Financial Institutions, Technology Adoption, and Sectoral Productivity Convergence*

Komla Avoumatsodo†

June 20, 2023

Abstract

I develop a multisector growth model to incorporate new empirical evidence on technology adoption and financial development, aiming to analyze the implications for sectoral productivity convergence. The model categorizes countries into three groups based on their levels of financial institutions and aggregate productivity. Initially, the first group, characterized by low aggregate productivity and weak financial institutions, experiences sectoral productivity divergence but eventually catches up with the second group. The second group demonstrates moderate levels of aggregate productivity and financial institutions, showcasing conditional convergence. On the other hand, the third group, characterized by high aggregate productivity and strong financial institutions, experiences unconditional convergence towards higher sectoral productivity. The model also suggests that convergence in sectors with faster growth rates at the technological frontier occurs at a later stage. Empirical evidence from the World Development Indicators dataset spanning 29 years and covering over 150 countries supports these and other predictions.

KEYWORDS: Sectoral Productivity Convergence, Technology adoption, Financial development, Sectoral proximity, Technology frontier.

JEL classification: O33, O40, O41, G28

*This paper would not have been possible without the mentorship of Alain Paquet and Pavel Sevcik . I am also thankful for insightful comments from Sophie Osotimehin, Marlon Seror, Julien Martin, Randal Verbrugge, Marius Adom, Isambert Leunga, Théophile Ndjanmou, Adam Touré, Narcisse Sandwidi, and participants at the UQAM internal seminars, 2022 African Econometric Society, 2022 Canadian Economic Association, 17th CIREQ Ph.D. Students' Conference, and Quebec Social Sciences PhD Students Presentations for their comments.

†PhD Candidate, Department of Economics (UQAM): avoumatsodo.komla@courrier.uqam.ca

1 Introduction

A consensus view in the literature is that the variations in income per capita across countries are mostly accounted for by differences in total factor productivity[1]. Jerzmanowski (2007) argues that observed differences in productivity growth are driven by disparities in the technology used, thus reinforcing the findings of Aghion et al. (2005) who had proved that technology adoption is a key channel through which productivity growth is achieved. Indeed, all countries should adopt the best technologies that would allow them to develop faster. However, this does not happen. In the presence of weak financial institutions, lending the optimal funds for implementing certain types of technologies that require significant financial resources may not be profitable for lenders.

In this paper, I study the role of financial development on the intensity of using adopted technologies, and on sectoral productivity convergence. I document a positive correlation between the level of financial development and the intensity of use of adopted technologies. However, this correlation becomes non-existent once the financial development level surpasses a threshold specific to each technology. Furthermore, my findings indicate that sectoral proximity to the technological frontier in terms of productivity is also positively correlated with the level of technology adoption. While these effects are widely recognized at the aggregate level, sectoral analysis offers a new perspective for understanding the relationship between financial development, technology adoption, and variations in the dynamics of productivity across different sectors.

The objective of this paper is to develop a model that is consistent with the aforementioned observations and to examine the implications of the model for sectoral productivity convergence among countries[2]. 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 feature of the model is that a country may be successful in technology adoption and not be able to catch-up with the frontier productivity. I consider that the level of productivity of a country after an adoption will depend not only on the productivity of the sector at the frontier but also on the intensity with which the new technology is used. Indeed, It has been documented by Comin & Mestieri (2018) that the intensity of use of technologies varies across countries.

The model is also extended by incorporating the entrepreneurial skills in order to take into account that entrepreneurs with more knowledge or skills in the sectors in which they wish to adopt technology could do so more easily given that technology transfer is a skill-intensive process. As in Howitt & Mayer-Foulkes (2005), I make the assumption that a country's stock of "effective skills" that can be used in adoption of technolgies depends on its level of development in each sector. Nelson & Phelps (1966) called it "absorptive capacity" which was in their model only an implicit function of human capital and Griffith et al. (2004) gave the evidence that skills are an important determinant of a country's absorptive capacity. Considering this absorptive capacity makes it possible to capture the variable of proximity to the technological frontier in the model as well as its impact on the adoption of successful technologies. To simplify the analysis and for mathematical convenience, I make the assumption that in the absence of credit constraints, countries would use the adopted technologies at the same intensity as the technological frontier[4]. Under this

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

[2] A large literature examines convergence of either GDP per capita or GDP per worker at the aggregate or regional level[3]. This study revisits the convergence debate at the sectoral level.

[4] While I acknowledge that factors like governance can influence technology adoption in a country, my focus is

assumption, it is expected that their 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 stylized facts described earlier. It shows that the intensity of technology use increases as sectors get closer to the technological frontier and as the level of financial development rises, up to a certain threshold of sectoral productivity proximity to the frontier and 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. Also, as a country's financial development improves, it gains the ability to allocate more funds towards adopting new technologies. This increased allocation continues until the constraint or limitation, which previously restricted the country's ability to invest in technology, is no longer a significant obstacle.

Furthermore, the model makes predictions regarding the convergence and divergence of sectoral productivities. It classifies countries into three distinct categories. The first group encompasses nations characterized by low levels of both aggregate productivity 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 aggregate productivity. These nations demonstrate conditional convergence towards their steady state and eventually transition to the third group. As aggregate productivity 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 aggregate productivity. These countries converge to a higher level of sectoral productivity unconditionally.

The implications of the model imply that differences in financial development and aggregate productivity are influential factors in shaping the convergence and divergence of sectoral productivities across countries. However, it is crucial to note that countries are not confined to a single category, particularly as aggregate productivity experiences continuous growth over time. In fact, at a certain point in time, the impact of the upper bound on borrowing, which is imposed on entrepreneurs, is counterbalanced by the country's growing wealth and the resulting spillover effect on the sector's technology adoption. Once this borrowing constraint is no longer binding within a specific sector, the role of financial development becomes less significant in determining productivity convergence of a country within that sector.

Additionally, the model predicts that both financial development and aggregate productivity have a positive impact on the speed of convergence. Countries with higher levels of financial development are expected to converge faster. Furthermore, sectors with higher growth rates at the technological frontier will experience slower convergence compared to sectors with lower growth rates in advanced countries. To support the predictions of the model, I present evidence by conducting a panel data regression analysis for agriculture, manufacturing and services. The regressions include sectoral labor productivity growth as the dependent variable and incorporate the initial level of sectoral productivity, financial development level multiplied by aggregate productivity, and an interaction term between these two variables. The analysis utilizes the World Development Indicators (WDI) dataset, encompassing data from more than 150 countries over the period 1991-2019.

specifically on examining the impact of institutional quality in the financial sector, using the credit constraint mechanism, on technological adoption levels. In the empirical facts analysis, I include control variables related to governance, such as government effectiveness, control of corruption, voice and accountability, political stability and absence of violence/terrorism, regulatory quality, and rule of law.

The empirical study reveals a significant and positive relationship between financial development, aggregate productivity, and the speed of convergence. The results of estimated equations indicate that a country with an initial product of financial institutions index and log of aggregate productivity level of 2 and with an initial sectoral productivity level of 0.1 relative to the top ten most productive countries would take approximately 32 years to reach 0.5 relative sectoral productivity in services, 57 years in manufacturing, and 508 years in agriculture. Increasing the initial product of financial institutions index and log of aggregate productivity level to 2.5 accelerates the rate of convergence in each sector, reducing the time required to achieve 0.5 productivity level relative to the frontier to 26 years in services, 42 years in manufacturing, and 169 years in agriculture.

These findings highlight the significance of a country's initial financial development and aggregate productivity level in influencing the rate of convergence across sectors. Countries with higher initial financial development and aggregate productivity levels converge faster to the frontier in their respective sectors. Furthermore, the study demonstrates significant variations in the time needed for countries to reach the frontier across sectors. The services sector exhibits the fastest rate of convergence, followed by manufacturing and then agriculture, reflecting differences in the productivity growth of these sectors at the frontier. Indeed, between 1991 and 2019, the top ten most productive countries experienced a higher average growth rate in agriculture, with a rate of 4.42%. In contrast, the average growth rate was 1.58% in manufacturing and 1.05% in services.

My paper is related to the broad literature analyzing the channels driving the differences in productivities across countries. Specifically, my paper relates to the literature seeking to find why poor countries do not adopt and use efficiently more productive technologies. One strand of the literature has related the role of distortions or barriers to technology adoption (e.g., Parente & Prescott (1999); Hsieh & Klenow (2014); Bento & Restuccia (2017)). According to this point of view, policies that make it possible to eradicate missallocation and especially in the financial system contribute to the adoption of technologies. Another strand of the literature emphasizes the role of complementarity and coordination of firms' decisions which can lead to more technology adoption (Matsuyama (1995); Buera et al. (2021)). The three papers most closely related to mine are Aghion et al. (2005), Cole et al. (2016) and Comin & Nanda (2019).

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 looks, at the sectoral level, the effect of financial development on the level of adoption of the most and the least advanced technologies. Besides explaining differences in technology adoption between countries, the model demonstrates that within a country, some sectors can use new technologies more intensively than others, even when the overall level of financial development is the same. This variation in technology use is influenced by the differing levels of productivity across sectors. Sectors that exhibit higher levels of productivity are more likely to adopt and employ new technologies to a greater degree because sectors with higher productivity possess a greater pool of knowledge and expertise related to technology adoption. They have a workforce that is more adept at understanding and integrating new technologies into their operations, allowing for a smoother adoption process.

In addition, Aghion et al. (2005) analyze convergence at the aggregate level, 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.

Cole et al. (2016) meanwhile build a model in which the advanced and intermediate technologies cannot be implemented when monitoring is not efficient and/or when there is a significant cash-flow problem. They presented a quantitative illustration where financial frictions induce entrepreneurs in India and Mexico to adopt less-promising ventures than in the United States, despite lower input prices. This framework differs in several aspects from their paper and documents how financial development can influence technology adoption based on a country's distance from the technology frontier. On the other hand, Comin & Nanda (2019) only focused on the role of the financial development in advanced technology adoption and conducted an empirical analysis on 16 major technologies, across 17 advanced economies, from 1870 to 2000. This current work extends beyond the findings of Comin & Nanda (2019) by being both theoretical and empirical. Moreover, it encompasses not only developing countries but also considers the sectoral proximity of countries.

Furthermore, the model's predictions on the convergence of sectoral productivity stand out, particularly when compared to Rodrik (2013), Kinfemichael & Morshed (2019), and Herrendorf et al. (2022). Indeed, in his article, Rodrik (2013) demonstrates that unconditional convergence exists in manufacturing labor productivity, irrespective of geography, policies, or other country-level factors. Similarly, Kinfemichael & Morshed (2019) found evidence of unconditional convergence in services. In contrast, Herrendorf et al. (2022) construct new data comparable across-countries and find that labor productivity gaps in manufacturing are larger than in the aggregate and there is no tendency for manufacturing labor productivity to converge unconditionally. This paper emphasizes the significance of aggregate productivity and financial development levels in determining whether countries experience convergence or divergence in sectoral productivity, as well as the speed at which convergence occurs in sectors and across countries.

This paper provides valuable insights into multiple aspects of the relationship between financial systems, technology adoption, and sectoral productivity productivity convergence. The subsequent sections are structured as follows. Section 2 provides a concise overview of the evidence concerning technology adoption, financial development, and the proximity of sectoral productivity to the frontier. Following that, 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. To empirically examine sectoral productivity convergence, Section 5 presents an in-depth analysis. Finally, the paper concludes in Section 6, summarizing the key findings and highlighting their implications.

2 Empirical evidence on technology adoption, sectoral productivity gap, and financial development

I summarize the empirical facts on technology adoption, financial development, and sectoral proximity to the technological frontier into three stylized "observations" that drive my model.

2.1 Data

I combine three types of data[5]. 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 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. Table I in Appendix A.1 lists the technologies used in the econometric regression.

As shown in Table I, the set of technologies covers the three economic sectors (agriculture, industry and service). 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: Description of technologies used in the econometric analysis

	Technology	**Measure**	**Sector**	**Countries**	**Obs.**
1	Harvesters	Number in operation	Agriculture	100	250
2	Tractors	Number in operation	Agriculture	130	358
3	Electric production	KwHr produced	Industry	120	267
4	Railroad	Km of track installed	Industry	82	146
5	Electric arc steel	Tons produced	Industry	74	195
6	Blast furnace steel	Tons produced	Industry	44	116
7	Aviation pkm	Million passenger kilometers	Services	70	70
8	Cable TV	Number of users	Services	88	192
9	Commercial vehicles	Number in operation	Services	78	129
10	Computers	Number in operation	Services	113	273
11	Internet users	Number of individuals	Services	128	294
12	Mail	Million units handled	Services	29	35
13	Radio	Number in operation	Services	120	216
14	Telegram	Telegrams sent	Services	24	27
15	Telephone	Number connected	Services	84	192
16	Private vehicles	Number owned	Services	103	206
17	Television	Number in operation	Services	123	275
	Total			**132**	**3, 271**

All data are aggregated to 5-year time periods spanning 1991-2003.

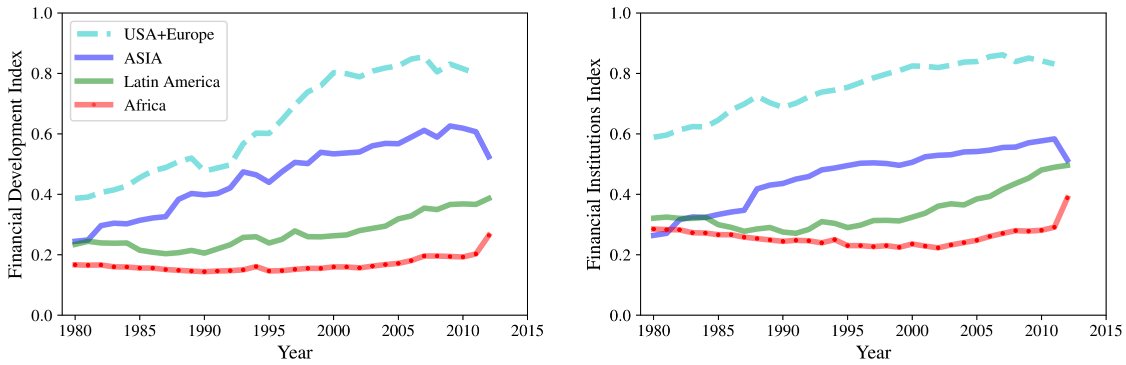
I use the Financial Development Index[7] (alternatively Financial Institutions Index) developed by International Monetary Fund (IMF) as a measure of financial development. It summarizes how developed financial institutions and financial markets are in terms of their depth (size and

[5]See Table XI in the Appendix A.1 for detailed and description and sources of data.

[6]Historical Cross-Country Technology Adoption

[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.

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 (Appendix A.1). Figure I shows the evolution over time of the financial institution and financial development indices.



(a) Financial Development

(b) Financial Institutions

FIGURE I: Average level by region of Financial Indexes over time

As productivity increases through investment and technological progress or changes in work organization, the level of 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 is calculated by dividing the country's productivity by the US sectoral productivity in the same sector. The productivity data used in this study are sourced from the WDI database.

Observation 1 : *Across countries, the intensity of use of adopted technologies is positively correlated with financial development index only for low financially developed countries.*

Figure II 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 techology adoption which vanishes once financial development has reached approximately a certain level. Figure II also includes scatter plots for additional technologies.

The association between the average intensity 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 falls between 0.3 and 0.4 for radio and commercial vehicles. This suggests that financial development plays a relatively smaller role in driving technological adoption in these sectors compared to adoption of tractors and electricity production. In the same country with the same level of financial development, some sectors, depending on their productivity at the technological frontier, may face more constraints than others.

[8] Also, in the theoretical model, the value added per worker is proportional to productivity, see equation (3.9)

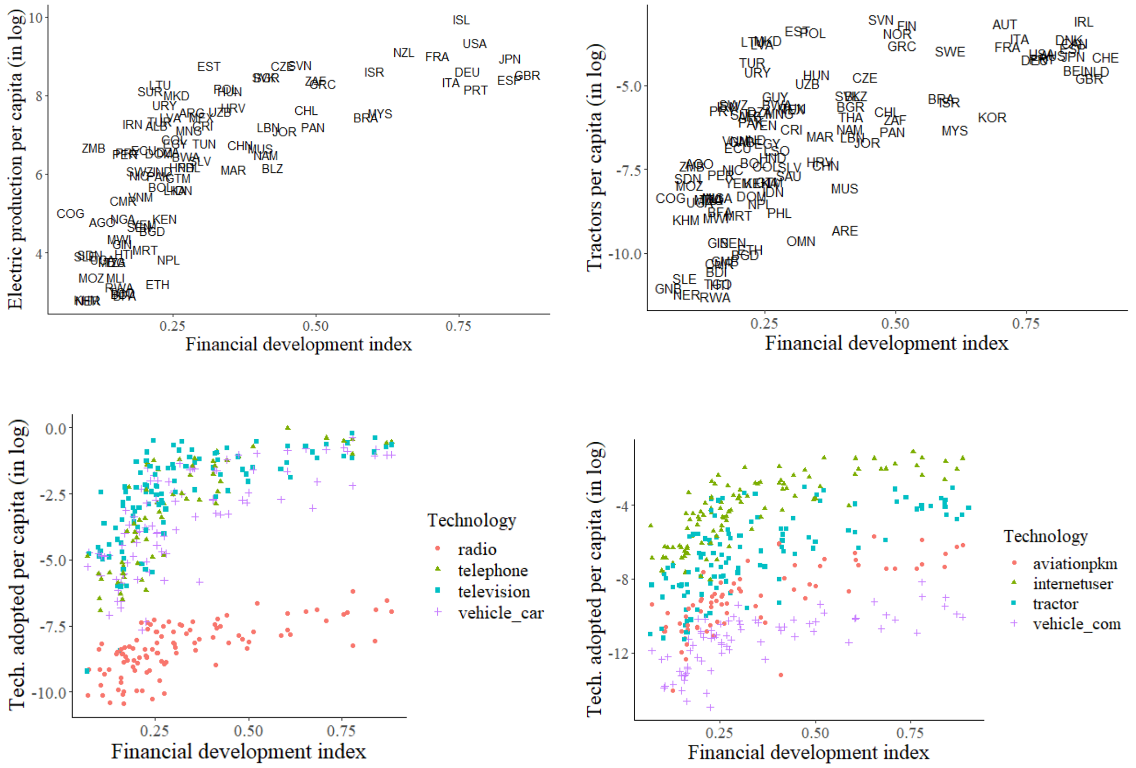


FIGURE II: Average levels of financial development and log technology adoption per capita, 1980-2003

Observation 2 : *Sectoral proximity to the frontier is positively associated with more use of adopted technologies across countries.*

Figure III displays scatter plots illustrating the association between the level of technology adoption and the sectoral proximity to the United States[9]. The top row of the figure presents two examples, one showing the relationship between the average total tractors per capita adopted from 1991 to 2003 and the proximity to the United States in the Agriculture sector, and the other depicting the relationship between the total electric production per capita and the proximity to the United States in the Industry sector. It is evident that countries with higher technology adoption levels are also closer to the United States in terms of productivity. These relationships, depicted in Figure III, hold consistently across different technologies and are statistically significant at the 1% level[10].

The positive relationship illustrated in Figure III obviously says nothing about the direction of causality. While the usual interpretation is that technological adoption increases productivity, my model not only explains that technological adoption moves closer to the frontier, but that some causality can also work in the opposite direction. Figures II and III only show the relation between average intensity of use of technology , financial development and the sectoral productivity proximity to the frontier. They do not deal with the problem of possible endogeneity of sectoral distance and financial intermediation. Nor do they control for the effects of any other possible in-

[9]The sectoral proximity to the frontier refers to the agricultural (industrial and service) productivity divided by the corresponding productivity in the United States.

[10]This analysis is intended for illustrative purposes only. A more comprehensive analysis will be conducted in section 2.2.

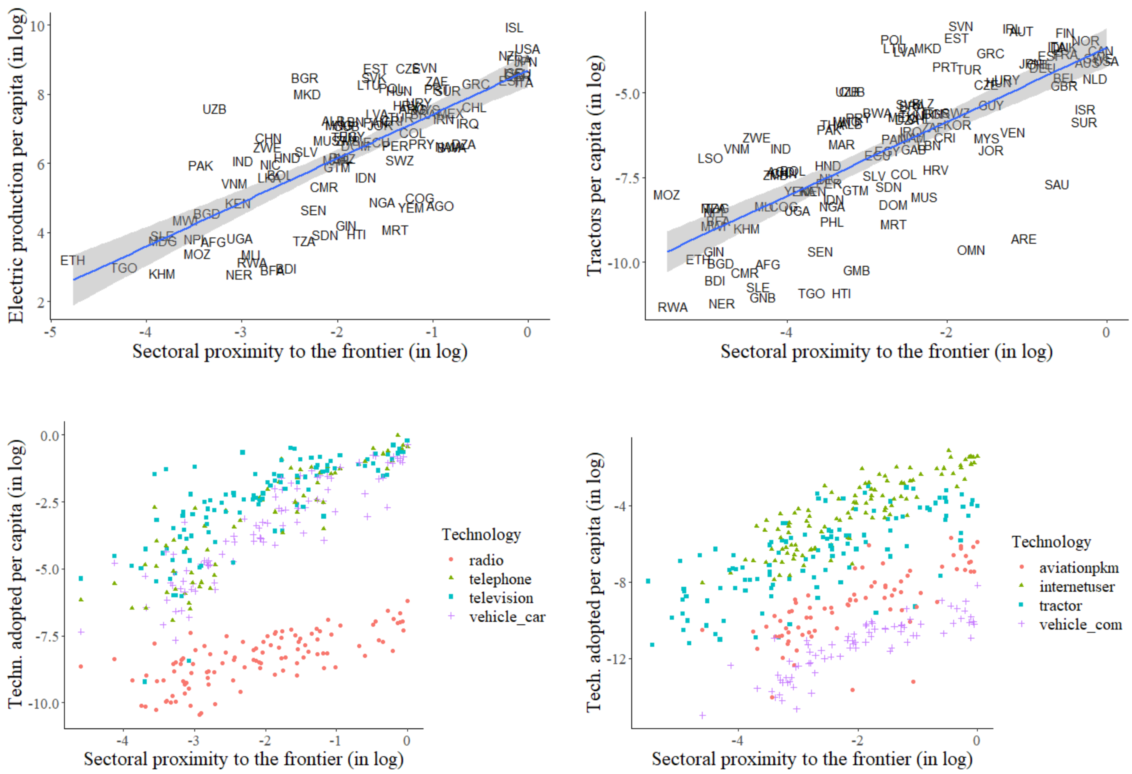


FIGURE III: Average levels of sectoral productivity proximity to the US and log intensity of use of technologies, 1991-2003

fluences on technology adoption. Indeed, a linear correlation analysis on data between 1991-2013 shows a positive coefficient of correlation between financial development index and the sectoral log productivity : 0.68 in Agriculture, 0.6 in Manufacturing and 0.76 in Services. Countries that are close to the frontier are the same time those whose are more financial institutional developed. Thus, the effect of one of these two variables on the intensity of using new adopted technologies may not be real but simply pass through the other variable. For these, I turn to the following regression specification in the subsection 2.2.

2.2 Econometric Specification

I previously illustrated that financial development is no longer correlated with intensity of use of technologies from a certain level of financial development. I also showed that sectoral productivity proximity to the frontier is positively correlated with the intensity of use of technologies. However, countries that are closest to the frontier are at the same time the most financially developed I test these correlations in a linear regression model (2.1). I also make the financial institution variable interact with the sectoral proximity productivity variable in the equation of intensity of use of technologies.

$$y_{cjt} = \eta_{jt} + \delta_c + \beta_1 FD_{ct-1} + \beta_2 dist_{cjt-1} + \beta_3 \left(FD_{ct-1} * dist_{cjt-1}\right) + \beta_4 \mathbf{X}_{ct} + \varepsilon_{cjt} \tag{2.1}$$

where y_{cjt} denotes the intensity of use of technology j in country c at period t. All measures are scaled by population. I deal with the heterogeneity of measures in two ways. First, I take logarithms of the per capita technology measures as Comin & Nanda (2019). This removes the units of the analysis which go to the constant term. Second, I introduce a full set of technology-times-year fixed effects, denoted by η_{jt} in the regression specification that captures the average diffusion path for each technology. Effectively these fixed effects imply that the dependent variable is the deviation of a country's adoption of a technology from the average adoption of that technology across countries. Many of the concerns related to cross-country econometric studies are the control for time-invariant unobserved country characteristics that can be correlated with the observed independent variables. I therefore include country-fixed effects, denoted by δ_c, to control for other country-specific factors that might impact the rate of adoption of technologies. FD_{ct-1} is the time-varying measure of financial development across countries. $dist_{cjt-1}$ is the proximity to the frontier of the country c at time $t-1$ in the sector of the technology j. Each technology is classified in one of the three economic sectors (agriculture, industry and services) as shown in the Table I. The frontier is considered here to be the United States of America and $dist_{cjt}$ is the logarithm of the productivity A_{cjt} of the country c in the sector of the technology j divided by the US sectoral productivity A^{us}_{jt} in the same sector at time t.

$$dist_{cjt} = \log\left(A^{c}_{jt}\right) - \log\left(A^{us}_{jt}\right) < 0$$

The lower the value of $dist_{cjt}$, the further the country is from the USA in terms of productivity. Therefore, β_1 (respectively β_2) represents the relationship between financial development (respectively sectoral productivity proximity to the frontier) and the country's intensity of use adopted technology j. The vector $\mathbf{X}_{ct}$ consists of control variables such as income per capita, the country's stock of human capital, governance, and their interaction with the level of financial development. It is important to include these control variables to mitigate potential sources of omitted variable bias that may arise from factors known to influence cross-country development, such as traditions or culture (Guiso et al., 2006) and the quality of governance (Manca and Ottaviano, 2010; Acemoglu et al., 2001).

To analyze the impact of distance to the frontier on the relationship between financial development and technology use, the introduction of the interaction variable between financial development and distance to the frontier is crucial. This interaction variable allows us to examine how the effect of financial development on technology diffusion varies depending on the level of proximity to the technological frontier. The marginal effect of financial development on the diffusion of technology can be determined by:

$$\frac{\partial y_{cjt}}{\partial FD_{ct-1}} = \beta_1 + \beta_3 * dist_{cjt-1} \tag{2.2}$$

The equation (2.2) shows that the marginal effect of financial development on the level of technology use depends on the sectoral distance of the country to the frontier. If $\beta_3 < 0$ then financial development makes it more easier for countries that are far from the frontier such as developing countries to adopt technologies than those who are close to the frontier. Based on the correlation analysis, β_1 is expected to be positive and β_3 negative so that the marginal effect of financial development is higher for countries that are far from the frontier. Similarly, the overall effect of sectoral proximity to the frontier on technology adoption is given by the equation (2.3) below. If β_3 is negative then sectoral proximity favors more technology adoption in low financially developed countries.

$$\frac{\partial y_{cjt}}{\partial dist_{cjt-1}} = \beta_2 + \beta_3 * FD_{ct-1} \tag{2.3}$$

2.3 Regression Results

Table II displays the results of the estimation for equation (2.1). The estimations include technology and country fixed effects dummies to account for any heterogeneity across technologies and countries.

Observation 3 : *The coefficient of association between financial development and intensity of technology use is higher for countries that are far from the technological frontier.*

As shown in Table II, the level of financial development (first row) is insignificantly correlated with the level of technology diffusion. However, the coefficient of the proximity to the frontier (second row) is significant and positive. More importantly, the association between distance and financial development is larger for less productive countries (most distant from the frontier countries). This implies that financial development plays a more important role on technology adoption in developing countries than in advanced countries since developed countries are characterized by a high level of financial development and developing countries by a low level of financial development.

TABLE II: Technology adoption, financial development and sectoral proximity to the frontier (1991-2003)

	log technology diffusion per capita					
	(1)	(2)	(3)	(4)	(5)	(6)
Finance	0.442	0.253	0.510	0.783	3.641	4.045
	(0.593)	(0.763)	(0.559)	(0.429)	(0.662)	(0.679)
Sectoral proximity (in log)	0.205**	0.202**	0.156*	0.228**	0.278***	0.227**
	(0.020)	(0.021)	(0.094)	(0.018)	(0.002)	(0.021)
Finance × Proximity	-0.573**	-0.545**	-0.550*	-0.777**	-0.841***	-0.772**
	(0.039)	(0.050)	(0.053)	(0.011)	(0.007)	(0.015)
GDP per capita (in log)		0.732	0.258	0.412	0.478	0.463
		(0.220)	(0.677)	(0.545)	(0.487)	(0.518)
GDP per capita × Finance					-0.500	-0.679
					(0.663)	(0.692)
Human capital			0.707	0.845		0.794
			(0.455)	(0.458)		(0.545)
Human capital× Finance						0.371
						(0.881)
Geography				0.031	0.012	0.004
				(0.269)	(0.832)	(0.946)
Geog.× Finance					0.052	0.061
					(0.640)	(0.578)
Technology-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,871	1,871	1,757	1,438	1,485	1,438
R-squared	0.960	0.960	0.961	0.964	0.964	0.964

Robust p-values in parentheses.
All data are aggregated to 5-year time periods spanning 1991-2003.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

According to the data, both Lithuania and Ethiopia[11] had almost the same level of financial development in 1995 (around 0.12 on a scale of 0 to 1). The estimates imply that increasing these two countries' financial development to the level of USA (0.69) in 1995 would have led to an increase in the adoption of technologies over the next 5 years in Lithuana's agrucultural sector by 197% and in Ethiopia by 540%; in Lithuana's industry by 134% and in Ethiopia by 492%; in Lithuana's service sectors by 117% and in Ethiopia by 475%. Since Ethiopia was less productive than Lithuana in all the three major economic sectors, Ethiopia would benefit more from financial development than Lithuana.

In columns 2–6 of Table II, a set of control variables is used one after another to assess the robustness and significance of the coefficients. The coefficient of the sectoral distance changes very slightly but continues to remain statistically significant while the direct effect of financial development is insignificant, suggesting that the control variables have addressed the relevant sources of omitted variable bias. However, the overall effect of financial development on technology adoption still remains positive and significant when considering the interaction with sectoral proximity. And this effect is higher for countries that are far from the technological frontier (lower $dist_c$) which implies that financial development plays more important role in the adoption of the most advanced technologies. The control variables such as GDP per capita and human capital are positively correlated with the level of technologies adopted across countries but not significantly. The panel structure of the data set has several important advantages over cross-sectional data sets. First of all, the data captures time variation as well as cross-sectional variation in the variables. Secondly, because the data set covers many different technologies and a large number of countries, we are able to consider the robustness of the results across technologies and countries.

Another argument that could be made in regard of robustness of the estimations is that a country lacking governance qualities may not be able to adopt new technologies. Omitting organizational and governance factors such as control of corruption, rule of law, political stability and absence of violence and terrorism can bias the estimates. In Table III, I therefore include a measure of governance variables[12], available from World Governance Indicators (2020) and find that the results are robust to the inclusion of these controls and their interaction with the measure of financial development. The estimations in Table III show that the governance variables as well as geography variable are not correlated with the level of technogy adoption however they have predictive power over the technology adoption measures in cross-section estimations.Indeed, variables such as governance and geography do not have much variation over time. This may explain why their effect are not significant in estimations taking into account the time dimension.

In terms of the econometric regression results, the level of technology adoption can vary across countries based on their financial system quality and productivity levels. The differences in technology adoption are not solely attributed to variations in financial development, but also to disparities in sector-specific productivity. Countries with higher productivity are more likely to experience lower adjustment costs and implementation barriers when adopting new technologies, making the process more cost-effective compared to countries with lower productivity levels. For instance, while India has exhibited a higher level of financial development compared to Mexico since the 1980s, Mexico has outperformed India in the adoption of almost all technologies listed in the HCCTA database. This can be attributed to Mexico's overall higher productivity across all

[11] They were both in the 50th of financial development in the dataset.

[12] Table VI reports the results from regressions where I look at non-lagged financial development and sectoral proximity. The results continue to remain robust using this specification. Also, I estimate the equation (3) with Financial Institutions Access (FIA), Financial Institutions Depth (FID) and Financial Markets Efficiency (FME) instead of the aggregate variable Financial Development (FD). The results are shown in Tables IV and V. The effects remain statistically significant with these new variables.

three economic sectors, distinguishing it from India's performance.

Motivated by these findings, the upcoming section introduces a model that incorporates the relationship between the intensity of technology use and both sectoral productivity proximity to the frontier and financial development. The model also explores the implications of financial development, aggregate productivity, and frontier sectoral productivity growth on the convergence of sectoral productivity across countries.

TABLE III: Robustess control with governance variables: dependent variable: log technology diffusion per capita

	Governance variables used					
	GE	**CC**	**VA**	**PV**	**RQ**	**RL**
Finance	4.896	3.300	3.988	4.257	4.262	3.757
	(0.631)	(0.734)	(0.681)	(0.669)	(0.680)	(0.699)
Sectoral proximity (in log)	0.221**	0.220**	0.220**	0.221**	0.222**	0.221**
	(0.027)	(0.027)	(0.027)	(0.027)	(0.026)	(0.027)
Finance×Proximity	-0.755**	-0.758**	-0.756**	-0.757**	-0.762**	-0.758**
	(0.018)	(0.017)	(0.018)	(0.018)	(0.016)	(0.018)
GDP per capita	0.055	0.068	0.060	0.141	-0.036	0.103
	(0.939)	(0.922)	(0.933)	(0.837)	(0.961)	(0.882)
GDP×Finance	-0.824	-0.469	-0.437	-1.010	-0.370	-0.534
	(0.664)	(0.782)	(0.804)	(0.603)	(0.848)	(0.753)
Human capital hc	0.810	0.816	0.483	0.669	0.595	0.763
	(0.528)	(0.565)	(0.706)	(0.617)	(0.647)	(0.605)
hc × Finance	-0.373	-0.112	0.269	0.472	0.382	-0.165
	(0.872)	(0.965)	(0.916)	(0.870)	(0.877)	(0.949)
Geography	0.024	0.011	0.022	0.018	0.044	0.015
	(0.678)	(0.882)	(0.694)	(0.736)	(0.347)	(0.829)
Finance×Geog.	0.048	0.057	0.057	0.048	0.071	0.052
	(0.666)	(0.681)	(0.602)	(0.664)	(0.515)	(0.720)
Governance	-0.080	-0.145	-0.069	-0.333	0.283	-0.085
	(0.873)	(0.785)	(0.847)	(0.201)	(0.483)	(0.879)
Finance×**Gov.**	0.795	0.072	-0.428	1.010	-0.912	0.222
	(0.571)	(0.972)	(0.820)	(0.303)	(0.491)	(0.926)
Technology-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,416	1,416	1,416	1,416	1,416	1,416
R-squared	0.965	0.965	0.965	0.965	0.965	0.965

All data are aggregated to 5-year time periods spanning 1991-2003. *** p<0.01, ** p<0.05, * p<0.1
Robust pvalues in parentheses, Governance variables are **GE** :Government Effectiveness, **CC**: Control of Corruption, **VA** : Voice and Accountability, **PV**: Political Stability and Absence of Violence/Terrorism, **RQ** : Regulatory Quality, **RL** : Rule of Law

TABLE IV: Robustess control with financial markets efficiency (FME) and financial institutions index (FI) variables, dependent variable: log technology diffusion per capita

	Finance variables used					
	FME			**FI**		
	(1)	(2)	(3)	(4)	(5)	(6)
Finance	-0.279	-3.490	-3.089	0.108	-1.213	0.716
	(0.430)	(0.172)	(0.299)	(0.923)	(0.884)	(0.946)
Sectoral proximity	0.135*	0.204***	0.155*	0.249**	0.369***	0.321***
	(0.053)	(0.006)	(0.057)	(0.011)	(0.000)	(0.002)
Finance×Proximity	-0.226*	-0.552***	-0.483**	-0.620**	-1.007***	-0.976***
	(0.096)	(0.009)	(0.025)	(0.024)	(0.001)	(0.001)
GDP per capita		0.595	0.553		0.599	0.678
		(0.401)	(0.426)		(0.456)	(0.468)
GDP ×Finance		0.313	0.208		0.005	-0.546
		(0.408)	(0.765)		(0.997)	(0.797)
Geography		0.022	0.018		0.010	0.025
		(0.614)	(0.682)		(0.917)	(0.752)
Geog.×Finance		0.006	0.005		0.021	0.024
		(0.914)	(0.920)		(0.894)	(0.874)
Human capital hc			1.025			0.586
			(0.380)			(0.702)
hc×Finance			0.267			1.174
			(0.855)			(0.683)
Technology-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,871	1,485	1,438	1,871	1,485	1,438
R-squared	0.960	0.964	0.964	0.960	0.964	0.964

All data are aggregated to 5-year time periods spanning 1991-2003. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Robust pvalues in parentheses, Financial variables are **FME** : Financial Markets Efficiency, and **FI** :Financial Institutions Index.

TABLE V: Robustess control with financial institutions access (FIA) and financial institutions depth (FID) variables, dependent variable: log technology diffusion per capita

	Finance variables used					
	FIA			**FID**		
	(1)	(2)	(3)	(4)	(5)	(6)
Finance	-0.217	-1.714	-0.731	-0.293	-5.083	-7.695
	(0.838)	(0.868)	(0.951)	(0.764)	(0.507)	(0.457)
Sectoral proximity	0.206***	0.250***	0.208**	0.178**	0.248***	0.200**
	(0.006)	(0.001)	(0.012)	(0.020)	(0.001)	(0.015)
Finance×Proximity	-0.706***	-0.896***	-0.870***	-0.600**	-0.925***	-0.845***
	(0.003)	(0.000)	(0.001)	(0.016)	(0.000)	(0.002)
GDP per capita		0.815	0.776		0.627	0.570
		(0.241)	(0.279)		(0.342)	(0.391)
GDP ×Finance		-0.119	-0.322		0.392	1.097
		(0.933)	(0.869)		(0.735)	(0.591)
Geography		0.022	0.001		0.005	-0.009
		(0.602)	(0.991)		(0.940)	(0.891)
Geog.×Finance		0.072	0.089		0.022	0.028
		(0.579)	(0.499)		(0.858)	(0.811)
Human capital hc			1.282			1.541
			(0.292)			(0.312)
hc×Finance			0.231			-1.475
			(0.932)			(0.587)
Technology-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,871	1,485	1,438	1,871	1,485	1,438
R-squared	0.960	0.964	0.964	0.960	0.964	0.964

All data are aggregated to 5-year time periods spanning 1991-2003. *** p<0.01, ** p<0.05, * p<0.1
Robust pvalues in parentheses, Financial variables are **FIA** : Financial Institutions Access, and **FID** :Financial Institutions Depth.

TABLE VI: Technology adoption, financial development and sectoral proximity to the frontier (1991-2003)

	log technology diffusion per capita					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Explanatory variables are 5-years lagged						
Finance	0.442	-0.162	-0.928	3.641	0.783	4.045
	(0.593)	(0.974)	(0.859)	(0.662)	(0.429)	(0.679)
Sectoral proximity	0.205**	0.205**	0.166*	0.278***	0.228**	0.227**
	(0.020)	(0.028)	(0.089)	(0.002)	(0.018)	(0.021)
Finance×Proximity	-0.573**	-0.559*	-0.614**	-0.841***	-0.777**	-0.772**
	(0.039)	(0.070)	(0.049)	(0.007)	(0.011)	(0.015)
GDP per capita (in log)		0.732	0.211	0.478	0.412	0.463
		(0.220)	(0.742)	(0.487)	(0.545)	(0.518)
GDP per capita × Finance		0.041	0.416	-0.500		-0.679
		(0.931)	(0.586)	(0.663)		(0.692)
Human capital			0.902		0.845	0.794
			(0.382)		(0.458)	(0.545)
Human capital× Finance			-0.884			0.371
			(0.629)			(0.881)
Geography				0.012	0.031	0.004
				(0.832)	(0.269)	(0.946)
Finance×Geog.				0.052		0.061
				(0.640)		(0.578)
Panel B: Explanatory variables are non-lagged						
Finance	0.199	-3.672	-4.399	-3.715	-0.084	-2.752
	(0.690)	(0.258)	(0.214)	(0.385)	(0.881)	(0.559)
Sectoral proximity	0.255***	0.243***	0.218***	0.303***	0.246***	0.266***
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Finance×Proximity	-0.571***	-0.657***	-0.726***	-0.890***	-0.740***	-0.844***
	(0.003)	(0.003)	(0.001)	(0.000)	(0.000)	(0.000)
GDP per capita (in log)		0.710**	0.700**	1.039***	1.105***	1.082***
		(0.013)	(0.021)	(0.002)	(0.001)	(0.002)
GDP per capita × Finance		0.341	0.561	0.171		0.087
		(0.263)	(0.262)	(0.778)		(0.914)
Human capital			0.111		-0.277	-0.092
			(0.858)		(0.682)	(0.891)
Human capital× Finance			-0.470			0.057
			(0.626)			(0.959)
Geography				-0.005	0.021	-0.001
				(0.880)	(0.208)	(0.964)
Finance×Geog.				0.039		0.034
				(0.540)		(0.572)
Technology-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,271	3,271	3,072	2,610	2,529	2,529
R-squared	0.960	0.960	0.961	0.964	0.964	0.964

All data are aggregated to 5-year time periods spanning 1991-2003.
Robust p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3 Theoretical model

The model economy follows Aghion et al. (2005) and economic activity occurs in countries which do not exchange goods or factors of production, but do use each others' technological ideas. Each country has a fixed population which is normalized to one, so that aggregate and per capita quantities coincide. Each individual lives two periods and is endowed with two units of labor in the first period and none in the second. At the end of the first period, households obtains an entrepreneurial skill level and invest their savings in a technology adoption[13] project as entrepreneurs. The saving rate $s \in (0,1)$ is exogenous and the utility function is linear[14] in consumption , so 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 of life, and $\beta \in (0,1)$ is the rate at wich individuals discount the utility of consumption in period 2 relative to that in period 1.

3.1 Goods production sectors

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

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

where $0 < \alpha < 1$, A_{jt} is the productivity in the 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 is 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 of each sector j to use in order to maximize its profit as follows:

$$\max_{\{L_t, [x_{jt}]_{j\in[0,1]}\}} L_t^{1-\alpha} \int_0^1 A_{jt}^{1-\alpha} x_{jt}^{\alpha} dj - \int_0^1 p_{jt} x_{jt} dj - w_t L_t \tag{3.2}$$

where p_{jt} is the price of the intermediate good of variety $j \in [0,1]$. The first order conditions for the firm in the final sector are given by:

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

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

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

[13]Technology adoption involves uncertain process of adapting ideas from the world technology frontier to the domestic economy. Innovation is necessary to transfer a technology because technology and technological expertise have tacit, country-specific qualities.

[14]For the sake of simplicity and tractability, utility is assumed to be linear, implying that asset returns are non-autocorrelated and do not depend on previous levels of consumption. This assumption ensures a given exogenous level of savings in the absence of arbitrage between present and future consumption. One may consider an endogenous savings rate, where if the level of financial development is low, projects are self-financed through a higher level of savings. However, given the lower savings rate in countries with weak financial institutions, we can limit ourselves to an exogenous savings rate without changing the results of the analysis.

Intermediate goods production. In each intermediate sector, there is a monopoly whose production technology consists in using a unit of the final good to produce a unit of the intermediate good. Given that the intermediate producer is in a monopoly situation, it practices the highest price that the final sector producer would be ready to pay for the variety j under the hypothesis of a drastic innovation[15]. It maximizes profit as follows:

$$\max_{\{x_{jt}\}} p_{jt}x_{jt} - x_{jt}$$
$$\text{s.t.} \qquad p_{jt} = \alpha x_{jt}^{\alpha-1} A_{jt}^{1-\alpha} L_t^{1-\alpha}$$

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

$$x_{jt} = \alpha^{\frac{2}{1-\alpha}} A_{jt} L_t \tag{3.4}$$

And the equilibrium price for the variety j is calculated by replacing (3.4) in the inverse demand function:

$$p_{jt} = \alpha^{-1} \tag{3.5}$$

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

$$\begin{aligned} \pi_{jt} &= \left(p_{jt} - 1\right) x_{jt} \\ &= \pi A_{jt} L_t \end{aligned} \tag{3.6}$$

where $\pi := (1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}}$. Thus, the profits generated by each sector depend positively on the productivity of this sector. And the production of the final good at equilibrium is obtained by substituting (3.4) in (3.1) :

$$Y_t = \alpha^{\frac{2\alpha}{1-\alpha}} A_t L_t \tag{3.7}$$

The wage rate w_t and the gross domestic production GDP_t are then given by : :

$$w_t = \omega A_t \tag{3.8}$$
$$GDP_t = \zeta A_t L_t \tag{3.9}$$

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

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 $z_{jt} - s w_t$ where w_t is the real wage and s the saving rate. The interest rate is noted r, and therefore the cost of repaying the loan is $(1+r)(z_{jt} - s w_t)$.

I introduce imperfections in the credit market into the model as in Aghion et al. (2005). This imperfection is linked to the presence of moral hazard, which means there is a possibility that the borrower does not repay her loan by hiding the profits made. The borrower can pay a cost $h z_{jt}$

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

proportional to the amount invested so as to avoid repaying her creditors when it succeeds. This cost is an indicator of the degree of creditor protection. However, the borrower has a probability q of being caught by the lender thus obliging her to repay her loan. Then, the total cost of being dishonest[16] is : $hz_{jt} + q(1+r)(z_{jt} - sw_t)$. The borrower is prompted to choose to stay honest if :

$$hz_{jt} + q(1+r)(z_{jt} - sw_t) \geq (1+r)(z_{jt} - sw_t) \tag{3.10}$$

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

$$z_{jt} \leq \frac{(1-q)(1+r)}{(1-q)(1+r)-h} sw_t \tag{3.11}$$

And the maximum amount that the lender would agree to lend so that the borrower chooses to be honest is given by:

$$l_t(q,h) = \frac{hsw_t}{(1-q)(1+r)-h} \tag{3.12}$$

$l_t(q,h)$ is proportional and increasing with the real wage w_t, increasing with the cost of being dishonest h and with the probability of being caught q, and decreasing with the interest rate r. Thus, if the financial system is less developed to the point that borrowers can cheat easily (low h) or/and it's hard to get caught (low q) then projects in more productive sectors at the frontier with higher level of investment can be constrained.

I assume that the lender can make efforts[17] 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:

$$C(q) := c \ln\left(\frac{1}{1-q}\right) \tag{3.13}$$

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

$$\max_{\{q\}} [\, q(1+r) + c\ln(1-q)]\,(z_{jt} - sw_t) \tag{3.14}$$

So the first order condition is :

$$q = 1 - \frac{c}{1+r} \tag{3.15}$$

Then, the condition (3.11) becomes:

$$z_{jt} \leq \kappa w_t \tag{3.16}$$

where $\kappa := \dfrac{s}{1-\hbar}$ is the level of financial development which is increasing with $\hbar = h/c$. $\hbar$ 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. A strong financial institutions, corresponding here, therefore to a higher κ allows for more efficient

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

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

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 subject to credit constraints, an entrepreneur cannot invest more than κw_t[18] which is constant across sectors regardless of the technology to be adopted. This can lead to an underinvestment for adoption of more productive technologies.

3.3 Technological progress and Productivity Growth

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

$$A_{jt+1} = \theta_{jt+1}\bar{A}_{jt} + (1-\theta_{jt+1})A_{jt} \tag{3.17}$$

where $\bar{A}_{jt}$ is frontier productivity[19] in the same sector at time t and $\theta_{jt+1} \in [0,1]$ is the intensity with which new technologies are used in the host country at period $t+1$ so that the productivity of the innovator does not jump immediately to the world frontier. Indeed, a country can succeed the adoption of a technology and do not use intensively this technology. Comin & Mestieri (2018) documented that adoption lags between poor and rich countries have converged, while the intensity of use of adopted technologies of poor countries relative to rich countries has diverged. Unlike Aghion et al. (2005) and the standard Schumpeterian models, which assume that the innovator adopts average technology 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 may vary across sectors. As in Aghion et al. (2005), I assume that local firms can access the frontier technology at a cost which increases with the level of productivity targeted $\bar{A}_{jt}$ which means the further ahead the frontier moves in sector j, the more difficult it is to adopt its technology in that sector. The intensity of use of technologies also increases with the amount of resources z_{jt} allocated by entrepreneurs so that the cost of an innovation is given by:

$$\frac{\lambda_{jt} z_{jt}}{\bar{A}_{jt}} = F\left(\theta_{jt+1}\right) \tag{3.18}$$

where F is a convex increasing cost function in the intensity of using new technologies simply defined here as : $F(\theta) = \eta\theta + \frac{\psi}{2}\theta^2$ with $\eta, \psi > 0$. And λ_{jt} is the entrepreneurial skills. Indeed, technology adoption projects can be affected by the lack of competent resources (engineers, technicians) during the implementation phase. One of the internal factors of success innovation projects is the presence of engineers and qualified scientists within the company and the leadership provided by a leader with a high level of academic training in the field of activity. Foster & Rosenzweig (1996) and Griffith et al. (2004) gave the evidence that skills are an important determinant of a country's absorptive capacity. By learning from the previous technologies, an entrepreneur can more be 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

[18] This paper does not explore the role of Foreign Direct Investment as a substitute for lending to local entrepreneurs knowing that Alfaro et al. (2004) and Suliman & Elian (2014) have shown that Foreign Direct Investment has an effect on economic activity only when the financial system is efficient.

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

existing systems, and improving implementation. Following Howitt & Mayer-Foulkes (2005)[20], I modeled this "learning by doing" effect through the entrepreneurial skills λ_{jt} which is assumed to be proportional to the productivity A_{jt}, reflecting knowledge spillover :

$$\lambda_{jt} = \lambda A_{jt} \tag{3.19}$$

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

From the equation (3.18), the adoption cost z_{jt} is then a function of the intensity of use of technologies θ_{jt+1} and the sectoral proximity to the frontier $a_{jt} := A_{jt}/\bar{A}_{jt}$:

$$z_{jt} = \frac{\frac{\psi}{2}\theta_{jt+1}^2 + \eta\theta_{jt+1}}{\lambda a_{jt}} \tag{3.20}$$

In equilibrium the innovator chooses θ_{jt+1} (or z_{jt}) in order to maximize the expected net payoff given by (3.21):

$$\max_{0\leq\theta_{jt+1}\leq 1} \beta\pi\left[\theta_{jt+1}\bar{A}_{jt} + (1-\theta_{jt+1})A_{jt}\right] - z_{jt} \tag{3.21}$$
$$\text{s.t. } z_{jt} \leq \kappa w_t \text{ and eq. (3.20)}$$

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:

$$\max_{0\leq\theta_{jt+1}\leq 1} \beta\pi\left[\theta_{jt+1}\bar{A}_{jt} + \left(1-\theta_{jt+1}\right)A_{jt}\right] - (\lambda a_{jt})^{-1}\left(\frac{\psi}{2}\theta_{jt+1}^2 + \eta\theta_{jt+1}\right) \tag{3.22}$$

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 asumption, without credit constraints, all entrepreneurs in the same country should be able to use technology with the same intensity as the frontier. In the following subsection, I will show that some adopted technologies may not be used efficiently in the presence of credit constraints.

3.4 Equilibrium Technology under Credit Constraints

Under credit constraints, the problem (3.21) of the innovator can be rewritten as follows:

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

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

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

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

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 proximity to the frontier technology, represented by a_{jt}. Therefore, when two countries adopt the same technology, the country that is closer to the frontier will have a higher level of technology usage. In fact, a country that is more productive in an industry j (higher a_{jt}) likely has more knowledge and expertise in that industry which has an impact on the cost of adopting new technologies in that industry. Higher productivity leads to greater efficiency and a skilled workforce which help to reduce the cost of adopting new technologies. The least productive countries in a sector will face higher costs and therefore more severe credit constraints related to training, integration with existing systems, etc.

Figure IV below, illustrates that as financial development increases, the intensity of technology adoption also increases. However, this effect vanishes beyond a certain threshold level of sectoral proximity to the frontier or financial development level. This finding aligns with Proposition I, which states that the impact of financial development on technology use becomes insignificant beyond a threshold level of financial development or when a certain level of proximity to the frontier is attained. Initially, when financial development is low, entrepreneurs may face significant barriers in accessing funding for technology adoption, limiting their ability to adopt new technologies.

However, as financial development improves, these constraints are gradually alleviated, enabling entrepreneurs to access the necessary capital for technology adoption. Once the constraints are no longer binding, the relationship between financial development and technology adoption becomes less significant. This suggests that the positive influence of financial development on technology adoption is primarily driven by its ability to overcome financial barriers faced by entrepreneurs. However, beyond a certain threshold level of financial development, where these constraints are effectively eliminated, the impact of financial development on technology adoption diminishes.

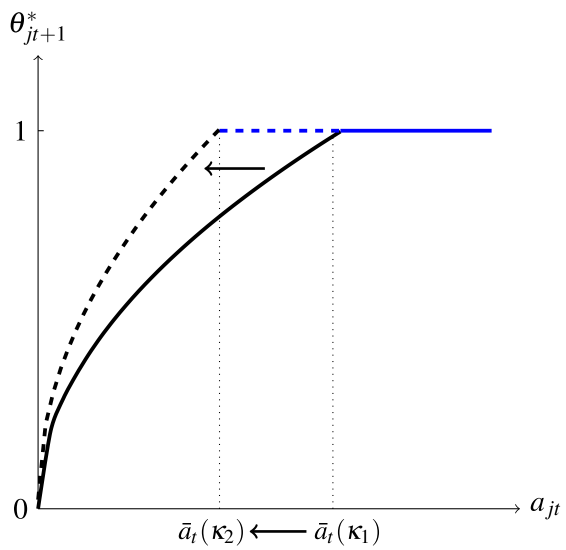


FIGURE IV: Effect of financial development on the intensity of using new technologies ($\kappa_1 < \kappa_2$)

Proposition I. *Financial development positively influences the intensity of use of adopted technologies only for countries far from the technological frontier :* $a_{jt} < \bar{a}_t$.

Proof. See Appendix A.2 ■

3.5 Sectoral Productivity Growth and Aggregate behavior

From the equation (3.17) sectoral productivity growth g_{jt} in sector j at time t can be derived as follows:

$$g_{jt} = \theta_{jt}\left(a_{jt-1}^{-1} - 1\right) \tag{3.23}$$

Sectors in countries that employ adopted technologies more intensively will experience faster productivity growth. As a result, financial development will impact solely the productivity growth of less advanced sectors ($a_{jt-1} < \bar{a}_t$). Let $a_t := A_t/\bar{A}_t$ be the inverse measure of the country's distance to the technological frontier at aggregate level. Then the growth rate g_t of the aggregate productivity A_t at time t is given by :

$$g_t = \frac{1}{A_{t-1}} \int_0^1 \theta_{jt}(\bar{A}_{jt-1} - A_{jt-1})\, dj \tag{3.24}$$

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

$$\begin{cases} g_t = a_{t-1}^{-1} - 1 & \text{if} \quad a_{jt-1} \geq \bar{a}_{t-1} \quad \forall j \\ g_t < a_{t-1}^{-1} - 1 & \text{if} \quad \exists j \ \text{ such that } \ a_{jt-1} < \bar{a}_{t-1} \end{cases}$$

The threshold level of κ beyond which financial development no longer influences the intensity of usage new technologies in the sector j is given by: $\underline{\kappa}_{jt} = \frac{2\eta+\psi}{2\lambda w_t a_{jt}}$. Within a country, some sectors may experience an increase in productivity growth while others may not when financial development increases. Let $\underline{\kappa}_t$ be defined as follow:

$$\underline{\kappa}_t = \max_j \underline{\kappa}_{jt} \tag{3.25}$$

For countries whose level of financial development κ is such that $\kappa < \underline{\kappa}_t$, financial development positively affects certain sectors and therefore growth. Beyond $\underline{\kappa}_t$ there is no effect of financial development on technology adoption in all sectors and growth.

The curve of the dynamics of sectoral proximity to the technological frontier will converge or diverge depending on the level of the aggregate productivity A_t and the level of financial development κ. In the next section, I analyze the long-run effect of financial development on the dynamics of the sectoral productivity gap.

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 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. By analyzing these issues, I hope to gain a deeper understanding of impact of financial development of sectoral productivity convergence across countries.

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 the equation (4.1) by $\bar{A}_{jt+1}$, the dynamics of the sectoral technology gap 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 :

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

Thus $a_{jt+1} = \min\left\{\frac{1}{1+\bar{g}_j}, f_{jt}(a_{jt})\right\}$ for all $a_{jt} \in [0,1]$. Note that $f_{jt}(a_{jt})$ is a concave[21] 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 $f(1)$ 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) :

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

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

Since $\frac{\psi+2\eta}{2\lambda\omega} > \frac{\eta\bar{g}_j}{\lambda\omega}$[22] 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 aggregate productivity countries.*

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

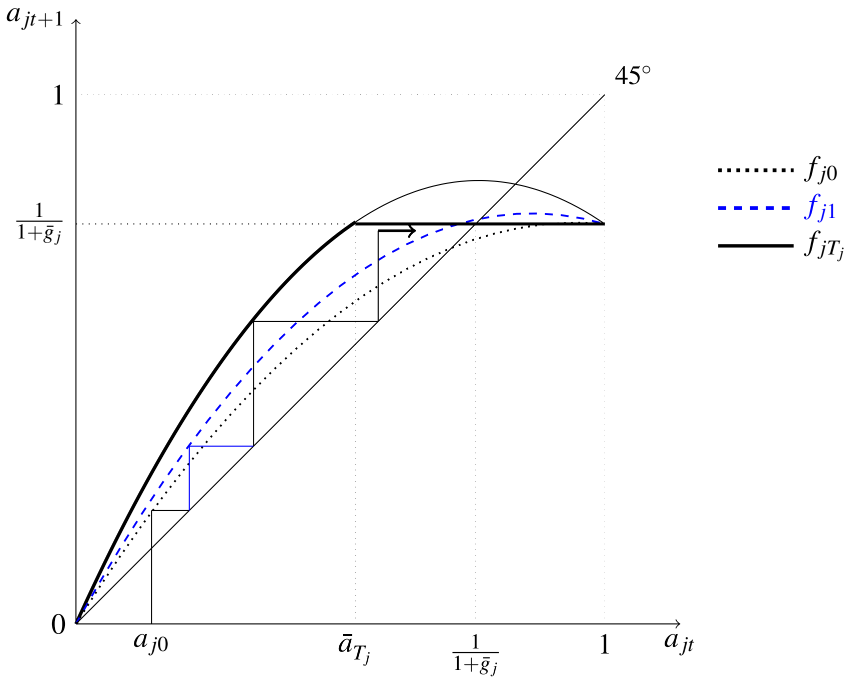


FIGURE V: Sectoral productivity gap dynamic when $\kappa A_0 > \frac{\psi+2\eta}{2\lambda\omega}$

- ***Case 2:*** *Conditional convergence toward a lower level of productivity for countries with moderate levels of financial development and aggregate productivity that are neither too high nor too low.*

  When financial development and aggregate productivity 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 define $\hat{a}_{jt}$ such that $\hat{a}_{jt} = f_{jt}(\hat{a}_{jt})$ $\forall t \geq 0$. If $a_{j0} < \hat{a}_{j0}$, sectoral productivity gap will increase to reach the fix point $\hat{a}_j$ of the function f_{jT} given by : $\hat{a}_j = f_{jT}(\hat{a}_j)$, where T is the switching date to unconditional convergence such that $\kappa A_T > \frac{\psi+2\eta}{2\lambda\omega}$. 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 gap is illustrated in Figure VI below for the case where

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

$a_{j0} < \hat{a}_{j0}$. Then countries in sector j will in long run conditionally converge to $\hat{a}_j$ less than the unconditional technology gap steady state $a_j^* = \frac{1}{1+\bar{g}_j}$.

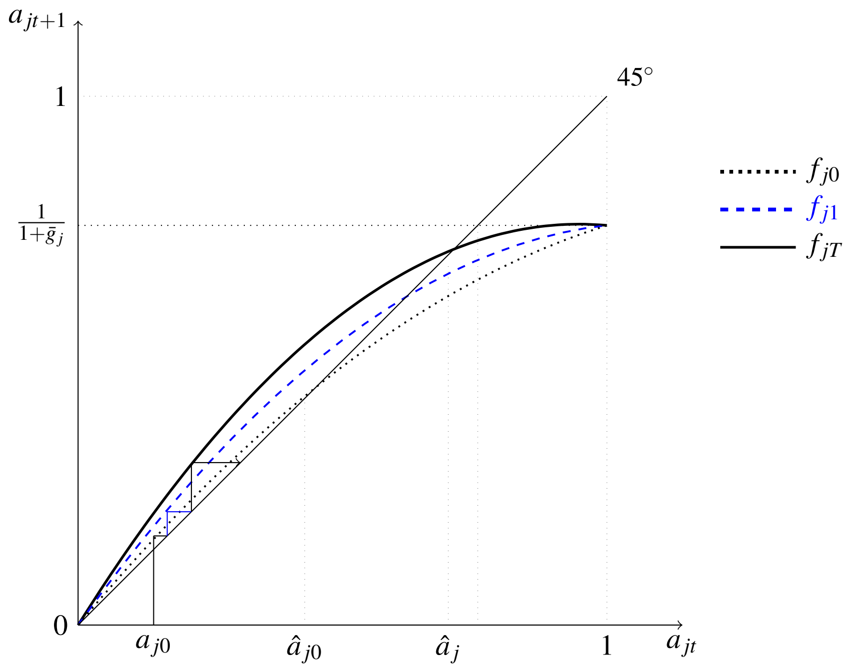


FIGURE VI: Sectoral productivity gap dynamic when $\frac{\eta \bar{g}_j}{\lambda \omega} < \kappa A_0 < \frac{\psi + 2\eta}{2\lambda \omega}$

- ***Case 3:*** *Transient divergence in sectoral productivity for low financial and low aggregate productivity countries or faster productivity growth at the frontier.*
When the level of financial development and aggregate producitivty are sufficiently low or the sector j productivity growth $\bar{g}_j$ is high that $\kappa A_0 < \frac{\eta \bar{g}_j}{\lambda \omega}$ then a_{jt} will decrease over time. The dynamics of the technology gap is illustrated in Figure VII. Under the condition of low productivity and low financial development, sectoral productivity gap will continue to widen until the level of the aggregate productivity or financial development reaches a certain level 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) and a strong credit constraint (due to weak financial institutions) ensure that if the sector grows quickly at the frontier, sectoral productivity gap is widening between developing country and developed countries since it becomes more difficult to catch up with the frontier which continues to progress more rapidly while the catch-up with previous technologies has not yet been made.

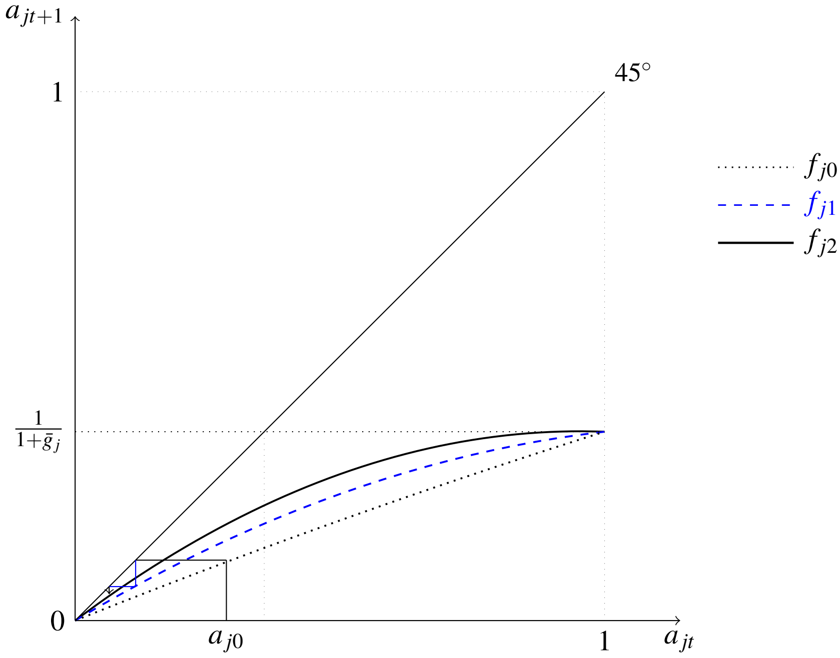


FIGURE VII: Sectoral productivity gap dynamic when $\kappa A_0 < \frac{\eta \bar{g}_j}{\lambda \omega}$

To sum up, based on the implications of the theoretical model, there are three categories of countries. The first category comprises countries with higher productivity at the aggregate level and robust financial institutions, which will experience convergence in various economic sectors. The second category includes emerging countries with a moderate level of financial institutional development and aggregate productivity that will conditionally converge toward a lower level and eventually move towards unconditional convergence as the aggregate productivity continue to increase over time. The third group comprises countries that initially diverge but eventually end up in the second category of countries.

A summary of the three categories of countries, as described above, is visually depicted in Figure VIII. This figure provides a representation of the distribution of countries based on their levels of financial institutions and aggregate productivity. The three distinct groups of countries, characterized by their convergence or divergence patterns, are clearly delineated in the figure. It serves as a visual reference to better understand the relationships between financial development, aggregate productivity, and the classification of countries into these distinct categories. Financial development and aggregate productivity have a significant impact on the convergence or divergence of countries across different sectors.

It is worth noting that countries are not restricted to a single category, as aggregate productivity continuously rises over time. Notably, the limitations on borrowing faced by entrepreneurs are counterbalanced by the country's wealth, and the spillover effect on technology adoption within the sector. When the borrowing constraint is no longer binding in a specific sector, the role of financial development in determining the country's productivity convergence in that sector becomes less significant.

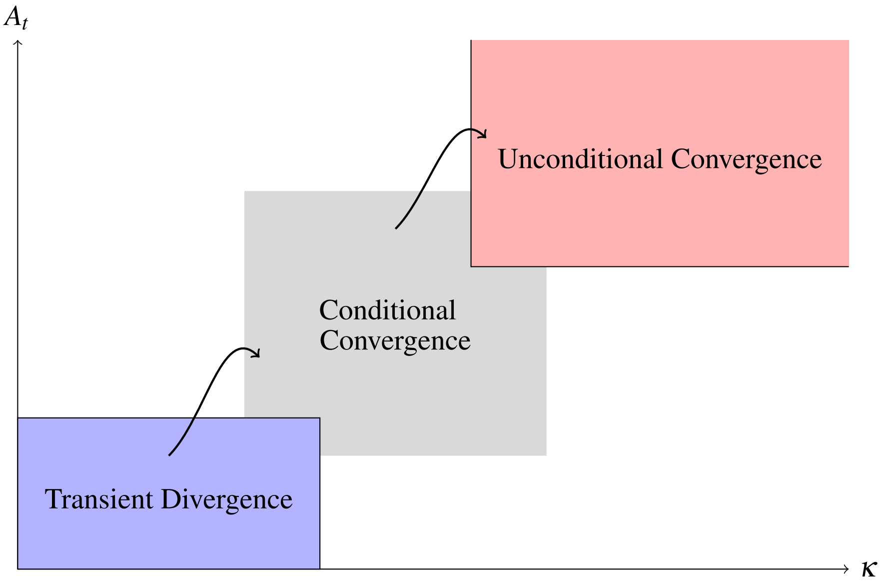


FIGURE VIII: Dynamic Transitions of Countries Across Financial Development and Aggregate Productivity Groups

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

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

As shown in the Figure V, sectoral productivity will converge asymptotically to the unconstrained steady state $a_j^* = \frac{1}{1+\bar{g}_j}$ where T_j is the convergence time in the sector j. Countries will experience faster convergence in sectors that grow slower at the frontier (low $\bar{g}_j$), i.e., T_j increases with $\bar{g}_j$. Differences in the credit multiplier affect in the short-run the intensity of using new technologies but do not affect the long-run technological gap results from the fact that the effect of the upper bound placed on the amount borrowed by the entrepreneur is compensated by the increase in the country's wealth and the spillover effect on the intensity of use of technologies. As soon as this constraint ceases to bind, then κ becomes irrelevant in determining the long-run dynamics of productivity. However, countries with high financial level of development will converge faster than countries with low financial development as proven in the Proposition II below.

Proposition II. *(i) Countries with high financial development (or high aggregate productivity) will converge faster than lower financial developed and lower aggregate productivity countries. (ii) Sectors that grow faster at the frontier will converge less quickly than those with a slower growth rate at the frontier.*

Proof. It can be simply explained that financial development (or aggregate productivity level) has a positive impact on the speed of convergence across countries because $\bar{a}_t = \frac{\psi+2\eta}{2\lambda\omega\kappa A_t}$ and $f_{jt}^{'}(1)$ decrease with κ (resp. with A_t) and $f_{jt}^{'}(0)$ increases with κ (resp. A_t) . Countries with high κ (resp. high A_t) will then be unconstrained more quickly as illustrated in the Figure IX where τ is a given date: If $\kappa_1 < \kappa_2$ then $f_{j\tau,\kappa_1} < f_{j\tau,\kappa_2}$ and $\bar{a}_\tau(\kappa_2) < \bar{a}_\tau(\kappa_1)$. Knowing that the unconstrained date and therefore the convergence speed T_j^κ is given by:

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

then $T_j^{\kappa_2} \leq T_j^{\kappa_1}$.

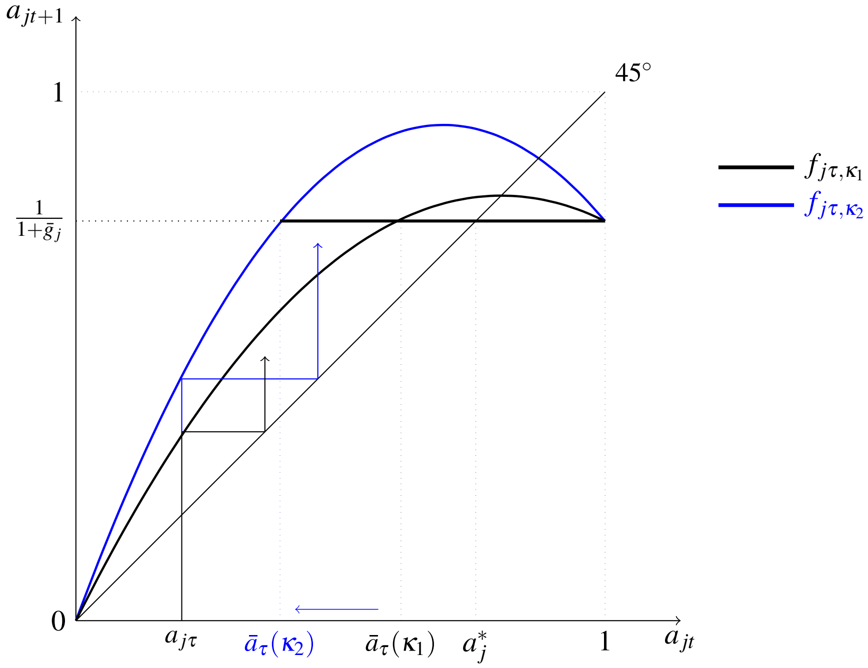


FIGURE IX: Financial development and convergence speed : $\kappa_1 < \kappa_2$

Given that the function f_{jt} has the same properties in financial development κ and in aggregate productivity A_0, one can easily and analogously prove that higher aggregate productivity countries will converge faster.
Let now j_1 and j_2 be two sectors such that: $\bar{g}_{j_1} < \bar{g}_{j_2}$. Let B_j be the set of all dates for which the sectoral proximity has reached its steady state's value a_j^* defined as follow:

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

Then, the time of convergence T_{j_1} and T_{j_2} of the sectors j_1 and j_2 are given by : $T_{j_1} = \min(B_{j_1})$ and $T_{j_2} = \min(B_{j_2})$. Let us now prove that T_{j_1} is less than T_{j_2}. Given that f_{jt} decreases with $\bar{g}_j$, if these two sectors start with the same proximity to the frontier a_0 then $a_{j_1t} > a_{j_2t}$ $\forall t$. Thus[23] $B_{j_2} \subset B_{j_1}$ and then $\min(B_{j_1}) \leq \min(B_{j_2})$. ■

Sectors will then converge with lags to their respective steady-state productivity. Countries with higher levels of the product of the financial institutions development and initial aggregate productivity (κA_0), are expected to experience faster convergence within each sector. The second group of countries is expected to converge after the first group, followed by the third group after a period of divergence. This statement suggests that the speed of convergence within each sector

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

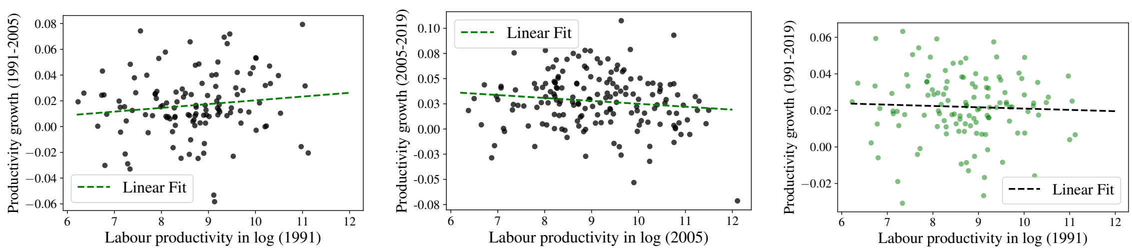
is positively correlated with a country's initial level of financial development and initial aggregate productivity. It also suggests that there may be some countries that initially experience a period of divergence before eventually converging with more developed countries.

5 Sectoral Producitivity Convergence: Evidence

In this section, I show evidence on sectoral productivity β-convergence and present at the end an overview of sectoral productivity σ-convergence, which focuses on the convergence of the standard deviation or variance of a data set over time. Specifically, I present that there is a tendancy for countries with lower initial levels of productivity in the three broad sectors (agriculture, manufacturing, and services) indexed by $j \in \{a,m,s\}$ to have higher productivity growth rates. By providing a comprehensive overview of the empirical evidence on sectoral productivity convergence, this section aims to shed light on the role of the initial aggregate productivity and financial development. To complete this, I use data from as many countries as possible described in the next subsection 5.1.

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 value added in current international US$ by value added in current US$. Second, I use the PPPs calculated to convert the sectoral productivities in constant 2015 US$ into sectoral productivities for 2015 in international US$. κ is calibrated to the country's financial institutions index (and alternatively global financial development index) provided by IMF for several countries between 1980 and 2013[26]. Figures X-XII show scatter plot and regression of equation (5.6) for



(a) 1991–2005 **(b)** 2005–2019 **(c)** 1991–2019

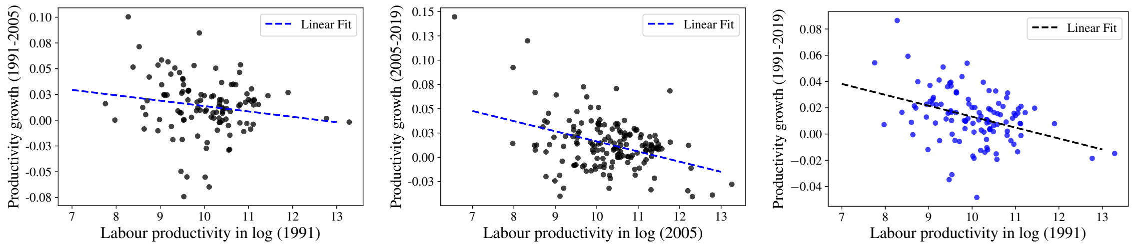
FIGURE X: Agriculture labor productivity convergence by periods

each sector for three periods, without any fixed effects and any country characteristics. Variables on vertical axis are growth in log of labour productivity in agriculture (respectively in manufacturing and in services) over 1991-2005, 2005-2019 and the overall period 1991-2019. A noticeable decline in the slope of the trend can be observed in the raw data for services and manufacturing productivity, whereas the slope in agriculture shifted to a negative value after manufacturing and services, which is consistent with Proposition II-*(ii)*. Indeed, the agricultural sector grows at the

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

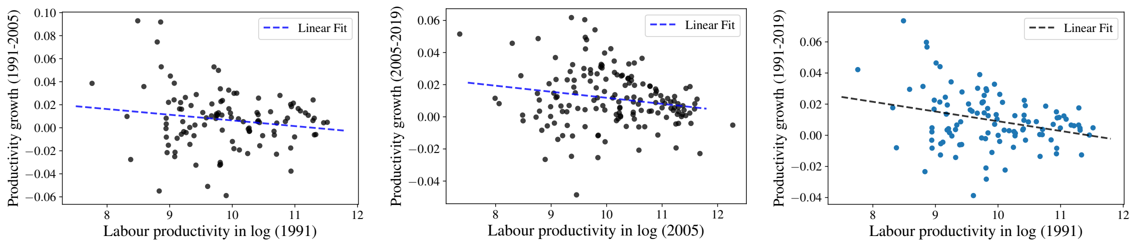
[25]Productivity here refers to labour producitivity which is considered to be the value added per worker.

[26]More details on financial data are presented in the subsection 2.1 and Appendix A.1



(a) 1991–2005 **(b)** 2005–2019 **(c)** 1991–2019

FIGURE XI: Manufacturing labor productivity convergence by periods

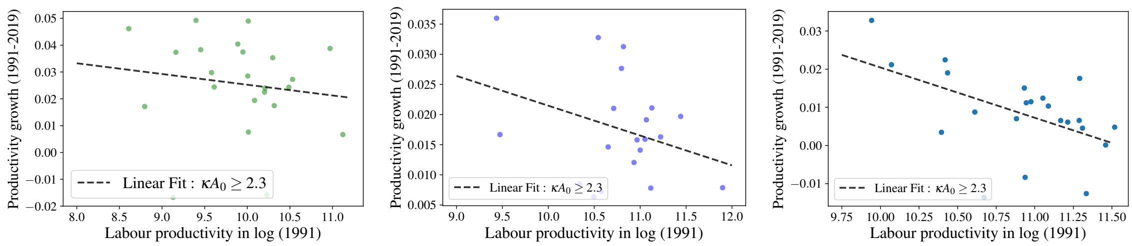


(a) 1991–2005 **(b)** 2005–2019 **(c)** 1991–2019

FIGURE XII: Services labor productivity convergence by periods

frontier almost twice as fast as the other sectors. During the period from 1991 to 2019, the growth rate of the average productivity for the top 10 more productive countries was 4.42% in Agriculture compared to 1.58% in Manufacturing and 1.05% in services.

Figure XIII depicts the convergence over the period 1991-2019 for the 4th quartile (33 to 37 countries) of the sample with higher institutional financial development level and aggregate productivity κA_0. Analysis of the graph reveals a steeper slope than the overall group of countries, suggesting unconditional convergence among countries with higher institutional development and aggregate productivity levels, confirming the predictions of the subsection 4.1.



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

FIGURE XIII: κA_0 fourth quartile uncondionnal convergence (1991-2019)

In sum, the evidence presented indicates a trend towards data convergence in agriculture, manufacturing, and services over the past two decades. In what follows, I test the significance of this trend and study whether this convergence is unconditional or conditional to country's level of aggregate productivity and financial institutional development.

5.2 Empirical 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^c_{jt} [27] on the initial level of log productivity :

$$\frac{1}{T}\Delta_T \log(A^c_{jt}) = \alpha_j + \beta_j \log(A^c_{jt}) + \rho_j \kappa^c_t \log(A^c_t) + \gamma_j \log(A_{jt}) \times \kappa^c_t \log(A^c_t) + D^c_j + D_{jt} + \varepsilon^c_{jt} \tag{5.1}$$

where $\frac{1}{T}\Delta_T \log(A^c_{jt})$ is the average annual growth rate of the sector j labor productivity A^c_{jt} in constant international prices in country c between periods t and $t+T$. D_{jt} are time fixed effects, D^c_j are country fixed effects, and ε^c_{jt} is the error term. Note that I added $\kappa^c_t \log(A^c_t)$ into the equation (5.1) to capture the impact of the level of financial institutional development κ^c_t and the level of aggregate productivity A^c_t[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^c_{jt} with respect to $\log(A^c_{jt-1})$ as follows:

$$\frac{\partial g^c_{jt}}{\partial \log(A^c_{jt})} = \beta_j + \gamma_j \times \kappa^c_t \log(A^c_t) \tag{5.2}$$

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 (5.2) is significant, I proceed to the following test on coefficients after regressions :

$$H_0 : \frac{\partial g^c_{jt}}{\partial \log(A^c_{jt})} = 0 \qquad \text{vs.} \qquad H_1 : \frac{\partial g^c_{jt}}{\partial \log(A^c_{jt})} \neq 0 \tag{5.3}$$

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

$$(\hat{\beta}_j + \hat{\gamma}_j \kappa_t A_t)^2 > z^2_{\frac{\alpha}{2}} \left[\mathrm{var}(\hat{\beta}_j) + \mathrm{var}(\hat{\gamma}_j)\,(\kappa_t A_t)^2 + 2\mathrm{cov}(\hat{\beta}_j, \hat{\gamma}_j)\,\kappa_t A_t\right] \tag{5.4}$$

i.e. the level of development κA_t exceeds[30] the threshold level κA^* solution of the equation $\phi_j(x) = 0$ where ϕ_j is a real function defined on the interval $[0, +\infty[$ by :

$$\phi_j(x) = (\hat{\beta}_j + \hat{\gamma}_j x)^2 - z^2_{\frac{\alpha}{2}} \left[\mathrm{var}(\hat{\beta}_j) + \mathrm{var}(\hat{\gamma}_j)\, x^2 + 2\mathrm{cov}(\hat{\beta}_j, \hat{\gamma}_j)\, x\right] \tag{5.5}$$

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

[28] A^c_t is calibrated here to the level of GDP per worker in international constant 2015 US$

[29] Demonstration is given in Appendix A.2.4

[30] ϕ_j is an increasing function on the intervall $[0, +\infty[$. Its variations are shown in Figure XVI in Appendix A.3.

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 or initial financial development level on speed of sectoral productivity convergence, I'll consider cross-section estimations for mathematical convenience[31]. The equation (5.6) below describes cross-countries estimation equation where N is the number of countries :

$$\frac{1}{T}\left[\log(A^c_{jT}) - \log(A^c_{j0})\right] = \alpha_j + \beta_j \log(A^c_{j0}) + \rho_j \kappa^c_0 \log(A^c_0) + \gamma_j \log(A^c_{j0}) * \kappa^c_0 \log(A^c_0) + \varepsilon^c_j \quad (5.6)$$

By taking the difference between the average annual growth rates of country c and the frontier from equation (5.6), we can deduce the convergence speed $S^c_j := \frac{1}{T^c_j}$[32] in sector j for country c as follow:

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

So if $\hat{\beta}_j < 0$, and $\hat{\gamma}_j < 0$, then the speed of convergence S^c_j increases with the absolute values of $\hat{\beta}_j$ and $\hat{\gamma}_j$ but decreases with $\hat{\rho}_j$ so that countries which are more productive at the aggregate level initially (or having a higher initial level of financial institutional 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^c_j with respect to $\kappa^c_0 \log(A^c_0)$ from the equation (5.7) as following:

$$\frac{\partial S^c_j}{\partial\left[\kappa^c_0 \log(A^c_0)\right]} = \frac{\hat{\rho}_j + \hat{\gamma}_j \log(A^c_{j0})}{\log(\bar{A}_{j0}) - \log(A^c_{j0})} \quad (5.8)$$

Thus, we can see that the marginal effect of aggregate productivity and the level of financial development on sectoral productivity convergence speed is positive as long as the level of the sectoral log productivity $\log(A^c_{j0})$ 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 VII presents the regression results for the 5-year time periods panel estimations on more than 150 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

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

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

TABLE VII: Panel regression results, dependent variable: Average Growth in log Producitivity

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\beta_j : \log(A_{jt})$	0.001	-0.041***	-0.007***	-0.059***	-0.003***	-0.056***
	(0.001)	(0.009)	(0.002)	(0.010)	(0.001)	(0.009)
$\rho_j : \kappa_t \log(A_t)$		0.117***		0.037		0.151***
		(0.020)		(0.032)		(0.026)
$\gamma_j : \kappa_t \log(A_t)$		-0.011***		-0.004		-0.014***
$\times \log(A_{jt})$		(0.002)		(0.003)		(0.002)
Country FE	No	Yes	No	Yes	No	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	176	157	171	152	174	155
Obs.	828	736	797	708	793	703
R-squared	0.01	0.49	0.05	0.52	0.05	0.62

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

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), with the difference that their estimates are not significant for the manufacturing sector. However, the R-squares of my estimations for unconditional convergence coefficients are very low.

The results show a positive and statistically significant coefficient ρ_j at the 1% level for agriculture and services. This implies that financial development and aggregate productivity have a positive impact on sectoral productivity growth. However, this marginal effect of development on productivity growth decreases with the country's initial sectoral productivity level, for γ_j is negative. One can conclude that the level of financial institutional development has a positive effect on the speed of convergence.

I checked the robustness of the estimations by first running the panel model with 10 years time period, and by using financial development index[33] instead of financial institutions index. Table VIII presents the estimations of the equation 2.1 with ten years time periods spanning 1991-2019. The results suggest a significance at the 1% level of conditional convergence estimates for all three sectors. The estimates for unconditional coefficients are similar to the five years period panel regression results. I also estimate the parameters in cross-country regression equations. Table X presents the results of the cross-section regressions, corresponding to the scatter plot displayed in Figures X-XII.

Cross-countries specifications do not contain period, or any other fixed effect, and cover 96–157 countries. The unconditional convergence results in columns (1), (3), and (5) are very similar for the manufacturing (-0.008) and services (-0.006), and more than five times for the agriculture (-0.001) during the overall period 1991-2019. The point estimate of β_a for agriculture is negative only from the the beginning of the 2000s but the overall significance of an unconditional con-

[33]The results for the panel estimation using financial development index are shown in Table XII in Appendix A.3. The estimations are very close to financial institutional index estimations.

TABLE VIII: 10 years period Panel Regression Results, dependent variable: Avergage Growth in log Producitivity

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\beta_j : \log(A_{jt})$	0.001	-0.042***	-0.007***	-0.063***	-0.003***	-0.042***
	(0.001)	(0.010)	(0.002)	(0.013)	(0.001)	(0.008)
$\rho_j : \kappa_t \log(A_t)$		0.097***		0.020		0.087***
		(0.019)		(0.042)		(0.025)
$\gamma_j : \kappa_t \log(A_t)$		-0.009***		-0.002		-0.008***
$\times \log(A_{jt})$		(0.002)		(0.004)		(0.002)
Country FE	No	Yes	No	Yes	No	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	175	156	170	151	171	152
Obs.	336	299	323	287	322	285
R-squared	0.01	0.83	0.08	0.79	0.03	0.88

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

vergence relationship is non existent in agriculture. On the other hand, given the cross-sectional estimates, one can consider an unconditional convergence in the manufacturing sector as Rodrik (2013) and in services like Kinfemichael & Morshed (2019) when considering a large number of countries including many developing countries. However, when the estimates are restricted to countries with a high level of financial institution[34] or high aggregate productivity, the R-squared for the overall period 1991-2019 estimation rises from 14% to 21% in Manufacturing and 8% to 37% in services (see columns (4) and (6) in Table IX). The conditional convergence coefficients with additional variables in column (2), (4), and (6) of Table X are also found to be significantly negative only for manufacturing and services and higher in magnitude than that of the unconditional convergence coefficients.

I have tested whether the convergence is faster for higher financial institutional countries or not by considering in the regressions only countries with a development level that occupied the fourth quartile of the data set. The estimates for unconditional convergence coefficients at cross-countries level in column (2), (4), and (6) of the Table IX, which correspond to the slopes of the scatter plots in Figure XIII, show a larger in absolute and significant unconditional convergence coefficients. The R squares are also higher and more statistically significant (0.37 for services and 0.21 for manufacturing).

Specifically, the cross-sectional model estimates in Table X column (6) were used to determine the threshold level of sectoral productivity in 1991, below which the marginal effect of financial development (or aggregate productivity) on the speed of sectoral convergence is positive. The results show that the threshold level is 14 for agriculture, 13.5 for manufacturing, and 12.3 for services. However, the maximum level of sectoral productivity in 1991 in the data used for the estimations is 11.12 for agriculture, 13.28 for manufacturing, and 11.52 for services. These findings provide evidence that the marginal impact of financial institutional quality (or aggregate produc-

[34]The results are similar when we consider Financial Institutions index instead of Financial Development index in the analysis.

TABLE IX: 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	-0.001	-0.002	-0.008***	-0.009**	-0.006***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
N	120	35	113	30	107	31
R^2	0.00	0.03	0.14	0.21	0.08	0.37

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

tivity) on the rate of sectoral productivity convergence is positive. Nevertheless, there exists a minimum level of $\kappa_t \log(A_t)$ at which sectoral convergence can be observed. According to the estimates of the equations, the services and manufacturing sectors began to converge already in the 1990s, indicating that regardless of the level of $\kappa_t \log(A_t)$, there is convergence. In other words, the marginal effect of sectoral productivity on productivity growth is negative and significant in services and the manufacturing sector, regardless of the level of $\kappa_t \log(A_t)$. However, this is not the case for the agricultural sector, where convergence only occurs for countries with a level of financial development and aggregate productivity $\kappa_t \log(A_t)$ above 1.12, which corresponds to fewer than half[35] of the countries included in the database in 1991.

Based on the initial levels of sectoral and aggregate productivities, as well as financial development, I am able to calculate a country's rate of convergence in a specific sector. Column (6) of Table X provides estimates indicating that if a country starts with an initial development level of $\kappa_0 \log(A_0) = 2$ and a sectoral productivity level of 0.1 relative to the top ten most productive countries, then it will take approximately 32 years to reach 0.5 relative sectoral productivity in services, 57 years in manufacturing, and 508 years in agriculture. Increasing the initial development level to $\kappa_0 \log(A_0) = 2.5$ will enhance the rate of convergence in each sector. Consequently, the time required to achieve 0.5 productivity level relative to the frontier will decrease to 26 years in services, 42 years in manufacturing, and 169 years in agriculture.

These estimates suggest that a country's initial level of financial development and aggregate productivity significantly impact its rate of convergence in different sectors. The higher the initial level of development and aggregate productivity, the faster the country will reach a comparable level of sectoral productivity relative to the frontier in the respective sector. Moreover, the estimates highlight the significant variation in the time required for a country to reach the frontier across different sectors. For instance, the fastest rate of convergence is in the services sector, followed by manufacturing, and then agriculture. This variation reflects differences in the nature of these sectors specially their productivity growth at the frontier.

[35] In Figure XVII, a visual representation is presented depicting the countries in 1991 based on their respective levels of financial development and aggregate productivity.

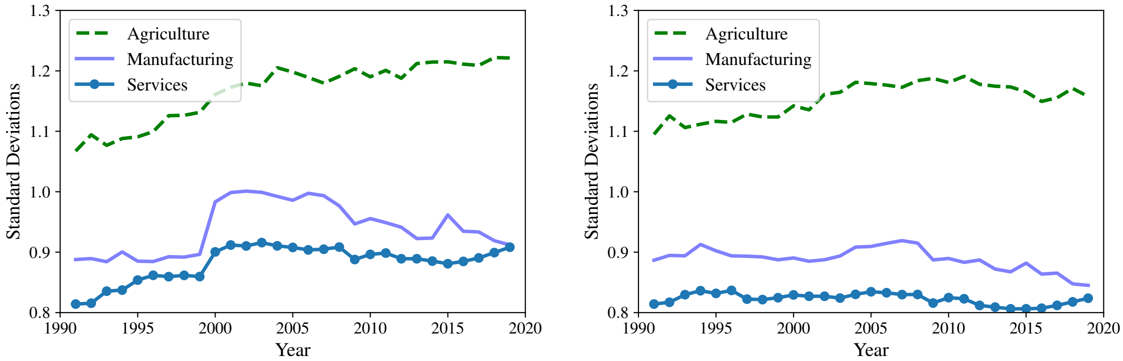
TABLE X: Cross-Countries Regression Results, dependent variable: Average Growth in log Producitivity

	1991–2005		2005–2019		1991–2019	
	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture equation						
$\beta_a : \log(A_{a0})$	0.003	0.003	-0.003	-0.002	-0.001	-0.002
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.002)
$\rho_a : \kappa_0 \log(A_0)$		0.071**		0.056***		0.028
		(0.031)		(0.013)		(0.022)
$\gamma_a : \kappa_0 \log(A_0)$		-0.007**		-0.005***		-0.002
$\times \log(A_{a0})$		(0.003)		(0.001)		(0.002)
Countries	121	107	166	148	120	107
R-squared	0.02	0.09	0.02	0.12	0.00	0.06
Manufacturing equation						
$\beta_m : \log(A_{m0})$	-0.005*	-0.009**	-0.010***	-0.017***	-0.008***	-0.010***
	(0.003)	(0.004)	(0.003)	(0.005)	(0.002)	(0.003)
$\rho_m : \kappa_0 \log(A_0)$		0.059		0.024		0.054
		(0.050)		(0.020)		(0.034)
$\gamma_m : \kappa_0 \log(A_0)$		-0.004		-0.002		-0.004
$\times \log(A_{m0})$		(0.005)		(0.002)		(0.003)
Countries	114	101	160	142	113	101
R-squared	0.03	0.16	0.15	0.25	0.14	0.29
Services equation						
$\beta_s : \log(A_{s0})$	-0.005	-0.015***	-0.004**	-0.004	-0.006***	-0.012***
	(0.003)	(0.006)	(0.001)	(0.003)	(0.002)	(0.004)
$\rho_s : \kappa_0 \log(A_0)$		0.107**		0.068***		0.086**
		(0.048)		(0.019)		(0.034)
$\gamma_s : \kappa_0 \log(A_0)$		-0.008*		-0.006***		-0.007**
$\times \log(A_{s0})$		(0.004)		(0.002)		(0.003)
Countries	108	96	157	139	107	96
R-squared	0.03	0.24	0.04	0.14	0.08	0.27

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

5.4 Sectoral Productivity Sigma–Convergence

In this subsection, I examine σ-convergence in agriculture, manufacturing and services for two panels of countries: *Panel A* which contains all of the 196 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[36]. 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 is when the cross-sectional standard deviation of log productivity decreases over time.



(a) *Panel A* : 196 countries of unbalanced panel   **(b)** *Panel B* : 108 countries of balanced panel

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

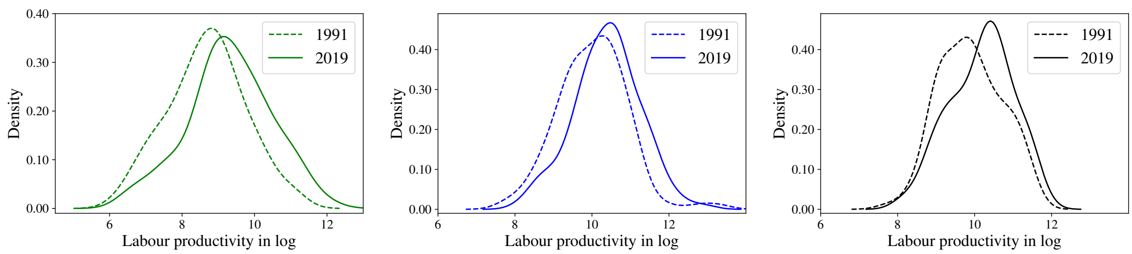
Young et al. (2008) documented the relationship between β-convergence and σ-convergence. They demonstrated that even if they found β-convergence in the United States using county-level data they could not detect any evidence of σ-convergence using the same data. Indeed β-convergence may fail to produce σ-convergence if countries are subject to different random shocks that move them away from each other. β-convergence is then a necessary but not sufficient condition for σ-convergence (see Young et al. (2008)).

Figure XIV 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. This finding supports the theoretical model which predicts that the sectoral productivity gap increases with the growth rate at the frontier in each sector. Indeed, the average growth rate between 1991 and 2019 for the top ten most productive countries is higher in agriculture and lower in services, with a growth rate of 4.42% in agriculture compared to 1.58% in manufacturing and 1.05% in services.

Contrary to Herrendorf et al. (2022), I do not find empirically evidence for divergence over time in the manufacturing standard deviation across countries when considering the balanced *Panel B*. Data with more developing countries (compared to Herrendorf et al. (2022)) seem to show that there is a slight σ-convergence in the manufacturing sector. Even when we analyze the graph on the unbalanced *Panel A*, we can see that the convergence takes shape from the 2000s and becomes faster from 2006. Agriculture, however, experienced a slight divergence in the 1990s, but since 2005 it exhibits stability in the standard deviation. On the other hand, there is little overall change for services productivity for the balanced panel data. Since the 2000s, globalization and technology diffusion through the adoption of the best production technologies have helped to reduce divergences and facilitate catching up.

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

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 in the services and in the manufacturing sector of the Figure XV shows that the distributions of productivities in manufacturing and services have become slightly more peaked or concentrated. This suggests that there is a trend towards σ-convergence in these sectors, as the countries are gradually catching up with the most productive ones. On the other hand, the density curve for the agricultural sector appears to undergo a translation over time with a slight reduction in peakness. This suggests that while there has been some progress in agricultural productivity in some countries, there is still significant heterogeneity in productivity levels across countries in the agricultural sector, which indicates that there is little evidence of sigma-convergence.



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

FIGURE XV: Sectoral productivities distribution over time

6 Conclusion

Previous work examining the role of financial development in technology adoption has shown the importance of better-developed financial markets in the efficient allocation of capital among investment opportunities. No theoretical model has yet clearly shown how financial development can affect sectoral productivity convergence across countries.

This paper is motivated by three main new empirical facts about technology adoption and financial development: First, in a country, technology adoption takes place more in sectors whose productivity is closer to that of the frontier (USA). Second, financial development impacts positively intensity of using new technologies until a threshold level. Finally, financial development plays a more important role in the adoption of more productive technologies. I build an endogenous growth model to explain these observed empirical facts. The model is an extension of Aghion et al. (2005) with two novel features. First, each entrepreneur adopts from the frontier the technology of the sector in which she wishes to produce, unlike the standard models in which all entrepreneurs opt for the same technology if they are successful. Second, the model takes into account the skills of the entrepreneurs and the intensity of using new technologies.

The predictions of the model provide an explanation of the role played by the financial institutions and aggregate productivity on sectoral productivity convergence. The model identifies that some countries with low levels of aggregate productivity and financial development will initially experience a temporary divergence in sectoral productivity before beginning a conditional convergence, such as countries with moderate levels of financial institution development and aggregate productivity. And, there are other countries with high levels of financial development and aggregate productivity that converge unconditionally. The theoretical model and the empirical assessments also predict that financial development and aggregate productivity positively influence the speed of convergence. They also show that sectors with higher productivity growth rates at the technological frontier (like agriculture) will experience slower convergence than sectors with lower productivity growth rates at the frontier (services and manufacturing).

There are several dimensions along which it will be important to extend the analysis carried out here. For example, this study highlights intensity of using new technologies through financial development as determinant of the differences in productivity gap convergence across countries. The analysis of sectoral convergence assumes that if all countries had the same levels of aggregate productivity and financial institution development, they would use the technologies with the same intensity, but other factors such as coordination between firms can be considered. Next steps in this research program could be, first, to explore what other factor can affect the intensity of technology use other than the level of financial development and country's aggregate productivity, and, second, to analyze how financial development through technology adoption, can explain the differences between the paths and rates of industrialization that is observed between developing countries and with developed countries.

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A Appendix

A.1 Data Appendix

A.1.1 Description of financial variables

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).

TABLE XI: Variables used in panel data regresssions

Variables	Description	Source	Period covered
GDP per capita	Real GDP per capita	World Bank (2021)	1960-2020
Productivity	Value added per worker	World Bank (2021)	1991-2019
FD/FI	Financial data	IMF (2015)	1980-2014
Population	Total of residents	World Bank (2021)	1960-2020
Human Capital	Human Capital Index	Penn World Table version 10.0	1960-2019
Governance	Traditions and Institutions	WGI (2021)	1996-2020
Geography	Lattitude	Geodata95 (link)	
Technology data	See Table I	HCCTAD (Comin & Hobijn (2004))	1750-2003

All data are aggregated to 5-year time periods spanning 1991-2003.
IMF : International Monetary Fund
WGI : Worldwide Governance Indicators
HCCTAD : Historical Cross-country Technology Adoption Data

A.1.2 Description of Governance variables

Governance is defined as the set of traditions and institutions by which authority in a country is exercised. This includes :
(1) the process by which governments are selected, monitored and replaced,
(2) the capacity of the government to effectively formulate and implement sound policies, and
(3) the respect of citizens and the state for the institutions that govern economic and social interactions among them.

The WGI (World Governance Indicators) measure six broad dimensions of governance:

1. **Voice and Accountability (VA)** – capturing perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media.

2. **Political Stability and Absence of Violence/Terrorism (PV)** – capturing perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism.

3. **Government Effectiveness (GE)** – capturing perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.

4. **Regulatory Quality (RQ)** – capturing perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.

5. **Rule of Law (RL)** – capturing perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.

6. **Control of Corruption (CC)** – capturing perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.

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 :

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

and

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

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

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

And finally,

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

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.2.4 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:

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

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 Convergence Appendix

TABLE XII: Panel regression results with Financial Development Index, dependent variable: Growth in log producitivity

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\beta_j : \log(A_{jt})$	0.001	-0.044***	-0.007***	-0.062***	-0.003***	-0.058***
	(0.001)	(0.008)	(0.002)	(0.009)	(0.001)	(0.008)
$\rho_j : \kappa_t \log(A_t)$		0.127***		0.023		0.173***
		(0.023)		(0.035)		(0.031)
$\gamma_j : \kappa_t \log(A_t)$		-0.012***		-0.003		-0.016***
$\times \log(A_{jt})$		(0.002)		(0.003)		(0.003)
Country FE	No	Yes	No	Yes	No	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	176	157	171	152	174	155
Obs.	828	736	797	708	793	703
R-squared	0.01	0.48	0.05	0.53	0.05	0.62

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

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 $|x_1 - x_0| \leq 10^{-6}$.

The variation of the function ϕ_j is shown in Figure XVI. The scatter plot in Figure XVII displays the distribution of data points representing different observations in 1991. Each data point corresponds to a specific combination of κ (financial institutions) and $\log(A_0)$ (aggregate productivity) values. The three groups correspond to specific percentile intervals of $\kappa \log(A_0)$. The first group represents values in the 0-50% percentile range, the second group represents values in the 50-75% percentile range, and the third group represents values in the 75-100% percentile range. Each group is assigned a different color.

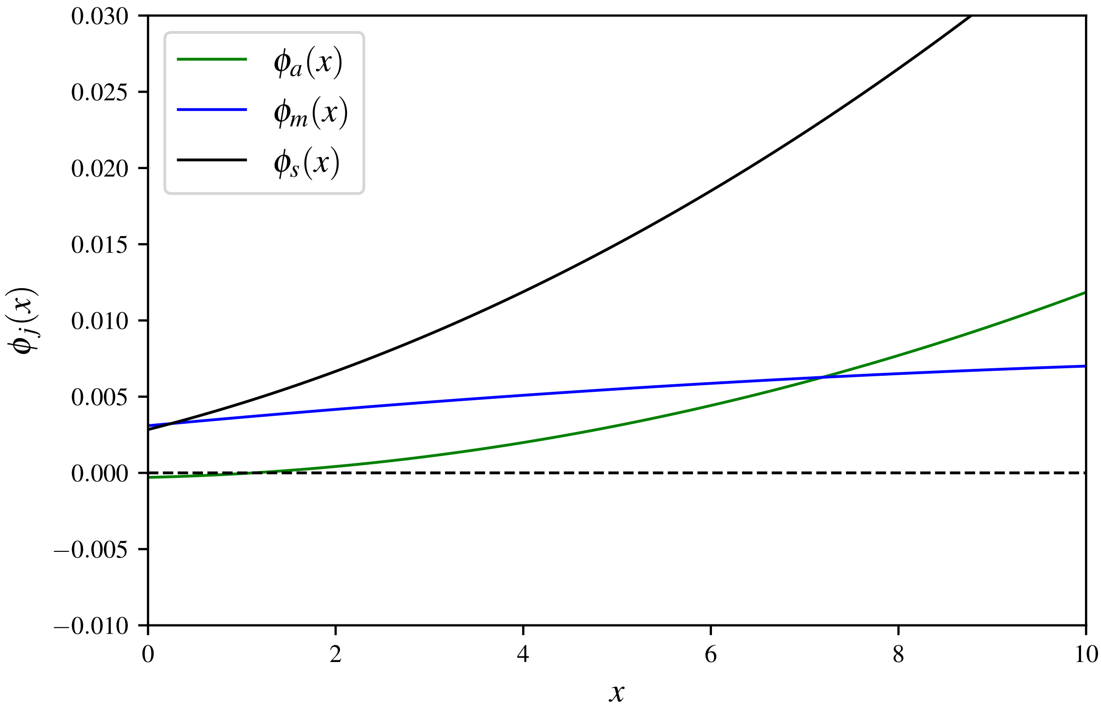

FIGURE XVI: Variations of functions ϕ_j

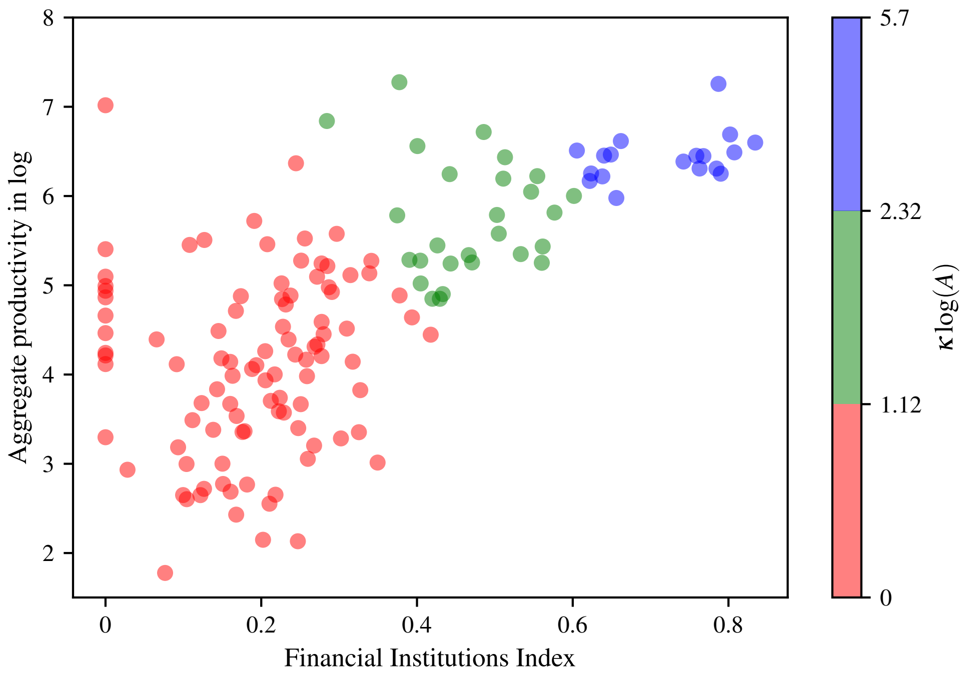

FIGURE XVII: Countries' financial development and aggregate productivity distribution in 1991