Financial Development, Technology Adoption, and Sectoral Productivity Convergence*

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Abstract

I document significant differences in the patterns of productivity convergence across key economic sectors and develop an endogenous growth model to explain these observed patterns. The model predicts that sectors with higher growth rates at the technological frontier, such as agriculture, will converge more slowly than those with lower frontier growth, like services. It also shows that the threshold level beyond which financial development no longer influences technology adoption varies by sector, with those closer to the frontier becoming unconstrained more quickly. Furthermore, the model categorizes countries into three groups based on their levels of financial development and GDP per capita, demonstrating divergent and conditional convergence for lower-income groups, and unconditional convergence for higher-income, financially developed countries. More importantly, as GDP per capita increases, leading to greater financing capacity, initially divergent sectors within a country can start to converge.

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

JEL classification: O33, O40, O41, G28

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1 Introduction

One of the central questions in development economics is whether developing countries can achieve faster income growth to catch up with more advanced economies. A consensus view in the literature is that differences in GDP per capita across countries are primarily due to variations in total factor productivity[1]. Jerzmanowski (2007) argues that observed differences in productivity growth stem from disparities in technology usage, thus reinforcing Aghion et al. (2005)'s findings that technology adoption is a crucial channel for achieving productivity growth. Since technology adoption occurs at the industry level, analyzing sectoral productivity is essential for understanding overall GDP per capita convergence. If convergence is observed across major sectors - such as agriculture, manufacturing, and services - it suggests that overall GDP per capita is likely to converge as well. This has prompted researchers to focus on sectoral productivity convergence. 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 reasons behind the lack of convergence in agriculture by examining how financial development influences the intensity of use of adopted technologies. First, I analyze sectoral productivity distributions from 1991 to 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 adopted technologies, which vanishes once financial development reaches a technology-specific threshold. Additionally, sectoral productivity proximity-the inverse of the sectoral productivity gap with the frontier-is positively correlated with technology adoption levels. While Comin & Nanda (2019) demonstrated that financial development positively influences the adoption of advanced technologies, this study reveals that the impact of financial development disappears beyond a sector-specific threshold level. This finding provides a new perspective on understanding the relationship between financial development, technology adoption, and productivity dynamics across different sectors.

The objective of this paper is then to develop a technology adoption model that is consistent with the aforementioned correlations and to examine the implications of the model for sectoral productivity convergence among countries. Therefore, 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.

The model is extended by incorporating entrepreneurial skills to account for the fact that entrepreneurs with greater knowledge or expertise in their sectors may facilitate more effective technology adoption, given that technology transfer is skill-intensive. Following Howitt & Mayer-Foulkes (2005), I assume that a country's stock of "effective skills" for technology adoption is influenced by its level of development in each sector. Nelson & Phelps (1966) termed this "ab-

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

sorptive capacity," which was implicitly related to human capital in their model. Griffith et al. (2004) provided evidence that skills are a key determinant of a country's absorptive capacity. By including absorptive capacity, the model captures the sectoral productivity proximity to the technological frontier and its impact on the intensity of technology use. To simplify the analysis, I assume that in the absence of credit constraints, countries use adopted technologies with the same intensity as those at the technological frontier. However, a country's financial development is strongly correlated with its governance indicators, including government effectiveness, control of corruption, voice and accountability, political stability, and the rule of law (Porta et al. (1998)). Thus, under the assumption of no credit constraints, it is expected that countries' productivities would catch up to the sectoral productivities of the technological frontier with a one-period lag.

The model's predictions are consistent with the observations described earlier. It shows that the intensity of use of technology increases as sectors get closer to the technological frontier and as the level of financial development rises, up to a certain threshold of financial development. When a country is close to the technological frontier and operates at a high level of productivity, it experiences reduced costs associated with adjusting to new technologies. As a result, with the same level of investment, such a country can integrate a greater number of technological innovations compared to a less productive country. As a country's financial development improves, it can allocate more resources to technology adoption, continuing until it overcomes the previous limitations that prevented it from reaching the technological frontier.

Furthermore, the model makes predictions regarding the convergence and divergence of sectoral productivities. It classifies countries into three distinct categories. The first group encompasses countries characterized by low levels of both GDP per capita and financial development. Initially, these countries experience a temporary divergence in their sectoral productivity before ultimately transitioning to the second group. The second category comprises countries with a moderate level of financial development and GDP per capita. These countries demonstrate conditional convergence towards their steady state and as GDP per capita continues to rise, countries in the second group move into the third group. Finally, the third category consists of countries boasting high levels of financial development and GDP per capita. These countries converge to a higher level of sectoral productivity unconditionally. The model suggests that differences in financial development and GDP per capita are key factors influencing sectoral productivity convergence and divergence across countries. However, countries are not static, especially as GDP per capita grows over time. As wealth increases, the borrowing constraints imposed on entrepreneurs are gradually offset, enhancing technology adoption within sectors.

The model also predicts that financial development and GDP per capita positively influence the speed of productivity convergence, with more financially developed countries expected to converge faster. Specifically, if two countries have the same initial sectoral productivity levels, the country with a higher level of financial development multiplied by GDP per capita will start to converge earlier and more rapidly, due to its greater financing capacity. Furthermore, sectors with higher growth rates at the technological frontier will experience slower convergence compared to those with lower growth rates. To test these predictions, I conduct a panel data regression analysis for agriculture, manufacturing, and services. Using sectoral labor productivity growth as the dependent variable, the regressions include initial sectoral productivity, financial development multiplied by GDP per capita, and an interaction term between the two. The analysis draws from the World Development Indicators (WDI) dataset, covering over 150 countries from 1991 to 2019.

The empirical analysis demonstrates a significant positive relationship between financial development, GDP per capita, and the rate of convergence. The cross-country regression results suggest 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–0.15 in agriculture, 0.17 in manufacturing, and 0.12 in services–in 1991, will take around 81 years to catch up with France in services, 185 years in manufacturing, and 305 years in agriculture. By increasing India's initial development from 1.9 to France's level of 4.52 in 1991, the convergence rate significantly improves, reducing the time needed to catch up with France to 37 years in services, 45 years in manufacturing, and 74 years in agriculture.The services sector exhibits the fastest rate of productivity convergence, followed by manufacturing and then agriculture, reflecting differences in productivity growth across these sectors at the frontier. Interestingly, between 1991 and 2019, the top ten most developed countries[2] 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, underscoring the dynamic interplay between sectoral growth in developed countries and the speed of sectoral convergence.

Related Literature. My paper contributes to the broad literature analyzing the channels driving productivity differences across countries. Specifically, it addresses the literature examining the dynamics of sectoral productivity gaps across countries (Rodrik (2013), Kinfemichael & Morshed (2019), and Herrendorf et al. (2022)). Another strand of this literature explores why poorer countries do not efficiently adopt and utilize the advanced technologies available in developed countries, which could help them grow faster and achieve similar levels of wealth. This strand includes studies that focus on the role of distortions or barriers to technology adoption (e.g., Parente & Prescott (1999), Hsieh & Klenow (2014), Bento & Restuccia (2017), 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 three 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 are important in explaining the cross-country differences in aggregate productivity, their model cannot explain why within the same country some sectors may not be successful in adopting advanced technologies. Indeed, in their paper, the framework is such that all innovators in the same country adopt the same average technology of the frontier without taking into account the specificity of each sector. As they pointed out in the conclusion of their working paper, financial development should be especially favorable to innovation in R&D-intensive sectors, where technology transfer requires much external finance.

This paper examines, at the sectoral level, the effect of financial development on the adoptions. In addition to explaining cross-country differences in technology adoption, the model demonstrates that within a given country, certain sectors can adopt and utilize new technologies more intensively than others, even when the overall level of financial development is identical. This variation in technology use is driven by the differing productivity gaps across sectors. Sectors with smaller productivity gaps are more likely to adopt and employ new technologies to a greater extent because higher-productivity sectors tend to possess a larger pool of knowledge and expertise in technology adoption. These sectors have a workforce that is more proficient in understanding and integrating 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

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

closer to the productivity frontier become financially unconstrained earlier than those further from the frontier.

In addition, Aghion et al. (2005) analyze convergence of GDP per capita, where countries are locked into specific country categories. This means that countries that diverge remain divergent. However, recent literature has shown that certain countries that experienced divergence in the 1960s start converging 30 years later, as highlighted in the concept of "converging to convergence" by Kremer et al. (2022). My work distinguishes itself by examining sector-specific dynamics, showcasing how countries transition from one group to another over time instead of remaining locked in a single category.

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 poorer 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. It also explains why the agricultural productivity gap is larger than in manufacturing and services. Although the analysis did not find evidence of convergence in manufacturing between 1991 and 2005, as noted by Herrendorf et al. (2022), there are clear signs of convergence in both services and manufacturing between 1991 and 2019. This finding deepens the study's insights into the interplay between financial systems, technology adoption, and sectoral productivity convergence, highlighting the evolving nature of these dynamics over time.

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 and assumptions. The qualitative implications of the model are then explored in Section 4. Section 5 examines the model's predictions in relation to the data. Finally, Section 6 concludes the paper by summarizing the key findings and highlighting their implications.

2 Convergence in Sectoral Productivity, Financial Development, and Technology Adoption

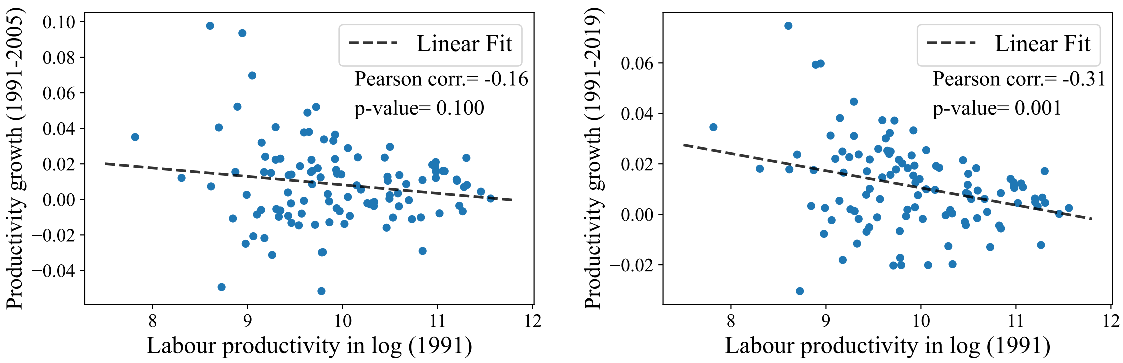
In this section, I analyze sectoral productivity trends from 1991 to 2019, focusing on how the evolution of productivity distributions differs across manufacturing, services, and agriculture. I also explore the relationship between technology adoption, financial development, and a country's sectoral productivity gap with the technological frontier, which motivates the development of the model.

2.1 Sectoral Productivity Convergence

In the literature on cross-country convergence, recent studies have shown varying results regarding the convergence of labor productivity across different sectors. For instance, Rodrik (2013) demonstrated that unconditional convergence in manufacturing labor productivity occurs regardless of geography, policies, or country-specific factors. Similarly, Kinfemichael & Morshed (2019) found evidence of unconditional convergence in the services sector. However, the agricultural sector does not exhibit clear evidence of such convergence, indicating a different dynamic compared to manufacturing and services. In the following, I analyze the differences in convergence patterns across sectors. Using sectoral labor productivity data from WDI (2022), measured as value added per worker in constant 2015 international US$[3], I show that sectors with higher average productivity growth in the most advanced countries tend to exhibit a trend toward convergence later than other sectors.

First, I conduct β-convergence analysis of sectoral productivities across countries. β-convergence 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 (5.8), 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. For the agriculture, manufacturing, and services sectors, there is a trend toward convergence from the period 1991-2005 to 1991-2019

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



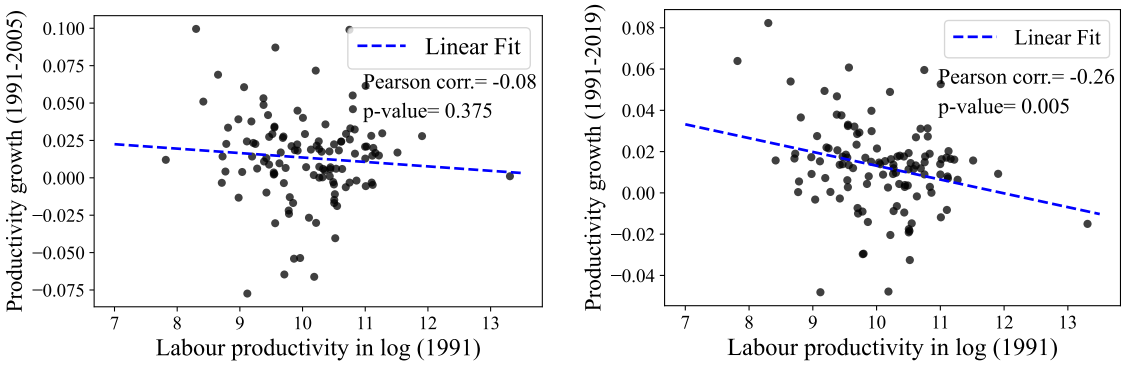
(a) 1991–2005

(b) 1991–2019

FIGURE I: Services Labour Productivity Convergence by Periods

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

[3]This process involves adjusting value added per worker using purchasing power parities (PPPs) to ensure comparability across countries and over time. For a detailed explanation, refer to Subsection .

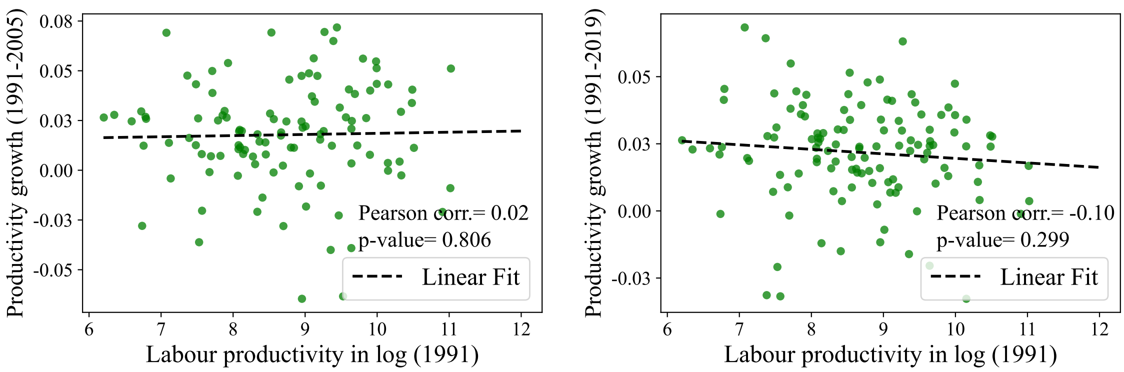


(a) 1991–2005 **(b)** 1991–2019

FIGURE II: Manufacturing Labour Productivity Convergence by Periods

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 II.

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

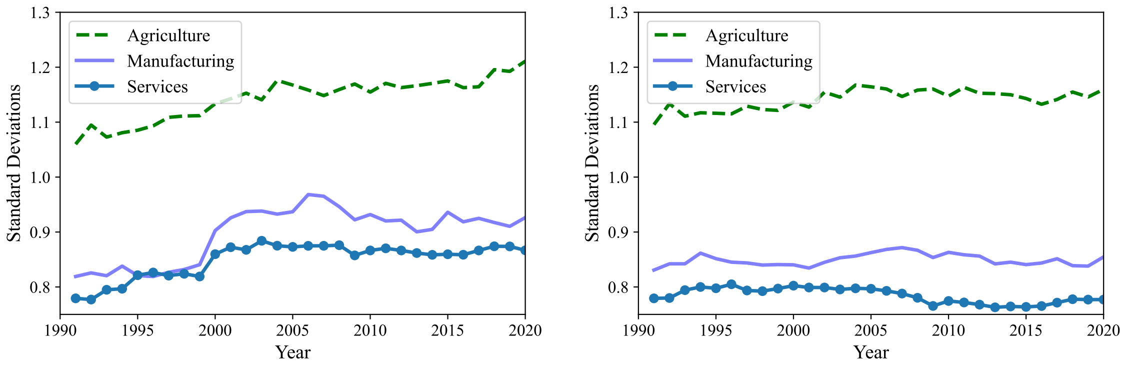


(a) 1991–2005 **(b)** 1991–2019

FIGURE III: Agriculture Labour Productivity Convergence by Periods

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 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 and nearly four times the growth rate in services. 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-convergence[4] in agriculture, manufacturing and services for two panels of countries: *Panel A* which contains all of the 180 countries for which data are available over the period 1991-2019 and *Panel B* which is limited to countries with no missing data in 1991[5]. 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.



(a) *Panel A* : 180 countries of unbalanced panel

(b) *Panel B* : 110 countries of balanced panel

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

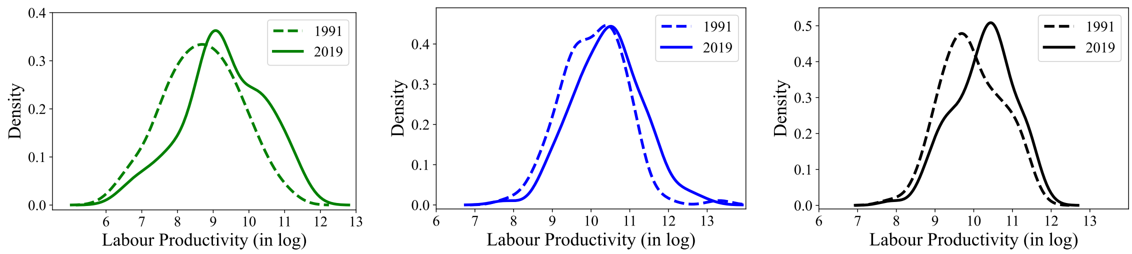
Figure IV plots the measure of standard deviation over the period 1991-2019 for both *Panel A and B*. It shows that the productivity gaps are largest in agriculture, smallest in services, and intermediate in manufacturing. Data encompassing a broader range of developing and developed countries, in comparison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

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

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

productivity in the services sector has become slightly more peaked or concentrated. This indicates a trend toward σ-convergence, as countries gradually catch up with the most productive ones. In manufacturing, the distribution, which was nearly bimodal in 1991, has evolved into a unimodal shape, providing evidence of a certain level of convergence among countries. Conversely, while



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

FIGURE V: Sectoral Productivity Distribution Over Time

the density curve for productivity in the agricultural sector exhibits a more elongated peak, 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 at the frontier and less evidence of convergence. These findings open avenues for further exploration into the relationship between technology adoption–an important driver of productivity growth–and financial development, as well as the gap between a country's productivity and the technological frontier across different sectors.

2.2 Model Motivation: Key Observations

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. Additionally, it is important to consider the productivity gap from the technological frontier. A larger gap may hinder or slow down the adoption of advanced technologies in the presence of credit constraints, making this correlation particularly relevant in understanding how countries progress towards technological convergence.

I combine three types of data. First, I use measures of technology diffusion from the HCCTA[6] 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

[6] Historical Cross-Country Technology Adoption

the last 200 years across a large set of countries. I then construct panel data at the technology-country-year level, measuring the quantity adopted of each technology in each country over time. As shown in Table I, the set of technologies covers the three economic sectors (agriculture, industry and services). The heterogeneous nature of the technologies explored is also reflected in their measures. Some technologies are measured by the number of units in operation (e.g., cars, computers, Radio) and some that capture the ability to produce something (electric arc steel, electricity, telegraphic services) are measured by the total production or by the number of users (e.g., cellphones). Following Comin & Nanda (2019), this metric will serve as a measure of the intensity of technology adoption and utilization.

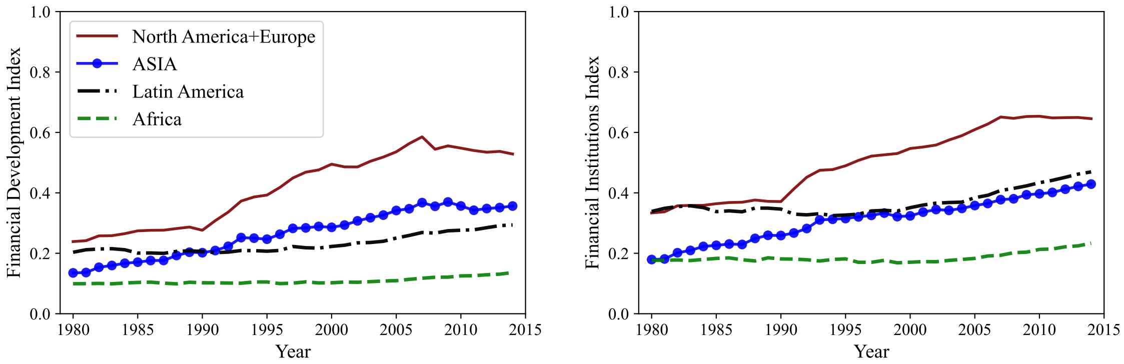
TABLE I: Summary of Technology Data

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

Second, I use the Financial Development Index[7] 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 discusssed in the Data Appendix A.1.

Figure VI shows the evolution over time of the financial institution and financial development indices. The financial development index varies significantly across the regions-North America and Europe, Asia, Latin America, and Sub-Saharan Africa-with notable differences in growth patterns. North America and Europe exhibit the highest level of financial development, with a significant acceleration in growth starting from 1990. This sharp increase reflects substantial improvements in financial infrastructure, the introduction of new financial technologies, and strengthened regulatory frameworks, making the region a global leader in financial development. In Asia, the financial development index shows steady and consistent growth. Starting at a lower level than Latin America in 1980, Asia countries gradually strengthened their financial systems and, by 1990, had surpassed Latin America. However, despite this progress, Asia's financial development has remained lower than that of North America and Europe, although the region has experienced impressive and continuous improvements due to widespread financial reforms and greater market access. Latin America displays low but positive growth, with most gains occurring after 2000. De-

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



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

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

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

spite some improvements, the region's financial development remains sluggish in comparison to other regions, hindered by economic and political challenges that limit its ability to expand financial infrastructure and services. In contrast, Sub-Saharan Africa countries show little to no growth in the average financial development index over time. While there have been advances in financial technologies, such as mobile banking, these innovations have not significantly impacted the overall financial development of the region. The financial system in Sub-Saharan Africa continues to face structural challenges, contributing to a near-flat trajectory.

The sectoral value added per worker is taken as a proxy for sectoral productivity level[8]. Following the literature (Aghion et al. (2005) for example) on technology adoption, I consider the United States of America to be the frontier in the three major economic sectors; and the sectoral proximity[9] is calculated by dividing the country's productivity by the US productivity in the same sector. The productivity data used in this study are sourced from the WDI database.

Observation 1 : *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 the total electric production per capita and the number of tractors adopted per capita acros countries from 1980 to 2003 against the average level of financial development index. It shows a positive correlation of financial development and the level of technology adoption which vanishes once financial development has reached approximately a certain level. Figure VII also includes scatter plots for additional technologies. The association between the average intensity of use of adopted technologies and the average level of financial development remains largely consistent across different technologies, with the exception of the threshold level at which the correlation becomes insignificant.

For instance, the threshold level at which financial development is no longer correlated with technological adoption ranges between 0.5 and 0.6 for tractors and electricity production, while it

[8] Also, in the theoretical model, the value added per worker is proportional to productivity, see equation (3.8)

[9] Sectoral proximity to the frontier refers to a sector's productivity relative to the productivity of the same sector in the United States.

falls between 0.3 and 0.4 for television and commercial vehicles. This suggests that financial development may play a relatively more important role in driving the adoption of tractors compared to commercial vehicles. Within the same country, even with the same level of financial development, some technologies may face more constraints than others. Figure VIII below displays scatter plots illustrating the association between the level of technology adoption and the sector's productivity gap with the United States.

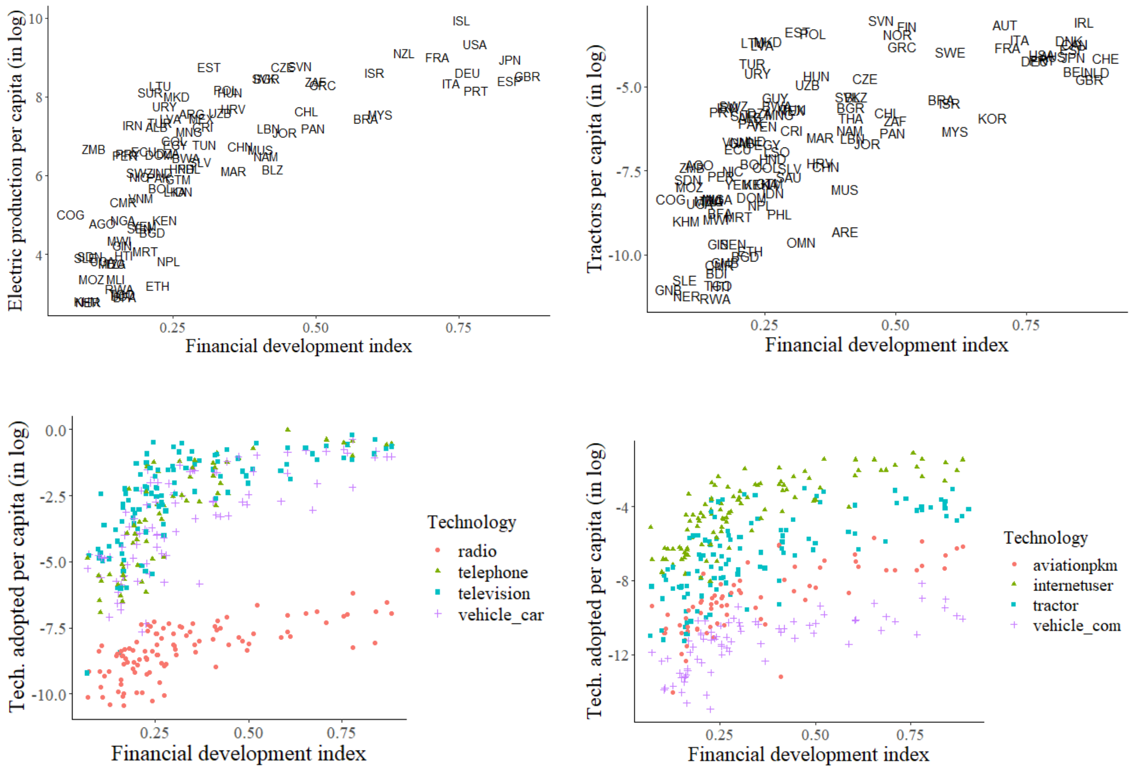


FIGURE VII: Average Levels of Financial Development and Log Technology Adoption per Capita (1980–2003)

Observation 2 : *Sectors closer to the frontier tend to adopt and use more technologies across countries.*

The top row of Figure VIII presents two examples. The first shows the relationship between the average number of tractors per capita adopted from 1991 to 2003 and the sectoral proximity to the United States in the Agriculture sector. The second depicts the relationship between total electric production per capita and the sectoral proximity to the United States in the Industry sector. It is evident that countries with higher levels of technology adoption are also closer to the United States in terms of productivity. These relationships, illustrated in Figure VIII, are consistently observed across different technologies and are statistically significant at the 1% level[10].

Figures VII and VIII illustrate the relationship between the average intensity of technology use, financial development, and sectoral productivity proximity to the frontier. However, these figures do not address potential endogeneity issues between sectoral proximity and financial development, nor do they control for other factors influencing technology adoption. For instance,

[10]This analysis is intended for illustrative purposes only.

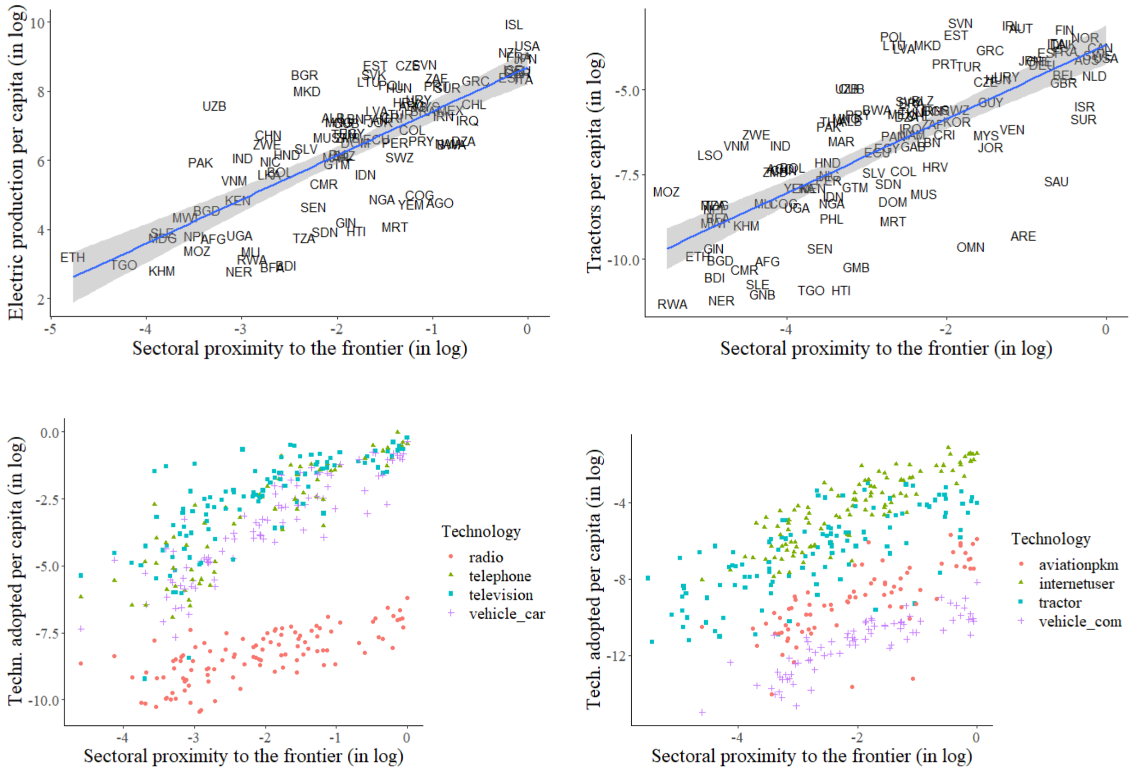


FIGURE VIII: Average Sectoral Productivity Proximity to the U.S. and Log Intensity of Technology Use (1991–2003)

a linear correlation analysis of data from 1991 to 2013 reveals a positive correlation between the financial development index and sectoral log productivity: 0.68 in Agriculture, 0.60 in Manufacturing, and 0.76 in Services. This suggests that countries closer to the frontier also tend to have more developed financial systems. Consequently, the observed effect of either variable on the intensity of technology adoption might be mediated by the other variable, rather than representing a direct causal relationship.

In the next section, I develop an endogenous growth model that accounts for this interaction. While the conventional view holds that technology adoption drives productivity growth, my model offers a more nuanced perspective. It explains not only how technology adoption helps sectors approach the productivity frontier but also suggests that causality may run in the opposite direction, where proximity to the frontier facilitates greater technology adoption.

3 Theoretical Model

The model economy is based on Aghion et al. (2005), where economic activity takes place in countries that do not trade goods or factors of production but do share technological ideas. Each country has a fixed population, and every individual lives for two periods. In the first period, they are endowed with two units of labor, and in the second period, they have none. At the end of the first period, households acquire entrepreneurial skills and invest their savings in a technology adoption project as entrepreneurs.[11] The saving rate $s \in (0,1)$ is exogenous, and the utility function is assumed to be linear,[12] such that $U(c_1, c_2) = c_1 + \beta c_2$, where c_1 is consumption in the first period of life, c_2 is consumption in the second period, and $\beta \in (0,1)$ represents the discount rate applied to second-period consumption relative to the first.

3.1 Goods Production Sectors

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

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

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

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

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

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

Intermediate Goods Production. In each intermediate sector, there is a monopoly whose production technology consists of using one unit of the final good to produce one unit of the intermediate good. Given that the intermediate producer operates in a monopoly, it charges the highest price that the final sector producer is willing to pay for variety j, under the assumption of a drastic innovation[13]. The monopolist maximizes profit as follows:

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

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

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

$$x_{jt} = \alpha^{\frac{2}{1-\alpha}} A_{jt} L_t \tag{3.3}$$

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

[12] Assuming linear utility simplifies the model and ensures tractability. It implies that asset returns are non-autocorrelated and do not depend on past consumption levels, resulting in a fixed exogenous savings rate. Although an endogenous savings rate could be considered - particularly where low financial development might lead to self-financing through higher savings - it's reasonable to maintain an exogenous savings rate given that countries with weaker financial institutions tend to have lower savings rates. This assumption doesn't alter the analysis's overall results.

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

The equilibrium price for variety j is then calculated by substituting (3.3) into the inverse demand function:

$$p_{jt} = \alpha^{-1} \tag{3.4}$$

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

$$\begin{aligned}\pi_{jt} &= \left(p_{jt} - 1\right) x_{jt} \\ &= \pi A_{jt} L_t \end{aligned} \tag{3.5}$$

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 (3.3) into (3.1):

$$Y_t = \alpha^{\frac{2\alpha}{1-\alpha}} A_t L_t \tag{3.6}$$

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

$$w_t = \omega A_t \tag{3.7}$$

$$GDP_t = \zeta A_t L_t \tag{3.8}$$

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.

3.2 Financial Intermediaries

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

I introduce imperfections in the credit market into the model as in Aghion et al. (2005). This imperfection arises from the presence of moral hazard, meaning there is a possibility that the borrower may choose not to repay her loan by concealing the profits made. The borrower can pay a cost hz_{jt}, which is proportional to the amount invested, to avoid repaying her creditors when successful. This cost serves as an indicator of the degree of creditor protection. However, there is a probability q that the borrower will be caught by the lender, thereby obliging her to repay the loan. The total cost of being dishonest[14] is then: $hz_{jt} + q(1+r)(z_{jt} - sw_t)$. The borrower is prompted to choose honesty if:

$$hz_{jt} + q(1+r)(z_{jt} - sw_t) \geq (1+r)(z_{jt} - sw_t). \tag{3.9}$$

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

$$z_{jt} \leq \frac{(1-q)(1+r)}{(1-q)(1+r) - h} sw_t. \tag{3.10}$$

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

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

$$l_t(q,h) = \frac{hsw_t}{(1-q)(1+r)-h}. \tag{3.11}$$

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

I assume that the lender can make efforts[15] to influence the probability q by spending a unit cost $C(q)$ per loan amount. The convex cost function $C(q)$ is defined such that it increases with the probability q:

$$C(q) := c\ln\left(\frac{1}{1-q}\right) \tag{3.12}$$

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

$$\max_{\{q\}} \left[q(1+r) + c\ln(1-q)\right](z_{jt} - sw_t). \tag{3.13}$$

The first-order condition is:

$$q = 1 - \frac{c}{1+r}. \tag{3.14}$$

Then, the condition (3.10) becomes:

$$z_{jt} \leq \kappa w_t, \tag{3.15}$$

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

In an economy characterized by credit constraints, an entrepreneur's ability to invest is fundamentally limited by the maximum loan amount available, expressed as κw_t. This constraint implies that regardless of the sector in which the entrepreneur operates, their investment capacity remains uniform and is tied directly to the prevailing real wage w_t. Such a situation creates a notable restriction on the potential for technological advancement and innovation. The constancy of κw_t across various sectors highlights a critical inefficiency: entrepreneurs may find themselves unable to finance the adoption of advanced or more productive technologies that require investments exceeding this threshold. When the investment required for a technology surpasses this limit, entrepreneurs are left with no viable means to access the necessary funds, thereby stifling their ability to innovate. This underinvestment is particularly detrimental in sectors where technological progress could yield substantial productivity gains.

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

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

3.3 Technological Progress and Productivity Growth

Productivity grows as a result of technology adoption, which allows monopolists to access an existing technology frontier. For each intermediate sector j, there is one individual born in each period t who is capable of producing innovation for the next period. If successful, this individual will become the monopolist in that sector during period $t+1$, and her productivity will be given by:

$$A_{jt+1} = \theta_{jt+1}\bar{A}_{jt} + (1-\theta_{jt+1})A_{jt} \tag{3.16}$$

where $\bar{A}_{jt}$ represents the frontier productivity[16] in the same sector at time t, and $\theta_{jt+1} \in [0,1]$ denotes the intensity 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. 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 the standard Schumpeterian models, which assume that the innovator reaches the average frontier productivity regardless of the sector, I posit that technology transfer is specific to each sector. Within a country, certain sectors are less advanced, making it easier to adopt technologies in those sectors compared to others. As a result, in equilibrium, the intensity of technology use and productivity may vary across sectors.

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

$$\frac{\lambda_{jt} z_{jt}}{\bar{A}_{jt}} = F\left(\theta_{jt+1}\right), \tag{3.17}$$

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

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

with $\eta, \psi > 0$. The parameter λ_{jt} denotes the skills of the entrepreneur. 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

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

leadership provided by a leader with a high level of academic training in the field of activity. Foster & Rosenzweig (1996) and Griffith et al. (2004) provide evidence that skills are an important determinant of a country's absorptive capacity. By learning from previous technologies, an entrepreneur becomes more likely to adopt new technologies. The knowledge and expertise that a country possesses in a particular industry can help to reduce the cost of adopting new technologies in that industry by improving understanding of the technology, reducing training costs, facilitating integration with existing systems, and enhancing implementation. Following Howitt & Mayer-Foulkes (2005)[17], I model this "learning by doing" effect through the entrepreneurial skills λ_{jt}, which are assumed to be proportional to the productivity A_{jt}, reflecting knowledge spillover:

$$\lambda_{jt} = \lambda A_{jt} \tag{3.18}$$

Scotchmer (1991) also modeled innovation as a cumulative process, whereby existing knowledge acts as an input in the production of new technologies.

From equation (3.17), the adoption cost z_{jt} is then a function of the intensity of technology use θ_{jt+1} and the sectoral productivity proximity to the frontier $a_{jt} := \frac{A_{jt}}{\bar{A}_{jt}}$:

$$z_{jt} = \frac{\frac{\psi}{2}\theta_{jt+1}^2 + \eta\theta_{jt+1}}{\lambda a_{jt}} \tag{3.19}$$

In equilibrium, the innovator chooses θ_{jt+1} (or z_{jt}) in order to maximize the expected net payoff given by (3.20):

$$\max_{0\leq\theta_{jt+1}\leq 1} \beta\pi\left[\theta_{jt+1}\bar{A}_{jt} + (1-\theta_{jt+1})A_{jt}\right] - z_{jt} \tag{3.20}$$
$$\text{subject to } \; z_{jt} \leq \kappa w_t \; \text{ and equation (3.19)}$$

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

$$\max_{0\leq\theta_{jt+1}\leq 1} \beta\pi\left[\theta_{jt+1}\bar{A}_{jt} + (1-\theta_{jt+1})A_{jt}\right] - (\lambda a_{jt})^{-1}\left(\frac{\psi}{2}\theta_{jt+1}^2 + \eta\theta_{jt+1}\right) \tag{3.21}$$

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

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

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

However, in the presence of credit constraints, the reality is quite different. Even when an entrepreneur successfully adopts a technology, the lack of sufficient funding can hinder their ability to invest the optimal amount of resources needed to use the technology at its full potential.

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

Since the cost of intensifying technology use (z_{jt}) depends on the amount of resources available, entrepreneurs facing credit constraints may be forced to adopt suboptimal levels of technology intensity, thereby failing to reach the productivity levels achievable at the frontier. This means that they might not be able to afford the necessary training, infrastructure, or complementary inputs required for efficient technology implementation.

In the next subsection, I will show that the inability to borrow beyond a certain limit κw_t restricts the entrepreneur's capacity to finance the full integration of some new technologies, leading to their underutilization. As a result, technologies with the potential to significantly improve productivity may only be partially implemented, resulting in an inefficient adoption process. This inefficiency arises not from a lack of access to technology itself but from financial constraints that prevent entrepreneurs from achieving the level of intensity required to fully realize the technology's benefits. Consequently, credit constraints can create a persistent gap between the productivity of local firms and that of the global technology frontier, ultimately slowing down the process of technological advancement and sectoral productivity growth within the country.

3.4 Equilibrium Technology under Credit Constraints

Under credit constraints, the problem (3.20) of the innovator can be rewritten as follows:

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

$$\text{s.t. } \theta_{jt+1} \leq -\frac{\eta}{\psi} + \left[\left(\frac{\eta}{\psi}\right)^2 + \frac{2\lambda\kappa w_t a_{jt}}{\psi}\right]^{\frac{1}{2}}$$

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

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

where $\bar{a}_t(\kappa) = \frac{\psi+2\eta}{2\lambda\kappa w_t}$ is decreasing in κ. The level of technology adoption, denoted by θ_{jt+1}^{*}, increases with the sectoral productivity proximity to the frontier technology, represented by a_{jt}. Consequently, when two countries with the same level of financial development adopt identical technologies, the country that is closer to the frontier will exhibit a higher level of technology usage. As a sector approaches the technological frontier, its productivity potential rises, enabling it to leverage advanced technologies more effectively. A country with higher productivity in industry j (i.e., a higher a_{jt}) possesses more knowledge and expertise in that industry, which significantly impacts the cost associated with adopting new technologies. 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 IX illustrates that as financial development increases, the intensity of technology adoption also rises. However, this positive effect vanishes 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 once a threshold level is reached, either in terms of financial development or sectoral proximity to the technological frontier. 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 null. This indicates that the primary role of financial development in facilitating technology adoption 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.

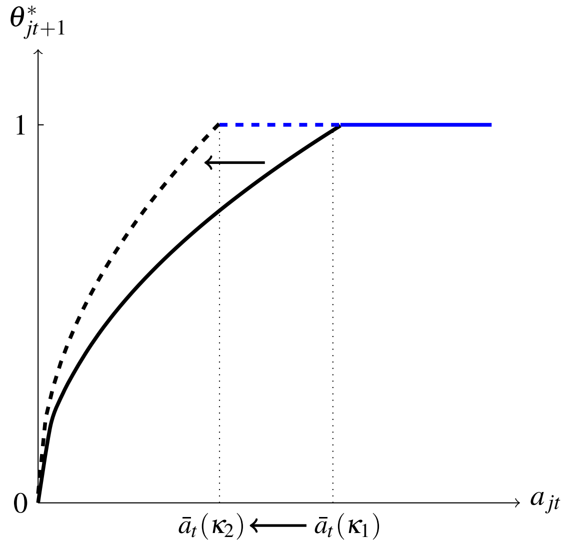


FIGURE IX: Effect of Financial Development on the Intensity of Use of Technologies ($\kappa_1 < \kappa_2$)

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 A.2 ■

As illustrated in Figure VII, financial development positively impacts the intensity of technology use up to a certain threshold level. Beyond this threshold, its influence becomes negligible. The threshold level, $\underline{\kappa}_{jt}$, beyond which financial development no longer affects the intensity of technology usage in sector j, is given by:

$$\underline{\kappa}_{jt} = \frac{2\eta + \psi}{2\lambda \omega A_t a_{jt}}, \tag{3.22}$$

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.

Sectors closer to the technological frontier, such as services, typically exhibit greater potential for effectively adopting and implementing advanced technologies. These sectors are better positioned to leverage existing knowledge and expertise, which may facilitate their movement toward higher productivity levels. Conversely, sectors like agriculture, which have a higher gap with the frontier, may face more significant challenges in technology adoption. As financial development progresses, sectors closer to the frontier, such as services, are likely to experience relatively quicker improvements in technology usage. This dynamic suggests that services may have the potential to set the stage for convergence in productivity levels before agriculture, which faces greater constraints due to its larger productivity gap with the frontier. This potential for convergence will be examined further in Section 4.

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[18] of the intensity of technology use first with respect to financial development, and then with respect to sectoral productivity proximity to the frontier:

$$\frac{\partial^2 \theta^*_{jt+1}}{\partial a_{jt} \partial \kappa} = \frac{\partial^2 \theta^*_{jt+1}}{\partial \kappa \partial a_{jt}} = \frac{\lambda w_t}{\psi} \left[\left(\frac{\eta}{\psi} \right)^2 + \frac{\lambda \kappa w_t a_{jt}}{\psi} \right] \left[\left(\frac{\eta}{\psi} \right)^2 + \frac{2\lambda \kappa w_t a_{jt}}{\psi} \right]^{-\frac{3}{2}} > 0 \tag{3.23}$$

The positive cross partial derivative indicates that before reaching certain threshold levels of financial development and sectoral proximity to the frontier, the two factors work together to increase the intensity of technology use. 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. This result suggests that early-stage financial development and technological advancement play a crucial role in boosting technology adoption. As sectors mature and approach the frontier, their reliance on financial development as a driving factor diminishes.

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 Sectoral Productivity Gap Dynamics and Financial Development

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

[18] if $a_{jt} \leq \bar{a}_t(\kappa)$.

convergence. Specifically, I will explore the extent to which the aggregate level of development will affect the dynamics of various sectors in the economy, and how the development of financial system can facilitate or hinder this process.

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 a recursive equation between a_{jt} and a_{jt+1} based on the following equation that describes changes in productivity:

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

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

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

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

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

Thus $a_{jt+1} = \min\left\{\frac{1}{1+\bar{g}_j}, f_{jt}(a_{jt})\right\}$ for all $a_{jt} \in [0,1]$. Note that $f_{jt}(a_{jt})$ is a concave[19] 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} on the interval $[0,1]$. If $f'_{jt}(0) < 1$ then $f'_{jt}(a_{jt})$ will be less than the the slope of the first bisector for all a_{jt} in $[0,1]$ because f'_{jt} is decreasing, and the function f_{jt} is a contraction mapping on $[0,1]$, and the sequence generated by the function f_{jt} will converge to 0 meaning the sectoral productivity is diverging. If $f'_{jt}(0) > 1$ then the sequence generated by the function f_{jt} will intersect the first bisector on the interval $[0,1]$ since $f_{jt}(1)$ is also less than 1. This will imply a convergence towards a non-zero point. After taking the derivative of the function f_{jt} and evaluating it at 0 and 1, I obtain the following system of equations:

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

From where, by replacing the wage rate w_t by ωA_t, 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) :

[19] See Appendix A.2.2 for calculations of the first and second derivative functions of f_{jt}.

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

Since $\frac{\psi+2\eta}{2\lambda\omega} > \frac{\eta\bar{g}_j}{\lambda\omega}$[20] countries will then be classified into three groups depending on the level of financial development κ, the growth of sectoral productivity at the frontier $\bar{g}_j$ and of aggregate productivity A_t.

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

  When financial development κ or the level of initial income per capita A_0 are sufficiently high such that $\kappa A_0 > \frac{\psi+2\eta}{2\lambda\omega}$, the evolution of the sectoral productivity gap is illustrated in Figure X below. Since $f_{jt} \leq f_{jt+1}$ and $\bar{a}_t$ is decreasing with t, while a_{jt} is increasing with t as long as f_{jt} is above the first bisector, there exists a date T_j such that $a_{jt} \geq \bar{a}_{T_j}$ and $a_{jt+1} = h_j(a_{jt})$ for all $t \geq T_j$. The sectoral productivity proximity to the frontier a_{jt} for $j \in [0,1]$ will therefore converge to the steady state $a^*_j = \frac{1}{1+\bar{g}_j}$, where T_j represents the date of convergence.

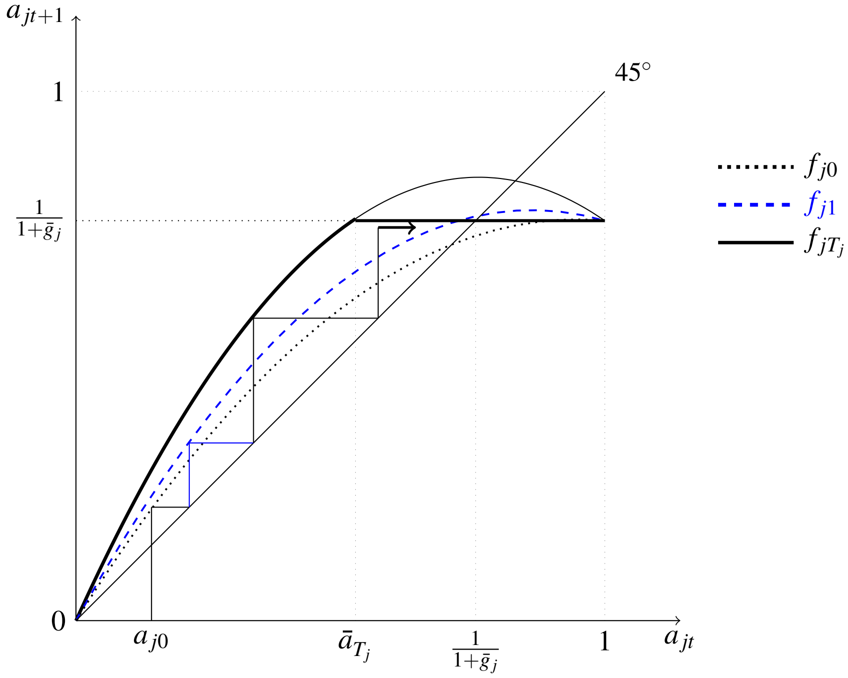


FIGURE X: Sectoral productivity gap dynamic when $\kappa A_0 > \frac{\psi+2\eta}{2\lambda\omega}$

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

---

20 $\frac{\eta\bar{g}_j}{\lambda\omega} / \frac{\psi+2\eta}{2\lambda\omega} = \frac{2\eta\bar{g}_j}{2\eta+\psi}$. As $2\eta\bar{g}_j \leq 2\eta$ and $\psi > 0$ then $\frac{\eta\bar{g}_j}{\lambda\omega} / \frac{\psi+2\eta}{2\lambda\omega} < 1$.

When financial development and initial income are neither too high nor too low so that $\frac{\eta \bar{g}_j}{\lambda \omega} < \kappa A_0 < \frac{\psi + 2\eta}{2\lambda \omega}$, then $f_{jt}(a_{jt}) < \frac{1}{1+\bar{g}_j}$ for all $0 \leq a_{jt} < 1$. Let us define $\hat{a}_{jt}$ such that $\hat{a}_{jt} = f_{jt}(\hat{a}_{jt}) \quad \forall t \geq 0$.

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

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

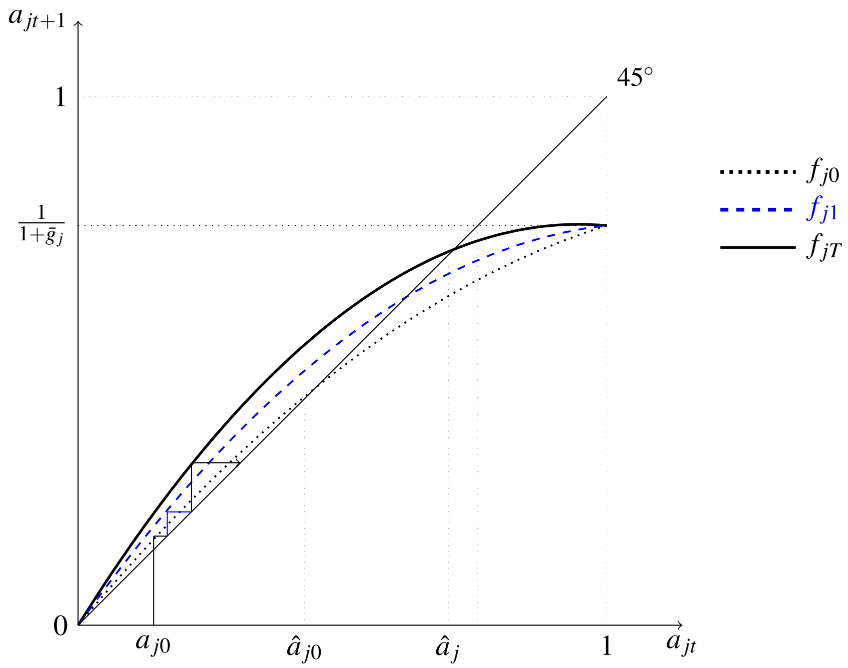


FIGURE XI: Sectoral productivity gap dynamic when $\frac{\eta \bar{g}_j}{\lambda \omega} < \kappa A_0 < \frac{\psi + 2\eta}{2\lambda \omega}$

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

  When the level of financial development and aggregate productivity are sufficiently low, or when the sector j productivity growth $\bar{g}_j$ is high such that $\kappa A_0 < \frac{\eta \bar{g}_j}{\lambda \omega}$, then a_{jt} will decrease over time. The dynamics of the sectoral productivity gap are illustrated in Figure XII. Under conditions of low income and low financial development, the sectoral productivity gap will continue to widen until a time τ where the level of income per capita or financial development reaches a certain threshold such that $\kappa A_\tau > \frac{\eta \bar{g}_j}{\lambda \omega}$. A low level of aggregate productivity (and therefore a low level of wealth available in the country) combined with strong credit constraints (due to weak financial development) ensures that if the sector grows quickly at the frontier, the sectoral productivity gap will widen between developing and developed countries. This is because it becomes increasingly difficult to catch up with the frontier, which continues to progress more rapidly, while the catch-up with previous technologies has not yet been achieved.

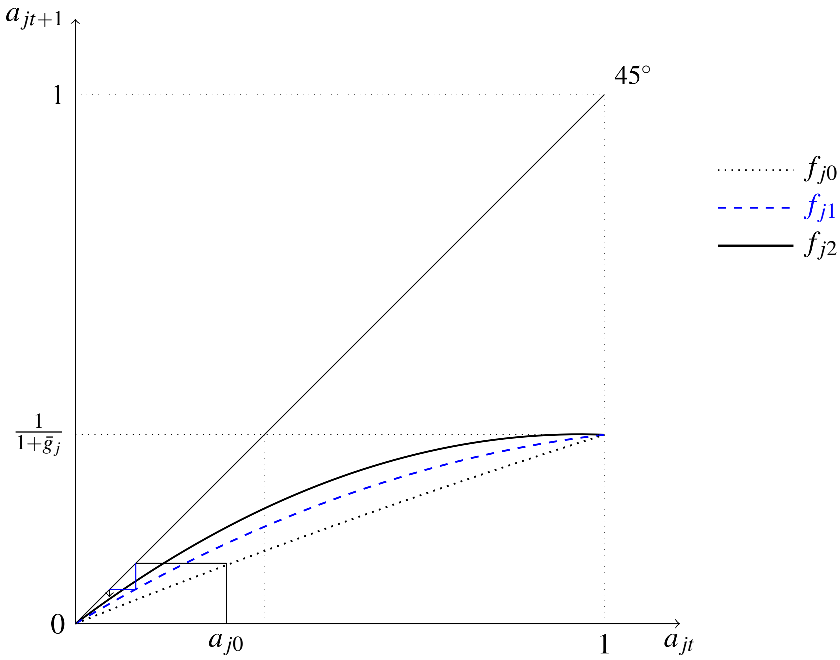


FIGURE XII: Sectoral productivity gap dynamic when $\kappa A_0 < \frac{\eta \bar{g}_j}{\lambda \omega}$

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

Contrary to the findings of Aghion et al. (2005), it is important to underscore that countries are not confined to a singular category. My model 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 productivity 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 constant. 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 later. 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 funding capacity for technology adoption $\kappa \omega A_t$ is below a minimum threshold of $\lambda^{-1} \eta \bar{g}_j$. This threshold represents the investment level that would ensure an intensity of use of adopted technologies, allowing sector j to achieve a productivity growth rate exceeding that of the frontier $\bar{g}_j$. Even as the gap with the frontier widens, the sector still witnesses positive productivity growth, as does the GDP per capita[21]. This results in an increasing funding capacity over time, implying that there exists a time from which $\kappa\omega A_t$ surpasses $\lambda^{-1}\eta\bar{g}_j$. Consequently, the sector can experience growth faster than that of the frontier and begin to converge because the wealth level guarantees a funding capacity and an investment level that ensures a higher intensity of use of adopted technologies.

For a country with a financing capacity $\kappa\omega A_t$ exceeding the threshold $\lambda^{-1}\eta\bar{g}_j$ - which allows it to grow faster than the frontier - but remains below the efficient level $\lambda^{-1}(\eta+\psi/2)$, it cannot utilize technologies at the same level as developed frontier countries. However, once its financing capacity surpasses the efficient level, there exists a point T_j from which sectoral proximity to the frontier exceeds $\bar{a}_{T_j}(\kappa) = \frac{\psi+2\eta}{\lambda\kappa\omega A_{T_j}}$. At this juncture, the financing capacity surpasses the financing need[22] $\bar{z}_{jt} = \frac{2\eta+\psi}{2\lambda a_{jt}}$, enabling 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.

4.2 Financial Development, Frontier Sectoral Productivity Growth, and Sectoral Productivity Convergence Speed

In this subsection, I explore the impact of the level of development (financial development and GDP per capita) and frontier sectoral productivity growth, $\bar{g}_j$, on the rate of convergence of sectoral productivity. To do this, I consider the case where κA_0 exceeds $\frac{\psi+2\eta}{2\lambda\omega}$ without loss of generality.

As shown in Figure X, sectoral productivity converges asymptotically to the unconstrained steady state, $a_j^* = \frac{1}{1+\bar{g}_j}$, where T_j denotes the convergence time in sector j. Sectors that grow more slowly at the frontier (lower $\bar{g}_j$) will experience faster convergence, meaning that T_j increases with $\bar{g}_j$. While differences in the credit multiplier affect the short-run intensity of technology adoption, they do not influence the long-run technological gap. This is because the upper bound on borrowing is offset by the country's wealth growth and spillover effects on technology usage. Once this constraint ceases to bind, κ becomes irrelevant for the long-run productivity dynamics. Nevertheless, as proven in Proposition II below, countries with higher levels of financial development converge faster than those with lower financial development.

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

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

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

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

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 speed T_j^κ is given by:

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

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

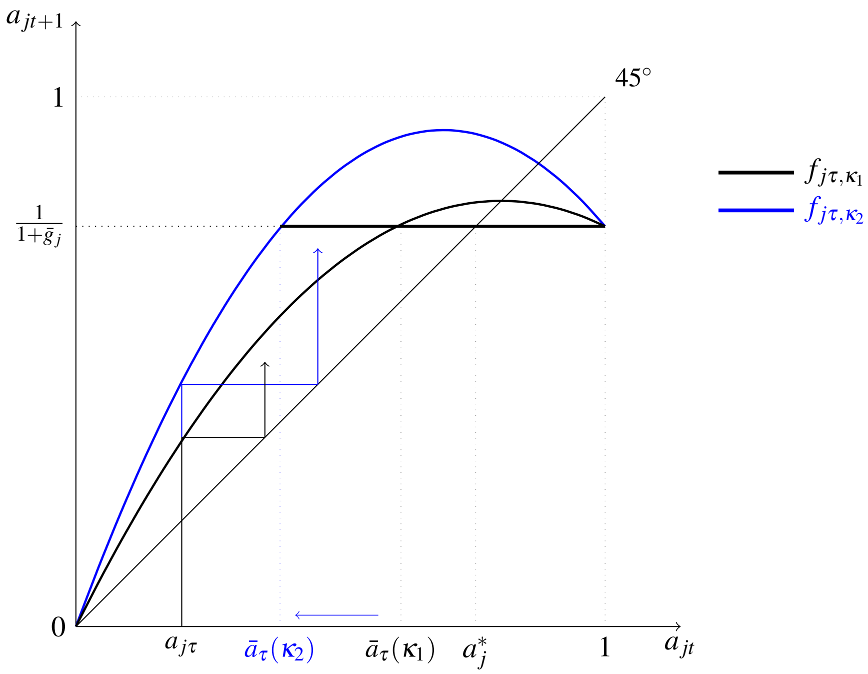


FIGURE XIII: Financial development and convergence speed : $\kappa_1 < \kappa_2$

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

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

The convergence times T_{j_1} and T_{j_2} for sectors j_1 and j_2 are given by $T_{j_1} = \min(B_{j_1})$ 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 $a_{j_1t} > a_{j_2t}$ for all t. Thus,[23] $B_{j_2} \subset B_{j_1}$, which implies that $\min(B_{j_1}) \leq \min(B_{j_2})$.

■

Sectors will then converge with lags to their respective steady-state productivity. Countries with a higher initial development level (κA_0) 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 development levels, may initially experience a period of divergence before eventually converging toward more developed countries. This

[23] See Appendix A.2.3 for more details on the demonstration.

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 before gradually catching up with developed nations in certain sectors, particularly those sectors that exhibit higher growth rates at the frontier.

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.

4.3 Sectoral Productivity Growth 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, we 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. By examining how different sectors respond to changes in financial conditions, we gain insights into the factors that drive convergence or divergence in productivity levels across sectors.

From Equation (3.16) sectoral productivity growth g_{jt} in sector j at time t can be derived as follows:

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

Sectors in countries that intensively employ adopted technologies will experience faster productivity growth. Consequently, financial development primarily influences the productivity growth of less advanced sectors where $a_{jt-1} < \bar{a}_t$. For sectors j with productivity proximity to the frontier such that $a_{jt} \geq \bar{a}_t(\kappa)$, the growth rate will be $a^{-1}_{jt} - 1$. This growth rate decreases with a_{jt}, indicating convergence, as sectors further from the frontier will experience higher growth rates. Thus, countries with sectors farther from the technological frontier will benefit more in terms of growth, fostering convergence over time.

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

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

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

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

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

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

Equation (4.6a) proves that if all sectors of the economy - namely agriculture, manufacturing, and services - 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 can facilitate growth in others, ultimately leading to a more integrated and robust economy.

Within a country, the impact of financial development on productivity growth can vary significantly across sectors. While some sectors may experience notable increases in productivity due to advancements in financial infrastructure and access to capital, others may not benefit to the same extent. To see how if affects the aggregate economy, I define the economy critical threshold level of financial development, denoted as $\underline{\kappa}_t$, which is given by:

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

where $\underline{\kappa}_{jt} := \frac{2\eta+\psi}{2\lambda \omega A_t a_{jt}}$ represents the sector j-specific threshold level of financial development below which finance affects technology adoption, as defined by equation (3.22). The critical financial development level $\underline{\kappa}_t$ for the entire economy is thus determined by the sector with the lowest sectoral productivity proximity to the frontier across all sectors. For countries where the level of financial development κ is below this threshold $\underline{\kappa}_t$, financial development positively influences technology adoption in some sectors, thereby enhancing overall economic growth. However, once a country exceeds the threshold $\underline{\kappa}_t$, the effect of financial development on technology adoption across all sectors disappears.

The relationship between sectoral productivity convergence and aggregate convergence is deeply dynamic and strongly influenced by the level of financial development. In a country, different sectors may be at varying distances from their respective productivity frontiers. 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 is below the level required for a sector to grow at the same rate as its frontier, these sectors act 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 productivity frontier.

However, the aggregate convergence path is not fixed. A country that is diverging at the aggregate level may start converging as sectors transition from divergence to convergence. As the country's GDP per capita grows even when there is divergence, it enhances the overall financing capacity, which helps to alleviate financial constraints in sectors that were previously unable to adopt more intensively advanced technologies. This increased financing allows these sectors to accelerate their productivity growth, contributing more substantially to aggregate convergence.

This interplay is crucial in understanding how a country's financial development and sectoral dynamics interact to shape aggregate convergence. Initially, some sectors might diverge, but as the economy's wealth and financing capacity increase, these sectors can shift towards convergence. The faster growth in these sectors then contributes to a renewed phase of aggregate growth, reinforcing the overall convergence process. Hence, the aggregate convergence is not merely the sum of sectoral outcomes but rather a dynamic process shaped by how financial development facilitates the transition of sectors from divergence to convergence, ultimately driving the country's economic growth.

5 Testing Model Predictions

In this section, I compare the theoretical predictions with empirical evidence. After outlining the data, I test the predictions of Proposition II using both panel and cross-country regressions, incorporating an interaction term between initial sectoral productivity and the product of the logarithm of initial GDP per capita and financial development. This test offers evidence supporting the model and the broader proposition that a country's convergence speed to the frontier is influenced by its level of financial development, GDP per capita, and the growth rate of the frontier sector.

5.1 Data Description

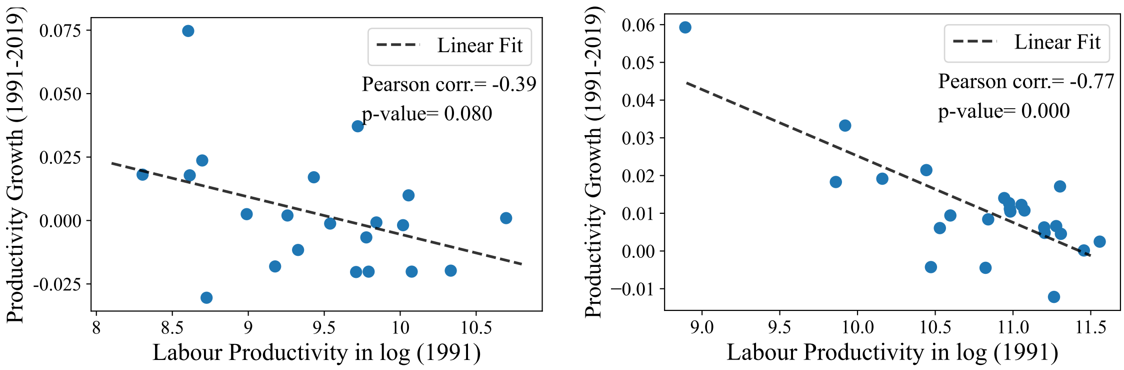
I use data from WDI (2022)[24] which provides sectoral value added per worker in constant 2015 US$ and has good coverage of countries (for up to 157 countries) from 1991 to 2019. I then construct sectoral productivity[25] levels in constant 2015 international US$ comparable across countries in the same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

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

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

κ is calibrated to the country's financial development index (and alternatively financial institutions index) provided by IMF for several countries between 1980 and 2013[26].

Figures XIV-XVI depict the convergence over the period 1991-2019 for the 1st and 4th quartile (20 to 25 countries) of development level–financial development level times log GDP per capita in 1991. The analysis of the graph 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 development. For the services



(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

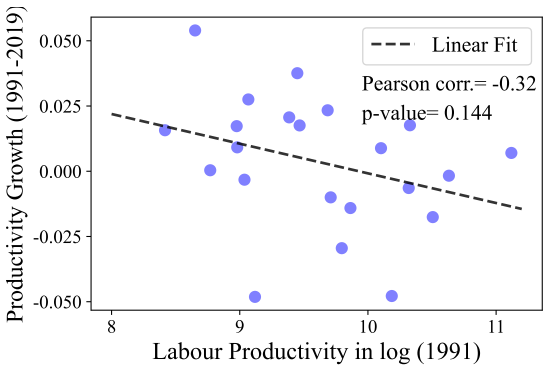
FIGURE XIV: Convergence of Services Labour Productivity Across Development Quartiles

sector, the Pearson correlation for the 4th quartile countries (Figure XIVb) is -0.77 (p-value = 0.000), demonstrating a significant and strong convergence, meaning that more advanced countries in this group are catching up with the productivity frontier at a faster rate. In contrast, the 1st quartile countries (Figure XIVa) exhibit a weaker and statistically insignificant (at the 5% level) correlation of -0.39 (p-value = 0.080), indicating a slower convergence trend. This pattern suggests

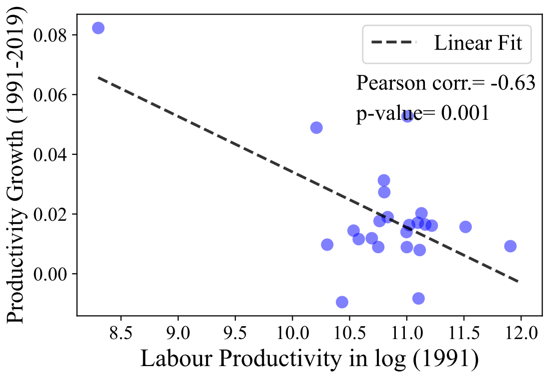
[24] WDI : World Development Indicators from the World Bank Group.
[25] Productivity here refers to labour producitivity which is considered to be the value added per worker.
[26] More details on financial data are presented in the subsection 2.2 and Appendix A.1

that financial development plays a crucial role in accelerating convergence in the services sector, with wealthier countries reaping greater productivity gains.

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



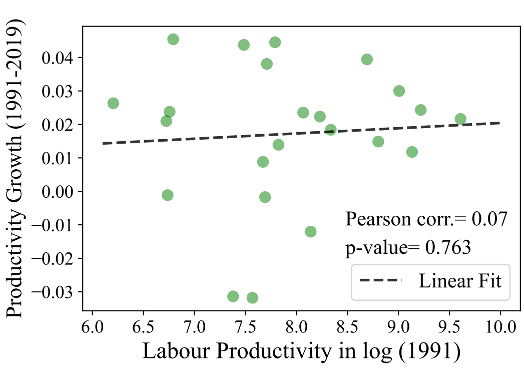
(a) First Quartile of $\kappa \times \log(\text{GDP per capita})$ in 1991



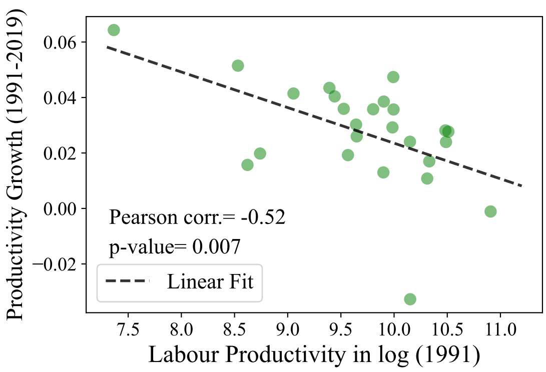
(b) Fourth Quartile of $\kappa \times \log(\text{GDP per capita})$ in 1991

FIGURE XV: Convergence of Manufacturing Labour 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 the most developed countries, even though the overall analysis suggests no clear convergence in the agricultural sector. This finding implies that advanced economies are catching up with the productivity frontier in agriculture. In contrast, the 1st quartile countries (Figure XVIa) exhibit a nearly flat correlation of 0.07 (p-value = 0.763), pointing to an almost complete absence of convergence. This lack of convergence among less developed countries suggests that structural barriers, limited access to technology, and slower rates of technological adoption are impeding productivity growth in the agricultural sector.



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

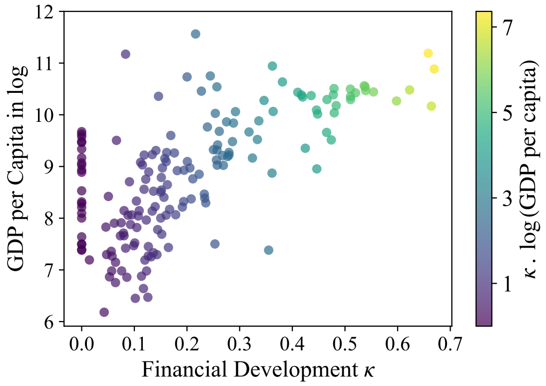


(b) Fourth Quartile of $\kappa \times \log(\text{GDP per capita})$ in 1991

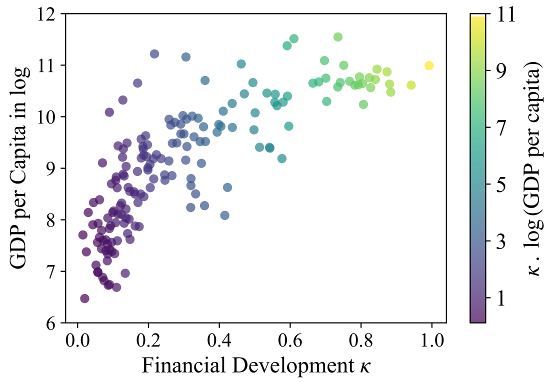
FIGURE XVI: Convergence of Agriculture Labour Productivity Across Development Quartiles

Overall, these results highlight that higher financial development and GDP per capita significantly enhance the speed of convergence, particularly in the services and manufacturing sectors. In contrast, countries with lower financial development show limited evidence of convergence, particularly in the agricultural sector, emphasizing the importance of financial and technological capabilities in driving productivity growth and catching up with the frontier.

Next, I conduct an econometric analysis using panel data to further explore how changes in financial development and GDP per capita levels influence productivity convergence across countries at sector level. As illustrated in Figure XVII, the movement of countries along the financial development and GDP per capita spectrum reveals significant shifts that can alter the dynamics of convergence.



(a) 1991



(b) 2005

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

5.2 Econometric Specification

In this subsection, I examine β-convergence in agriculture, manufacturing and service for 157 countries in WDI data. I follow the standard approach in the literature by regressing for each sector $j \in \{a,m,s\}$ the average growth in log productivity g_{jt}^c [27] on the initial level of log productivity :

$$\frac{1}{T}\Delta_T \log(A_{jt}^c) = \alpha_j + \beta_j \log(A_{jt}^c) + \rho_j \kappa_t^c \log(A_t^c) + \gamma_j \log(A_{jt}) \times \kappa_t^c \log(A_t^c) + D_j^c + D_{jt} + \varepsilon_{jt}^c \tag{5.3}$$

where $\frac{1}{T}\Delta_T \log(A_{jt}^c)$ is the average annual growth rate of the sector j labor productivity A_{jt}^c in constant international prices in country c between periods t and $t+T$. D_{jt} are time fixed effects, D_j^c are country fixed effects, and ε_{jt}^c is the error term. Note that I added $\kappa_t^c \log(A_t^c)$ into Equation (5.3) to capture the impact of the level of financial development κ_t^c and the level of aggregate productivity A_t^c [28] at period t in country c on sectoral convergence.

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_{jt}^c with

[27]The average growth rate g_{jt}^c from date t is given by : $g_{jt}^c = \frac{1}{T}\Delta_T \log(A_{jt}^c) = \frac{1}{T}\left[\log(A_{jt+T}^c) - \log(A_{jt}^c)\right]$

[28]A_t^c is calibrated here to the level of GDP per capita in international constant 2015 US$

respect to $\log(A^c_{jt-1})$ as follows:

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

The coefficient β_j then measures the conditional speed of convergence. If β_j is negative, then each country converges towards a productivity trajectory that is determined by its institutional conditions, aggregate productivity level and other economic characteristics captured by country-fixed effects D^c_j. The use of a panel model helps to correct for omitted-variable bias by capturing country-specific characteristics and any time trend as inflation through the fixed effects D^c_j and D_{jt}. 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 institutional development κ^c_t or aggregate productivity $\log(A^c_t)$. According to the predictions of the theoretical model in Proposition II-*(i)*, γ_j is expected to be negative.

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

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

Thus, countries would converge in a sector j as long as the following inequality remains valid[29] :

$$(\hat{\beta}_j + \hat{\gamma}_j \kappa_t \log(A_t))^2 > z^2_{\frac{\alpha}{2}} \left[\mathrm{var}(\hat{\beta}_j) + \mathrm{var}(\hat{\gamma}_j)\,(\kappa_t \log(A_t))^2 + 2\mathrm{cov}(\hat{\beta}_j, \hat{\gamma}_j)\,\kappa_t \log(A_t)\right] \tag{5.6}$$

i.e. the level of development $\kappa \log(A_t)$ exceeds the threshold level $\kappa \log(A)^*$ solution of the equation $\phi_j(x) = 0$ where ϕ_j is a real function defined on the interval $[0, +\infty[$ by :

$$\phi_j(x) = (\hat{\beta}_j + \hat{\gamma}_j x)^2 - z^2_{\frac{\alpha}{2}} \left[\mathrm{var}(\hat{\beta}_j) + \mathrm{var}(\hat{\gamma}_j) x^2 + 2\mathrm{cov}(\hat{\beta}_j, \hat{\gamma}_j) x\right] \tag{5.7}$$

where $z_{\frac{\alpha}{2}} = F^{-1}\left(1 - \frac{\alpha}{2}\right)$ is the critical value at $\alpha\%$ level of the standard normal distribution function F, and coefficients with hats denote parameter estimates.

To study the effect of the initial aggregate productivity and initial financial development level on speed of sectoral productivity convergence, I consider cross-section estimations for mathematical convenience[30]. Equation (5.8) below describes cross-countries estimations where N is the number of countries :

$$\begin{aligned} \frac{1}{T}\left[\log(A^c_{jT}) - \log(A^c_{j0})\right] =& \alpha_j + \beta_j \log(A^c_{j0}) + \rho_j \kappa^c_0 \log(A^c_0) + \gamma_j \log(A^c_{j0}) * \kappa^c_0 \log(A^c_0) \\ & + \varepsilon^c_j \quad ; \; c = 1, 2, ..., N \end{aligned} \tag{5.8}$$

and $\frac{1}{T}\left[\log(A^c_{jT}) - \log(A^c_{j0})\right]$ represents the average annual growth rate of labor productivity in sector j between the initial period 1991 and the final period T. Here, A^c_{j0} denotes the initial productivity of sector j in country c, κ^c_0 indicates the initial level of financial development in country c, A^c_0 stands for the initial GDP per capita of country c, and ε^c_j is the error term. By taking

[29] Demonstration is given in Appendix A.3.1

[30] Cross-sectional estimations only contain a single base year which gives the advantage of not considering time fixed effects and changes in the initial year in calculations.

the difference between the average annual growth rates of country c and the frontier from equation (5.8), we can deduce the convergence speed $S_j^c := \frac{1}{T_j^c}$[31] in sector j for country c as follow:

$$S_j^c = -\hat{\beta}_j - \hat{\rho}_j \frac{\left[\bar{\kappa}_0 \log(\bar{A}_0) - \kappa_0^c \log(A_0^c)\right]}{\log(\bar{A}_{j0}) - \log(A_{j0}^c)} - \hat{\gamma}_j \frac{\left[\bar{\kappa}_0 \log(\bar{A}_0) \log(\bar{A}_{j0}) - \kappa_0^c \log(A_0^c) \log(A_{j0}^c)\right]}{\log(\bar{A}_{j0}) - \log(A_{j0}^c)} \tag{5.9}$$

So 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 development 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 (5.9) as following:

$$\frac{\partial S_j^c}{\partial\left[\kappa_0^c \log(A_0^c)\right]} = \frac{\hat{\rho}_j + \hat{\gamma}_j \log(A_{j0}^c)}{\log(\bar{A}_{j0}) - \log(A_{j0}^c)} \tag{5.10}$$

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). The results of the estimations are discussed in the following subsection 5.3.

5.3 Empirical Results on Beta-Convergence

For each sector $j \in \{a, m, s\}$, I estimate regression equations with and without fixed effects. A negative and significant coefficient estimate of initial labor productivity without the country fixed effect indicates unconditional convergence, while the same estimate with the country fixed effect indicates conditional convergence. Standard errors are clustered at the country level in all specifications.

Table II presents the regression results for the 5-year time periods panel estimations on 157 to 177 countries spanning 1991-2019. Estimations using panel data have the advantage of take into account the specificities of each country over time. The dependent variable is the average growth rate of the 5 years average of log productivity, and the explanatory variables are the the initial 5-year average levels of labor productivity in log, the average development level $\kappa_t \log(A_t)$ over the previous 5 years, and the interaction of these two variables, with the fixed effects for each period, and country. The unconditional convergence results in columns (1), (3), and (5) are significant for manufacturing and services at the 1% level but non significant for agriculture. The estimates of the unconditional convergence coefficients are of the same magnitude as those of Herrendorf et al. (2022).

I checked the robustness of the estimations by first running the panel model with 10-year time periods and by using the financial institutions index[32] instead of the financial development index. Table IV presents the estimations of Equation (5.3) with ten-year time periods spanning 1991–2019. The results suggest that the estimates for conditional convergence are significant at the 1% level across all three sectors–Agriculture, Manufacturing, and Services. Furthermore, the unconditional convergence coefficients obtained are quite similar to the results from the five-year period panel regression, with higher R-squared values observed in the ten-year period estimations.

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

[32] The results for the panel estimation using the financial institutions index are shown in Table III. The estimations are very close to those obtained using the financial development index.

This indicates that the model captures a greater degree of variation in the data over longer time intervals, thereby reinforcing the robustness of the convergence dynamics identified in this study.

TABLE II: 5-Year Period Panel Regression Results, Dependent Variable: Average Growth in log Productivity

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\beta_j : \log(A_{jt})$	0.001	-0.045***	-0.005**	-0.065***	-0.003***	-0.059***
	(0.001)	(0.008)	(0.002)	(0.010)	(0.001)	(0.009)
$\rho_j : \kappa_t \log(A_t)$		0.073***		-0.010		0.102***
		(0.014)		(0.018)		(0.020)
$\gamma_j : \kappa_t \log(A_t)$		-0.007***		0.001		-0.009***
$\times \log(A_{jt})$		(0.001)		(0.002)		(0.002)
Country FE	No	Yes	No	Yes	No	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	177	157	177	159	174	159
Obs.	831	744	822	736	804	719
R-squared	0.01	0.49	0.03	0.54	0.06	0.59

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

TABLE III: 5-Year Panel regression results with Financial Institutions Index, dependent variable: Average Growth in log producitivity

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\beta_j : \log(A_{jt})$	0.001	-0.042***	-0.005**	-0.063***	-0.003***	-0.056***
	(0.001)	(0.009)	(0.002)	(0.011)	(0.001)	(0.009)
$\rho_j : \kappa_t \log(A_t)$		0.064***		0.004		0.090***
		(0.011)		(0.018)		(0.017)
$\gamma_j : \kappa_t \log(A_t)$		-0.006***		-0.001		-0.008***
$\times \log(A_{jt})$		(0.001)		(0.002)		(0.002)
Country FE	No	Yes	No	Yes	No	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	177	157	177	159	174	159
Obs.	831	744	822	736	804	719
R-squared	0.01	0.50	0.03	0.54	0.06	0.59

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

TABLE IV: 10 Years Period Panel Regression Results, Dependent Variable: Average Growth in log Productivity

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\beta_j : \log(A_{jt})$	0.000	-0.050***	-0.006**	-0.071***	-0.004***	-0.042***
	(0.001)	(0.009)	(0.002)	(0.012)	(0.001)	(0.008)
$\rho_j : \kappa_t \log(A_t)$		0.081***		-0.023		0.071***
		(0.019)		(0.022)		(0.019)
$\gamma_j : \kappa_t \log(A_t)$		-0.007***		0.002		-0.006***
$\times \log(A_{jt})$		(0.002)		(0.002)		(0.002)
Country FE	No	Yes	No	Yes	No	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	177	157	177	159	174	159
Obs.	337	302	334	299	327	292
R-squared	0.01	0.82	0.05	0.81	0.04	0.87

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

TABLE V: Cross-Countries Regression Results

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependant Variable: Average Growth in Log Productivity Between 1991 and 2019						
$\beta_j : \log(A_{j0})$	-0.002	-0.002	-0.007***	-0.008**	-0.007***	-0.009**
	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)
$\rho_j : \kappa_0 \log(A_0)$		0.028**		0.041*		0.048**
		(0.013)		(0.021)		(0.021)
$\gamma_j : \kappa_0 \log(A_0)$		-0.003*		-0.003*		-0.004**
$\times \log(A_{j0})$		(0.001)		(0.002)		(0.002)
Countries	121	107	116	103	110	97
R-squared	0.01	0.10	0.07	0.27	0.10	0.27

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

I also estimated the parameters using cross-country regression equations. Table V presents the results of these cross-sectional regressions, corresponding to the scatter plots displayed in Figures I–III. The cross-country specifications do not include time periods or any other fixed effects and cover a sample of 97 to 174 countries. The unconditional convergence estimates in columns (1), (3), and (5) indicate that the manufacturing and services sectors exhibit similar coefficients of -0.007, which are statistically significant at the 1% level over the entire period from 1991 to 2019. In contrast, the coefficient for the agriculture sector is -0.002 and is not statistically significant. For the overall period 1991–2019, the results in columns (2), (4), and (6) of Table V show that the coefficient associated with the interaction between financial development and GDP per capita is positive, being 0.028 for agriculture (significant at 5%), 0.041 for manufacturing (significant at 10%), and 0.048 for services (also significant at 5%). This indicates that higher financial development and GDP per capita facilitate greater productivity growth across the three sectors during this period. Additionally, the coefficients γ_j are negative: -0.003 (significant at 10%) for both agriculture and manufacturing, and -0.004 (significant the 5%) for services. This implies that between two countries with the same level of financial development multiplied by GDP per capita, the country with a lower initial level of sectoral productivity will experience faster productivity growth. Moreover, if two countries have the same initial sectoral productivity, the one with a higher initial level of financial development, interacted with GDP per capita, will experience a more rapid convergence process.

Additionally, I estimated the cross-country regression equations for three ten-year periods: 1991–2000, 2000–2009, and 2009–2019, with the results presented in Table VI. The findings indicate that the estimate for the unconditional convergence parameter, β_a, in the agriculture sector is negative (-0.002) only in the last period; however, it remains statistically insignificant. For the manufacturing sector, there was no indication of convergence before 2000; yet, the results suggest the onset of a convergence trend in the late 2000s to 2010s. As shown in Table VI, financial development and GDP per capita have increasingly facilitated productivity growth in the manufacturing sector since the 2000s. In contrast, this effect emerged earlier for the services sector, where evidence of conditional convergence began to appear in the 1990s. Specifically, the results for the 1991–2000 period show a negative coefficient of -0.014 for β_s in the services sector, significant at the 10% level, and a positive coefficient of 0.072 at the 5% level for the interaction term between initial financial development and GDP per capita. These findings support the model's prediction that sectors with lower productivity growth at frontier will start showing evidence of convergence earlier than those with higher growth rates at frontier. In this case, considering the period each sector begins to exhibit such evidence, we observe that the services sector shows signs of convergence first, followed by the manufacturing sector, and finally the agriculture sector.

Furthermore, I tested whether convergence is faster among countries with higher financial development and GDP per capita compared to the total sample by focusing on countries within the fourth quartile of the dataset in terms of development level. The estimates for the unconditional convergence coefficients at the cross-country level, shown in columns (2), (4), and (6) of Table VII, correspond to the slopes of the scatter plots in Figures XIVb, XVb, and XVIb. These estimates indicate larger absolute values for the unconditional convergence coefficients, which are also statistically significant. Additionally, the R-squared values are higher and more statistically significant, reaching 0.40 for the services sector and 0.24 for manufacturing.

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

Nevertheless, there exists a minimum level of development at which sectoral convergence can be observed in the agricultural sector. According to the estimates in Table V, the coefficients for the services and manufacturing sectors are already significant for β_j. In other words, the marginal effect of sectoral productivity on productivity growth is negative and significant in both

TABLE VI: 10-Year Period Cross-Countries Regression Results, Dependant Variable: Average Growth in Log Productivity

	Agriculture		Manufacturing		Services	
Period 1991-2000						
	(1)	(2)	(3)	(4)	(5)	(6)
$\beta_j : \log(A_{j0})$	0.000	-0.003	-0.005	-0.009	-0.005	-0.014*
	(0.003)	(0.005)	(0.004)	(0.007)	(0.004)	(0.008)
$\rho_j : \kappa_0 \log(A_0)$		0.047*		0.059		0.072**
		(0.026)		(0.037)		(0.034)
$\gamma_j : \kappa_0 \log(A_0)$		-0.004		-0.005		-0.006*
$\times \log(A_{j0})$		(0.003)		(0.003)		(0.003)
Countries	122	108	117	104	110	97
R-squared	0.00	0.11	0.01	0.21	0.01	0.19
Period 2000-2009	**Agriculture**		**Manufacturing**		**Services**	
	(1)	(2)	(3)	(4)	(5)	(6)
$\beta_j : \log(A_{j0})$	0.000	0.002	-0.008**	-0.010	-0.009***	-0.010**
	(0.002)	(0.004)	(0.004)	(0.007)	(0.002)	(0.004)
$\rho_j : \kappa_0 \log(A_0)$		0.015		0.034*		0.042***
		(0.014)		(0.018)		(0.015)
$\gamma_j : \kappa_0 \log(A_0)$		-0.001		-0.003*		-0.004***
$\times \log(A_{j0})$		(0.001)		(0.002)		(0.001)
Countries	161	144	158	141	153	136
R-squared	0.00	0.01	0.05	0.09	0.11	0.16
Period 2009-2019	**Agriculture**		**Manufacturing**		**Services**	
	(1)	(2)	(3)	(4)	(5)	(6)
$\beta_j : \log(A_{j0})$	-0.002	0.003	-0.006*	-0.017***	0.001	0.004
	(0.002)	(0.005)	(0.003)	(0.005)	(0.001)	(0.002)
$\rho_j : \kappa_0 \log(A_0)$		0.052***		-0.003		0.039***
		(0.012)		(0.014)		(0.009)
$\gamma_j : \kappa_0 \log(A_0)$		-0.005***		0.001		-0.003***
$\times \log(A_{j0})$		(0.001)		(0.001)		(0.001)
Countries	174	156	173	155	170	152
R-squared	0.00	0.18	0.04	0.15	0.00	0.11

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

TABLE VII: Cross-Section Unconditional Convergence by Quartile in 1991, Dependent Variable: Average Growth in Log Productivity Between 1991 and 2019

	Agriculture		**Manufacturing**		**Services**	
	Sample	4th quartile	Sample	4th quartile	Sample	4th quartile
	(1)	(2)	(3)	(4)	(5)	(6)
β_j	-0.002	-0.003	-0.007***	-0.012**	-0.007***	-0.012***
	(0.002)	(0.004)	(0.002)	(0.005)	(0.002)	(0.003)
Countries	121	39	116	37	110	37
R-squared	0.01	0.03	0.07	0.24	0.10	0.40

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

the services and manufacturing sectors, regardless of the level of $\kappa_t \times \log(A_t)$. However, this is not the case for the agricultural sector. Here, the marginal effect of initial productivity in 1991 on subsequent productivity growth, as derived from equation (5.4), is negative and significant only for countries with a level of financial development times log GDP per capita above 0.69, which corresponds to just above the 25th percentile of countries in 1991. This includes 24 developing countries from the database in 1991[33].

When considering the period from 1991 to 2000, the cross-country estimates in Table VI indicate that, regardless of the level of development, the services sector started to exhibit signs of convergence, as evidenced by the negative and significant coefficient β_s. In contrast, both the manufacturing and agricultural sectors demonstrate a threshold beyond which convergence occurs. For agriculture, this threshold is 1.6, corresponding to 63 countries, and for manufacturing, it is 0.52, corresponding to 18 countries. This implies that during the 1990s, 18 countries were diverging in the manufacturing sector, while 63 countries were diverging in agriculture. By the end of 2019, the situation had shifted. All 18 countries previously diverging in manufacturing began converging, and 39 countries moved from divergence to convergence in agriculture, leaving 24 countries still diverging in agriculture.

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 V, specifically columns (2), (4), and (6), presents estimates indicating that a country like India, which has approximately the same relative productivity levels in the three major sectors compared to France–0.15 in agriculture, 0.17 in manufacturing, and 0.12 in services–will require different amounts of time across different sectors to catch up with France. Starting from an initial development level of $\kappa_t \log(A_t) = 1.9$ in 1991, the estimates[34] suggest that it will take India approximately 81 years to catch up with France in the services sector, 185 years in manufacturing, and 305 years in agriculture.

However, if India's initial financial development were raised to match France's level of 4.52 in 1991, the convergence rates across sectors would improve significantly. In this case, the time needed to catch up with France would shorten to roughly 37 years in services, 45 years in man-

[33] Figure XVII provides a visual representation of the countries in 1991 and 2005 based on their respective levels of financial development and GDP per capita.

[34] I use equation (5.9) 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.

ufacturing, and 74 years in agriculture. These estimates indicate that a country's initial levels of financial development and income play a crucial role in determining its convergence rate across different sectors. The higher the initial financial development and GDP per capita, the faster the country will achieve a comparable level of sectoral productivity relative to the frontier in each sector. Additionally, the estimates underscore the significant variation in the time required for a country to reach the frontier across sectors. For example, convergence occurs most rapidly in the services sector, followed by manufacturing, and lastly agriculture.This variation reflects the differences in the inherent characteristics of these sectors, particularly their average annual productivity growth rates at the frontier, which between 1991 and 2019 were 3.06% in agriculture, 1.97% in manufacturing, and 0.85% in services for the top ten most developed countries.

6 Conclusion

Previous research on the role of financial development in technology adoption has highlighted the importance of well-developed financial markets in efficiently allocating capital to investment opportunities. However, no theoretical model has yet explicitly demonstrated how a country's income and financial development influence sectoral productivity convergence across countries, nor has any model clarified the forces driving differences in the speed of convergence across sectors.

This paper begins by documenting the distinct patterns of productivity convergence between agriculture, manufacturing, and services at the aggregate level. Motivated by two new empirical findings on technology adoption and financial development, 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, as opposed to standard models where all entrepreneurs opt for the same technology if successful. Second, the model accounts for a country's pre-existing knowledge of a specific technology before adoption. Third, it considers the intensity of use of adopted technologies as a key factor determining productivity growth, acknowledging that even if two countries successfully adopt the same technology, they may utilize it at different intensities, as documented by Comin & Mestieri (2018).

The model's predictions provide insights into the role of financial development and income on sectoral productivity convergence. It identifies that countries with low levels of income and financial development may initially experience a temporary divergence in sectoral productivity before eventually beginning conditional convergence, similar to countries with moderate levels of financial development and income. In contrast, countries with high levels of financial development and income converge unconditionally. Both the theoretical model and the empirical findings predict that financial development and income positively influence the speed of convergence. Moreover, they show that sectors with higher productivity growth rates at the technological frontier (such as agriculture) will experience slower convergence than sectors with lower productivity growth rates (such as services).

There are several avenues for extending this analysis. For instance, this study emphasizes the intensity of technology use, facilitated by financial development, as a key determinant of differences in productivity gap convergence across countries. The analysis assumes that if all countries had the same levels of income and financial development, they would use technologies with similar intensity. However, while governance correlates with financial development, other factors–such as coordination between firms or sectoral linkages–should be considered. Future research could explore additional factors affecting the intensity of technology use beyond financial development and wealth. Additionally, it could examine how financial development, through its impact on technology adoption, explains the divergent industrialization paths and rates observed between developing and developed countries.

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A Appendix

A.1 Data Appendix

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

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

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

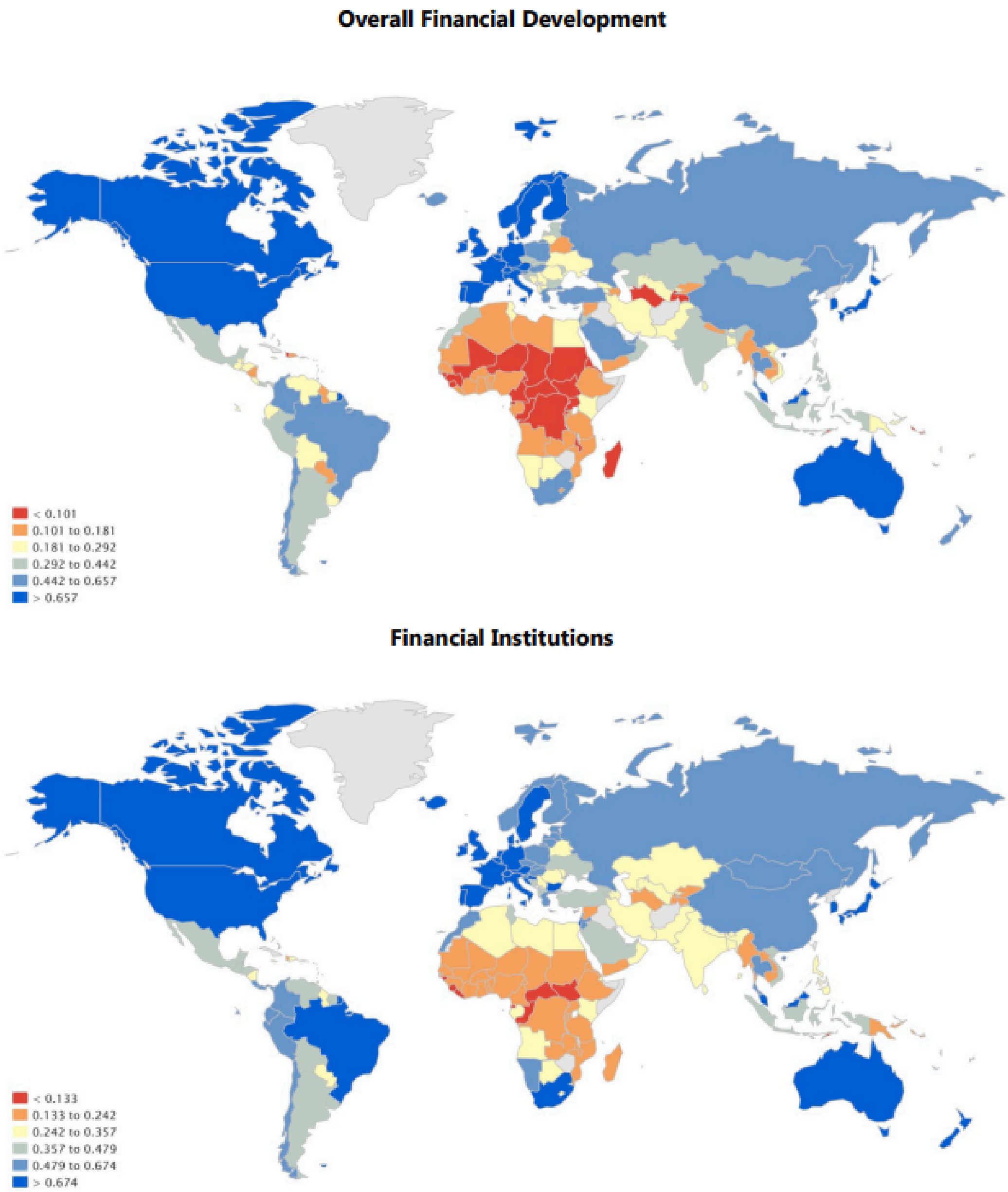

FIGURE XVIII: Global Financial Development and Institutions Map (2014)

Next, I represent the average level of intensity of technology use (in log) relative to sectoral proximity (not in log). In subsection 2.2, I plotted the intensity of adopted technologies against the log of sectoral proximity, showing a positive correlation. However, in Figure XIX, the correlation with sectoral proximity (at its level) is positive up to a threshold, as predicted by the model.

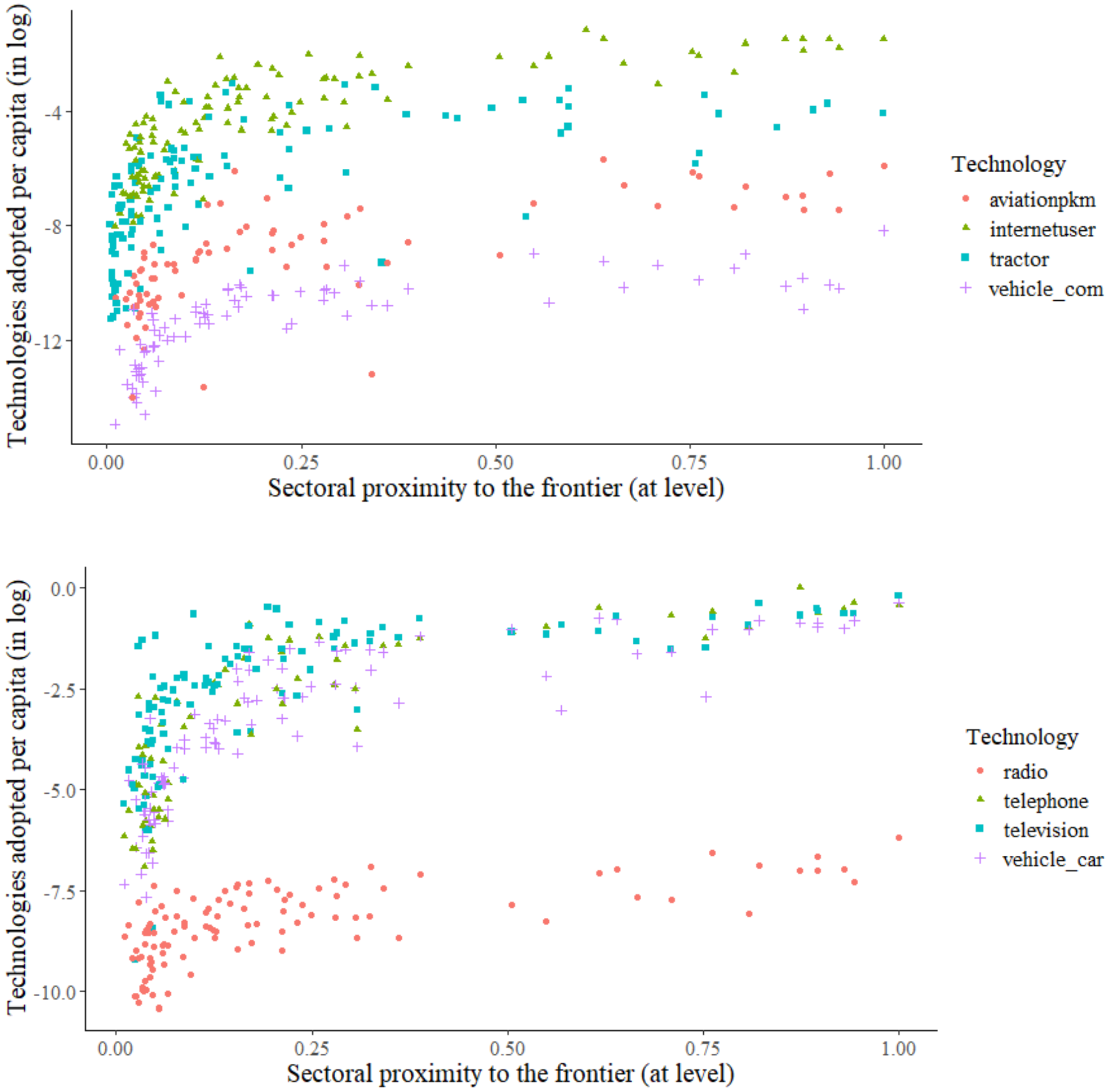

FIGURE XIX: Average Levels of Sectoral Proximity at Level and Log Technology Adoption per Capita (1991–2003)

A.2 Mathematical demonstrations

A.2.1 Proof for Proposition I

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

$\bar{a}_t(\kappa_1)$ is greater than $\bar{a}_t(\kappa_2)$. Then, we have :

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

and

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

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

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

And finally,

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

Beyond the level of sectoral proximity $a_t(\kappa_1)$, financial development no longer has an effect on the intensity of technology use. Increasing the level of financial development from κ_1 to κ_2 had no impact on the intensity of technology use. Only countries that are below this threshold will experience an increase in their technology use level if their level of financial development moves from κ_1 to κ_2. ■

A.2.2 Variation study of f_{jt}

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

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

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

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

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

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

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

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

A.2.3 Demonstration details of Proposition II.

Let us proove that $B_{j_2} \subset B_{j_1}$.
If $\tau \in B_{j_2}$ then $a_{j_2,\tau} = \dfrac{1}{1+\bar{g}_{j_2}}$.

$$\begin{aligned} a_{j_2,\tau} = \frac{1}{1+\bar{g}_{j_2}} &\Longrightarrow a_{j_2,\tau-1} \geq \bar{a}_{\tau-1} \\ &\Longrightarrow a_{j_1,\tau-1} > \bar{a}_{\tau-1}\,, \quad \text{for} \quad a_{j_1,t} > a_{j_2,t} \;\; \forall t \\ &\Longrightarrow a_{j_1,\tau} = \frac{1}{1+\bar{g}_{j_2}} \\ &\Longrightarrow \tau \in B_{j_1}. \end{aligned}$$

From where $B_{j_2} \subset B_{j_1}$ and $\min(B_{j_2}) \geq \min(B_{j_1})$.

A.3 Convergence Appendix

A.3.1 Test of significance

To test the significance of the marginal effect of sectoral initial productivity on sectoral productivity growth, I perform the following test:
$H_0 : \beta_j + \gamma_j * \kappa_t A_t = 0$ vs $H_1 : \beta_j + \gamma_j * \kappa_t A_t \neq 0$
The Student's test statistic is given by:

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

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

$$(\hat{\beta}_j + \hat{\gamma}_j \kappa_t A_t)^2 > z^2_{\frac{\alpha}{2}} \left[\mathrm{var}(\hat{\beta}_j) + \mathrm{var}(\hat{\gamma}_j)\,(\kappa_t A_t)^2 + 2\mathrm{cov}(\hat{\beta}_j, \hat{\gamma}_j)\,\kappa_t A_t\right] \tag{A.3}$$

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.

A.3.2 Zeros of ϕ_j

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

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