 0.629), reflecting an absence of convergence. By 2019, although the correlation slope has shifted to -0.11 (p-value = 0.262), 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 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 -convergence⁸ 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

⁸ σ -convergence refers to the reduction in the dispersion of productivity levels across countries over time.

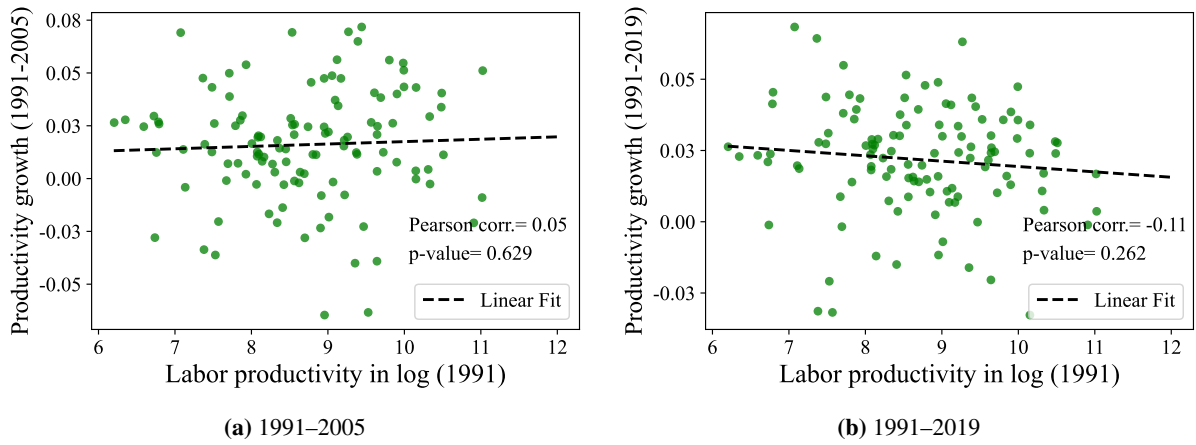


FIGURE III: Agriculture Labor Productivity Convergence by Periods

Note: This figure shows average annual growth in agricultural productivity over 1991–2005 and 1991–2019, plotted against initial productivity in 1991 using WDI data.

1991–2019 and *Panel B* which is limited to countries with no missing data in 1991⁹. 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.

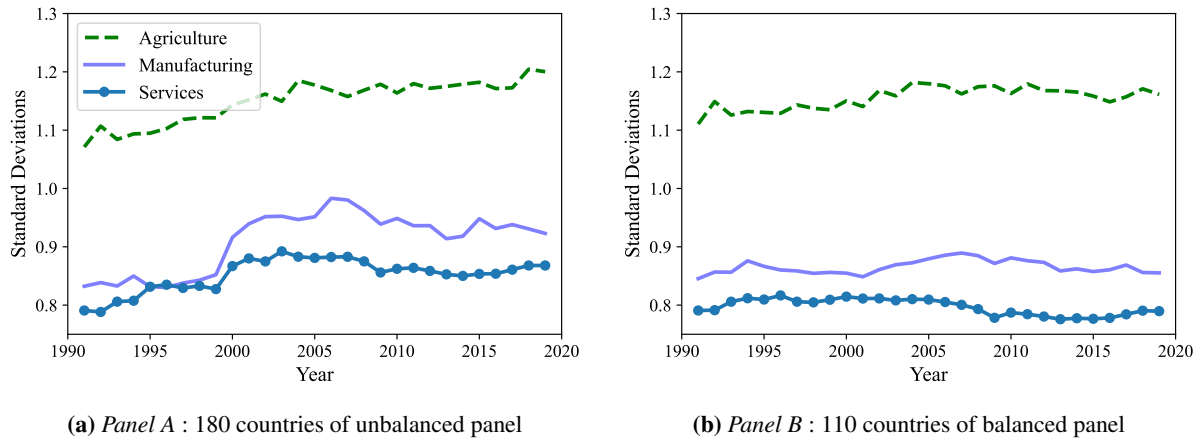


FIGURE IV: σ -Convergence in Agriculture, Manufacturing, and Services

Note: This figure shows σ -convergence in agriculture, manufacturing, and services by plotting the standard deviation of productivity across countries over time, using both an unbalanced panel of 180 countries (*Panel A*) and a balanced panel of 110 countries with no missing data in 1991 (*Panel B*).

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

⁹Countries that have data for earlier years generally have non missing data for late years in World Bank database.

manufacturing. Data encompassing a broader range of developing and 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.

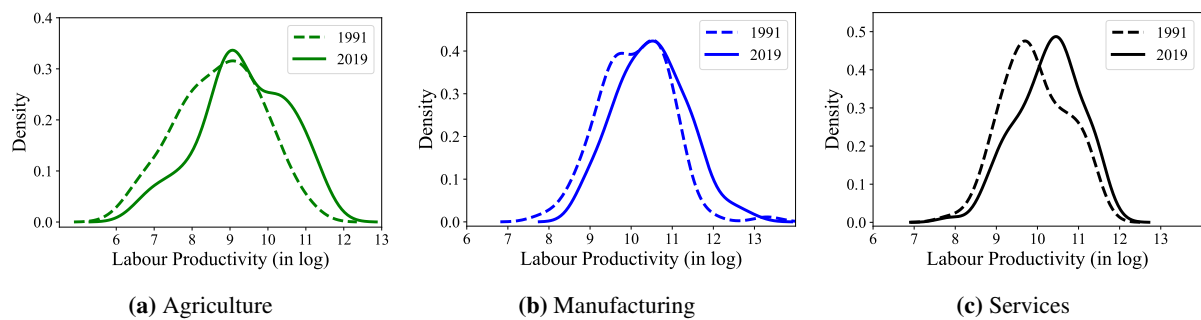


FIGURE V: Sectoral Productivity Distribution Over Time

Note: This figure shows the cross-country distribution of productivity in 1991 (solid lines) and 2019 (dashed lines) for agriculture (green), manufacturing (blue), and services (black). The density is estimated across countries using WDI data. for a panel of 110 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 countries 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.¹⁰

¹⁰For 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.

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 HCCTA¹¹ 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	Manufacturing	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 Index¹² 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 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 discussed in the Data Appendix A.

Figure VI shows the evolution over time of the financial institution and financial development in-

¹¹HCCTA: Historical Cross-Country Technology Adoption

¹²A 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.

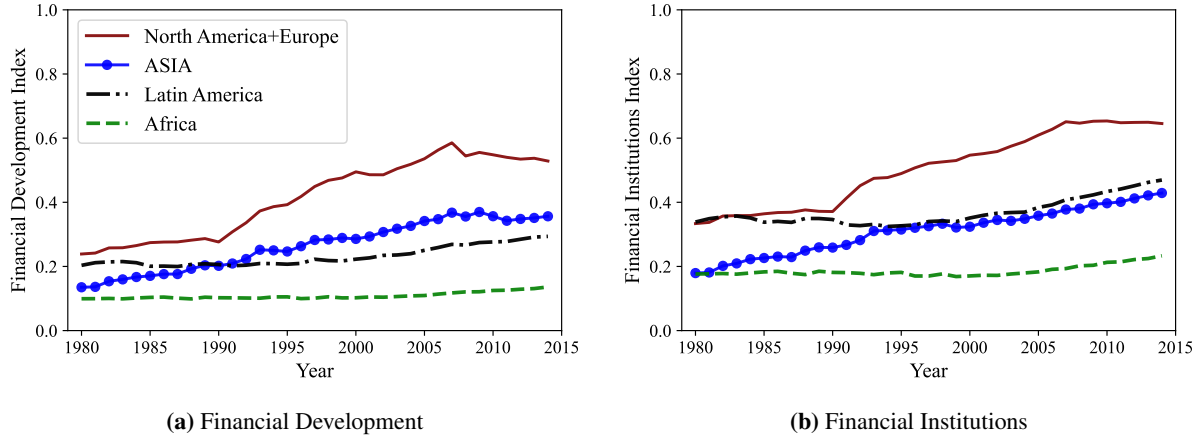


FIGURE VI: Average Regional Levels of Financial Development Indexes Over Time

Note: This figure illustrates the average level of financial development over time across different regions. The data include 40 countries from Asia (blue line with filled circle markers), 33 from Latin America (black dashed dotted line), 43 from North America and Europe combined (solid red line), and 46 from Sub-Saharan Africa (dashed green line).

dices, 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 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. The figure also presents scatter plots for additional technologies, demonstrating a similar pattern; however, the threshold where the correlation loses significance differs among 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

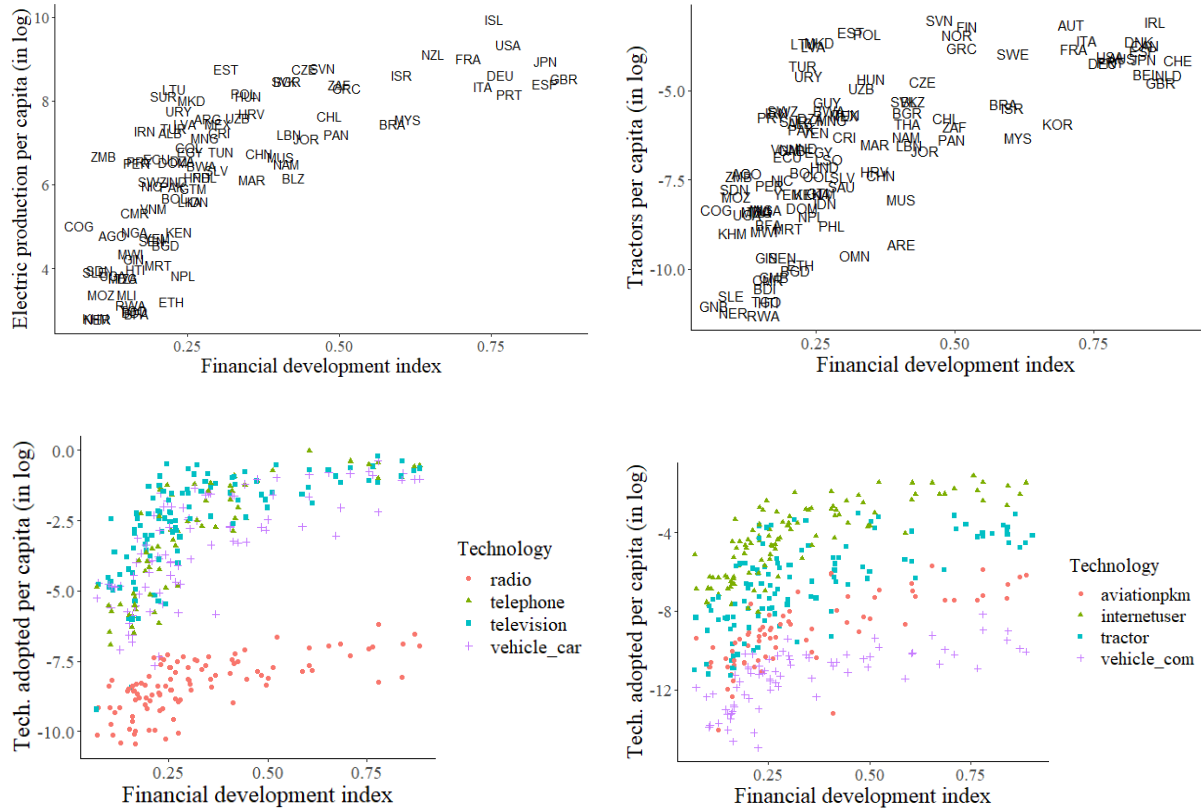


FIGURE VII: Average Levels of Financial Development and Log Technology Adoption per Capita (1980–2003)

Note: This figure shows the relationship between financial development and the adoption of various technologies across countries over the period 1980–2003. A positive correlation is observed initially, which diminishes beyond specific thresholds unique to each technology.

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 builds on the theoretical Schumpeterian growth paradigm developed over the past two decades by [Aghion et al. \(2005\)](#), [Howitt & Mayer-Foulkes \(2005\)](#), and [Acemoglu et al. \(2006\)](#). In this framework, time is discrete, and economic activity occurs in countries that do not trade goods or

factors of production but share technological ideas. The population in each period is normalized to one, $L \equiv 1$, so that aggregate and per capita quantities coincide. Each individual born at time t lives for two periods: in the first period, they supply two units of labor, earning a wage w_t , and in the second period, they supply no labor and act as entrepreneurs. The utility function is linear¹³, given by:

$$U(c_{1t}, c_{2t}) = c_{1t} + \beta c_{2t}, \text{ for all } t \geq 1, \quad (3.1)$$

where c_{1t} is consumption in the first period (when young, at time t), c_{2t} is consumption in the second period (when old, at time $t + 1$), and $\beta \in (0, 1)$ is the discount factor for second-period consumption. Households consume $c_{1t} = (1 - s_t)w_t$ in the first period and save $s_t w_t$. At the end of the first period, they acquire skills and invest z_{jt+1} in a technology adoption project in sector j for next period¹⁴. To finance this investment, they borrow $z_{jt+1} - (1 + r_t)s_t w_t$ at interest rate r_{t+1} . If technology adoption is successful, they earn monopoly profits π_{jt+1} and repay $(1 + r_{t+1})(z_{jt+1} - s_t w_t)$ at the end of the second period such that : $c_{2t} = \int_0^1 \{ \pi_{jt+1} - (1 + r_{t+1})[z_{jt+1} - (1 + r_t)s_t w_t] \} dj$.

Initial Setup. The economy begins in period 1 with two cohorts: adults born in period 0 and the young generation born in period 1. The adults from period 0 act as entrepreneurs in period 1. They borrow from the young in order to maximize their profits $\{\pi_{j1}\}_{j \in [0,1]}$, and subsequently, their consumption $c_{2,0}$, given the initial conditions $\{w_0, r_0, s_0, A_{j0}\}_{j \in [0,1]}$.

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:

$$Y_t = L_t^{1-\alpha} \int_0^1 A_{jt}^{1-\alpha} x_{jt}^\alpha dj, \quad (3.2)$$

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:

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

¹³Following [Aghion et al. \(2005\)](#), I assume individuals have linear utility, implying indifference regarding the location of investment irrespective of a country's technological or financial development. All investment is assumed to be financed domestically. Nonetheless, if the discount factor β were identical across countries, the model could be extended to incorporate perfect capital mobility without altering the main results. Moreover, adopting a strictly concave utility function would allow for an analysis of capital flows from less financially developed countries toward more financially developed ones.

¹⁴Technology 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.

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

$$x_{jt} = \alpha^{\frac{1}{1-\alpha}} p_{jt}^{-\frac{1}{1-\alpha}} A_{jt} L_t. \quad (3.3)$$

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 innovation¹⁵. The monopolist maximizes profit as follows:

$$\begin{aligned} \max_{\{p_{jt}\}} & p_{jt} x_{jt} - x_{jt} \\ \text{subject to} & \quad p_{jt} = \alpha x_{jt}^{\alpha-1} A_{jt}^{1-\alpha} L_t^{1-\alpha}. \end{aligned} \quad (3.4)$$

Thus, the equilibrium¹⁶ profit of the intermediate goods producer in sector j is given by:

$$\pi_{jt} = \pi A_{jt} L_t, \quad (3.5)$$

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:

$$w_t = \omega A_t, \quad (3.6)$$

$$GDP_t = (1 + \alpha) w_t L_t, \quad (3.7)$$

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 $t + 1$, the investment made by an innovator for technology adoption is denoted as z_{jt+1} . 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. Due to imperfections in the financial system, there are constraints on the total amount that can be borrowed for technology adoption projects, which limits the entrepreneur to invest no more than a finite multiple of their accumulated wealth:

$$z_{jt+1} \leq \kappa_t w_t, \quad (3.8)$$

A highly developed financial system, indicated by a higher κ_t , is closely linked to effective governance and law enforcement which enhance creditor protection and build confidence in financial transactions as shown by [Aghion et al. \(2005\)](#). Better legal frameworks ensure fair contract enforcement and encourage

¹⁵The innovator is not forced into price competition.

¹⁶Further details on the calculations are provided in Appendix B.

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 $\kappa_t w_t$. 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 presence of credit constraints 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:

$$A_{jt+1} = \theta_{jt+1} \bar{A}_{jt} + (1 - \theta_{jt+1}) A_{jt}, \quad (3.9)$$

where \bar{A}_{jt} represents the frontier productivity¹⁷ in the same sector at time t , and $\theta_{jt+1} \in [0, 1]$ denotes the intensity¹⁸ with which new technologies are utilized in the host country at period $t + 1$. 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+1} allocated by entrepreneurs. Consequently, the cost of an innovation is given by:

$$\frac{\lambda_{jt} z_{jt+1}}{\bar{A}_{jt}} = F(\theta_{jt+1}), \quad (3.10)$$

¹⁷I assume that the frontier in sector j expands at a constant growth rate \bar{g}_j due to innovation.

¹⁸ $\theta_{jt+1} = 0$ 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.

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

$$F(\theta_{jt}) = \eta\theta_{jt} + \frac{\psi}{2}\theta_{jt}^2, \quad (3.11)$$

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 \(2005\)](#), 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 spillover¹⁹:

$$\lambda_{jt} = \lambda A_{jt}. \quad (3.12)$$

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

$$z_{jt+1} = \frac{\frac{\psi}{2}\theta_{jt+1}^2 + \eta\theta_{jt+1}}{\lambda a_{jt}}. \quad (3.13)$$

In equilibrium, the innovator chooses θ_{jt+1} (or z_{jt+1}) in order to maximize the expected net payoff given by (3.14):

$$\begin{aligned} \max_{0 \leq \theta_{jt+1} \leq 1} \quad & \beta\pi [\theta_{jt+1}\bar{A}_{jt} + (1 - \theta_{jt+1})A_{jt}] - z_{jt+1} \\ \text{subject to } & z_{jt+1} \leq \kappa_t w_t \text{ and equation (3.13).} \end{aligned} \quad (3.14)$$

¹⁹This 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.

3.4 Equilibrium

The equilibrium in this economy consists of a sequence of aggregate allocations $\{c_{1t}, c_{2t}, s_t, Y_t\}_{t \geq 1}$, aggregate prices $\{r_t, w_t\}_{t \geq 1}$, and pricing, production, and investment decisions for intermediate monopolists $\{p_{jt}, x_{jt}, z_{jt}, \theta_{jt}, a_{jt}\}_{j \in [0,1], t \geq 1}$, as well as the allocation $c_{2,0}$ for the initial adult generation, such that households choose consumption and savings to maximize lifetime utility; final good producers behave competitively and maximize profits given prices; entrepreneurs and intermediate-good monopolists choose investment levels subject to financial constraints and set prices to maximize profits; the asset market and the final goods market clear in every period :

- Labor Market: $L_t = 1$,
- Goods Market: $Y_t = c_{1t} + c_{2t-1} + \int_0^1 (x_{jt} + z_{jt}) dj$,
- Credit Market: $s_{t+1}w_{t+1} = \int_0^1 [z_{jt+1} - (1 + r_t)s_t w_t] dj$,

Assuming that, under perfect credit markets, each entrepreneur can borrow an unlimited amount at the interest rate, all sectors within the same country would have the capacity to utilize technologies with an intensity comparable to that of the global frontier, thereby fully exploiting 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+1} , 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. Under credit constraints, the problem (3.14) of the innovator can be rewritten as follows:

$$\begin{aligned} \max_{0 \leq \theta_{jt+1} \leq 1} \quad & \beta \pi [\theta_{jt+1} \bar{A}_{jt} + (1 - \theta_{jt+1}) A_{jt}] - (\lambda a_{jt})^{-1} \left(\frac{\psi}{2} \theta_{jt+1}^2 + \eta \theta_{jt+1} \right) \\ \text{s.t. } \quad & \theta_{jt+1} \leq -\frac{\eta}{\psi} + \left[\left(\frac{\eta}{\psi} \right)^2 + \frac{2\lambda \kappa_t w_t a_{jt}}{\psi} \right]^{\frac{1}{2}} \end{aligned} \quad (3.15)$$

An equilibrium exists and is unique due to the strict convexity of the cost function $F(\theta_{jt+1})$, which ensures that the entrepreneur's objective is strictly concave. In equilibrium, the intensity of use of adopted technologies is given by :

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

where $\bar{a}_t = \frac{\psi+2\eta}{2\lambda \kappa_t w_t}$ is decreasing in κ_t and w_t . 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 XII in Appendix C 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 C. ■

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:

$$\underline{\kappa}_{jt} = \frac{2\eta + \psi}{2\lambda w_t a_{jt}}, \quad (3.16)$$

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 $a_{jt} \leq \bar{a}_t$) of the intensity of technology use first with

respect to financial development, and then with respect to sectoral productivity proximity to the frontier:

$$\frac{\partial^2 \theta_{jt+1}^*}{\partial a_{jt} \partial \kappa_t} = \frac{\partial^2 \theta_{jt+1}^*}{\partial \kappa_t \partial a_{jt}} = \frac{\lambda w_t}{\psi} \left[\left(\frac{\eta}{\psi} \right)^2 + \frac{\lambda \kappa_t w_t a_{jt}}{\psi} \right] \left[\left(\frac{\eta}{\psi} \right)^2 + \frac{2\lambda \kappa_t w_t a_{jt}}{\psi} \right]^{-\frac{3}{2}} > 0. \quad (3.17)$$

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 use²⁰. 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 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 Financing Capacity and the Evolution of Productivity Gaps

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:

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

²⁰The positive interaction between financial development and sectoral proximity is represented in Figure [XII](#) by the dashed red lines.

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:

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

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 :

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

$$\quad (4.3b)$$

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 concave²¹ 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} , $t = 0, 1, 2, \dots$, on the interval $[0, 1]$. If $f'_{jt}(0) < 1$ then $f'_{jt}(a_{jt})$ will be less than 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:

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

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) :

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

Since $\frac{\psi + 2\eta}{2\lambda} > \frac{\eta \bar{g}_j}{\lambda}$ ²² 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

²¹ See Appendix D for calculations of the first and second derivative functions of f_{jt} .

²² $\frac{\eta \bar{g}_j}{\lambda} / \frac{\psi + 2\eta}{2\lambda} = \frac{2\eta \bar{g}_j}{2\eta + \psi}$. As $2\eta \bar{g}_j \leq 2\eta$ and $\psi > 0$ then $\frac{\eta \bar{g}_j}{\lambda} / \frac{\psi + 2\eta}{2\lambda} < 1$.

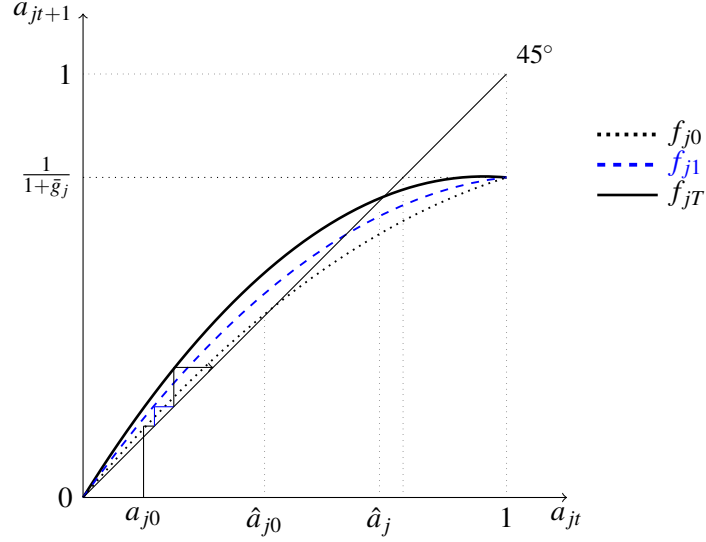


FIGURE IX: Sectoral productivity gap dynamic when $\frac{\eta \bar{g}_j}{\lambda} < \kappa_0 w_0 < \frac{\psi+2\eta}{2\lambda}$

Note: This figure shows the evolution of the sectoral productivity proximity in a scenario where initial financial development and income are at an intermediate level (i.e., $\frac{\eta \bar{g}_j}{\lambda} < \kappa_0 w_0 < \frac{\psi+2\eta}{2\lambda}$). In this case, the economy converges gradually, with the productivity gap in sector j narrowing over time but not unconditionally.

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

When the level of initial financial development and aggregate income are sufficiently low, or when the

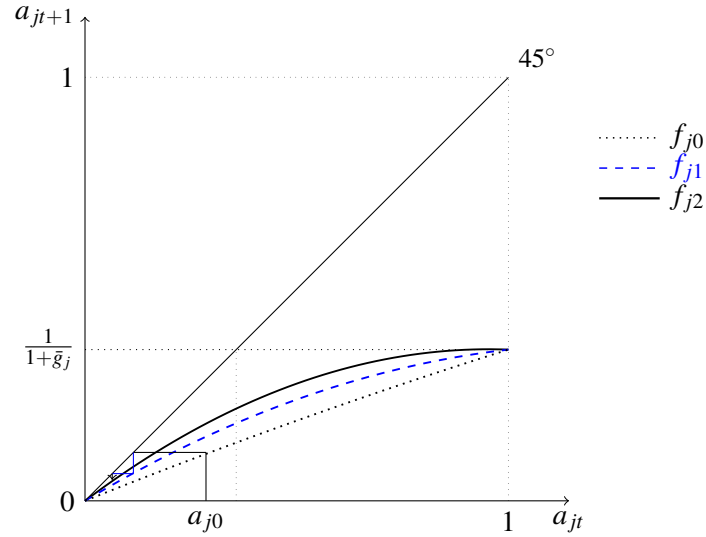


FIGURE X: Sectoral productivity gap dynamic when $\kappa_0 w_0 < \frac{\eta \bar{g}_j}{\lambda}$

Note: This figure shows the evolution of the sectoral productivity proximity when initial financial development and aggregate income are low, or when productivity growth in sector j is sufficiently high such that $\kappa_0 w_0 < \frac{\eta \bar{g}_j}{\lambda}$. In this case, the relative productivity a_{jt} declines over time, and the productivity gap widens.

sector j productivity growth \bar{g}_j is high such that $\kappa_0 w_0 < \frac{\eta \bar{g}_j}{\lambda}$, then a_{jt} will decrease over time. The dynamics of the sectoral productivity gap is illustrated in Figure X. 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 $\kappa_{\tau_j} w_{\tau_j} > \frac{\eta \bar{g}_j}{\lambda}$.

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 $\kappa_t w_t$ 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 capita²³. This results in an increasing financing capacity over time, implying that there exists a time from which $\kappa_t w_t$ surpasses $\lambda^{-1} \eta \bar{g}_j$. Consequently, the sector can experience faster growth 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 $\kappa_t w_t$ 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 $\bar{a}_{T_j}(\kappa_t) = (\psi + 2\eta)/\lambda \kappa_t w_{T_j}$. At this juncture, the financing capacity surpasses the financing need²⁴ $\bar{z}_{jt} = (2\eta + \psi)/2\lambda a_{jt}$, 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 demonstrated in Proposition II below, countries with higher levels of financial development converge more rapidly than those with lower levels of financial development. Similarly, sectors that grow more slowly at the frontier (i.e., with lower \bar{g}_j) will experience faster convergence. This implies that the time required for a country to catch up with the frontier in sector j increases with \bar{g}_j .

While it may appear intuitive that faster frontier technology progress in a particular sector could lead

²³As 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.

²⁴The 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, $\kappa_t w_t$, also increases over time, there exists a time T_j such that $\bar{z}_{jt} = \kappa_t w_t$. Beyond this time T_j , the constraint is lifted.

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, would experience higher growth rates in developing countries.

However, two key challenges constrain this catch-up potential. First, even if the agricultural sector achieves higher growth in developing countries, its growth relative to the frontier remains lower compared to that of 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 E. ■

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

$$g_{jt} = \theta_{jt}^* \left(a_{jt-1}^{-1} - 1 \right). \quad (4.4)$$

The sectoral productivity growth, g_{jt} , varies across sectors due to differences in both the proximity to the technological frontier a_{jt-1} and the intensity of technology adoption θ_{jt}^* . In the Equation (4.4), we observe two primary factors at play. The first is the Catch-up Effect: a larger technology gap (i.e., a lower a_{jt-1}) implies a greater potential for growth. The second key factor is the technology adoption intensity, θ_{jt}^* , which increases with financing capacity and decreases with the sector's technology gap. This implies that in sectors where the technology gap is substantial, the catch-up effect may be dampened by the inability to adopt technologies effectively, making the second channel of financing constraints a crucial determinant for productivity growth.

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 :

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

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 $a_{t-1}^{-1} - 1$ as follows:

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

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

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_t 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:

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

where $\underline{\kappa}_{jt} := (2\eta + \psi)/(2\lambda w_t a_{jt})$ represents the sector j -specific threshold level of financial development below which finance affects technology adoption, as defined by Equation (3.16). 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_t 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 initial financing capacity.²⁵ 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)²⁶ 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 productivity²⁷ 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 US\$ into sectoral productivities in constant 2015 international US\$ as follows:

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

$$A_{jt}^{PPP_{2015}} = PPP_{2015} \times A_{jt}^{\text{constant \$}}. \quad (5.2)$$

²⁵Financing capacity is captured by the interaction between the log of initial GDP per capita and initial financial development index.

²⁶WDI : World Development Indicators from the World Bank Group.

²⁷I follow the same approach as Herrendorf et al. (2022) and Rodrik (2013), where sectoral productivity refers to sectoral labor productivity, defined as sectoral value added per worker.

κ_t is calibrated to the country's financial development index provided by IMF for several countries between 1980 and 2014²⁸.

Figures XIV-XVI in Appendix F 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 Cross-Country Analysis

In this subsection, I examine β -convergence in agriculture, manufacturing, and services for 99 countries using the World Development Indicators (WDI) data. Following the standard approach in the literature, I regress the average annual growth in log productivity²⁹, g_{j0}^c , for each sector $j \in \{a, m, s\}$ on the initial level of log productivity for country $c = 1, 2, \dots, N$ as follows:

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

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

$$\frac{\partial g_{j0}^c}{\partial \log(A_{j0}^c)} = \beta_j + \gamma_j \times \kappa_0^c \log(A_0^c). \quad (5.4)$$

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_t^c or income $\log(A_t^c)$. 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 :

$$H_0 : \frac{\partial g_{j0}^c}{\partial \log(A_{j0}^c)} = 0 \quad \text{vs.} \quad H_1 : \frac{\partial g_{j0}^c}{\partial \log(A_{j0}^c)} \neq 0. \quad (5.5)$$

²⁸More details on financial data are presented in Appendix A

²⁹The average growth rate, g_{j0}^c , from date 0 to T is defined as:

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

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 $\phi_j(x) = 0$.³⁰

Convergence Speed. Cross-country analysis offers the advantage of allowing a straightforward mathematical derivation of convergence speeds across sectors and countries. To examine how initial GDP per capita and the initial level of financial development influence the speed of sectoral productivity convergence, I compute the difference between the average annual growth rate of country c and the technological, based on Equation (5.3). From this difference, I derive the sector-specific convergence speed for country c in sector j , denoted by $S_j^c := 1/T_j^c$ ³¹ as follow:

$$S_j^c = -\hat{\beta}_j - \hat{\rho}_j \frac{[\bar{\kappa}_0 \log(\bar{A}_0) - \kappa_0^c \log(A_0^c)]}{\log(\bar{A}_{j0}) - \log(A_{j0}^c)} - \hat{\gamma}_j \frac{[\bar{\kappa}_0 \log(\bar{A}_0) \log(\bar{A}_{j0}) - \kappa_0^c \log(A_0^c) \log(A_{j0}^c)]}{\log(\bar{A}_{j0}) - \log(A_{j0}^c)} \quad (5.7)$$

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:

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

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.

Empirical Results on Beta-Convergence. For each sector $j \in \{a, m, s\}$, I estimate cross-country regression models both with and without including human capital index level³². In the theoretical model, human capital — that is, the entrepreneur's knowledge in the sector of technology adoption — reduces the training and adaptation costs of new technologies, such that the effect of human capital on technology adoption operates through financing capacity. However, I include human capital in the regression to control for its direct effects on productivity growth that are independent of financing constraints. In all estimations, I employ robust standard errors to address potential heteroscedasticity.

³⁰Demonstration is given in Appendix G. ϕ_j is a real function defined on the interval $[0, +\infty[$ by :

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

³¹ T_j^c 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 $\log(\bar{A}_{j0})$.

³²Human capital index data comes from Penn World Table version 10.0.

Table II presents the results of the cross-sectional regressions. For the overall period 1991–2019, the results show that the coefficient $\hat{\rho}_j$ associated with the interaction between financial development and GDP per capita is positive and statistically significant across countries. This indicates that higher

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)
$\hat{\beta}_j : \log(A_{j0})$	-0.005* (0.003)	-0.004 (0.002)	-0.011*** (0.003)	-0.012*** (0.003)	-0.010** (0.004)	-0.012** (0.004)
$\hat{\rho}_j : \kappa_0 \log(A_0)$	0.030** (0.012)	0.028** (0.011)	0.034* (0.019)	0.043** (0.018)	0.046** (0.020)	0.046** (0.018)
$\hat{\gamma}_j : \kappa_0 \log(A_0)$ $\times \log(A_{j0})$	-0.003** (0.001)	-0.003** (0.001)	-0.003 (0.002)	-0.003** (0.002)	-0.004** (0.002)	-0.004** (0.002)
Human capital		0.008*** (0.003)		0.008* (0.004)		0.011** (0.005)
Countries	99	87	99	87	99	87
R-squared	0.18	0.19	0.37	0.43	0.28	0.35

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

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 for both agriculture and manufacturing, and -0.004 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.

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 (1), (3), and (5), 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 estimates³³ suggest that it will take India approximately 77 years to catch up with France in the services sector, 140 years in manufacturing, and 200 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 time needed to catch up with France would shorten to roughly 37 years in services, 44 years in manufacturing, and 60 years in agriculture. These estimates indicate that a country's initial levels of financial development and income

³³I 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.

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.

5.3 Panel Regressions

In this subsection, I extend the analysis by first examining the relationship in a panel data framework, which allows for controlling unobserved heterogeneity and capturing temporal dynamics that may affect sectoral productivity growth. I then assess the robustness of the results by employing an alternative data source for sectoral productivity.

Panel data models allow for controlling country-specific unobserved heterogeneity and capturing time variation, thereby reducing potential biases arising from omitted variables. Specifically, I estimate the following equation for each sector using data from the WDI dataset:

$$g_{jt}^c = \alpha_j + \beta_j \log(A_{jt}^c) + \rho_j \kappa_t^c \log(A_t^c) + \gamma_j \log(A_{jt}) \times \kappa_t^c \log(A_t^c) + D_j^c + D_{jt} + \varepsilon_{jt}^c, \quad (5.9)$$

where g_{jt}^c represents the average annual growth rate³⁴ 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 the panel regression equations with and without country fixed effects. Standard errors are clustered at the country level in all specifications. The dependent variable is the average growth rate of the 5 years average of log productivity, and the explanatory variables are 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. I also include the five-year lagged average of the human capital index in the estimations. Table III presents the regression results for the 5-year panel estimations covering 134 to 161 countries from the 1991–2019 period, using data from the WDI dataset. The estimated coefficients of conditional convergence in the panel estimation are significant for all three sectors, with higher magnitudes compared to the cross-country estimations. Additionally, the values of $\hat{\rho}_j$ (resp. $\hat{\gamma}_j$) are positive (resp. negative) and significant for agriculture and services, and their magnitudes are

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

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

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{jt})$	-0.047*** (0.010)	-0.046*** (0.010)	-0.069*** (0.013)	-0.060*** (0.014)	-0.060*** (0.011)	-0.062*** (0.012)
$\hat{\rho}_j : \kappa_t \log(A_t)$	0.070*** (0.014)	0.069*** (0.016)	-0.015 (0.026)	-0.006 (0.027)	0.099*** (0.020)	0.106*** (0.020)
$\hat{\gamma}_j : \kappa_t \log(A_t)$ $\times \log(A_{jt})$	-0.006*** (0.001)	-0.006*** (0.001)	0.001 (0.002)	0.000 (0.002)	-0.009*** (0.002)	-0.010*** (0.002)
Human capital		0.041 (0.027)		-0.003 (0.021)		0.005 (0.013)
Country FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓
Countries	161	134	161	134	161	134
Observations	728	621	728	621	728	621
R-squared	0.52	0.52	0.53	0.52	0.60	0.64

All data are aggregated to 5-year time periods spanning 1991-2019.

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

also higher than those observed in the cross-country estimates. This suggests that short-term variations in financing capacity play a more prominent role in explaining convergence dynamics in agriculture and services when using panel data. In contrast, the values of $\hat{\rho}_m$ and $\hat{\gamma}_m$ for manufacturing in the panel estimations are not significant. However, the value of $\hat{\beta}_j$ is higher for manufacturing compared to agriculture in the panel estimations.

Alternative Data. I now 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 sub-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:

$$VA_Q_{jt}^{2017} = VA_Q_{jt}^{2015} \times \frac{VA_{j2017}}{VA_Q_{j2017}^{2015}}. \quad (5.10)$$

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:

$$A_{jt}^{PPP_{2017}} = \frac{VA_{jt}^{2017}}{EMP_{jt} \times PPP_{2017}}. \quad (5.11)$$

I then run the panel regressions for agriculture, manufacturing, and services³⁵ from Equation (5.9). Table IV presents the results based on GGDC data. The estimates using GGDC data across 48 countries reveal that the conditional coefficients for $\hat{\beta}_j$ are negative and significant, $\hat{\rho}_j$ is positive and significant for the services sector, and $\hat{\gamma}_j$ is negative and significant for both the agriculture and services sectors.

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)
$\hat{\beta}_j : \log(A_{jt})$	-0.041*** (0.012)	-0.041*** (0.012)	-0.066*** (0.018)	-0.066*** (0.018)	-0.031* (0.017)	-0.031* (0.017)
$\hat{\rho}_j : \kappa_t \log(A_t)$	0.027 (0.020)	0.028 (0.021)	0.023 (0.045)	0.019 (0.043)	0.063* (0.033)	0.061* (0.032)
$\hat{\gamma}_j : \kappa_t \log(A_t)$ $\times \log(A_{jt})$	-0.004* (0.002)	-0.004* (0.002)	-0.002 (0.004)	-0.002 (0.004)	-0.006* (0.003)	-0.006* (0.003)
Human capital		-0.011 (0.044)		-0.062 (0.043)		-0.018 (0.019)
Country FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓
Countries	48	48	48	48	48	48
Observations	235	235	235	235	235	235
R-squared	0.46	0.46	0.53	0.54	0.60	0.60

All data are aggregated to 5-year time periods spanning 1990-2018.

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

I also estimate the panel model using 10-year intervals and with the financial institutions index and the financial markets index (see results³⁶ in Appendix J), instead of the financial development index. Table VIII presents the results of Equation (5.9), 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.

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

³⁵Employment and value added in 2017 PPP are aggregated into three sectors (see Appendix A.2).

³⁶Estimations using different financial indicators remain similar to those obtained with the financial development index.

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).

The scatter plot in Figure [XI](#) shows the distribution of data points for different observations in 1991 and 2005. Each point represents a country, defined by its combination of κ_0 (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 [XI](#), the movement of countries along the financial development and GDP per capita spectrum highlights significant shifts that can influence the dynamics of convergence.

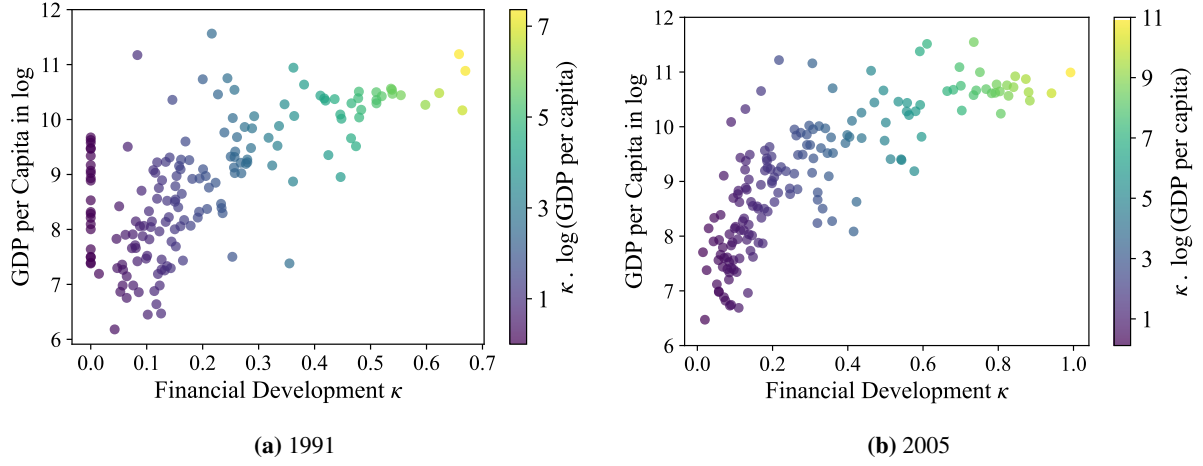


FIGURE XI: Countries' Financial Development and GDP per capita Distribution Over Time

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:

$$\begin{aligned} & \max_{\{x_{jt}\}} p_{jt}x_{jt} - x_{jt} \\ & \text{subject to} \quad p_{jt} = \alpha x_{jt}^{\alpha-1} A_{jt}^{1-\alpha} L_t^{1-\alpha} \end{aligned}$$

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:

$$p_{jt} = \alpha^{-1} \quad (\text{B.2})$$

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:

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

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 (3.2):

$$Y_t = \alpha^{\frac{2\alpha}{1-\alpha}} A_t L_t \quad (\text{B.4})$$

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

$$w_t = \omega A_t \quad (\text{B.5})$$

$$GDP_t = \zeta A_t L_t \quad (\text{B.6})$$

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 Proof for Proposition I

Proof. Let's assume that $\kappa_1 < \kappa_2$ and $\theta_{jt}^{(1)}$ (respectively $\theta_{jt}^{(2)}$) 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 :

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

and

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

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

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

And finally,

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

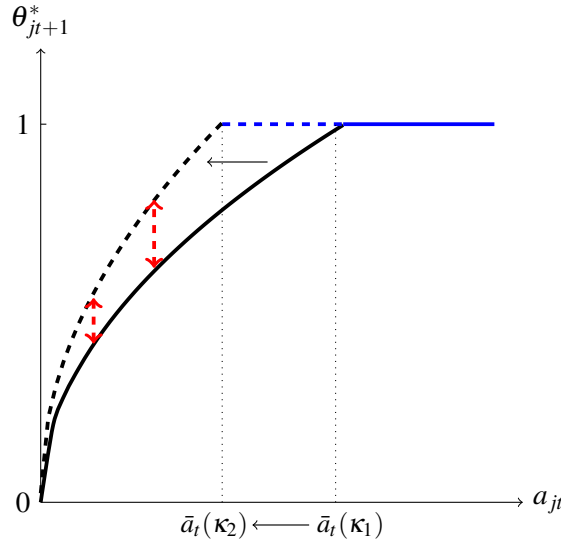


FIGURE XII: Effect of Financial Development on the Intensity of Use of Technologies ($\kappa_1 < \kappa_2$)

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. ■

D Variation study of f_{jt}

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

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

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

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

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

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

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

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

E Demonstration of Proposition II.

Proof: Financial development and income level positively impact the speed of convergence across countries because $\bar{a}_t = \frac{\psi + 2\eta}{2\lambda \kappa_t w_t}$, and $f'_{jt}(1)$ decreases with κ_t (respectively with A_t), while $f'_{jt}(0)$ increases with κ_t (respectively with A_t). Therefore, countries with higher κ_t (or higher w_t) will become unconstrained more quickly, as illustrated in Figure XIII, 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:

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

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.

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:

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

The convergence times T_{j_1} and T_{j_2} for sectors j_1 and j_2 are given by $T_{j_1} = \min(B_{j_1})$ and $T_{j_2} = \min(B_{j_2})$. 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 $a_{j_1 t} > a_{j_2 t}$ for all t . I begin by assuming that $\tau \in B_{j_2}$, which

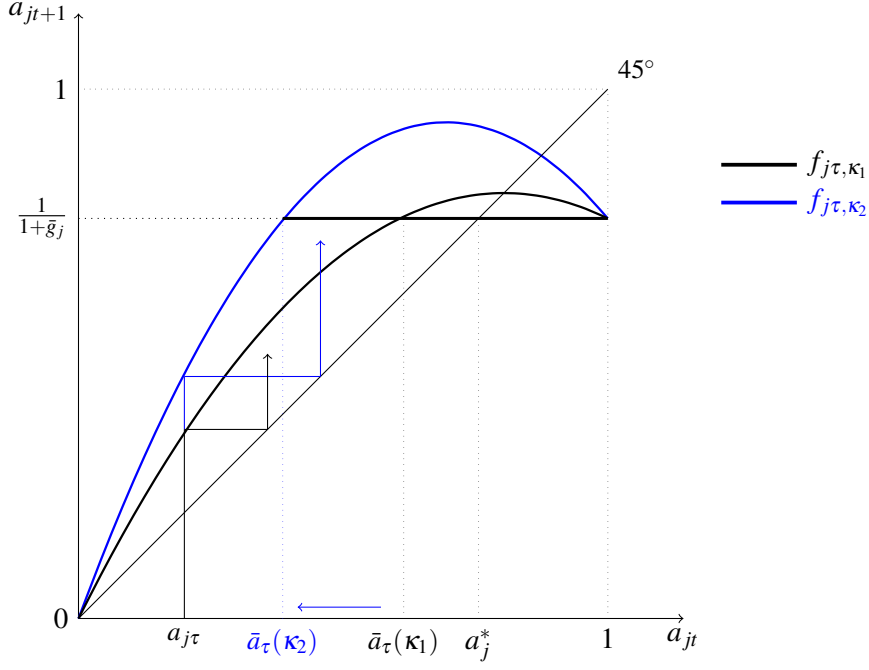


FIGURE XIII: Financial development and convergence speed : $\kappa_1 < \kappa_2$

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}_τ , which leads us to conclude that:

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

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

F Convergence Across Development Quartiles

Figures XIV-XVI 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

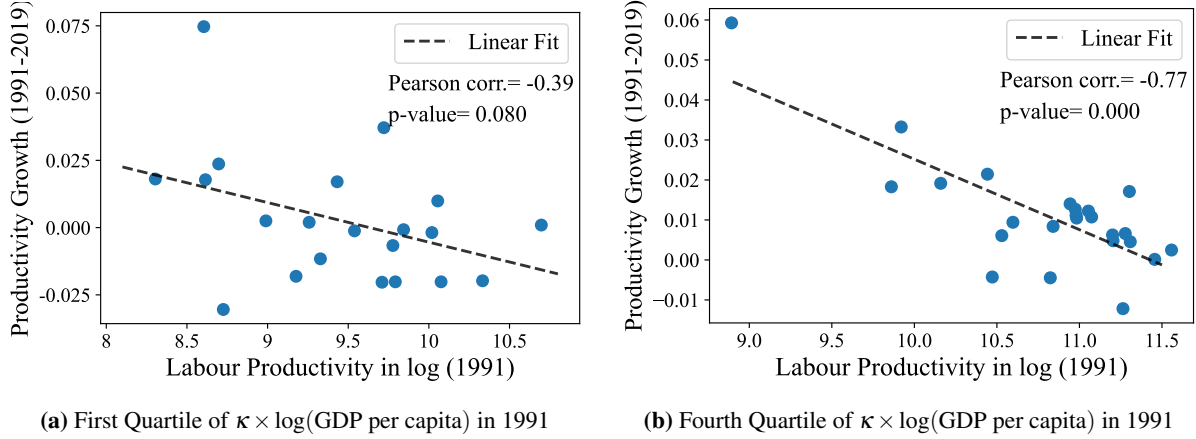


FIGURE XIV: Convergence of Services Labor Productivity Across Financing Capacity Quartiles

sector, the Pearson correlation for the 4th quartile countries (Figure XIVb) is -0.77 ($p\text{-value} = 0.000$), 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 XIVa) exhibit a weaker and statistically insignificant (at the 5% level) correlation of -0.39 ($p\text{-value} = 0.080$), indicating a slower convergence trend.

In the manufacturing sector, the 4th quartile countries (see Figure XVb) also display a significant negative correlation of -0.63 ($p\text{-value} = 0.001$), indicating substantial convergence. Meanwhile, the 1st quartile countries (Figure XVa) exhibit a much weaker correlation of -0.32 ($p\text{-value} = 0.144$), 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.

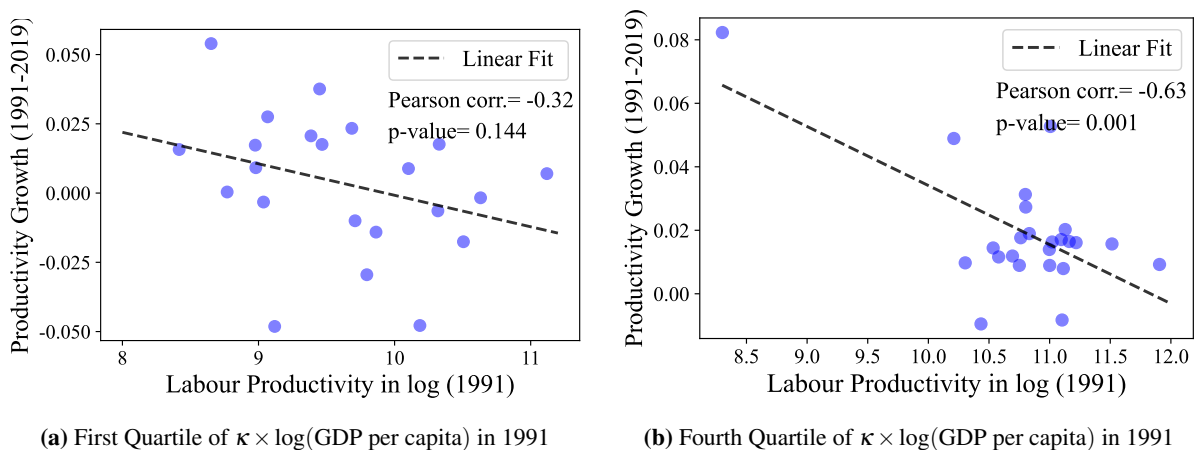
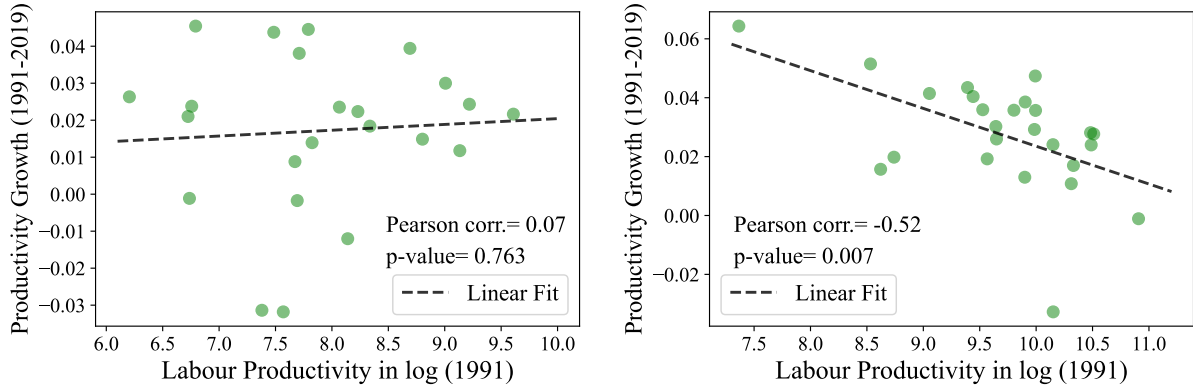


FIGURE XV: Convergence of Manufacturing Productivity Across Development Quartiles

Lastly, in the agriculture sector, the trend is particularly revealing. The correlation for the 4th quartile group (Figure XVIb) 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 XVIa) exhibit a nearly flat correlation of 0.07 (p-value = 0.763), indicating a 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 XVI: Convergence of Agriculture Labor Productivity Across Financing Capacity Quartiles

G Test of significance

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

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

The Student's test statistic is given by:

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

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:

$$(\hat{\beta}_j + \hat{\gamma}_j \kappa_t A_t)^2 > z_{\frac{\alpha}{2}}^2 \left[\text{var}(\hat{\beta}_j) + \text{var}(\hat{\gamma}_j) (\kappa_t A_t)^2 + 2\text{cov}(\hat{\beta}_j, \hat{\gamma}_j) \kappa_t A_t \right] \quad (\text{G.1})$$

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.

H 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 $x_1 = x_0 - \frac{\phi_j(x_0)}{\phi'_j(x_0)}$.
4. *Step 4.* Repeat steps 2 and 3 until the desired level of accuracy is reached i.e $|x_1 - x_0| \leq 10^{-6}$.

I 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.

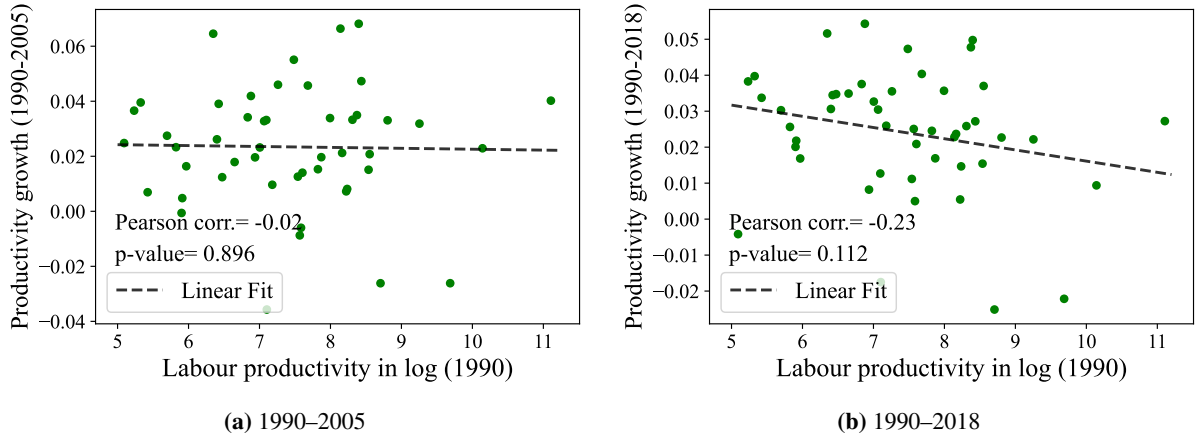


FIGURE XVII: Agriculture Labor Productivity Convergence in GGDC data

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 -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.

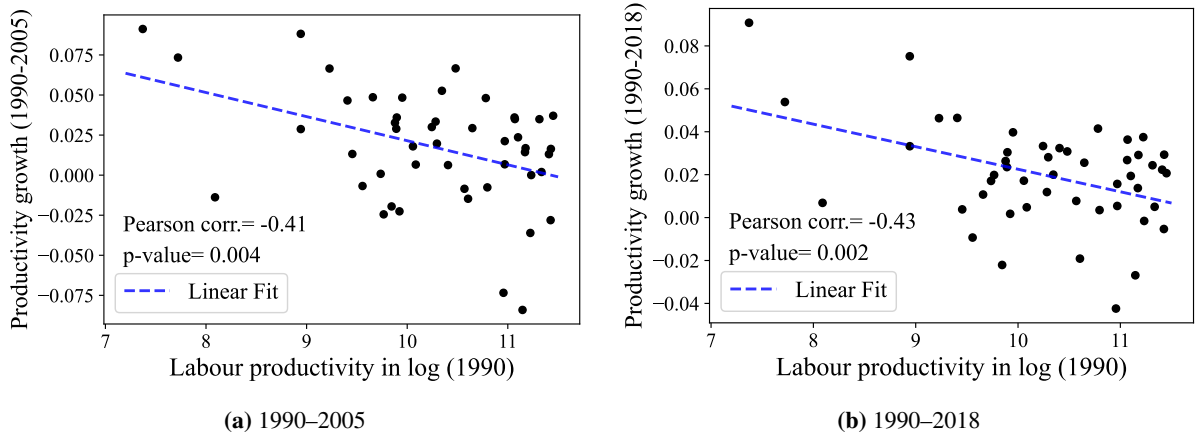


FIGURE XVIII: Manufacturing Labor Productivity Convergence in GGDC data

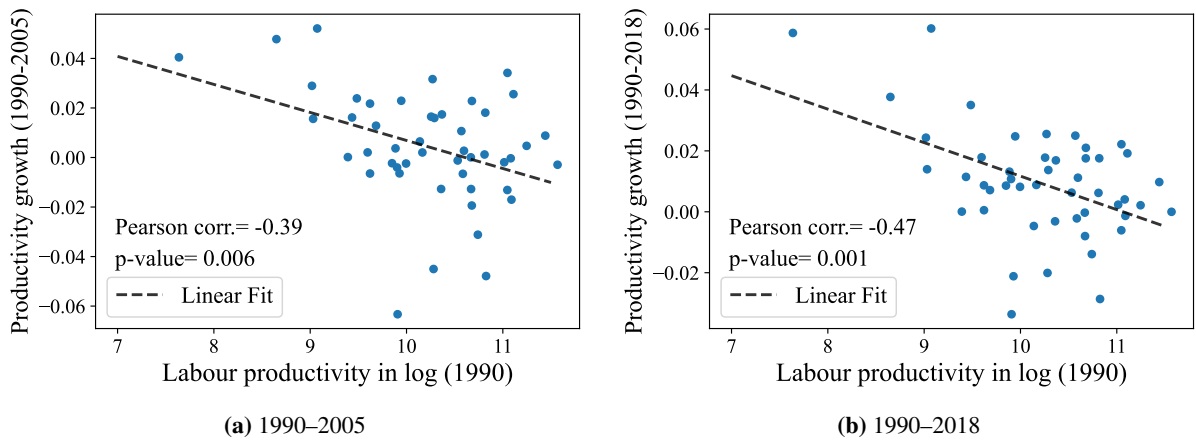


FIGURE XIX: Services Labor Productivity Convergence in GGDC data

J Regression Outputs

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

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{j0})$	-0.006** (0.003)	-0.004** (0.002)	-0.012*** (0.003)	-0.015*** (0.003)	-0.010*** (0.003)	-0.013*** (0.004)
$\hat{\rho}_j : \kappa_l \log(A_0)$	0.027** (0.013)	0.038*** (0.011)	0.031* (0.018)	0.029 (0.018)	0.044*** (0.014)	0.044*** (0.015)
$\hat{\gamma}_j : \kappa_0 \log(A_0)$ $\times \log(A_{j0})$	-0.002 (0.001)	-0.004*** (0.001)	-0.002 (0.002)	-0.002 (0.002)	-0.004*** (0.001)	-0.004** (0.001)
Human capital		0.008*** (0.003)		0.009** (0.004)		0.011** (0.005)
Countries	99	87	99	87	99	87
R-squared	0.21	0.23	0.37	0.43	0.25	0.33

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

TABLE VI: 5-Year Panel Regression Results Using WDI data and Financial Market Index: 1991–2019

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{jt})$	-0.054*** (0.009)	-0.054*** (0.010)	-0.070*** (0.012)	-0.061*** (0.013)	-0.066*** (0.011)	-0.068*** (0.013)
$\hat{\rho}_j : \kappa_t \log(A_t)$	0.043*** (0.013)	0.040*** (0.014)	-0.020 (0.022)	-0.010 (0.024)	0.059*** (0.017)	0.066*** (0.018)
$\hat{\gamma}_j : \kappa_t \log(A_t)$ $\times \log(A_{jt})$	-0.004*** (0.001)	-0.004*** (0.001)	0.002 (0.002)	0.001 (0.002)	-0.005*** (0.002)	-0.006*** (0.002)
Human capital		0.047* (0.026)		-0.004 (0.021)		0.005 (0.013)
Country FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓
Countries	161	134	161	134	161	134
Observations	728	621	728	621	728	621
R-squared	0.51	0.51	0.53	0.52	0.59	0.62

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 VII: 5-Year Panel Regression Results Using WDI data and Financial Institutions Index: 1991–2019

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{jt})$	-0.044*** (0.010)	-0.042*** (0.011)	-0.068*** (0.015)	-0.059*** (0.015)	-0.057*** (0.011)	-0.059*** (0.012)
$\hat{\rho}_j : \kappa_t \log(A_t)$	0.063*** (0.013)	0.064*** (0.014)	-0.001 (0.025)	0.002 (0.026)	0.086*** (0.018)	0.092*** (0.019)
$\hat{\gamma}_j : \kappa_t \log(A_t)$ $\times \log(A_{jt})$	-0.006*** (0.001)	-0.006*** (0.001)	0.000 (0.002)	-0.000 (0.002)	-0.008*** (0.002)	-0.008*** (0.002)
Human capital		0.046 (0.028)		-0.004 (0.021)		0.008 (0.013)
Country FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓
Countries	161	134	161	134	161	134
Observations	728	621	728	621	728	621
R-squared	0.53	0.53	0.53	0.52	0.60	0.64

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

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{jt})$	-0.050*** (0.009)	-0.051*** (0.010)	-0.071*** (0.012)	-0.063*** (0.011)	-0.045*** (0.008)	-0.046*** (0.007)
$\hat{\rho}_j : \kappa_t \log(A_t)$	0.077*** (0.021)	0.073*** (0.022)	-0.017 (0.023)	-0.018 (0.023)	0.069*** (0.019)	0.065*** (0.020)
$\hat{\gamma}_j : \kappa_t \log(A_t)$ $\times \log(A_{jt})$	-0.007*** (0.002)	-0.007*** (0.002)	0.001 (0.002)	0.001 (0.002)	-0.006*** (0.002)	-0.006*** (0.002)
Human capital		0.014 (0.022)		0.003 (0.021)		0.003 (0.014)
Country FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓
Countries	161	134	161	134	161	134
Observations	295	251	295	251	295	251
R-squared	0.84	0.85	0.82	0.81	0.87	0.89

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 IX: 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)
$\hat{\beta}_j : \log(A_{jt})$	-0.049*** (0.010)	-0.051*** (0.012)	-0.073*** (0.012)	-0.064*** (0.012)	-0.039*** (0.008)	-0.040*** (0.007)
$\hat{\rho}_j : \kappa_t \log(A_t)$	0.056*** (0.013)	0.054*** (0.012)	-0.015 (0.019)	-0.014 (0.021)	0.057*** (0.015)	0.058*** (0.015)
$\hat{\gamma}_j : \kappa_t \log(A_t)$ $\times \log(A_{jt})$	-0.005*** (0.001)	-0.005*** (0.001)	0.001 (0.002)	0.001 (0.002)	-0.006*** (0.001)	-0.006*** (0.001)
Human capital		0.031 (0.022)		0.000 (0.021)		0.010 (0.013)
Country FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓
Countries	161	134	161	134	161	134
Observations	295	251	295	251	295	251
R-squared	0.84	0.84	0.82	0.81	0.88	0.89

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: 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)
$\hat{\beta}_j : \log(A_{jt})$	-0.052*** (0.013)	-0.054*** (0.014)	-0.071*** (0.016)	-0.062*** (0.015)	-0.048*** (0.011)	-0.050*** (0.010)
$\hat{\rho}_j : \kappa_t \log(A_t)$	0.065** (0.030)	0.056* (0.031)	-0.014 (0.029)	-0.010 (0.028)	0.073*** (0.026)	0.064** (0.025)
$\hat{\gamma}_j : \kappa_t \log(A_t)$ $\times \log(A_{jt})$	-0.006** (0.003)	-0.005* (0.003)	0.001 (0.003)	0.001 (0.002)	-0.007*** (0.002)	-0.006** (0.002)
Human capital		0.024 (0.030)		-0.000 (0.031)		-0.001 (0.020)
Country FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓
Countries	161	134	161	134	161	134
Observations	295	251	295	251	295	251
R-squared	0.84	0.84	0.82	0.81	0.87	0.89

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