Financial Constraints, Technology Adoption, and Convergence*

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Abstract

This paper documents heterogeneous productivity convergence patterns across key economic sectors and develops an endogenous growth model to explain how financial development, technology adoption, and sector-specific characteristics influence countries' transitions across different convergence paths. The model predicts that sectors with higher productivity growth at the technological frontier, such as agriculture, tend to exhibit slower and more delayed convergence dynamics. It also shows that even sectors initially diverging from the global technological frontier ultimately shift toward a convergence path, driven by increasing technology adoption. Consequently, aggregate divergence eventually transitions into convergence as lagging sectors catch up. As income rises, financial constraints ease, allowing these sectors to adopt technologies more intensively and accelerate productivity growth. Even when a country diverges from the technological frontier, this process reinforces income growth and creates a positive feedback loop. Financial development strengthens this transition by reducing financing frictions, thereby accelerating the shift from divergence to convergence.

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

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

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1 Introduction

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

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

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

To simplify the analysis, I assume that, in the absence of credit constraints, countries can borrow without limit and adopt technologies at the same intensity as those at the technological frontier. Consequently, in the absence of institutional weaknesses—such as weak creditor pro-

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

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

tections or market imperfections that create credit constraints[3]—it is expected that countries' technology adoption would align with that of developed countries. This assumption allows the model to generate a correlation between financial development and technology adoption that vanishes once financial development reaches a time-varying threshold level.

The model demonstrates that financial constraints hinder technology adoption more in industries further from the technological frontier. Consequently, these industries experience slower convergence to the frontier, leading to varying cross-country productivity convergence patterns at the industry or sectoral level. Thus, industries with high investment requirements for technology adoption, particularly in countries with low initial incomes, face substantial delays due to financial constraints, which widens the gap between these industries and the technological frontier, leading to divergence.

However, even when these industries lag behind, they continue to achieve productivity growth[4]. As a result, overall economic growth can still take place, gradually easing financial constraints as the country's financing capacity improves with rising income. This improved financing capacity allows these lagging sectors to adopt technologies more effectively and at a greater scale than before, accelerating their growth and contributing to overall income growth, thereby creating a reinforcing feedback loop. A key implication is that even industries initially diverging from the technological frontier can eventually shift to a convergence path, leading overall aggregate productivity to transition from divergence to convergence.

Financial development plays an important role in shaping the timing and speed of the transition from divergence to convergence. Economies with higher initial levels of financial development are more likely to experience an earlier and faster convergence process. Enhanced financial intermediation facilitates more efficient allocation of capital, promotes technology adoption, and supports sustained productivity growth. Nevertheless, convergence can still occur in the absence of significant improvements in financial development, provided that income levels continue to rise. In such cases, however, the divergence phase tends to be prolonged, and the shift toward convergence is delayed relative to economies with more advanced financial systems. This underscores the catalytic function of financial development in accelerating structural transformation and closing income gaps.

The empirical analysis, based on data from the World Development Indicators (WDI), supports the model's theoretical predictions. The regression results show that a country such as India, with an initial financing capacity[5] of 1.9 and sectoral productivity ratios in 1991 comparable to those of France (0.15 in agriculture, 0.17 in manufacturing, and 0.12 in services), would require approximately 77 years to converge with France in services, 140 years in manufacturing, and 200 years in agriculture. However, when India's initial financing capacity is raised to the 1991 French level of 4.52, the convergence process accelerates markedly. The time required to

[3] A country's financial development is strongly correlated with its governance indicators, including government effectiveness, control of corruption, voice and accountability, political stability, and the rule of law (Porta et al., 1998).

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

[5] In the empirical analysis, financing capacity is proxied by the product of the financial development index and the logarithm of GDP per capita.

catch up with France declines to 37 years in services, 44 years in manufacturing, and 60 years in agriculture. This illustrates the critical role of financial capacity in shaping the speed of structural convergence.

The services sector exhibits the fastest rate of productivity convergence, followed by manufacturing and then agriculture, reflecting differences in productivity growth across these sectors in developed countries. Interestingly, between 1991 and 2019, the top ten most developed countries[6] experienced the highest average annual growth rate in agriculture, at 3.06%, compared to 1.97% in manufacturing and 0.86% in services. This inverse relationship confirms that sectors with higher growth rates at the frontier tend to have slower convergence rates, while those with lower growth rates at the frontier converge more rapidly.

Although faster frontier technological progress in a given sector may intuitively slow convergence, it can also enhance catch-up opportunities. However, this paper shows that in agriculture, larger productivity gaps do not lead to faster relative productivity growth. Compared to manufacturing and services, agricultural productivity in developing countries converges more slowly, largely due to tighter financial constraints that impede technology adoption.

Related Literature. Among the expanding literature on convergence, four studies are particularly relevant to this paper: Aghion et al. (2005), Rodrik (2013), Kinfemichael and Morshed (2019), and Herrendorf et al. (2022). The first of these, Aghion et al. (2005), develops a Schumpeterian growth model to show that financial development plays a central role in shaping cross-country convergence dynamics. In their framework, countries with sufficiently deep financial systems are able to adopt frontier technologies and converge, whereas those with underdeveloped financial markets are trapped in divergence. However, their model does not account for the possibility that countries may transition between convergence regimes over time. As noted by Kremer et al. (2022), some economies that diverged in earlier decades later shifted to a convergence path—a phenomenon they describe as "converging to convergence." This empirical pattern cannot be explained by Aghion et al. (2005)'s framework, which effectively locks countries into permanent convergence outcomes based on their initial financial development level.

This paper contributes to the literature by providing a theoretical framework that rationalizes these transitions through two key mechanisms: industry-specific technology adoption and collateral-based financial constraints. Unlike Aghion et al. (2005), the model incorporates heterogeneous sectoral productivity gaps and links industry-specific technology adoption costs proportional to the gap between an industry's current technology level and its frontier. Financing capacity, in turn, increases with overall income levels—even under divergence—which eventually enables sectors to overcome adoption costs and shift toward convergence. This allows the model to explain how countries can switch from divergence to convergence trajectories without requiring abrupt changes in their financial sector.

A further distinction lies in the treatment of sectoral heterogeneity. While Aghion et al. (2005) assume that all innovators within a country adopt the same average frontier technology, this paper emphasizes the uneven impact of financial constraints across sectors. This addresses a

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

limitation highlighted by Comin and Nanda (2019), who show that financial development plays a more critical role in capital-intensive industries that require substantial external financing. Building on these insights, the model developed here demonstrates that the productivity gap between a sector and the global technological frontier is a key determinant of the intensity of technology adoption. Sectors with smaller gaps are more likely to absorb and implement new technologies effectively, owing to lower adoption costs and greater absorptive capacity. As a result, in contrast to Aghion et al. (2005), the threshold beyond which financial development no longer constrains productivity growth is sector-specific: sectors closer to the frontier become financially unconstrained earlier than those further behind.

By integrating sectoral heterogeneity in both productivity gaps and financial constraints, this paper extends the convergence literature and provides a richer account of the structural transformation processes that underlie long-run development paths.

The second and third closely related studies are Rodrik (2013) and Kinfemichael and Morshed (2019), who document unconditional convergence in labor productivity in manufacturing and services, respectively. Rodrik (2013) shows that convergence in manufacturing holds across 118 countries regardless of institutional or geographic differences, while Kinfemichael and Morshed (2019) reports a similar pattern in services across 95 countries. In contrast, the fourth study by Herrendorf et al. (2022), using new internationally comparable data, finds no evidence of such unconditional convergence in manufacturing among 64 countries.

This paper extends and reconciles these contrasting findings by highlighting the role of the country's financing capacity in shaping sectoral convergence. It contributes to the literature by modeling the speed of convergence and demonstrating that countries may transition from divergence to convergence paths depending on their initial conditions and the rate of frontier growth. In doing so, it emphasizes that convergence is neither automatic nor uniform across sectors or countries, but rather conditional on the specific set of countries and the time horizon required for convergence to materialize.

More generally, this paper contributes to the broad literature analyzing the channels that drive cross-country differences in technology adoption. This literature seeks to explain why poorer countries fail to efficiently adopt and utilize advanced technologies developed in richer economies—technologies that could potentially accelerate growth and help close the income gap. A prominent strand of this literature emphasizes the role of distortions or barriers to adoption, particularly in financial markets (e.g., Parente and Prescott, 1999; Hsieh and Klenow, 2014; Chen et al., 2002; Samaniego, 2006; Bento and Restuccia, 2017; Cole et al., 2016; Comin and Nanda, 2019). Within this framework, policies that reduce misallocation, especially those improving financial development, are viewed as key to fostering better technology diffusion.

Recent contributions to this literature, such as Cole et al. (2016) and Comin and Nanda (2019), highlight the role of financial frictions in shaping technology adoption. Cole et al. (2016) shows that weak monitoring and cash-flow constraints in financially underdeveloped countries lead firms to adopt suboptimal technologies, while Comin and Nanda (2019) documents empirically that financial development facilitates the diffusion of major technologies across advanced economies. This paper builds on and extends these insights by showing that the effect of financial development on technology adoption is positive up to a threshold level, beyond which its influence vanishes. At that stage, technology diffusion no longer depends on sectoral productivity gaps.

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

2 Empirical facts

This section examines the evolution of sectoral productivity across agriculture, manufacturing, and services over the period 1991–2019. The analysis focuses on the cross-country distribution of sectoral productivity levels and the extent to which convergence or divergence patterns emerge across sectors. Understanding these dynamics is critical, as sectoral productivity growth is a central driver of structural transformation and long-run income convergence.

Given that technological progress underpins productivity growth, the analysis further explores the role of technology adoption and its interaction with financial development. Financial systems influence the allocation of resources and the ability of firms to adopt frontier technologies, particularly in sectors with distinct capital requirements and innovation profiles. Thus, examining financial development alongside sectoral trends provides key insights into the mechanisms underlying heterogeneous productivity convergence and motivates the structure of the theoretical model that follows.

2.1 Heterogeneous Productivity Convergence Across Sectors

While the literature on cross-country productivity convergence has traditionally focused on aggregate measures, understanding convergence at the sectoral level is equally important, given the distinct structural roles that agriculture, manufacturing, and services play in economic development. Some recent studies have begun to examine sector-specific convergence patterns. For instance, Rodrik (2013) provides evidence of unconditional convergence in manufacturing labor productivity, while Kinfemichael and Morshed (2019) find similar patterns in services. In contrast, the agricultural sector does not exhibit clear signs of convergence, suggesting that sectoral dynamics may differ substantially. These observations underscore the need to study convergence through a sectoral lens and to consider how structural and technological factors contribute to differences in productivity dynamics across sectors.

To explore these sectoral differences in convergence dynamics, I analyze labor productivity trends across agriculture, manufacturing, and services using data from the World Development Indicators (WDI, 2022). Productivity is measured as value added per worker,[7] expressed in

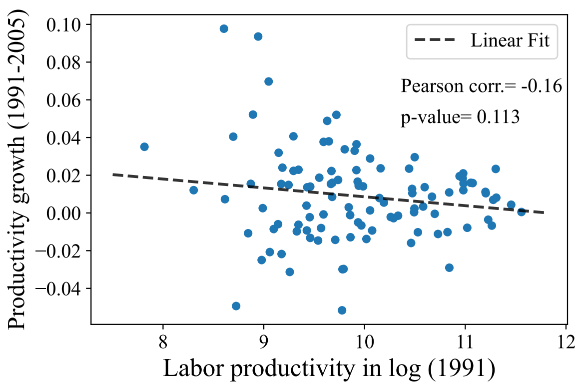
[7] I rely on labor productivity—defined as value added per worker—rather than sectoral total factor productivity (TFP), due to the limited availability and reliability of sector-specific inputs necessary for TFP estimation. This approach also ensures comparability with prior studies that have adopted similar metrics for convergence

constant 2015 international dollars.[8] This framework enables a consistent cross-country comparison of productivity levels over the 1991–2019 period and allows for an assessment of whether convergence patterns differ systematically across sectors. This analysis also complements recent work by Kremer et al. (2022), who document a converging-to-convergence pattern in aggregate income across countries over time, suggesting a shift in the global distribution of income. By disaggregating this analysis across agriculture, manufacturing, and services, the present study sheds light on whether such convergence dynamics are similarly reflected—or diverge—at the sectoral level.

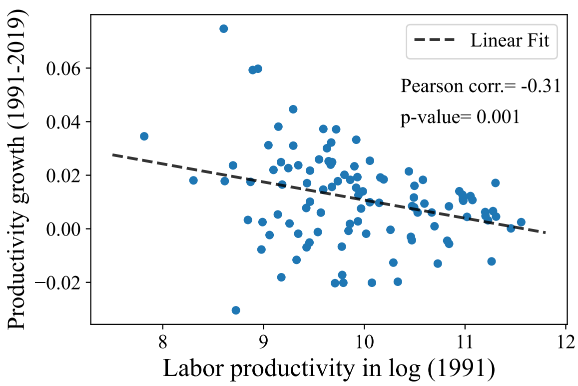
To assess convergence dynamics, I first conduct a standard β-convergence analysis. Under this approach, convergence is indicated if countries with lower initial productivity levels exhibit faster subsequent productivity growth, thereby reducing the productivity gap. Although β-convergence is a necessary condition for catch-up growth, it is not sufficient on its own to imply long-run convergence.

Figures 1–3 plot the average annual growth rate of the logarithm of labor productivity in agriculture, manufacturing, and services against initial productivity levels, over two distinct periods: 1991–2005 and 1991–2019.

In the services sector, the estimated correlation between initial productivity and subsequent growth for the full sample period (1991–2019) is -0.31 (p-value $= 0.001$), consistent with statistically significant β-convergence. This indicates that countries with initially lower service-sector productivity experienced faster growth rates, narrowing the productivity gap relative to more advanced economies. However, the earlier period (1991–2005) shows a weaker correlation of -0.16 (p-value $= 0.113$), suggesting a less pronounced convergence trend during the early years. The stronger convergence signal in the extended period implies that some lagging countries began to catch up only after 2005, possibly reflecting delayed structural changes or improvements in service-sector competitiveness.



(a) 1991–2005



(b) 1991–2019

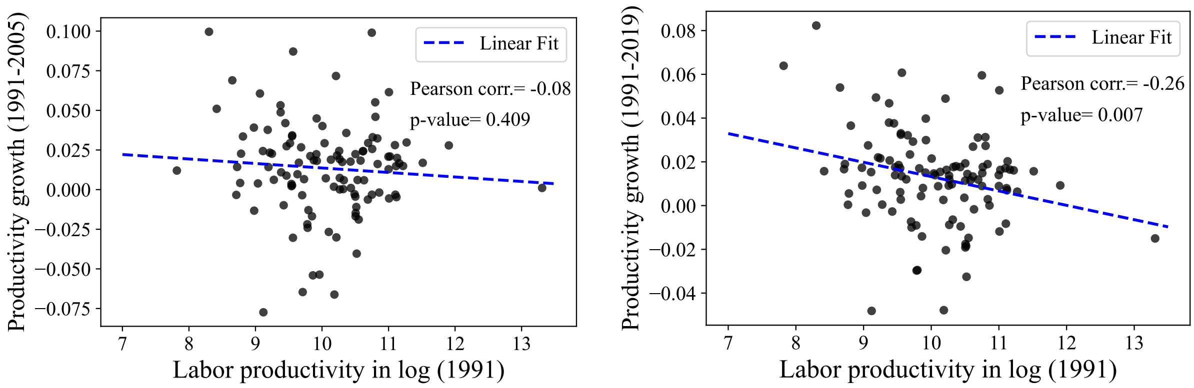
Figure 1: Services Labor Productivity Convergence by Periods

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

analysis.

[8] Value added per worker figures are converted into constant 2015 international US dollars using purchasing power parity (PPP) adjustments, ensuring cross-country comparability over time. For additional details, see Subsection 5.1.

In the manufacturing sector, the correlation between initial labor productivity and subsequent growth over the period 1991–2019 is -0.26 (p-value = 0.007), indicating significant β-convergence. However, for the earlier period 1991–2005, the correlation is much weaker and statistically insignificant (-0.08, p-value = 0.409), suggesting an absence of convergence during those years. This result stands in contrast to Rodrik (2013), who report unconditional convergence in manufacturing for 1995–2005 using UNIDO data in nominal US dollars. The discrepancy may stem from differences in data sources and measurement. Like Herrendorf et al. (2022), this analysis uses comparable cross-country data from the WDI (2022) in PPP-adjusted constant international dollars, which better accounts for price-level differences across countries and over time. These findings suggest that convergence in manufacturing has become more pronounced over time, a pattern reflected in the steeper slope of the fitted trend line for the 1991–2019 period shown in Figure 2b.



(a) 1991–2005

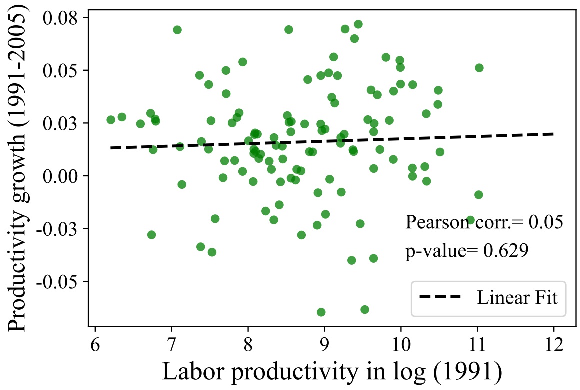
(b) 1991–2019

Figure 2: Manufacturing Labor Productivity Convergence by Periods

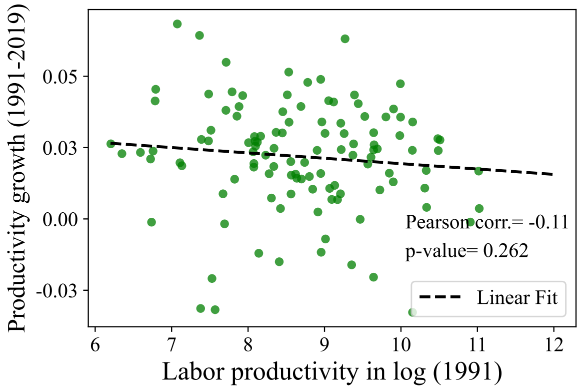
Note: This figure shows average annual growth in manufacturing productivity over 1991–2005 and 1991–2019, plotted against initial productivity in 1991 using WDI data.

In the agriculture sector, the results indicate no evidence of convergence. For the period 1991–2005, the correlation between initial labor productivity and subsequent average growth is weak and statistically insignificant (slope = 0.05, p-value = 0.629). While the correlation becomes negative by 2019 (slope = -0.11, p-value = 0.262), it remains non-significant, suggesting that convergence had not yet emerged by the end of the period.

The persistent lack of convergence in agriculture may reflect the sector's distinct productivity dynamics, which have been extensively discussed in the structural change literature. A number of studies, including Chen (2020), Herrendorf et al. (2014), Duarte and Restuccia (2010), and Ngai and Pissarides (2007), document that productivity growth tends to be uneven across sectors, with agriculture often exhibiting faster growth at the technological frontier relative to manufacturing and services. This pattern is also evident in the data used in this study: among the ten most productive countries in agriculture in 1991, the average annual productivity growth rate between 1991 and 2019 was 3.06%, compared to 1.9% in manufacturing and 0.86% in services. Such a steep growth trajectory at the frontier implies that lagging countries must achieve exceptionally high growth rates to converge, making catch-up more difficult in agriculture than in other sectors. In contrast, the slower pace of frontier growth in manufacturing and services lowers the threshold



(a) 1991–2005



(b) 1991–2019

Figure 3: Agriculture Labor Productivity Convergence by Periods

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

for convergence, helping to explain why these sectors exhibit stronger convergence dynamics over the same period.

Next, I examine σ-convergence[9] in agriculture, manufacturing, and services using two panels of countries. *Panel A* includes all 180 countries with available data between 1991 and 2019, while *Panel B* is restricted to countries with non-missing data in 1991[10]. The use of Panel B allows for assessing changes in dispersion among a consistent set of countries with data at both the beginning and end of the period. σ-convergence is observed when the cross-sectional standard deviation of log productivity declines over time. It is important to note that while β-convergence is a necessary condition for σ-convergence, it is not sufficient. Thus, evidence of β-convergence does not imply that σ-convergence must occur. As illustrated by Young et al. (2008), U.S. counties exhibited β-convergence in GDP per capita without corresponding evidence of σ-convergence. This highlights that differing shocks or structural conditions can affect the evolution of dispersion independently of average catch-up dynamics.

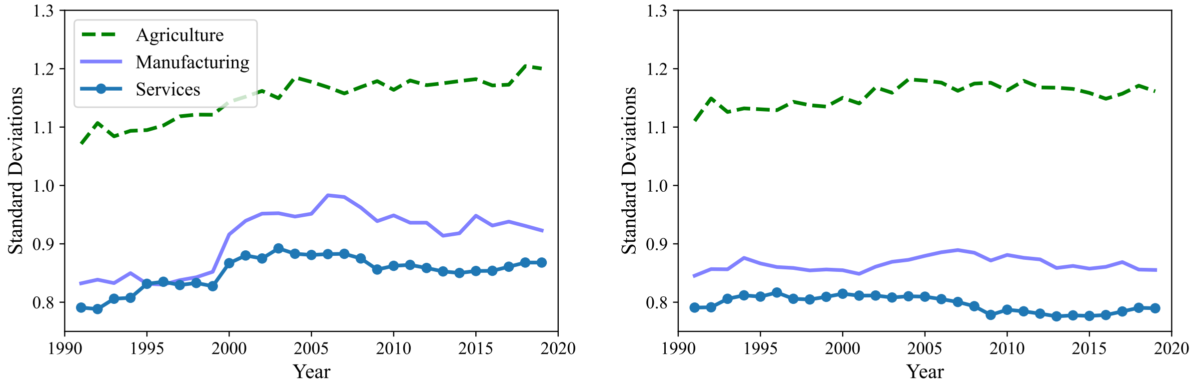
Figure 4 plots the standard deviation of log productivity from 1991 to 2019 for both *Panel A* and *Panel B*. The figure shows that productivity gaps are largest in agriculture and smallest in services. While services and manufacturing exhibit a modest decline in dispersion over the period, the agricultural sector experienced an increase in dispersion during the 1990s, followed by a stabilization in the standard deviation of productivity after 2005.

To complement this analysis, Figure 5 compares the distributions of sectoral productivity levels in 1991 and 2019 across 110 countries. This comparison provides insights into how the shape of the distribution has shifted over time, indicating whether productivity has become more evenly distributed or increasingly skewed, and how countries have transitioned across productivity brackets.

The analysis of the kernel density curves shows that the distribution of productivity in the services sector has become slightly more concentrated over time. Notably, the minor peak on the

[9] σ-convergence refers to a decline in the cross-country dispersion of productivity levels over time.

[10] Countries with data in earlier years generally have complete observations for later years in the World Bank database.

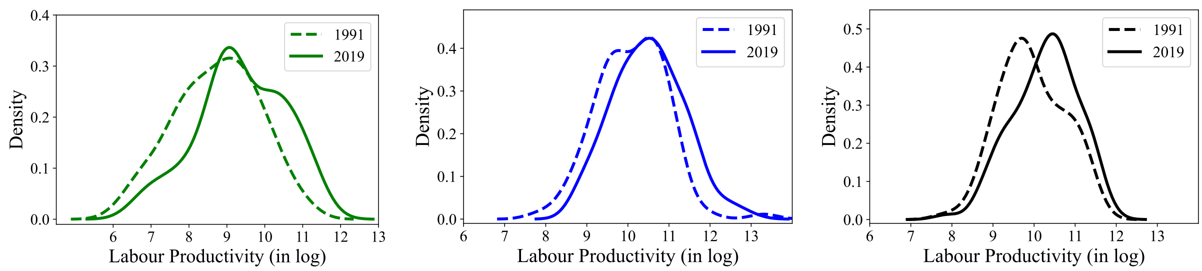


(a) *Panel A* : 180 countries of unbalanced panel **(b)** *Panel B* : 110 countries of balanced panel

Figure 4: σ-Convergence in Agriculture, Manufacturing, and Services

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

right tail of the 1991 distribution—corresponding to a group of highly productive countries—has disappeared by 2019, suggesting a movement toward σ-convergence as lagging countries catch up. In manufacturing, the initially bimodal distribution observed in 1991 has evolved into a more unimodal shape by 2019, indicating increasing similarity in productivity levels across countries and supporting the presence of convergence dynamics in this sector.



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

Figure 5: Sectoral Productivity Distribution Over Time

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

Conversely, while the density curve for productivity in the agricultural sector exhibits a more elongated peak in 2019, it also features a noticeable hump extending toward the right. This suggests that some developed countries have achieved even greater growth in agricultural productivity between 1991 and 2019. Thus, although progress in agricultural productivity is evident among certain countries, substantial heterogeneity in productivity levels persists across countries within the agricultural sector.

In summary, the analysis of productivity trends across sectors reveals distinct patterns of convergence and divergence, which align with the growth rates of sectoral productivity among the top ten most developed countries from 1991 to 2019. Manufacturing and services sectors show stronger trends toward convergence over time, characterized by diminishing productivity gaps and lower growth rates at the frontier. In contrast, the agricultural sector exhibits relatively higher productivity growth among developed countries, with limited evidence of convergence across the global distribution.

These findings underscore the importance of investigating the underlying drivers of sectoral productivity growth, particularly the roles of technology adoption and financial development. For example, Madsen and Timol (2011) highlight the importance of research and development (R&D) and financial development in fostering productivity convergence across OECD manufacturing sectors. This raises the question of whether similar mechanisms apply more broadly across countries and sectors.

2.2 Financial Development and Technology Adoption

Previous studies, including King and Levine (1993), Rajan and Zingales (1998), Levine (1997), Beck et al. (2000), Aghion et al. (2005), and Buera et al. (2011) have demonstrated that financial development exerts a significant positive impact on both capital accumulation and productivity growth. While Comin and Nanda (2019) focus on the role of financial development in facilitating the adoption of advanced technologies across developed economies, this paper extends their analysis by showing that, beyond a certain technology-specific threshold, financial development ceases to exert a meaningful influence on technology adoption.

To conduct this analysis, I combine three types of data. First, I use measures of technology diffusion from the HCCTA[11] dataset introduced by Comin and Hobijn (2004), given the lack of comprehensive cross-country data on technology adoption. The HCCTA provides historical data on the diffusion of major technologies over the past 200 years across a broad sample of countries. I construct a panel dataset at the technology-country-year level, capturing the quantity of each technology adopted in each country over time.

Table 1: Summary of Technology Data

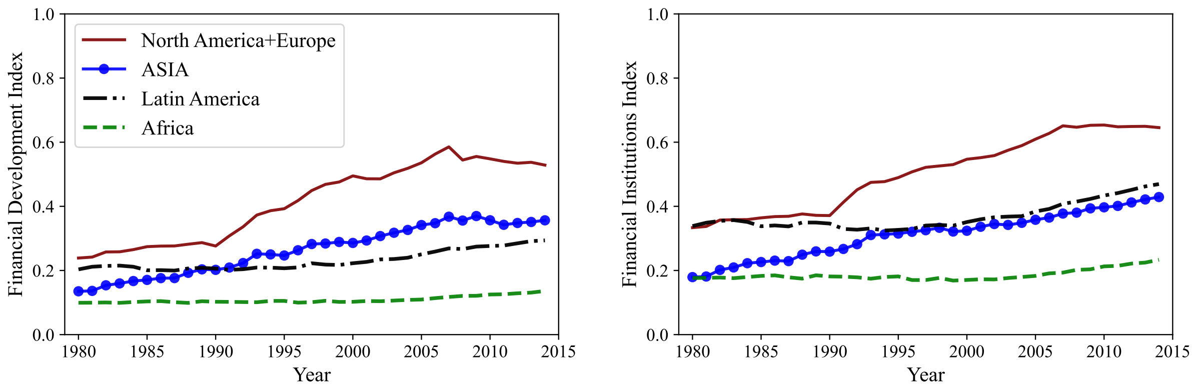
Technology	**Measure**	**Countries**
Tractors	Number in operation	130
Electric production	KwHr produced	120
Aviation pkm	Million passenger kilometers	70
Commercial vehicles	Number in operation	78
Internet users	Number of individuals	128
Radio	Number in operation	120
Telephone	Number connected	84
Private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

As shown in Table 1, the set of technologies spans the three main economic sectors—agriculture, industry, and services. The heterogeneity of the technologies is also reflected in their measurement. Some are recorded by the number of operational units (e.g., cars, tractors, radios), while

[11] HCCTA: Historical Cross-Country Technology Adoption

others are quantified by production capacity or number of users (e.g., electricity, cell phones). Following Comin and Nanda (2019), this metric serves as a proxy for the intensity of technology adoption and utilization.

Second, I use the Financial Development Index[12] developed by the International Monetary Fund (IMF) as a proxy for financial development. This index captures the development of both financial institutions and financial markets along three dimensions: depth (size and liquidity of financial systems), access (the ability of individuals and firms to access financial services), and efficiency (the capacity of financial institutions to deliver services at low cost, with sustainable revenues, and the level of activity in capital markets). The index is normalized to range between 0 and 1 and is available for over 180 countries at an annual frequency from 1980 to 2014. Further details regarding its construction are provided in Appendix A.



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

Figure 6: Average Regional Levels of Financial Development Indexes Over Time

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

Figure 6 presents the evolution of the Financial Institutions and Financial Development Indices over time, highlighting substantial regional disparities. The financial development index varies significantly across major world regions—North America and Europe, Asia, Latin America, and Sub-Saharan Africa—reflecting distinct trajectories of financial system advancement. North America and Europe exhibit the highest levels of financial development, with a pronounced acceleration beginning in the early 1990s. This increase coincides with notable improvements in financial infrastructure, the diffusion of new financial technologies, and the strengthening of regulatory frameworks, consolidating these regions' positions as global financial leaders.

By comparison, Asia demonstrates steady and sustained growth in its financial development index. Although it began at a lower level than Latin America in 1980, the region gradually enhanced its financial systems, overtaking Latin America by the early 1990s. While Asia's financial development remains below that of North America and Europe, ongoing reforms and greater market access have led to substantial progress. Latin America, meanwhile, displays

[12]The index offers a comprehensive, multidimensional measure of financial development that is comparable across countries and over time, making it suitable for empirical analysis of structural effects.

low but positive growth, with most improvements occurring after 2000. However, the region's advancement has been constrained by persistent economic volatility and institutional fragility. Sub-Saharan Africa exhibits minimal improvement in financial development over the period, with gains from mobile banking innovations failing to compensate for deeper structural deficiencies in the formal financial system.

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

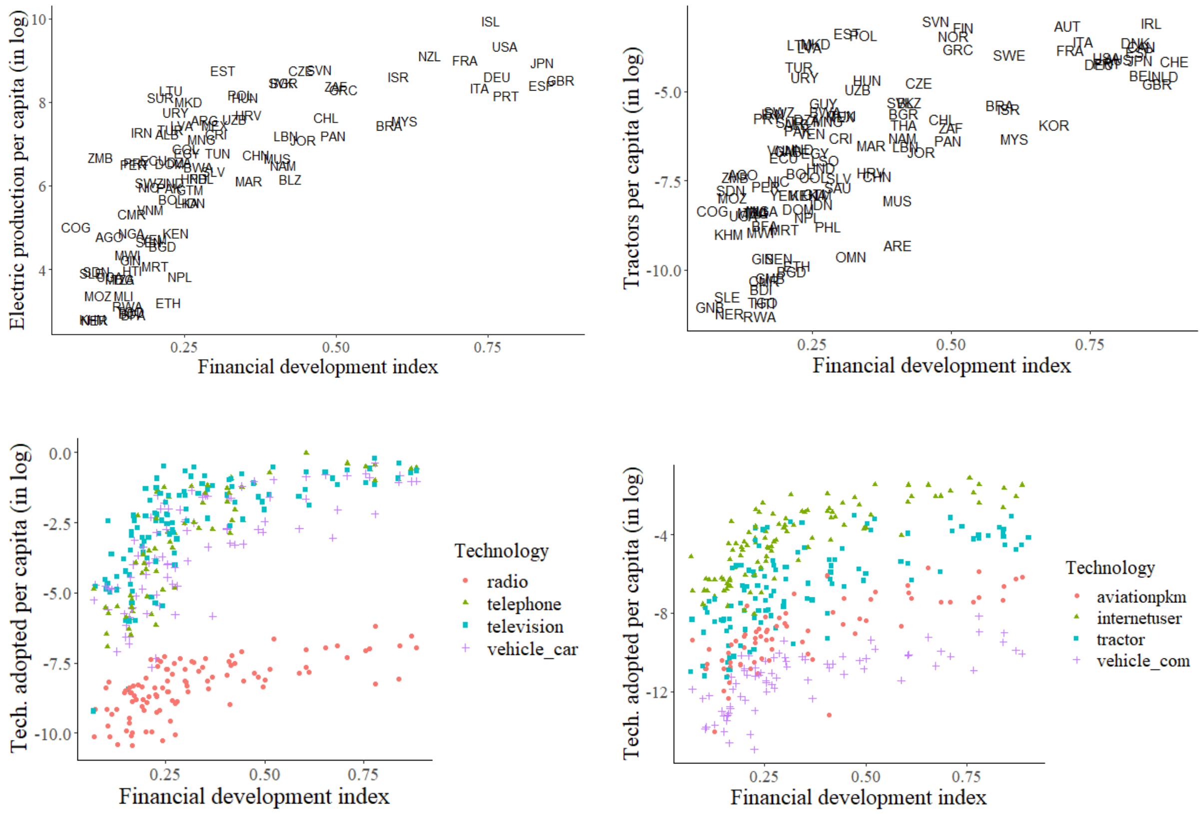


Figure 7: Average Levels of Financial Development and Log Technology Adoption per Capita (1980–2003)

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

Figure 7 plots the average logarithm of total electricity production per capita and the number of tractors per capita across countries from 1980 to 2003 against the average level of the Financial Development Index. The figure reveals a positive relationship between financial development and technology adoption, which tends to weaken once financial development surpasses a certain threshold. Additional scatter plots included in the figure display similar patterns for other technologies; however, the threshold at which the correlation becomes negligible varies across technologies.

Specifically, the turning point beyond which financial development is no longer significantly associated with technology adoption lies between 0.4 and 0.5 for tractors and electricity production, but between 0.25 and 0.3 for televisions and commercial vehicles. These differences suggest that financial development has a relatively stronger influence on the adoption of tractors than on that of commercial vehicles. Furthermore, even within a given country and at a comparable level of financial development, certain technologies may face more binding constraints to adoption than others.

In the next section, I develop an endogenous growth model that incorporates these mechanisms, emphasizing how financial constraints shape sectoral productivity convergence through their influence on technology adoption.

3 Theoretical Framework

The model economy builds on the theoretical Schumpeterian growth paradigm developed over the past two decades by Aghion et al. (2005), Howitt and Mayer-Foulkes (2005), and Acemoglu et al. (2006). In this framework, time is discrete, and economic activity occurs in countries that do not trade goods or factors of production but share technological ideas. The population in each period is normalized to one, $L \equiv 1$, so that aggregate and per capita quantities coincide. Each individual born at time t lives for two periods: in the first period, they supply two units of labor, earning a wage w_t, and in the second period, they supply no labor and act as entrepreneurs. The utility function is linear[13], given by:

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

where c_{1t} is consumption in the first period (when young, at time t), c_{2t} is consumption in the second period (when old, at time $t+1$), and $\beta \in (0,1)$ is the discount factor for second-period consumption. Households consume $c_{1t} = (1 - s_t)w_t$ in the first period and save $s_t w_t$. At the end of the first period, they acquire skills and invest z_{jt+1} in a technology adoption project in sector j for next period[14]. To finance this investment, they borrow $z_{jt+1} - (1 + r_t)s_t w_t$ at interest rate r_{t+1}. If technology adoption is successful, they earn monopoly profits π_{jt+1} and repay $(1 + r_{t+1})(z_{jt+1} - s_t w_t)$ at the end of the second period such that :

$$c_{2t} = \int_0^1 \{\pi_{jt+1} - (1 + r_{t+1})[z_{jt+1} - (1 + r_t)s_t w_t]\} \, dj.$$

Initial Setup. The economy begins in period 1 with two cohorts: adults born in period 0 and the young generation born in period 1. The adults from period 0 act as entrepreneurs in period

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

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

1. They borrow from the young in order to maximize their profits $\{\pi_{j1}\}_{j\in[0,1]}$, and subsequently, their consumption $c_{2,0}$ during the period 1, given the initial conditions $\{w_0, r_0, s_0, A_{j0}\}_{j\in[0,1]}$.

3.1 Goods Production Sectors

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

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

where $0 < \alpha < 1$, A_{jt} is the productivity in sector j at time t, and x_{jt} is the input of the latest version of intermediate good j used in final good production at time t. L_t represents the total labor 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 labor and the quantity of intermediate goods from each sector j to use in order to maximize its profit as follows:

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

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

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

Intermediate Goods Production. In each intermediate sector, there is a monopoly whose production technology consists of using one unit of the final good to produce one unit of the intermediate good. Given that the intermediate producer operates in a monopoly, it charges the highest price that the final sector producer is willing to pay for variety j, under the assumption of a drastic innovation[15]. The monopolist maximizes profit as follows:

$$\max_{\{p_{jt}\}} p_{jt} x_{jt} - x_{jt} \tag{3.4}$$

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

Thus, the equilibrium[16] profit of the intermediate goods producer in sector j is given by:

$$\pi_{jt} = \pi A_{jt} L_t, \tag{3.5}$$

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

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

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

$$w_t = \omega A_t, \tag{3.6}$$

$$GDP_t = (1+\alpha) w_t L_t, \tag{3.7}$$

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

3.2 Credit Constraints and Financial Development

Following Aghion et al. (2005), the model introduces credit market imperfections that limit the financing capacity of entrepreneurs undertaking technology adoption. These constraints arise from moral hazard, where borrowers may strategically default by concealing profits, leading lenders to impose borrowing limits based on observable wealth.

Formally, investment in technology adoption in sector j at time $t+1$ is constrained by:

$$z_{jt+1} \leq \kappa_t w_t, \tag{3.8}$$

where κ_t is an exogenous parameter capturing the degree of financial development, and w_t is the wage rate. The product $\kappa_t w_t$ defines the country's *financing capacity*, representing the maximum investment that can be credibly financed through external borrowing given existing institutional conditions.

In economies with higher financial development, reflected in a larger κ_t, stronger legal frameworks and more effective enforcement mechanisms increase lender confidence and expand credit access. As emphasized by Aghion et al. (2005), improved creditor protection facilitates the enforcement of financial contracts, thereby supporting higher levels of investment.

This borrowing constraint imposes a uniform upper bound on investment across all sectors, as it depends solely on the economy-wide level of financial development κ_t and the wage rate w_t. However, the implications of this constraint are not uniform across sectors. Because the cost of adopting frontier technologies can vary significantly by sector—being typically higher in sectors with more complex or capital-intensive technologies—financial underdevelopment disproportionately restricts investment in those sectors. In economies with low κ_t, sectors requiring higher adoption costs are more likely to face binding credit constraints, which slows their technological progress relative to others. As a result, financial development shapes not only the aggregate level of investment but also the sectoral composition of technological upgrading, with important implications for structural transformation and long-run convergence.

In addition to financial development, the level of wealth w_t also plays a key role in determining the financing capacity $\kappa_t w_t$ available for technology adoption. A higher w_t implies that entrepreneurs possess greater internal resources, which can be leveraged for external borrowing under the credit constraint. As a result, even when two countries share the same degree of financial development κ_t, differences in wealth levels can lead to variation in effective investment capacity. Poorer countries, with lower w_t, face tighter constraints and are thus more likely to experience underinvestment in technology adoption, particularly in sectors with higher adoption costs. This wealth-driven asymmetry contributes to persistent differences in the speed of technological upgrading across countries. Hence, convergence is not solely determined by financial deepening, but also by the evolution of real income, which jointly shapes an economy's ability to allocate resources toward productivity-enhancing innovation.

3.3 Technological Progress and Productivity Growth

Technological adoption drives productivity growth in this model, enabling successful innovators to move closer to the global technological frontier. In each period t, one individual in each sector j undertakes an innovation project intended for implementation in period $t+1$. If the project succeeds, the innovator becomes the sectoral monopolist in the following period, operating with productivity given by:

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

where $\bar{A}_{jt}$ denotes the frontier productivity in sector j at time t, and $\theta_{jt+1} \in [0,1]$ captures the intensity with which the new technology is implemented in the domestic economy. A value of $\theta_{jt+1} = 0$ indicates project failure, while $\theta_{jt+1} = 1$ corresponds to successful adoption and full utilization of the technology.

Importantly, even when technologies are successfully adopted, the intensity of their use may fall short of the frontier benchmark. Comin and Mestieri (2018) document that although cross-country gaps in technology adoption have narrowed over time, gaps in the intensity of use have persisted or even widened, particularly between high- and low-income economies. These findings highlight that catching up to the frontier involves not only acquiring new technologies but also deploying them effectively within firms and sectors.

In contrast to Aghion et al. (2005) and standard Schumpeterian frameworks, which assume that all successful innovators reach the same average productivity frontier across sectors, the present model allows for sector-specific technology transfer. Some sectors may face a smaller gap to the frontier, making technology adoption more feasible. As a result, in equilibrium, both the intensity of use θ_{jt+1} and realized productivity A_{jt+1} may differ across sectors, even within the same country.

Consistent with Aghion et al. (2005), accessing the frontier in sector j involves a cost that increases with the level of targeted productivity. In particular, the intensity of technology use depends positively on the resources z_{jt+1} allocated to the adoption project. The cost of innovation is therefore given by:

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

where $F(\cdot)$ is a strictly increasing, convex function capturing the cost of achieving a given intensity of technology use. For analytical tractability, I assume:

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

with $\eta, \psi > 0$. The parameter λ_{jt} reflects the sector-specific knowledge of the entrepreneur. In practice, adoption costs are influenced by the availability of human capital, particularly engineers, technicians, and scientists with sector-relevant expertise. The presence of technically skilled personnel, alongside leadership with strong academic or professional training, is a key determinant of successful implementation.

This perspective aligns with empirical evidence from Foster and Rosenzweig (1996) and Griffith et al. (2004), who emphasize the role of skills in shaping a country's absorptive capacity—that is, its ability to recognize, assimilate, and effectively utilize new technologies. As firms accumulate knowledge through experience and learning, their capacity to adopt and use new technologies intensifies, reinforcing a dynamic feedback loop between past experience and future innovation success.

Sector-specific knowledge and expertise are captured in the model through the entrepreneurial skill parameter λ_{jt}, which is assumed to be proportional to sectoral productivity A_{jt}, following Howitt and Mayer-Foulkes (2005):

$$\lambda_{jt} = \lambda A_{jt}. \tag{3.12}$$

This specification reflects the idea that sectors with higher productivity possess a more advanced knowledge base, better technical capabilities, and stronger absorptive capacity, which collectively lower the cost of adopting new technologies. Since technological progress is uneven across sectors due to differences in human capital, infrastructure, and accumulated experience, modeling λ_{jt} as proportional to productivity captures sectoral heterogeneity in the capacity to implement and integrate frontier technologies effectively.

This mechanism is consistent with Scotchmer (1991), who conceptualize innovation as a cumulative process in which existing knowledge serves as an input into future technological development. In the model, sector-specific knowledge λ_{jt}, which reflects a sector's absorptive capacity, captures the role of existing productivity in facilitating new technology adoption. As such, cost differentials in adoption arise from variation in productivity proximity to the technological frontier across sectors. Sectors that are closer to the frontier, and therefore possess higher absorptive capacity, face lower implementation costs. To see this, substitute Equation (3.12) into Equation (3.10) to express the adoption cost z_{jt+1} as a function of sectoral proximity to the frontier, captured by the relative productivity term $a_{jt} := A_{jt}/\bar{A}_{jt}$:

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

In equilibrium, the entrepreneur selects the intensity of technology use $\theta_{jt+1} \in [0,1]$ to maximize the expected net payoff from adoption:

$$\max_{0 \le \theta_{jt+1} \le 1} \; \beta\pi \left[\theta_{jt+1}\bar{A}_{jt} + (1-\theta_{jt+1})A_{jt}\right] - z_{jt+1}, \tag{3.14}$$
$$\text{subject to} \quad z_{jt+1} \le \kappa_t w_t \quad \text{and Equation (3.13).}$$

3.4 Equilibrium

The equilibrium in this economy consists of a sequence of aggregate allocations $\{c_{1t}, c_{2t}, s_t, Y_t\}_{t\geq 1}$, aggregate prices $\{r_t, w_t\}_{t\geq 1}$, and pricing, production, and technology decisions for intermediate monopolists $\{p_{jt}, x_{jt}, z_{jt}, \theta_{jt}, a_{jt}\}_{j\in[0,1],\, t\geq 1}$, as well as the allocation $c_{2,0}$ for the initial adult generation, such that, given initial conditions $\{r_0, s_0, w_0, A_{j0}\}_{j\in[0,1]}$, households choose consumption and savings to maximize lifetime utility; final good producers behave competitively and maximize profits given prices; entrepreneurs and intermediate-good monopolists choose investment levels subject to financial constraints and set prices to maximize profits; the asset market and the final goods market clear in every period :

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

Assuming perfect credit markets, entrepreneurs would face no borrowing limits, enabling all sectors within a country to adopt and utilize new technologies at an intensity comparable to that of the global frontier. Under such conditions, firms could fully exploit the productivity gains embodied in frontier technologies.

However, in the presence of credit constraints, this ideal scenario is rarely observed. Even when a technology is adopted, limited access to financing may prevent entrepreneurs from operating at the optimal intensity level required to fully realize the technology's productivity potential. Since the cost of adoption z_{jt+1} is bounded by the country's financing capacity, suboptimal resource allocation results in inefficient technology use. As a consequence, financially constrained firms may adopt technologies at lower intensities, thereby limiting productivity gains and impeding long-term growth. Under credit constraints, the problem (3.14) of the innovator can be rewritten as follows:

$$\max_{0\leq\theta_{jt+1}\leq 1} \beta\pi\left[\theta_{jt+1}\bar{A}_{jt} + \left(1-\theta_{jt+1}\right)A_{jt}\right] - (\lambda a_{jt})^{-1}\left(\frac{\psi}{2}\theta_{jt+1}^2 + \eta\theta_{jt+1}\right) \tag{3.15}$$

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

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

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

The intensity of technology use θ_{jt+1}^* increases with sectoral proximity to the frontier, a_{jt}, up to a threshold level $\bar{a}_t = (\psi + 2\eta)/2\lambda\kappa_t w_t$. Sectors with $a_{jt} > \bar{a}_t$ adopt technologies at full intensity ($\theta_{jt+1}^* = 1$), while those below this threshold exhibit partial adoption. The threshold $\bar{a}_t$ plays a central role in shaping adoption patterns: it is decreasing in both financial development (κ_t) and the wage rate (w_t), which together determine the financing capacity of the economy. As w_t or κ_t increases, the threshold $\bar{a}_t$ falls, enabling more sectors to reach full adoption.

This result highlights that improvements in financing capacity—through either higher wages or enhanced financial development—reduce the productivity gap required for full adoption. Consequently, sectors that are further from the frontier can afford to intensify their technology use. Moreover, when two countries face the same financing conditions, the one with higher sectoral productivity (i.e., higher a_{jt}) adopts technologies more intensively. This occurs because sectors closer to the frontier benefit from accumulated expertise and lower complementary adoption costs, such as training and system integration (see Nelson and Phelps, 1966). Conversely, sectors with low a_{jt} face higher effective costs and tighter credit constraints, leading to lower adoption intensity despite having access to the same technologies.

Furthermore, the model predicts that technology adoption increases with the country's level of financial development and income.[17] However, this positive effect vanishes beyond a sector-specific threshold. This outcome is consistent with the pattern illustrated in Figure 7, where the cross-country correlation between financial development and technology adoption weakens once financial development surpasses a critical level that varies by technology. Specifically, the model identifies a threshold level of financial development, denoted $\underline{\kappa}_{jt}$, beyond which the intensity of technology use in sector j is no longer constrained by financial frictions:

$$\underline{\kappa}_{jt} = \frac{2\eta + \psi}{2\lambda w_t a_{jt}}. \tag{3.16}$$

This threshold is sector-specific and evolves over time as wages and sectoral productivity change. Even for sectors with identical proximity to the frontier in two countries, differences in income (reflected by w_t) imply different thresholds. As wages rise, financing capacity improves, lowering the critical level of financial development required for full technology adoption. Consequently, sectors in wealthier countries can overcome financial constraints more quickly than those in poorer economies.

Within a given country, sectors closer to the frontier (i.e., with higher a_{jt}) achieve unconstrained adoption more rapidly than sectors with larger productivity gaps. For instance, if agriculture lags further behind the global frontier than services or manufacturing, its adoption of frontier technologies will remain limited until financial development or income sufficiently improves.

In financially underdeveloped economies, entrepreneurs face significant barriers to obtaining the capital necessary for adopting new technologies. These constraints limit their ability to increase the intensity of technology use. As financial systems deepen or national income rises, these constraints are progressively relaxed, enabling broader and more intensive adoption of frontier technologies. Once financial constraints no longer bind, the marginal effect of financial development on adoption intensity becomes negligible.

Next, I examine how financial development interacts with a sector's proximity to the technological frontier in influencing the intensity of technology use. Specifically, I analyze whether financial development has a stronger effect in sectors closer to the frontier by differentiating

[17] See Figure A.1 in Appendix C.

technology intensity with respect to financial development and sectoral proximity (for $a_{jt} \leq \bar{a}_t$):

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

The positive cross-partial derivative indicates that, before reaching their respective threshold levels, financial development and sectoral proximity to the frontier jointly contribute to increasing the intensity of technology use.[18] In other words, when financial development is relatively low and a sector remains distant from the frontier, improvements in either dimension amplify the effect of the other on technology adoption. This highlights a complementary relationship between financial development and technological proximity during the early stages of sectoral advancement.

In the following section, I analyze the long-run effects of financing capacity on the dynamics of the sectoral productivity gap and the interplay between aggregate and sectoral productivity convergence.

4 Financing Capacity and the Evolution of Productivity Gaps

This section examines the dynamics of sectoral proximity to the technological frontier over time, focusing on how countries shift from one convergence path to another—as documented by Kremer et al. (2022)—and how initial levels of financial development and income influence the speed of such transitions.

4.1 Dynamics of Sectoral Productivity Gap

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

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

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

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

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 Equation (4.3a) : $a_{jt+1} = f_{jt}(a_{jt})$ when

[18] The positive interaction between financial development and sectoral proximity is illustrated by the dashed red lines in Figures A.1 and 7 in Appendix C.

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

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

Thus $a_{jt+1} = \min\left\{\frac{1}{1+\bar{g}_j}, f_{jt}(a_{jt})\right\}$ for all $a_{jt} \in [0,1]$. Note that $f_{jt}(a_{jt})$ is a concave[19] function in a_{jt} with $f_{jt}(0) = 0$ and $f_{jt}(1) = 1/(1+\bar{g}_j)$. I will now use the first derivative test to analyze the convergence behavior of the sequence generated by the function f_{jt}, $t = 0, 1, 2...$, on the interval $[0,1]$. If $f'_{jt}(0) < 1$ then $f'_{jt}(a_{jt})$ will be less than the the slope of the first bisector for all a_{jt} in $[0,1]$ because f'_{jt} is decreasing, and the function f_{jt} is a contraction mapping on $[0,1]$, and the sequence generated by the function f_{jt} will converge to 0 meaning the sectoral productivity is diverging. If $f'_{jt}(0) > 1$ then the sequence generated by the function f_{jt} will intersect the first bisector on the interval $[0,1]$ since $f_{jt}(1)$ is also less than 1. This will imply a convergence towards a non-zero point. After computing the derivative of the sectoral productivity proximity transition function f_{jt} at the endpoints $a_{jt} = 0$ and $a_{jt} = 1$, I obtain the following system of equations:

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

These expressions characterize how the marginal return to technology adoption varies with the level of financing capacity, $\kappa_t w_t$. In particular, the derivative $f'_{jt}(0)$ captures the responsiveness of the sectoral productivity proximity transition function when a sector is far from the frontier. This derivative can be used to assess whether an economy is on a convergence path. When $f'_{jt}(0)$ is less than or equal to one—the slope of the 45-degree line—the economy is likely to diverge. Conversely, if the derivative exceeds one, convergence is more likely. Solving for these threshold values yields the following conditions:

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

Since[20] $(\psi + 2\eta)/2\lambda > \eta\bar{g}_j/\lambda$, one can categorize countries into three groups within each sector, based on their income levels and financial development. These conditions define three distinct regimes of convergence, depending on the country's financing capacity and the sector's frontier productivity growth rate $\bar{g}_j$. First, high-income countries with strong financial systems exhibit unconditional convergence, characterized by robust technology adoption across sectors. Second, middle-income countries with moderate financial development display conditional convergence, where productivity growth depends on initial conditions. Third, low-income or financially under-

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

[20] Note that: $\frac{\eta\bar{g}_j}{\lambda} / \frac{\psi+2\eta}{2\lambda} = \frac{2\eta\bar{g}_j}{2\eta+\psi} < 1$, as $2\eta\bar{g}_j \leq 2\eta$ and $\psi > 0$.

developed countries face initial divergence, as weak financial systems hinder technology adoption and delay convergence.

Category 1: Unconditional convergence in countries with high financing capacity. When financial development or the level of initial income per worker are sufficiently high such that $\kappa_0 w_0 > (\psi + 2\eta)/2\lambda$, the evolution of the sectoral productivity gap is illustrated in Figure 8. Since $f_{jt} \leq f_{jt+1}$ and $\bar{a}_t$ is decreasing with t, while a_{jt} is increasing with t as long as f_{jt} is above the first bisector, there exists a date T_j such that $a_{jt} \geq \bar{a}_{T_j}$ and $a_{jt+1} = h_j(a_{jt})$ for all $t \geq T_j$. The sectoral productivity proximity to the frontier a_{jt} for $j \in [0,1]$ will therefore converge to the steady state $a_j^* = \frac{1}{1+\bar{g}_j}$, where T_j represents the date of convergence.

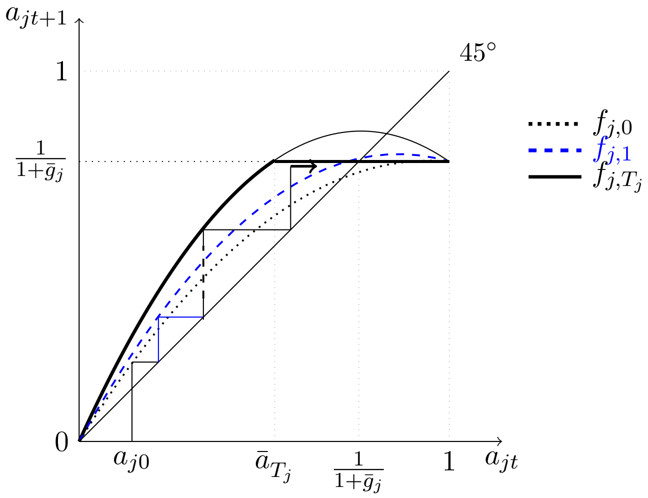


Figure 8: Sectoral Productivity Gap Dynamics when $\kappa_0 w_0 > \frac{\psi+2\eta}{2\lambda}$

Note: This figure shows the evolution of the sectoral productivity proximity when the country's initial financing capacity is sufficiently high (i.e., $\kappa_0 w_0 > (\psi + 2\eta)/2\lambda$), allowing the country to close the productivity gap in sector j.

Category 2: Conditional convergence in countries with moderate financing capacity. When financial development and initial income are neither too high nor too low so that $\eta\bar{g}_j/\lambda < \kappa_0 w_0 < (\psi + 2\eta)/2\lambda$, then $f_{jt}(a_{jt}) < \frac{1}{1+\bar{g}_j}$ for all $a_{jt} \in [0,1]$. Let us define $\hat{a}_{jt}$ such that $\hat{a}_{jt} = f_{jt}(\hat{a}_{jt}) \quad \forall t \geq 0$.

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

If $a_{j0} > \hat{a}_{j0}$, then a_{jt} will decrease until a date T_0 from which $a_{jT_0} < \hat{a}_{jT_0}$ and will begin to grow again to converge towards $\hat{a}_j$. The dynamics of the sectoral productivity proximity is illustrated in Figure 9 for the case where $a_{j0} < \hat{a}_{j0}$. Thus, countries in sector j will, in the long run, conditionally converge to $\hat{a}_j$, which is less than the unconditional sectoral productivity proximity steady state $a_j^* = 1/(1 + \bar{g}_j)$.

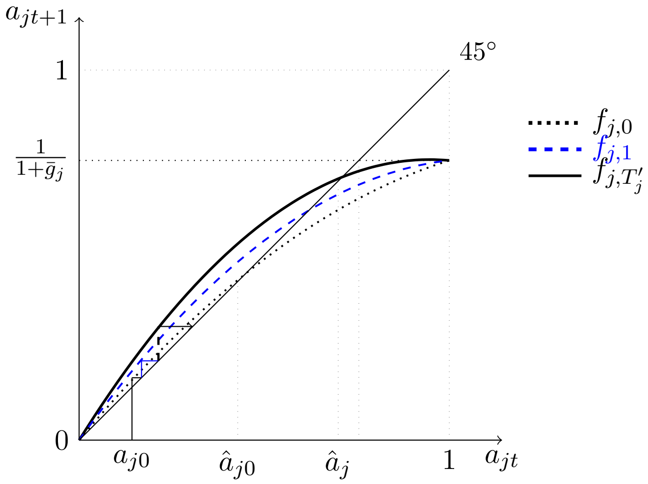


Figure 9: Sectoral Productivity Gap Dynamics when $\eta\bar{g}_j/\lambda < \kappa_0 w_0 < (\psi + 2\eta)/2\lambda$

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

Category 3: Transient divergence in countries with low financing capacity. When the level of initial financial development and aggregate income are sufficiently low, or when the sector j technological frontier productivity growth $\bar{g}_j$ is high such that $\kappa_0 w_0 < \eta\bar{g}_j/\lambda$, then a_{jt} will decrease over time. The dynamics of the sectoral productivity gap is illustrated in Figure 10. Under conditions of low income and low financial development, the sectoral productivity gap will continue to widen until a time τ_j where the level of income reaches a certain threshold such that $\kappa_{\tau_j} w_{\tau_j} > \eta\bar{g}_j/\lambda$.

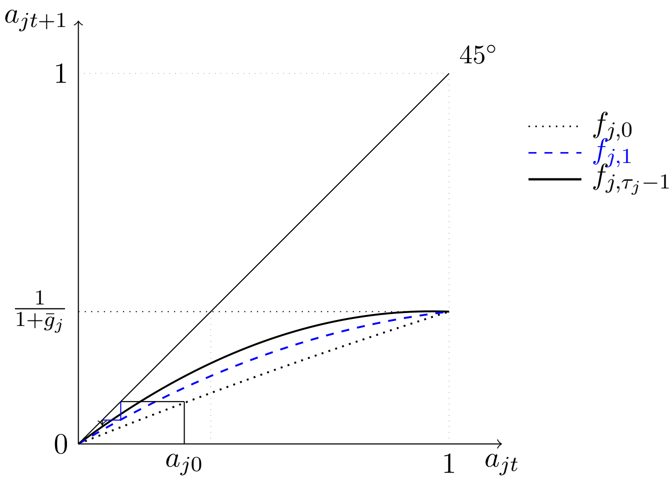


Figure 10: Sectoral productivity gap dynamic when $\kappa_0 w_0 < \eta\bar{g}_j/\lambda$

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

Sectors gradually converge, with lags, toward their respective steady-state productivity gap levels. The timing of this convergence is systematically linked to a country's initial level of financing capacity. Economies with relatively advanced financial development tend to initiate convergence earlier, whereas those with weaker financial systems often experience an initial phase of divergence. Over time, however, such countries may transition into a convergence regime as financial constraints ease. This dynamic suggests a positive correlation between a country's initial financial development and the timing of sectoral convergence. Furthermore, as shown in Proposition I, the speed of convergence increases with financing capacity. In sectors with faster technological frontier growth, temporary divergence tends to be more prolonged, particularly in economies with low financing capacity.

Proposition I.

(i) Countries with higher initial levels of financial development and income converge faster than those with lower levels.

(ii) Sectors experiencing faster technological frontier growth converge later and more slowly than those with slower frontier growth.

Proof. See Appendix E. ■

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

4.2 Sectoral Productivity Convergence and Aggregate Behavior

Understanding the interaction between sectoral dynamics and aggregate productivity growth is central to the study of long-run economic development. Sectoral productivity growth—influenced by heterogeneity in sectoral productivity gaps and technology utilization—constitutes the micro-foundation upon which aggregate performance rests. In this subsection, I formally characterize how sector-level productivity growth rates (g_{jt}) aggregate into the economy-wide growth rate (g_t), emphasizing the role of cross-sectoral dispersion in financial frictions and distance to frontier.

Recall from Equation (3.9) that sectoral productivity growth in sector j at time t is given by:

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

where θ^*_{jt} captures the intensity of technology adoption—increasing in financing capacity—and a_{jt-1} denotes the proximity of sector j to the technological frontier at time $t-1$. The expression above highlights two distinct channels. First, the *catch-up margin*, governed by the inverse of a_{jt-1}, reflects potential for convergence. Second, the *adoption intensity margin*, captured by θ^*_{jt}, determines the realized extent of this convergence. In the presence of financial frictions, θ^*_{jt} remains heterogeneous across sectors and countries, thereby generating persistent deviations in productivity growth.

At the aggregate level, let $a_t := A_t/\bar{A}_t$ denote the country's inverse relative distance to the world technological frontier. Then, the per capita GDP growth rate at time t satisfies:

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

Equation (4.5) establishes that the aggregate growth rate is a weighted integral of sectoral gaps to the frontier, modulated by sector-specific adoption intensities. This formulation implies the following comparative statics:

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

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

Equation (4.6a) characterizes the benchmark case of frictionless financial markets in which all sectors converge to the frontier at the maximal feasible rate. In this setting, growth is uniquely determined by the aggregate distance to the frontier. In contrast, Equation (4.6b) describes the case of binding sectoral credit constraints, wherein adoption intensities fall below optimal levels in at least one sector, generating aggregate growth losses.

The implication is straightforward: sectoral convergence is a necessary and sufficient condition for aggregate convergence. Thus, in the presence of frictions, even when average proximity to the frontier is relatively high, weak adoption intensity in lagging sectors may depress aggregate growth. Policies aimed at relaxing credit constraints and improving sector-specific absorptive capacity therefore play a pivotal role in accelerating macroeconomic convergence.

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

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

Within a country, the impact of financial development on productivity growth varies across sectors. Some sectors may experience notable increases in productivity due to improvements in financial development and access to capital, while others may not benefit as much. In Equation (4.7), I define the critical threshold level of financial development for the whole economy beyond which finance does not affect economic growth, denoted as $\underline{\kappa}_t$, which is given by:

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

where $\underline{\kappa}_{jt} := (2\eta + \psi)/(2\lambda w_t a_{jt})$ represents the sector j-specific threshold level of financial development below which finance affects technology adoption, as defined by Equation (3.16). The critical financial development level $\underline{\kappa}_t$ for the entire economy is thus determined by the sector with the highest productivity gap (lowest proximity) to the frontier across all sectors. For countries where the level of financial development κ_t is below this threshold $\underline{\kappa}_t$, financial development positively influences technology adoption in some sectors, thereby enhancing overall economic growth. However, once a country exceeds the threshold $\underline{\kappa}_t$, the effect of financial development on technology adoption across all sectors disappears.

4.3 Discussion

The model developed in this paper provides a mechanism to understand how financial constraints shape sectoral productivity convergence through their influence on technology adoption. In each sector j, divergence emerges when the country's financing capacity for technology adoption, denoted by $\kappa_t w_t$, falls below a critical threshold $\lambda^{-1}\eta\bar{g}_j$. This threshold corresponds to the minimum investment required to achieve an intensity of technology use sufficient to generate productivity growth that outpaces the sectoral technological frontier $\bar{g}_j$. As established in Subsection 4.1, when financing capacity exceeds this threshold, i.e., $\kappa_t w_t > \lambda^{-1}\eta\bar{g}_j$, the recurrence function for the sectoral productivity gap satisfies $f'_{jt}(0) > 1$, ensuring that productivity proximity increases monotonically over time, and that sectoral growth rates exceed those at the frontier.

Conversely, in cases where financial capacity remains below the threshold, the sector fails to catch up with the frontier, though it still experiences positive productivity growth. In line with Comin and Mestieri (2018), this outcome reflects the reality that while technological diffusion has become global, the intensity of technology use remains highly unequal. In the model, this intensity is endogenously determined by the country's financing capacity, which grows with income and financial development. Since initial income levels are positive, productivity in each sector continues to improve, albeit more slowly, until the financing threshold is eventually surpassed. Once this occurs, convergence becomes inevitable, as higher incomes relax the collateral constraints that limit the intensity of technology adoption.

This theoretical structure helps rationalize observed empirical patterns. As sectoral productivity gradually improves, aggregate income rises, which in turn increases financing capacity and allows countries to transition from divergence to convergence. The model thus provides a mechanism for understanding the "converging to convergence" phenomenon documented by Kremer et al. (2022), wherein countries that diverged for decades eventually embarked on convergence paths. Unlike earlier models such as Aghion et al. (2005), in which countries are permanently locked into particular convergence regimes, the present framework allows for dynamic transitions shaped by endogenous changes in income and sector-specific technology gaps.

A key insight of this model is the importance of sectoral specificity in both the cost and trajectory of technology adoption. Industries with initially high adoption costs or countries with low levels of income face severe financing constraints. Since adoption cost is proportional to the productivity gap with the technological frontier and financing capacity scales with income, some sectors may experience divergence before income growth relaxes the constraint. For instance, agricultural technologies such as tractors are well-known but remain underutilized in countries with lower levels of financial development. This gap contributes to the persistent cross-country disparities in agricultural productivity, despite the global availability of these technologies.

Such industry-specific dynamics also explain why convergence patterns vary across sectors. As documented in the empirical literature (e.g., Rodrik, 2013; Kinfemichael and Morshed, 2019; Herrendorf et al., 2022), there is no universal evidence of convergence across all sectors. In the empirical section, I show that manufacturing and services display clear signs of convergence, while agriculture does not. These sectoral differences reflect the heterogeneous impacts of financial development and the varying capital intensity of technologies across sectors. Moreover, incorporating these differences into the model offers a first step toward understanding how technology adoption at the sectoral level may influence structural transformation over time.

A further implication of the model concerns the relationship between convergence speed and the frontier growth rate $\bar{g}_j$. While a higher frontier growth rate increases the productivity gap and thus the potential for catch-up, this potential is only realized if financing constraints do not severely impede adoption. Sectors characterized by fast-growing frontiers—such as agriculture or high-tech manufacturing—may experience slower convergence precisely because they require more capital-intensive investments. Uniform financing constraints across sectors disproportionately affect those with faster-growing frontiers, delaying convergence.

The framework also highlights that eventual convergence can occur even in the absence of rapid improvements in financial institutions. As long as income continues to grow, the economy's financing capacity will eventually become sufficient to overcome the increasing cost of catching up to the frontier. This mechanism contrasts with models that rely on sharp exogenous improvements in financial development and better captures the gradual and sector-dependent nature of observed convergence paths.

In sum, the model emphasizes that productivity convergence is neither automatic nor uniform across sectors. Instead, it is shaped by the interaction between sector-specific technological frontiers, endogenous technology adoption dynamics, and financial constraints that evolve with aggregate income. These mechanisms offer new insights into both persistent divergence and late convergence, and help reconcile empirical heterogeneity in the pace and direction of economic development across sectors and countries.

5 Testing Model Predictions

In this section, I assess how the model's predictions align with the data. After describing the dataset, I test Proposition I using cross-country and panel regressions, incorporating an interaction term between initial sectoral productivity and initial financing capacity.[21] The results

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

illustrate the model's predictions, showing that a country's sectoral convergence speed is influenced by its financial development and income, and varies across sectors.

5.1 Data Description

I use data from WDI (2022)[22] 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[23] levels in constant 2015 international US$ comparable across countries in the same year and over time. To do this, first, I calculate international prices in 2015 by dividing the GDP per capita in current international US$ by GDP per capita in constant US$. Second, I use the PPPs calculated to convert the sectoral productivities in constant 2015 US$ into sectoral productivities in constant 2015 international US$ as follows:

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

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

κ_t is calibrated to the country's financial development index provided by IMF for several countries between 1980 and 2014[24].

Figures A.3–A.5 in Appendix F depict the convergence patterns from 1991 to 2019 for countries in the first and fourth quartiles of financing capacity, defined as the product of financial development and the logarithm of GDP per capita in 1991. The graphs reveal that countries in the fourth quartile exhibit a significantly steeper negative slope compared to those in the first quartile, which have lower levels of financing capacity. This suggests that countries with higher financing capacity are able to close the productivity gap more rapidly as predicted by the model in Proposition I–(i).

5.2 Cross-Country Analysis

I examine β-convergence in agriculture, manufacturing, and services across a sample of 99 countries for which sectoral data are available, using data from the World Development Indicators (WDI). Following the standard approach in the literature, I regress the average annual growth in log productivity[25], g_{j0}^c, for each sector $j \in \{a, m, s\}$ on the initial level of log productivity for country $c = 1, 2, ..., N$ as follows:

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

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

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

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

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

[25] Following the literature, for example de la Fuente (1997) and Young et al. (2008), the average growth rate, g_{j0}^c, from date 0 to T is defined as: $g_{j0}^c = \frac{1}{T}\Delta_T \log(A_{j0}^c) = \frac{1}{T}\left[\log(A_{jT}^c) - \log(A_{j0}^c)\right]$.

ε_j^c is the error term.

β-convergence, which refers to the process by which less productive economies grow faster and close the gap with more developed economies, is obtained by the partial derivative of g_{j0}^c with respect to $\log(A_{j0}^c)$ as follows:

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

The coefficient β_j then measures the conditional speed of convergence. If β_j is negative, then each country converges towards a productivity trajectory that is determined by its financial conditions, and income level. If $\beta_j < 0$ and $\gamma_j < 0$ then the convergence of productivity across countries in sector j will be faster for countries with higher levels of financing capacity $\kappa_0^c \log(A_t^c)$. According to the predictions of the theoretical model in Proposition I-*(i)*, γ_j is expected to be negative.

Convergence Speed. Cross-country analysis offers the advantage of allowing a straightforward mathematical derivation of convergence speeds across sectors and countries. To examine how initial level of financing capacity influences the speed of sectoral productivity convergence, I compute the difference between the average annual growth rate of country c and the technological frontier, based on Equation (5.3). From this difference, I derive the sector-specific convergence speed for country c in sector j, denoted by $S_j^c := 1/T_j^c$[26] as follow:

$$S_j^c = -\hat{\beta}_j - \hat{\rho}_j \frac{\left[\bar{\kappa_0} \log(\bar{A}_0) - \kappa_0^c \log(A_0^c)\right]}{\log(\bar{A}_{j0}) - \log(A_{j0}^c)} - \hat{\gamma}_j \frac{\left[\bar{\kappa_0} \log(\bar{A}_0) \log(\bar{A}_{j0}) - \kappa_0^c \log(A_0^c) \log(A_{j0}^c)\right]}{\log(\bar{A}_{j0}) - \log(A_{j0}^c)} \tag{5.5}$$

If $\hat{\beta}_j < 0$ and $\hat{\gamma}_j < 0$, then the speed of convergence S_j^c increases with the absolute values of $\hat{\beta}_j$ and $\hat{\gamma}_j$ but decreases with $\hat{\rho}_j$ so that countries with higher initial income and higher initial level of financial development will converge more quickly. To see this, we can analyze in data, the effect of the country's initial level of financing capacity on its sectoral productivity convergence speed by calculating the partial derivative of S_j^c with respect to $\kappa_0^c \log(A_0^c)$ from Equation (5.5) as following:

$$\frac{\partial S_j^c}{\partial \left[\kappa_0^c \log(A_0^c)\right]} = \frac{\hat{\rho}_j + \hat{\gamma}_j \log(A_{j0}^c)}{\log(\bar{A}_{j0}) - \log(A_{j0}^c)}. \tag{5.6}$$

Thus, we can see that the marginal effect of financing capacity on sectoral productivity convergence speed is positive as long as the level of the sectoral productivity is less than $-\frac{\hat{\rho}_j}{\hat{\gamma}_j}$ (which is the case in data).

In addition, I can calculate and compare the speeds of convergence across sectors for the same country, using the estimated parameters $\hat{\beta}_j$, $\hat{\rho}_j$, and $\hat{\gamma}_j$, alongside the initial levels of financing capacity and sectoral productivities of the country and the technological frontier, as specified in Equation (5.5). The results of these estimations are discussed below.

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

Empirical Results on Beta-Convergence. For each sector $j \in \{a, m, s\}$, I estimate cross-country regression models both with and without including human capital index level[27]. In the theoretical model, human capital, that is, the entrepreneur's knowledge in the sector of technology adoption, reduces the training and adaptation costs of new technologies, such that the effect of human capital on technology adoption operates through financing capacity. However, I include human capital in the regression to control for its direct effects on productivity growth that are independent of financing constraints. In all estimations, I employ robust standard errors to address potential heteroscedasticity.

Table 2 presents the results of the cross-sectional regressions. For the overall period 1991–2019, the results show that the coefficient $\hat{\rho}_j$ associated with the financing capacity is positive and statistically significant across sectors. This indicates that higher financial development and income

Table 2: Cross-Countries Regression Results : Dependant Variable: Average Growth in Productivity Between 1991 and 2019

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{j0})$	-0.005*	-0.004	-0.011***	-0.012***	-0.010**	-0.012**
	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
$\hat{\rho}_j : \kappa_0 \log(A_0)$	0.030**	0.028**	0.034*	0.043**	0.046**	0.046**
	(0.012)	(0.011)	(0.019)	(0.018)	(0.020)	(0.018)
$\hat{\gamma}_j : \kappa_0 \log(A_0)$	-0.003**	-0.003**	-0.003	-0.003**	-0.004**	-0.004**
$\times \log(A_{j0})$	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Human capital		0.008***		0.008*		0.011**
		(0.003)		(0.004)		(0.005)
Countries	99	87	99	87	99	87
R-squared	0.18	0.19	0.37	0.43	0.28	0.35

Note: This table reports the results of cross-country regression analyses using WDI productivity data and financial development index for the period 1991–2019. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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

I now analyze the differences in convergence speed across various sectors and countries. By considering initial sectoral productivity levels, GDP per capita, and financial development, I can calculate the rate of convergence in a specific sector for a given country. Table 2, specifically columns (1), (3), and (5), presents estimates indicating that a country like India, which has

[27] Human capital index data comes from Penn World Table version 10.0.

approximately the same relative productivity levels in the three major sectors compared to France (0.15 in agriculture, 0.17 in manufacturing, and 0.12 in services) will require different amounts of time across different sectors to catch up with France. Starting from an initial financing capacity level of $\kappa_0 \log(A_0) = 1.9$ in 1991, the estimates[28] suggest that it will take India approximately 77 years to catch up with France in the services sector, 140 years in manufacturing, and 200 years in agriculture.

However, if India's initial financing capacity were raised to match France's level of 4.52 in 1991, the convergence rates across sectors would improve significantly. In this case, the time needed to catch up with France would shorten to roughly 37 years in services, 44 years in manufacturing, and 60 years in agriculture. These estimates indicate that a country's initial levels of financial development and income play a crucial role in determining its convergence rate across different sectors. The higher the initial financial development and GDP per capita, the faster the country will achieve a comparable level of sectoral productivity relative to the frontier in each sector.

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

5.3 Panel Regressions

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

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

$$g_{jt}^c = \alpha_j + \beta_j \log(A_{jt}^c) + \rho_j \kappa_t^c \log(A_t^c) + \gamma_j \log(A_{jt}) \times \kappa_t^c \log(A_t^c) + D_j^c + D_{jt} + \varepsilon_{jt}^c, \tag{5.7}$$

where g_{jt}^c represents the average annual growth rate[29] of sector j labor productivity A_{jt}^c in constant international prices for country c between periods t and $t+\Delta t$. The terms D_j^c and D_{jt} represent country and time fixed effects, respectively. The inclusion of D_j^c accounts for country-specific characteristics, while D_{jt} captures time-specific shocks common across countries. ε_{jt}^c denotes the error term, and $\kappa_t^c \log(A_t^c)$ reflects the level of financial development, κ_t^c, alongside

[28] I use Equation (5.5) to calculate the speed of convergence for India in the three sectors, allowing me to deduce the time required for India to catch up with France in each sector.

[29]
$$g_{jt}^c = \frac{1}{\Delta t}\left[\log(A_{jt+\Delta t}^c) - \log(A_{jt}^c)\right]$$

income per capita, $\log(A_t^c)$. By including both D_j^c and D_{jt}, the model corrects for omitted-variable bias by capturing unobserved heterogeneity across countries and time.

For each sector $j \in \{a, m, s\}$, I estimate the panel regression equations with and without human capital index. Standard errors are clustered at the country level in all specifications. The dependent variable is the annual growth rate of the 5 years average of log productivity, and the explanatory variables are the the initial 5-year average levels of labor productivity in log, the average financing capacity level over the previous 5 years, and the interaction of these two variables, with the fixed effects for each period, and country. Table 3 presents the regression

Table 3: 5-Year Panel Regression Results using WDI dataset, Dependent Variable: Average Annual Growth in Productivity

	Agriculture		**Manufacturing**		**Services**	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{jt})$	-0.053***	-0.058***	-0.050***	-0.048***	-0.059***	-0.062***
	(0.010)	(0.011)	(0.012)	(0.013)	(0.015)	(0.016)
$\hat{\rho}_j : \kappa_t \log(A_t)$	0.077***	0.070***	0.002	0.003	0.090***	0.095***
	(0.017)	(0.020)	(0.025)	(0.026)	(0.022)	(0.023)
$\hat{\gamma}_j : \kappa_t \log(A_t)$	-0.007***	-0.006***	-0.000	-0.001	-0.008***	-0.009***
$\times \log(A_{jt})$	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Human capital		0.045		-0.004		0.001
		(0.031)		(0.022)		(0.014)
Country FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓
Countries	99	87	99	87	99	87
Observations	495	435	495	435	495	435
R-squared	0.50	0.49	0.50	0.51	0.59	0.61

Note: This table reports the results of panel regression analyses using WDI productivity data and the financial development index for the period 1991–2019. All data are aggregated into 5-year time intervals: 1991–1995, 1996–2000, 2001–2005, 2006–2010, 2011–2015, and 2015–2019. Robust standard errors are reported in parentheses. Standard errors clustered at the country level are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

results for the 5-year panel estimations covering 99 countries from the 1991–2019 period, using data from the WDI dataset. The estimated coefficients of conditional convergence in the panel estimation are significant for all three sectors, with higher magnitudes compared to the cross-country estimations. Additionally, the values of $\hat{\rho}_j$ (resp. $\hat{\gamma}_j$) are positive (resp. negative) and significant for agriculture and services, and their magnitudes are also higher than those observed in the cross-country estimates. In contrast, the values of $\hat{\rho}_m$ and $\hat{\gamma}_m$ for manufacturing in the panel estimations are not significant. This suggests that short-term variations in financing capacity play a more prominent role in explaining convergence dynamics in agriculture and services when using panel data.

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

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

$$VA\_Q_{jt}^{2017} = VA\_Q_{jt}^{2015} \times \frac{VA_{j2017}}{VA\_Q_{j2017}^{2015}}. \tag{5.8}$$

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

$$A_{jt}^{PPP_{2017}} = \frac{VA\_Q_{jt}^{2017}}{EMP_{jt} \times PPP_{j2017}}. \tag{5.9}$$

Table 4: 5-Year Panel Regression Results Using GGDC dataset, Dependent Variable: Average Annual Growth in Productivity

	Agriculture		Manufacturing		Services	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{jt})$	-0.041***	-0.041***	-0.066***	-0.066***	-0.031*	-0.031*
	(0.012)	(0.012)	(0.018)	(0.018)	(0.017)	(0.017)
$\hat{\rho}_j : \kappa_t \log(A_t)$	0.027	0.028	0.023	0.019	0.063*	0.061*
	(0.020)	(0.021)	(0.045)	(0.043)	(0.033)	(0.032)
$\hat{\gamma}_j : \kappa_t \log(A_t)$	-0.004*	-0.004*	-0.002	-0.002	-0.006*	-0.006*
$\times \log(A_{jt})$	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
Human capital		-0.011		-0.062		-0.018
		(0.044)		(0.043)		(0.019)
Country FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓
Countries	48	48	48	48	48	48
Observations	235	235	235	235	235	235
R-squared	0.46	0.46	0.53	0.54	0.60	0.60

Note: This table reports the results of panel regression analyses using GGDC productivity data and the financial development index for the period 1990–2018. All data are aggregated into 5-year time intervals: 1990–1994, 1995–1999, 2000–2004, 2005–2009, 2010–2014, and 2014–2018. Robust standard errors are reported in parentheses. Standard errors clustered at the country level are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

I then run the panel regressions for agriculture, manufacturing, and services[30] from Equation (5.7). Table 4 presents the results based on GGDC data. The estimates using GGDC data

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

across 48 countries reveal that the conditional coefficients for $\hat{\beta}_j$ are negative and significant, $\hat{\rho}_j$ is positive and significant for the services sector, and $\hat{\gamma}_j$ is negative and significant for both the agriculture and services sectors.

I also estimate the panel model using alternative measures of financial development, including the financial institutions index and the financial markets index (see results in Appendix H). The results obtained using these alternative financial indicators remain consistent with those based on the financial development index, reinforcing the robustness of the empirical findings.

6 Conclusion

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

The model shows that countries with low income and financial development levels may initially experience temporary sectoral productivity divergence, particularly in industries with high investment requirements due to higer technology gap. However, as income grows and financing capacity improves, these industries can shift to a path of convergence, even if at a slower and less efficient pace than in the absence of credit constraints. This sectoral transition drives aggregate convergence, enabling the overall economy to move from divergence to convergence as lagging sectors close productivity gaps and contribute more significantly to economic growth. The model predicts that both financial development and income positively influence the speed of sectoral productivity convergence. Moreover, sectors characterized by higher productivity growth at the technological frontier (e.g., agriculture) not only exhibit slower convergence rates but also initiate convergence later than sectors with lower frontier growth rates (e.g., services), thereby lagging behind.

There are several promising directions for extending this analysis. The current framework assumes that technologies are strictly sector-specific. However, many technologies—particularly general-purpose ones—can be applied across multiple sectors. Introducing such technological interdependencies may reveal additional channels through which financial constraints influence the speed and scope of technology adoption. In financially constrained economies, the diffusion of cross-sectoral technologies may be delayed or uneven, reinforcing sectoral divergence. Future work could explore how the interaction between financing capacity and multi-sector technology adoption shapes productivity convergence across countries.

Another direction for future research is to examine how financial development and technology adoption jointly contribute to divergent patterns of structural transformation between developing and advanced economies. Differences in the timing, pace, and direction of resource reallocation across sectors may help explain long-run disparities in income and productivity levels, even under shared exposure to the global technological frontier.

References

Acemoglu, D., Aghion, P. and Zilibotti, F. (2006), 'Distance to frontier, selection, and economic growth', *Journal of the European Economic Association* **4**(1), 37–74.

Aghion, P., Howitt, P. and Mayer-Foulkes, D. (2005), 'The Effect of Financial Development on Convergence: Theory and Evidence', *The Quarterly Journal of Economics* **120**(1), 173–222.

Beck, T., Levine, R. and Loayza, N. (2000), 'Finance and the sources of growth', *Journal of Financial Economics* **58**(1-2), 261–300.

Bento, P. and Restuccia, D. (2017), 'Misallocation, Establishment Size, and Productivity', *American Economic Journal: Macroeconomics* **9**(3), 267–303.

Buera, F. J., Kaboski, J. P. and Shin, Y. (2011), 'Finance and Development: A Tale of Two Sectors', *American Economic Review* **101**(5), 1964–2002.

Caselli, F. (2005), Chapter 9 Accounting for Cross-Country Income Differences, *in* P. Aghion and S. N. Durlauf, eds, 'Handbook of Economic Growth', Vol. 1, Elsevier, pp. 679–741.

Chen, B.-L., Mo, J.-P. and Wang, P. (2002), 'Market frictions, technology adoption and economic growth', *Journal of Economic Dynamics and Control* **26**(11), 1927–1954.

Chen, C. (2020), 'Capital-skill complementarity, sectoral labor productivity, and structural transformation', *Journal of Economic Dynamics and Control* **116**, 103902.

Cole, H. L., Greenwood, J. and Sanchez, J. M. (2016), 'Why Doesn't Technology Flow From Rich to Poor Countries?', *Econometrica* **84**(4), 1477–1521.

Comin, D. and Hobijn, B. (2004), 'Cross-Country Technology Adoption: Making the Theories Face the Facts', *Journal of Monetary Economics* **51**(1), 39–83.

Comin, D. and Mestieri, M. (2018), 'If Technology Has Arrived Everywhere, Why Has Income Diverged?', *American Economic Journal: Macroeconomics* **10**(3), 137–178.

Comin, D. and Nanda, R. (2019), 'Financial Development and Technology Diffusion', *IMF Economic Review* **67**(2), 395–419.

de la Fuente, A. (1997), 'The empirics of growth and convergence: A selective review', *Journal of Economic Dynamics and Control* **21**(1), 23–73.

Duarte, M. and Restuccia, D. (2010), 'The Role of the Structural Transformation in Aggregate Productivity', *The Quarterly Journal of Economics* **125**(1), 129–173.

Foster, A. D. and Rosenzweig, M. R. (1996), 'Technical Change and Human-Capital Returns and Investments: Evidence from the Green Revolution', *American Economic Review* **86**(4), 931–953.

Griffith, R., Redding, S. and Reenen, J. V. (2004), 'Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries', *Review of Economics and Statistics* **86**(4), 883–895.

Herrendorf, B., Rogerson, R. and Valentinyi, A. (2014), 'Growth and Structural Transformation', *Handbook of Economic Growth* **2**, 855–941.

Herrendorf, B., Rogerson, R. and Valentinyi, A. (2022), 'New Evidence on Sectoral Labor Productivity: Implications for Industrialization and Development', p. 43. NBER Working Paper, 29834.

Howitt, P. and Mayer-Foulkes, D. (2005), 'R&D, Implementation, and Stagnation: A Schumpeterian Theory of Convergence Clubs', *Journal of Money, Credit and Banking* **37**(1), 147–177.

Hsieh, C.-T. and Klenow, P. J. (2014), 'The Life Cycle of Plants in India and Mexico *', *The Quarterly Journal of Economics* **129**(3), 1035–1084.

Jerzmanowski, M. (2007), 'Total Factor Productivity differences: Appropriate Technology vs. Efficiency', *European Economic Review* **51**(8), 2080–2110.

Jones, C. I. (2016), The Facts of Economic Growth, *in* 'Handbook of Macroeconomics', Vol. 2, Elsevier, pp. 3–69.

Kinfemichael, B. and Morshed, A. M. (2019), 'Unconditional Convergence of Labor Productivity in the Service Sector', *Journal of Macroeconomics* **59**, 217–229.

King, R. G. and Levine, R. (1993), 'Finance and growth: Schumpeter might be right*', *The Quarterly Journal of Economics* **108**(3), 717–737.

Klenow, P. J. and Rodrìguez-Clare, A. (1997), 'The Neoclassical Revival in Growth Economics: Has It Gone Too Far?', *NBER Macroeconomics Annual* **12**, 73–103.

Kremer, M., Willis, J. and You, Y. (2022), 'Converging to Convergence', *NBER Macroeconomics Annual* **36**, 337–412.

Kruse, H., Mensah, E., Sen, K. and de Vries, G. (2023), 'A Manufacturing (Re)Naissance? Industrialization in the Developing World', *IMF Economic Review* **71**(2), 439–473.

Levine, R. (1997), 'Financial Development and Economic Growth: Views and Agenda', *Journal of Economic Literature* **35**(2), 688–726.

Madsen, J. B. and Timol, I. (2011), 'Long-run convergence in manufacturing and innovation-based models', *Review of Economics and Statistics* **93**(4), 1155–1171.

Nelson, R. R. and Phelps, E. S. (1966), 'Investment in Humans, Technological Diffusion, and Economic Growth', *American Economic Review* **56**(1/2), 69–75.

Ngai, L. R. and Pissarides, C. A. (2007), 'Structural Change in a Multisector Model of Growth', *American Economic Review* **97**(1), 429–443.

Parente, S. L. and Prescott, E. C. (1999), 'Monopoly Rights: A Barrier to Riches', *American Economic Review* **89**(5), 1216–1233.

Porta, R. L., Lopez-de Silanes, F., Shleifer, A. and Vishny, R. W. (1998), 'Law and finance', *Journal of political economy* **106**(6), 1113–1155.

Prescott, E. (1998), 'Needed: A Theory of Total Factor Productivity', *International Economic Review* **39**(3), 25–51.

Rajan, R. and Zingales, L. (1998), 'Financial dependence and growth', *American Economic Review* **88**(3), 559–586.

Rodrik, D. (2013), 'Unconditional Convergence in Manufacturing*', *The Quarterly Journal of Economics* **128**(1), 165–204.

Samaniego, R. M. (2006), 'Industrial subsidies and technology adoption in general equilibrium', *Journal of Economic Dynamics and Control* **30**(9-10), 1589–1614.

Scotchmer, S. (1991), 'Standing on the Shoulders of Giants: Cumulative Research and the Patent Law', *Journal of Economic Perspectives* **5**(1), 29–41.

Young, A. T., Higgins, M. J. and Levy, D. (2008), 'Sigma Convergence versus Beta Convergence: Evidence from US County-Level Data', *Journal of Money, Credit and Banking* **40**(5), 1083–1093.

Appendix

A Data Appendix

A.1 Financial Data

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

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

A.2 Sector Classification

- Agriculture corresponds to the International Standard Industrial Classification (ISIC) tabulation categories A and B (revision 3) or tabulation category A (revision 4), and includes forestry, hunting, and fishing as well as cultivation of crops and livestock production.
- Manufacturing corresponds to the International Standard Industrial Classification (ISIC) tabulation categories C-F (revision 3) or tabulation categories B-F (revision 4), and includes mining and quarrying (including oil production), manufacturing, construction, and public utilities (electricity, gas, and water).
- Services corresponds to the International Standard Industrial Classification (ISIC) tabulation categories G-P (revision 3) or tabulation categories G-U (revision 4), and includes

wholesale and retail trade and restaurants and hotels; transport, storage, and communications; financing, insurance, real estate, and business services; and community, social and personal services.

B Goods Production

The monopolist maximizes profit as follows:

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

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

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

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

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

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

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

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

where $\pi := (1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}}$. Thus, the profits generated by each sector depend positively on the productivity of that sector. The production of the final good in equilibrium is obtained by substituting (B.1) into (3.2):

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

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

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

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

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

C Impact of Financial Development on Technology Adoption

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

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

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

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

And finally,

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

Beyond the threshold level of sectoral proximity, denoted $\bar{a}_t(\kappa_1)$, the marginal effect of financial development on the intensity of technology use becomes negligible. That is, an increase in the financial development index from κ_1 to κ_2 does not yield a higher level of technology adoption for countries whose sectoral proximity already exceeds the threshold (i.e., $a_{jt} \geq \bar{a}_t(\kappa_1)$). In such cases, additional improvements in financial development no longer serve as a binding constraint on technology diffusion.

By contrast, for countries with sectoral proximity levels below this critical threshold, financial development continues to play a pivotal role. Specifically, an increase from κ_1 to κ_2 enhances the intensity of technology adoption, facilitating convergence toward the productivity frontier. These findings suggest that while financial development is instrumental in accelerating technological catch-up for lagging economies, its relevance diminishes once a certain degree of technological proximity is achieved. For more advanced economies, other structural or institutional factors may become the primary determinants of sustained productivity growth. ■

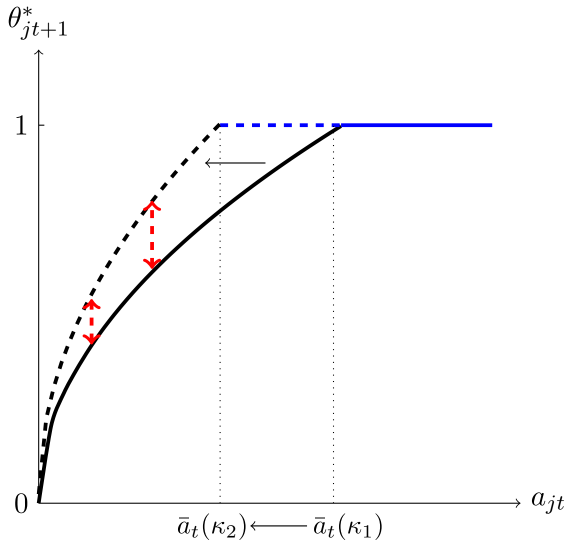


Figure A.1: Effect of Financial Development on the Intensity of Use of Technologies ($\kappa_1 < \kappa_2$)

Note: This figure shows the model-predicted evolution of technology use intensity with respect to sectoral proximity (solid black line). The dashed black line illustrates the effect of increased financial development on technology use. The positive interaction between financial development and sectoral proximity on technology use is represented by the dashed red lines.

D Variation study of f_{jt}

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

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

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

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

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

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

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

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

E Demonstration of Proposition I.

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

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

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

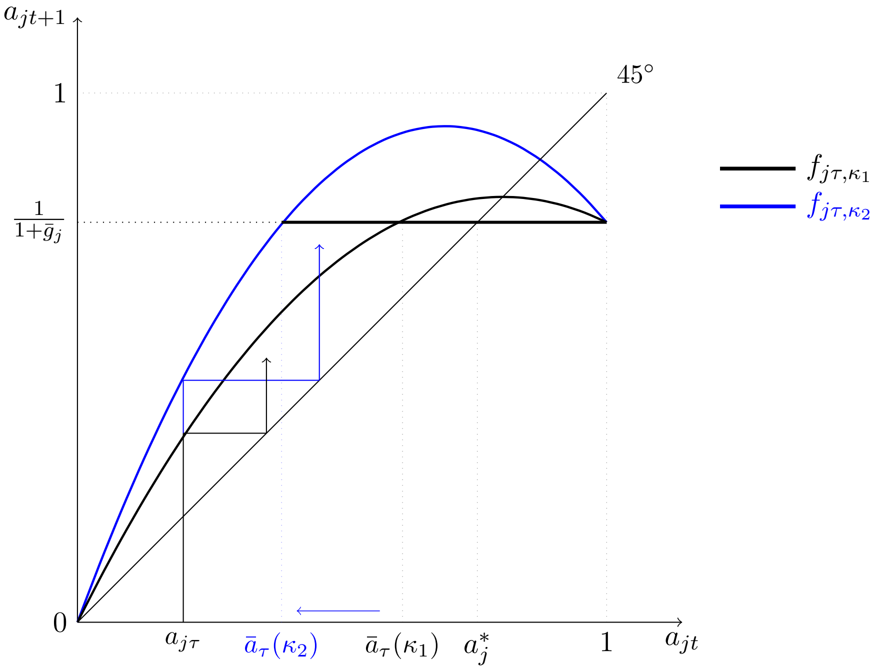


Figure A.2: Financial development and convergence speed : $\kappa_1 < \kappa_2$

Note: This figure illustrates the model-predicted dynamics of the sectoral productivity gap in response to an increase in financial development. The blue line represents a country with a higher level of financial development ($\kappa_2 > \kappa_1$), which converges more rapidly toward the sectoral steady state a_j^*.

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

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

The convergence times T_{j_1} and T_{j_2} for sectors j_1 and j_2 are given by $T_{j_1} = \min(B_{j_1})$ and

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

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

From this assumption, it follows that:

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

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

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

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

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

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

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

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

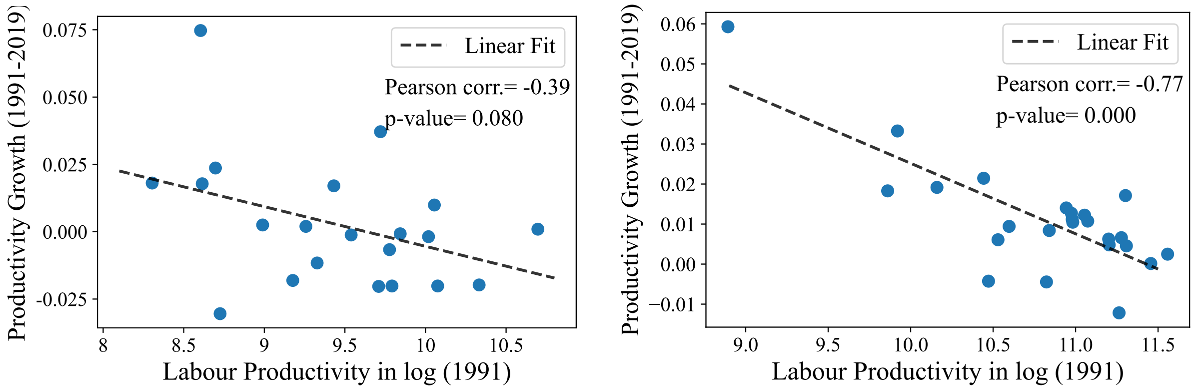
$$\min(B_{j_2}) \geq \min(B_{j_1}).$$

This completes the proof.

F Convergence Across Development Quartiles

Figures A.3-A.5 illustrate the convergence over the period 1991-2019 for the 1st and 4th quartiles of financing capacity levels, measured as the financial development level multiplied by the log of GDP per capita in 1991. The analysis of the graphs indicates that countries in the 4th quartile–those with the highest levels of financial development and GDP per capita–exhibit a much steeper negative slope compared to countries in the 1st quartile, which have lower levels of financing capacity. For the services sector, the Pearson correlation for the 4th quartile countries (Figure A.3b) is -0.77 (p-value $= 0.000$), demonstrating a significant and strong convergence, meaning that more advanced countries in this group are catching up with the productivity frontier at a faster rate. In contrast, the 1st quartile countries (Figure A.3a) exhibit a weaker and statistically insignificant (at the 5% level) correlation of -0.39 (p-value $= 0.080$), indicating a slower convergence trend.

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

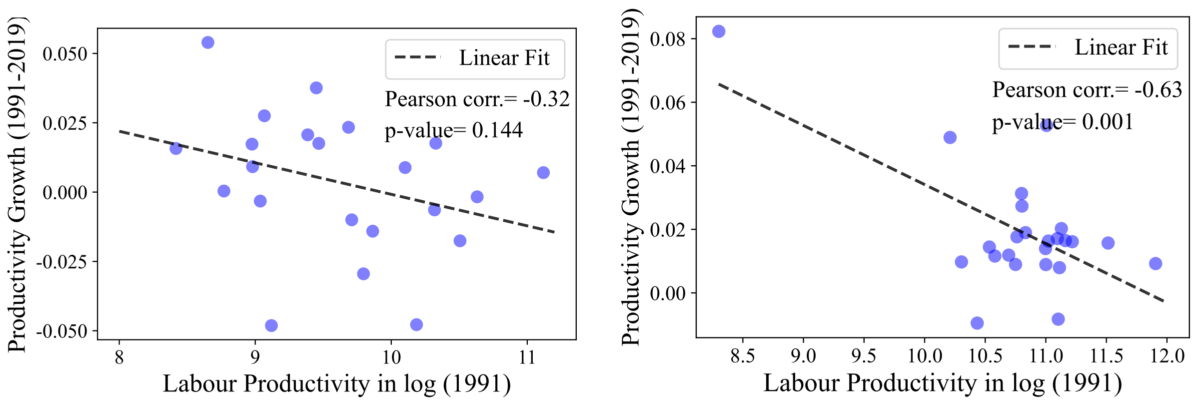


(a) First Quartile of $\kappa \times \log(\text{GDP per capita})$ in 1991 **(b)** Fourth Quartile of $\kappa \times \log(\text{GDP per capita})$ in 1991

Figure A.3: Convergence of Services Labor Productivity Across Financing Capacity Quartiles

Note: This figure illustrates cross-country differences in the speed of convergence in the services sector. Panel (a) presents results for countries with high financing capacity (top quartile), while Panel (b) displays results for countries with low financing capacity (bottom quartile), based on the joint distribution of financial development and income per capita in 1991.

(p-value $= 0.144$), which is not statistically significant. This comparison highlights that manufacturing convergence is more pronounced among countries with higher levels of financial development and income, likely due to their ability to adopt advanced technologies and improve productivity more efficiently.

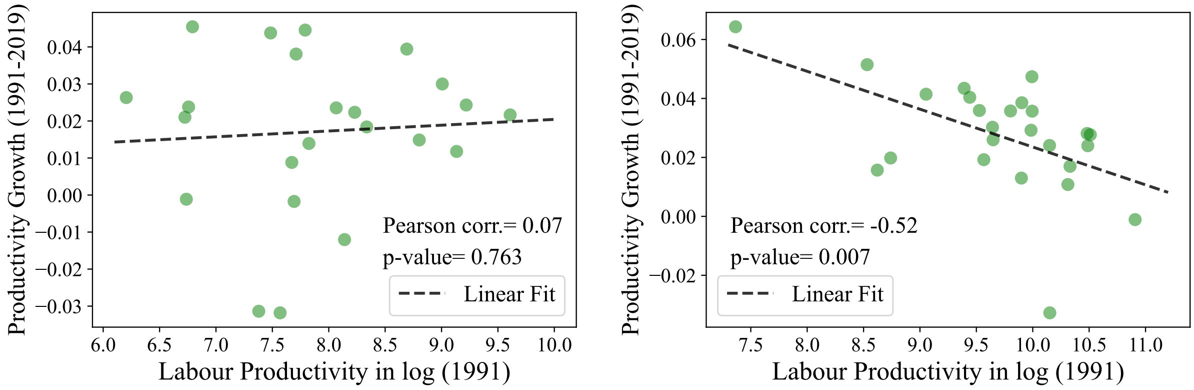


(a) First Quartile of $\kappa \times \log(\text{GDP per capita})$ in 1991 **(b)** Fourth Quartile of $\kappa \times \log(\text{GDP per capita})$ in 1991

Figure A.4: Convergence of Manufacturing Productivity Across Development Quartiles

Note: This figure illustrates cross-country differences in the speed of convergence in the manufacturing sector. Panel (a) presents results for countries with high financing capacity (top quartile), while Panel (b) displays results for countries with low financing capacity (bottom quartile), based on the joint distribution of financial development and income per capita in 1991.

Lastly, in the agriculture sector, the trend is particularly revealing. The correlation for the 4th quartile group (Figure A.5b) is -0.52 (p-value $= 0.007$), indicating a significant convergence among countries with high level of financing capacity, even though the overall analysis suggests no clear convergence in the agricultural sector. In contrast, the 1st quartile countries (Figure A.5a) exhibit a nearly flat correlation of 0.07 (p-value $= 0.763$), indicating a lack of convergence in the agricultural sector among countries with the lowest level of financing capacity.



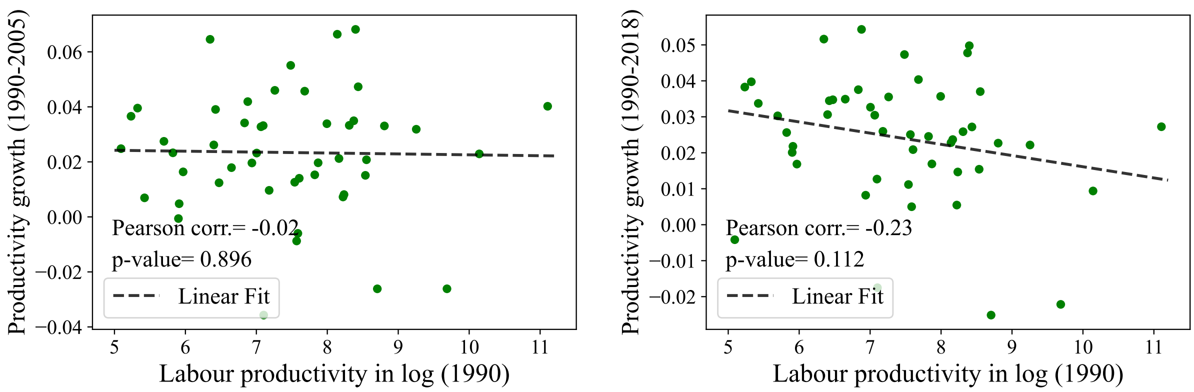
(a) First Quartile of $\kappa \times \log(\text{GDP per capita})$ in 1991 **(b)** Fourth Quartile of $\kappa \times \log(\text{GDP per capita})$ in 1991

Figure A.5: Convergence of Agriculture Labor Productivity Across Financing Capacity Quartiles

Note: This figure illustrates cross-country differences in the speed of convergence in the agricultural sector. Panel (a) presents results for countries with high financing capacity (top quartile), while Panel (b) displays results for countries with low financing capacity (bottom quartile), based on the joint distribution of financial development and income per capita in 1991.

G Sectoral Productivity Convergence in GGDC Data

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

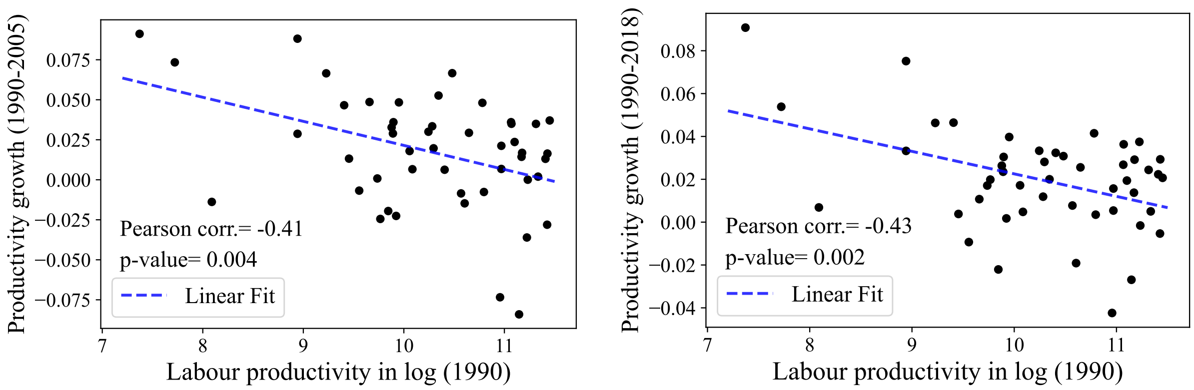


(a) 1990–2005 **(b)** 1990–2018

Figure A.6: Agriculture Labor Productivity Convergence in GGDC data

Note: This figure shows average annual growth in agricultural productivity over 1990–2005 and 1990–2018, plotted against initial productivity in 1991 using GGDC data.

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

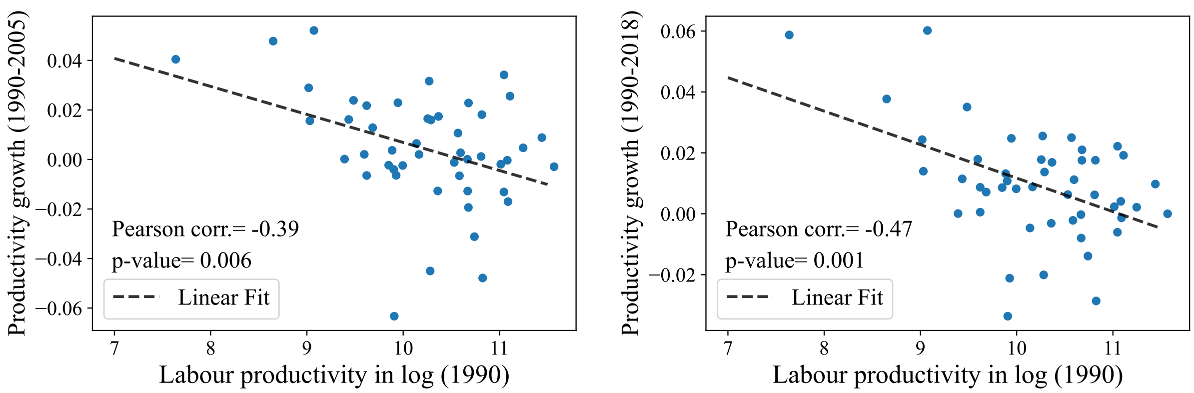


(a) 1990–2005

(b) 1990–2018

Figure A.7: Manufacturing Labor Productivity Convergence in GGDC data

Note: This figure shows average annual growth in manufacturing productivity over 1990–2005 and 1990–2018, plotted against initial productivity in 1991 using GGDC data.



(a) 1990–2005

(b) 1990–2018

Figure A.8: Services Labor Productivity Convergence in GGDC data

Note: This figure shows average annual growth in services productivity over 1990–2005 and 1990–2018, plotted against initial productivity in 1991 using GGDC data.

However, between 1990 and 2005, the correlations between initial productivity levels and subsequent growth exhibit a weaker pattern of convergence compared to the 1990–2018 period. In agriculture, the correlation is almost nonexistent at -0.02 with a p-value of 0.896, showing no relationship between initial productivity and growth. Both manufacturing and services also display weaker correlations during this earlier period, with Pearson coefficients of -0.41 and -0.39, respectively, though still statistically significant. This indicates that while productivity convergence was already present in these sectors by 2005 in GGDC data, it became more pronounced in the following years.

H Regression Outputs

Table A.1: 5-Year Panel Regression Results Using WDI data and Financial Market Index: 1991–2019

	Agriculture		**Manufacturing**		**Services**	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j : \log(A_{jt})$	-0.056***	-0.056***	-0.074***	-0.066***	-0.068***	-0.070***
	(0.009)	(0.009)	(0.014)	(0.016)	(0.011)	(0.012)
$\hat{\rho}_j : \kappa_t \log(A_t)$	0.041***	0.038***	-0.022	-0.014	0.060***	0.067***
	(0.013)	(0.013)	(0.023)	(0.025)	(0.018)	(0.018)
$\hat{\gamma}_j : \kappa_t \log(A_t)$	-0.004***	-0.004***	0.002	0.001	-0.006***	-0.006***
$\times \log(A_{jt})$	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Human capital		0.047*		-0.003		0.004
		(0.025)		(0.021)		(0.013)
Country FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓
Countries	99	87	99	87	99	87
Observations	728	621	728	621	728	621
R-squared	0.51	0.51	0.52	0.51	0.59	0.62

Note: This table reports the results of panel regression analyses using WDI productivity data and the financial market index for the period 1991–2019. All data are aggregated into 5-year time intervals: 1991–1995, 1996–2000, 2001–2005, 2006–2010, 2011–2015, and 2015–2019. Robust standard errors are reported in parentheses. Standard errors clustered at the country level are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A.2: 5-Year Panel Regression Results Using WDI data and Financial Institutions Index: 1991–2019

	Agriculture		**Manufacturing**		**Services**	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_j$: $\log(A_{jt})$	-0.045***	-0.043***	-0.072***	-0.066***	-0.059***	-0.061***
	(0.010)	(0.011)	(0.017)	(0.019)	(0.011)	(0.012)
$\hat{\rho}_j$: $\kappa_t \log(A_t)$	0.063***	0.064***	-0.002	-0.001	0.090***	0.095***
	(0.013)	(0.014)	(0.027)	(0.028)	(0.018)	(0.019)
$\hat{\gamma}_j$: $\kappa_t \log(A_t)$	-0.006***	-0.006***	0.000	0.000	-0.008***	-0.009***
$\times \log(A_{jt})$	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)
Human capital		0.044		-0.004		0.006
		(0.027)		(0.021)		(0.013)
Country FE	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓
Countries	99	87	99	87	99	87
Observations	728	621	728	621	728	621
R-squared	0.53	0.53	0.52	0.51	0.60	0.64

Note: This table reports the results of panel regression analyses using WDI productivity data and the financial institutions index for the period 1991–2019. All data are aggregated into 5-year time intervals: 1991–1995, 1996–2000, 2001–2005, 2006–2010, 2011–2015, and 2015–2019. Robust standard errors are reported in parentheses. Standard errors clustered at the country level are reported in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.