Resource capacity and economic growth convergence*

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Abstract

Resource accumulation has been identified, with technological change, as a major explanatory factor of economic growth convergence. At the same time, resource capacity may act as a growth limiting factor. Under-investment may have a moderator effect on the economic growth convergence process, while path-dependencies may be observed. Using a tailored non-parametric model and a unique sample of 92 countries all around the world for the 1965–2019 period, we study the role of resource capacity from a new angle. First, we measure potential countries' under-investment. Next, we quantify its role in the economic growth convergence process. Our findings reveal that under-investment exists and that it represents a brake on economic growth convergence. However, such an effect can be counterbalanced by promoting technological advances or creating a more favourable resource environment. Finally, we run several sensitivity tests to assess the robustness of our findings.

Keywords: economic growth; convergence; under-investment; non-parametric.

JEL Codes: C67, L60, O33, O47.

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1 Introduction

Economic growth convergence, i.e. whether worse performers catch up best performers over time, has been studied from various angles in the literature. The first aspect is establishing economic growth convergence using a methodology and a particular definition. Several definitions have been suggested such as $\beta-$convergence, i.e. a negative partial correlation between economic growth and its initial level, $\sigma-$convergence, i.e. a gradual reduction in dispersion, distributional convergence, i.e. economic growth distributions move over time, and club convergence, i.e. the existence of distinct economic growth regimes. Popular methodologies include cross-sectional and panel regressions, parametric and non-parametric statistical tests, economic growth decomposition, and counterfactual approaches.

Starting with the classical papers of Baumol (1986) and Barro (1991), the economic growth convergence puzzle has received considerable attention in the literature.[1] When economic growth convergence has been defined and a methodology has been selected, economic growth has to be measured. Popular choices include output per capita, i.e. output divided by total population, and labor productivity, i.e. output divided by total labor force.[2] An advantage of using labor productivity is that both the numerator and the denominator correspond to the market sector, which is not the case for the denominator of output per capita. This might be particularly problematic for countries with non-market production activity (Jones, 1997). Also, labor productivity is established as a crucial indicator of welfare in the macroeconomic literature (Henderson and Russell, 2005).

Once economic growth convergence or divergence is established, the next step is to investigate how the sources of economic growth contribute to the convergence or divergence process. Again, several methodologies have been employed and several sources have been highlighted.[3] Nevertheless, they all agree that technological change,

[1]A non-exhaustive list of works includes Quah (1996a), Rey (2001), Shioji (2001), Bloom et al. (2002) Acemoglu et al. (2006), Graham and Temple (2006), Fiaschi and Lavezzi (2007), Maasoumi et al. (2007), Phillips and Sul (2007), Young et al. (2008), Magnus et al. (2007), Owen et al. (2009), Henderson et al. (2012) Stokey (2015), Krause (2016), Mirestean and Tsangarides (2016), Walheer (2016), Haupt et al. (2018), Fukase and Martin (2020), Gao et al. (2021), Kremer et al. (2022) and Walheer (2023). However, despite such attention, empirical studies have not led to many definitive conclusions.

[2]Bernanke and Parkinson, 1991; Aizcorbe, 1992; Kumar and Russell, 2002; Henderson and Russell, 2005; Jajri and Ismail, 2010; Preenen et al., 2017; Gibson and Shrader 2018; McMillan and Zeufack, 2022; Walheer, 2021).

[3]Solow, 1956; Temple, 1999; Kumar and Russell, 2002; Henderson and Russell, 2005; Wong, 2007;

i.e. innovation, and resource accumulation, mainly capital and labor, are the main drivers.

In this paper, we study the role of resources in labor productivity convergence from a new angle. Our starting point is the potential impacts of resource capacity on the economic growth convergence process. Under-investment in resources may act as a constraint preventing the economic growth convergence from happening. That is, under-investment has a moderator effect on labor productivity convergence. At the same time, under-investment may present a second undesirable feature: path dependence. That is, countries with lower performances have larger under-investment over time. If both features are combined, this may lead to a virtuous circle from which it is difficult to get out.

To the best of our knowledge, while the role of resources, mainly capital and labor, in the economic growth process has been acknowledged (Piketty et al., 2019; Caunedo and Keller, 2021; Koopman and Wacker, 2023; Walheer and Bigandi, 2024), there is no formal definition of the resource capacity constraint on economic growth in the literature. We suggest a simple way by comparing how countries generate labor productivity with and without the resources. That is, we first measure potential labor productivity ignoring the resources; and, next, we compute potential labor productivity taking the resources into account. From a mathematical point of view, the resource capacity constraint is therefore measured as a ratio between these two potential labor productivities. By comparing this ratio to unity, we can verify whether countries do not optimally use the resources, or whether more resources are needed to raise labor productivity (i.e. under-investment occurs). Note that, we expect to empirically observe the latter case only.

While moderator effects and path-dependencies are been studied before in the economic literature (Eliasson, 1989; Redding, 2002; Dutt, 2009; Bellaïche, 2010; Harada, 2010; Forte and Moura, 2013; Aghion et al., 2016; Teixeira and Queirós, 2016; Sainz-Fernandez et al., 2018; Dada and Abanikanda, 2022), this study is the first to do so for the resource capacity. Moreover, another particularity of our empirical work is to distinguish two complementary dimensions of the resource capacity impact. The first is the change in the resource capacity that captures the extent to which the eval-

Badunenko et al., 2008; Li and Liu, 2011; Vu, 2011; Badunenko et al., 2014; Sinelnikov-Murylev and Kazakova, 2014; Jones, 2016; Shen et al., 2017; Lafuente et al., 2020; Walheer, 2021; AlKathiri, 2022; Meng et al., 2023).

uated countries get closer to their best practice benchmark over time. The second is the change in the resource environment measuring the shift in the best practice performances.

To estimate the resource constraint, we rely on a non-parametric estimation: Farrell's (1957) deterministic production-frontier. The basic idea is to use observed data to reconstruct a production function that fulfills certain technology axioms (such as monotonicity and quasi-concavity). Such procedure has gained popularity in studying economic growth convergence (Kumar and Russell, 2002; Henderson and Russell, 2005; Badunenko et al., 2008; Badunenko et al., 2014; Filippetti and Peyrache, 2015; Walheer, 2016, 2021, 2023; Chambers and Pieralli, 2020; AlKathiri, 2022). Our reasons for using such an estimation procedure are twofold. On the one hand, parametric estimation methods heavily rely on typically unverifiable assumptions about certain aspects of the growth process, such as technology, market structure, technological change, and market imperfections. On the other hand, parametric estimation methods study the first or second moment of the economic growth process. However, it is recognized, since Quah (1996b, 1997), Galor (1996), and Jones (1997), that labor productivity distribution is bi-modal. Finally, to be fair, a disadvantage of the deterministic production-frontier is that it ignores measurement errors and is affected by outliers. To mitigate such aspects, we rely on a bootstrap procedure (Simar, 2003).

In terms of data, we use the most recent Penn World Table to measure labor productivity and resources (Feenstra et al., 2015). By removing missing data, we obtain a balanced panel of 92 countries all around the world for the 1965–2019 period. This represents a unique opportunity to quantify the resource constraint impacts on a long-term basis. Our results reveal the growing importance of under-investment over time, but not for all countries. Next, technological change is positive and the resource environment is more favourable in the world over time. Path dependence is not observed for the resource constraint, while a moderator effect. However, $\beta-$convergence is possible by promoting technological advances or creating a more favourable resource environment. Finally, we run three sensitivity tests to verify the robustness of our results: we partition countries in groups, we remove potential extreme values, and we consider $\sigma-$convergence. Our sensitivity analyses support our previous findings while highlighting some additional interesting features.

The rest of the paper unfolds as follows. In Section 2, we present our data and some preliminary analyses to motivate our study. Next, we move to our empirical investigation in Section 3. There, we also study resource capacity from two angles: path-dependence and moderator effect. We run several sensitivity tests in Section 4 and conclude in Section 5.

2 Data and preliminary analyses

We assume that we observe a balanced panel of n countries during a time interval $[b, c]$, where b and c denote the base and current time period, respectively. We adopt the standard macroeconomic modelling for the production process: each country i produces output Y_{it} using labor L_{it} and physical capital K_{it} at time t. Variables are constructed using the common practice in the literature. In particular, the output is measured by output-side real GDP at chained PPPs, capital in stock term, and labor in persons engaged. Also, output and capital are deflated and expressed in constant US$. Data are taken from the most recent Penn World Table 10.1 (Feenstra et al., 2015).[4] By removing missing values, we obtain a balanced sample of 92 countries for the time span 1965–2019 (i.e. $b = 1965$ and $c = 2019$). Descriptive statistics for our variables are given in Table 1. There, we present the minimum, mean, median, and maximum for 1965, 2019, and for the change between these two time periods.

Output has importantly increased between 1965–2019 with an average change of 1,186%. It is more than labor (342%) but less than capital (1,988%). This means that countries are becoming more capital-intensive over time. The crucial role of capital accumulation has also by pointed out in Piketty (2017). Note that the medians confirm these patterns but to a lesser extent for output and capital, highlighting the presence of extreme countries. Moreover, labor productivity raises more than capital productivity (369% versus 89%). It reveals the labor specialisation over time. Each employee produced, on average, 50,454 US$ in 2019 against 16,944 US$ in 1965. The medians mitigate this claim: 40,291 US$ in 2019 and 12,646 US$ in 1965. Finally, it is worth noticing the population change with an average of 284%. It implies that labor has increased slightly more than the population on the period 1965–2019, while capital and output have more than tripled the population change.

As discussed in the Introduction, we study the change in labor productivity, denoted $y_{it} = Y_{it}/L_{it}$ for country i at time t, between our initial and final years. Note that all years between these two time periods will be taken into account in the es-

[4] Data can be freely downloaded at www.ggdc.net/pwt.

Table 1: Descriptive statistics

statistics	Y mil. US$	L mil.	K mil. US$	Y/L US$	K/L US$	Y/K –	POP mil.
1965							
min	340	0.08	805	1,535	459	0.06	0.19
mean	157,458	11.77	606,540	16,944	68,514	0.57	30.90
median	31,430	2.75	98,921	12,646	37,577	0.30	8.01
max	4,515,720	292.88	17,730,630	59,019	266,294	4.58	721.82
2019							
min	3,507	0.13	22,509	612	2,831	0.04	0.29
mean	1,196,243	31.96	5,127,079	50,452	222,057	0.30	72.84
median	286,947	8.21	1,205,383	40,291	139,860	0.27	19.99
max	20,595,844	798.81	99,608,664	221,661	796,137	0.96	1,433.78
1965–2019							
min	9%	85%	183%	2%	43%	2%	100%
mean	1,186%	342%	1,988%	369%	637%	89%	284%
median	834%	334%	963%	270%	332%	84%	272%
max	11,159%	984%	18,830%	2,184%	7,938%	316%	831%

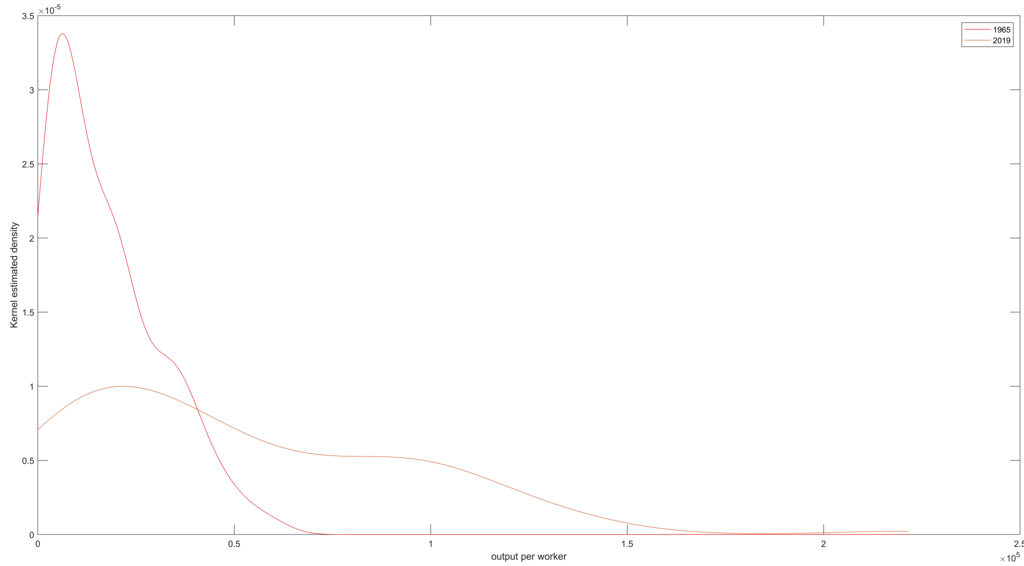
timation (see Section 3.1). We start our discussion with two important graphical representations of labor productivity in Figure 1. First, we verify how labor productivity has changed over time by plotting (kernel) distributions. This representation is used to quantify labor productivity change and verify whether this improvement is similar across countries. Second, we plot the initial level of labor productivity and its change between the initial and final time periods. In other words, we look for $\beta-$convergence:

$$ln(y_{ic}/y_{ib}) = \alpha + \beta y_{ib} + u_i \tag{1}$$

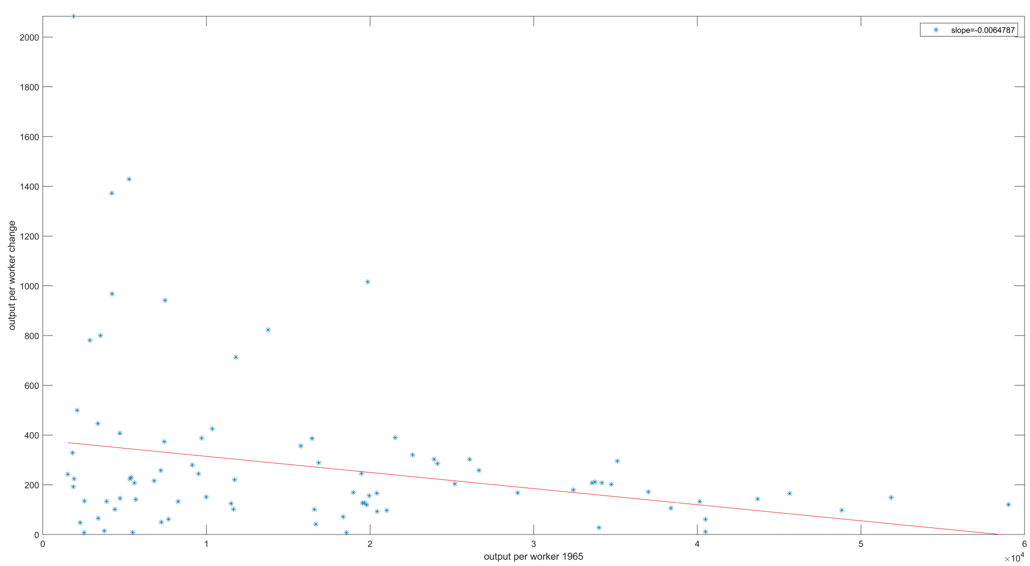
$\beta-$convergence occurs when the slope coefficient β is negative. This means that smaller initial labor productivity values (y_{ib}) are associated with larger economic growth levels ($ln(y_{ic}/y_{ib})$). Putting this differently, countries with the worst economic performances have faced more important positive performance changes if $\beta-$convergence is observed.

Figure 1(a) highlights a positive shift of labor productivity over time, but it also reveals a transformation of the world labor productivity distribution from uni- to a multi-modal distribution. In Figure 1(b), we see that higher output per worker is, on

Figure 1: Labor productivity



(a) Distributions



(b) Convergence

average, associated with lower change. In other words, labor productivity convergence is observed. To formally test whether our observations are statistically true we rely on three statistical tests. We make use of a level of 5% in the paper (unless otherwise stated). First, we make use of the nonparametric Kolmogorov–Smirnov (KS) test to compare the distribution in 1965 and 2019.[5] The $p-$value, given in Table 2, is worth 0.000 confirming the improvement between the two years. Next, we use calibrated Silverman's (1981) test for multimodality.[6] We cannot reject the hypothesis that the 1965 labor productivity distribution has more than one mode. On the contrary, this hypothesis is rejected for 2019. Two groups of countries are thus observed in 2019: those with labor productivity close to the 1965 values and those with larger labor productivity. Finally, we find a negative and significant GLS slope coefficient that is worth -0.0051 supporting the existence of $\beta-$convergence.

Table 2: Labor productivity tests

Test	*Alternative hypothesis*	*$p-$value*
KS	2019 distribution is larger than 1965 distribution	0.000
Silverman	there are more than one mode in 1965	0.654
	there are more than one mode in 2019	0.002
	there are more than two modes in 2019	0.452
$t-$test	the slope coefficient is negative	0.000

3 Empirical investigation

We start off by defining the technology by means of a non-parametric reconstruction, and we explain how we measure under-investment non-parametrically. Next, we estimate the moderator effect of resource constrain on economic growth, and its path-dependence.

3.1 Technology and inefficiency

The starting points of our modelling are, on the one hand, the definition of time-varying production functions and, on the other hand, the existence of inefficiency

[5] H_0: two distributions are equal; H_1: 2014 labor productivity distribution is larger than 1965 labor productivity distribution. Note that an alternative test is Li's test by Simar and Zelenyuk (2006). We obtain similar conclusions with that test.

[6] H_0: the distribution has one mode; H_1: the distribution has more than one mode. In practice, it is advised to use the bootstrapped version of the calibrated Silverman's (1981) test due to Hall and York (2001). We also refer to Henderson et al. (2008) for more statistical discussions of the Silverman's test.

behaviours implying potential productivity gains. We assume that the production function is unobserved but fulfils standard macroeconomic assumptions: it is quasi-concave, continuous, strictly increasing, and satisfies constant returns-to-scale. Making such assumptions is weaker than relying on a parametric specification for the production functions. Given our assumptions on the production function, we can redefine the production process by $\langle y_{it}, k_{it} \rangle$, where $k_{it} = K_{it}/L_{it}$ represents capital per worker at time t for country i :

$$y_{it} = f_t(k_{it}) \times e_t(k_{it}). \tag{2}$$

In words, $f(k_{it})$ is the time-varying production function at time t, and therefore represents potential output. The distance between actual and potential outputs is captured by $e_t(k_{it})$ which can be interpreted as an (in)efficiency component reflecting the inability to properly convert capital and labor into output using a certain technology. It is the inverse of the maximal amount that output y_{it} can be expanded while keeping the inputs (k_{it}) constant. When potential output exceeds actual one, we have $e_t(k_{it}) < 1$, revealing an inefficiency behaviour and thus a potential productivity gain. $e_t(k_{it}) = 1$ is, therefore, the benchmark situation when actual and potential outputs are equal. Finally, note that it might be surprising that no error term appears in (2), this will be discussed hereafter.

In practice, both $f_t(k_{it})$ and $e_t(k_{it})$ are unobserved. To estimate $f_t(k_{it})$, we make use of a well-known linear programming technique: Data Envelopment Analysis (DEA) introduced by Charnes et al. (1972). As noticed in Section 2, our preliminary investigations support the convergence but also highlight the existence of groups. A direct implication is the suspicion of empirical analyses based on the first moment (or even higher moments). Another concern is how to specify a functional form for the production function. Choosing a functional form for the technology is not insidious and may have important impacts on the empirical analysis (Kumar and Russell, 2002). Moreover, the use of more sophisticated statistical methods often requires relatively large samples and, given the limited number of countries in the world, such techniques can 'ask a lot of the available'.

Formally, potential outputs for each country i at time t are obtained by running linear programming using the other countries as peers. In addition, we consider that technological degradation is not possible over time (Henderson and Russell, 2005;

Chambers and Pieralli, 2020; Walheer, 2021). Intuitively, this means that knowledge accumulates over time; that is, it is important to take what has happened in the past into account. Practically, we adopt a sequential reconstruction of the production process (Diewert, 1980): potential outputs at time t are computed using all available observations at time t, i.e. data at time t and before.

To be fair, a disadvantage of using linear programming is that measurement errors and potential outliers are ignored. While such aspects are probably less severe when relying on well-respected aggregated data as those given in the Penn World Table, they can not be ignored. To mitigate these shortcuts, we adopt the well-known order-m estimator to compute the potential outputs (Daraio and Simar, 2007). The basic principle is to compute expected potential outputs obtained with random sub-samples of m peers. Practically, the sampling procedure is repeated B times to obtain the expected potential outputs. In this study, we set $B = 1,000$ and $m = 30$.[7] That is, the linear programming is run for each sub-sample and the expected potential output is simply the arithmetic average of the sub-sample potential outputs. The estimated potential output for country i at time t when considering sub-sample s is computed as follows:

$$\hat{f}_t^s(k_{it}) = \max\left(y \;\middle|\; \begin{array}{c} y \leq \sum_{\tau=1}^{t}\sum_{j=1}^{n}\lambda_{j\tau}y_{j\tau}, \\ k_{it} \geq \sum_{\tau=1}^{t}\sum_{j=1}^{n}\lambda_{j\tau}k_{j\tau}, \\ 1 \geq \sum_{\tau=1}^{t}\sum_{j=1}^{n}\lambda_{j\tau}, \\ \lambda_{j\tau} \geq 0 \; \forall j, \forall \tau. \end{array} \right). \tag{3}$$

Two remarks have to be made about the linear programming in (3). First, we can verify that technological degradation is impossible by noting that previous observations are included in (3) avoiding an implosion of the production process. Second, constant returns-to-scale is assumed for the production process $\langle Y_{it}, K_{it}, L_{it} \rangle$ which implies that non-decreasing returns-to-scale is observed for labor productivity.[8] Such assumption is standard in macroeconomics (Bernanke and Parkinson, 1991; Aizcorbe, 1992; Kumar and Russell, 2002; Henderson and Russell, 2005; Gibson and Shrader 2018; Walheer, 2021). Once the linear programmings are solved B times, i.e. one time for each sub-sample s, we can obtain the expected estimated potential output

[7]Note that results do not change if we increase B and are very similar if we increase m.

[8]This is formally captured by the third constraint: $1 \geq \sum_{\tau=1}^{t}\sum_{j=1}^{n}\lambda_{j\tau}$ (Banker et al., 2004). See Appendix A for a formal proof.

that we will use in the following:

$$\hat{f}_t(k_{it}) = \mathbb{E}\left[\hat{f}_t^s(k_{it})\right]. \tag{4}$$

Finally, using (2), we can obtain the estimated efficiency score for each country i at time t:

$$\hat{e}_t(k_{it}) = \frac{y_{it}}{\hat{f}_t(k_{it})} \tag{5}$$

The estimated efficiency score $\hat{e}_t(k_{it})$ has to be interpreted as the theoretical counterpart $e_t(k_{it})$: the benchmark value is unity and lower values reflect greater inefficiency behaviour and, thus, more potential productivity gains. Note that the price to pay is to the decomposition discussed after does not probably hold with equalities. At the same time, as we take the expectation (see (4)), we are probably close enough to the equalities.[9]

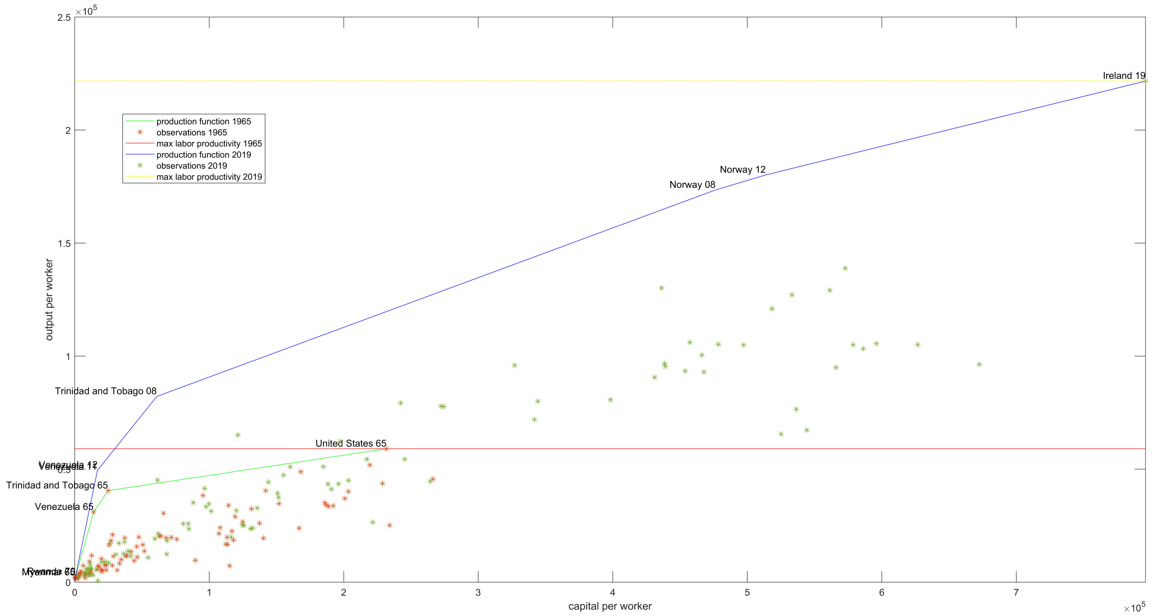
We present the reconstructed production functions for our initial and final time periods in Figure 2. There, we also show the observations in 1965 and 2019 and the largest labor productivity. Countries that defined the world technology in 1965 are Myanmar, Venezuela, Trinidad and Tobago, and the United States. In 2019, we have Myanmar (1965, 1966), Rwanda (1970), Venezuela (2011, 2012), Trinidad and Tobago (2008), Norway (2008, 2012), and Ireland (2019).

The production possibilities have exploded over time. Two groups of countries are present in 2019: those that remain rather close to their 1965 point, and those that have moved up and right. We note that only one point of 2019 lies on the production function in 2019: Ireland. Maximal labor productivity has moved from 59,019 US$ (United States, 1965) to 221,661 US$ (Ireland, 2019), i.e. a change of 375.58 %. Two important dimensions are highlighted in Figure 2: how the production functions move over time, and how countries move towards the production functions. In both cases, capital per worker plays a crucial role. Using the (in)efficiency component in (2), we can define two indexes capturing these two dimensions.[10] Both dimensions have to be used in a complementary fashion to understand the full picture. The indexes are

[9] This is an interesting topic for further research.

[10] Another option is to use a difference. The ratio is preferred for several reasons such as it is unit-free, easy to interpret, and to measure over time. It is fairly easy to adapt the indexes developed here to a difference version.

Figure 2: Reconstructed production functions



given for country i between time periods b and c as follows:

$$\nabla e(k_{ib}, k_{ic}) = \frac{e_c(k_{ic})}{e_b(k_{ib})}, \tag{6}$$

$$\nabla tech(k_{ib}, k_{ic}) = \left[\frac{e_b(k_{ic})}{e_c(k_{ic})} \times \frac{e_b(k_{ib})}{e_c(k_{ib})}\right]^{1/2}. \tag{7}$$

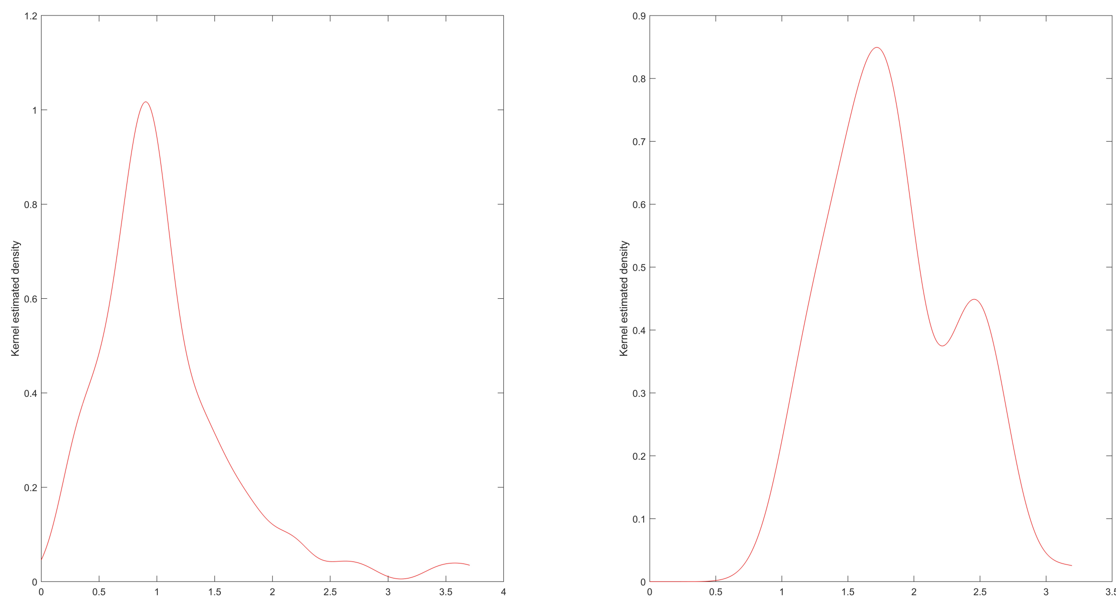
In both cases, an index larger (smaller) than unity implies a performance progression (decrease) for country i between periods b and c. $\nabla e(k_{ib}, k_{ic})$ captures the catching-up of a country with the best practice, while $\nabla tech(k_{ib}, k_{ic})$ reflects technological change, i.e. change in the best practice. We highlight that the $\nabla tech(k_{ib}, k_{ic})$ is defined as a geometric average of two path-dependent indexes as there are two ways to evaluate technological change between periods b and c: one with respect to observations at time c, $\frac{e_b(k_{ic})}{e_c(k_{ic})}$, and another when time b is chosen as the referent time period $\frac{e_b(k_{ib})}{e_c(k_{ib})}$. Such geometric average procedure is known as the Fisher ideal decomposition (Caves et al., 1982) and overcomes choosing a particular reference point. This is the most used procedure in practice (Kumar and Russell, 2002; Henderson and Russell, 2005; Badunenko et al., 2008; Badunenko et al., 2014; Filippetti and Peyrache, 2015;

Walheer, 2016, 2021, 2023; Chambers and Pieralli, 2020; AlKathiri, 2022). Note that $\nabla tech(k_{ib}, k_{ic})$ involves two counterfactual (in)efficiency measurements that can both easily be computed using the linear programming in (3). Descriptive statistics and statistical tests for the estimated indexes are provided in Table 3 and (kernel) distributions in Figure 3.[11]

Table 3: Efficiency and technological changes

statistics	$\nabla e(k_b, k_c)$	$\nabla tech(k_b, k_c)$
min	0.21	1
mean	1.08	1.84
median	0.96	1.79
max	3.71	3.20
more than one mode	0.574	0.044
more than two modes	0.854	0.685

Figure 3: Efficiency and technological changes

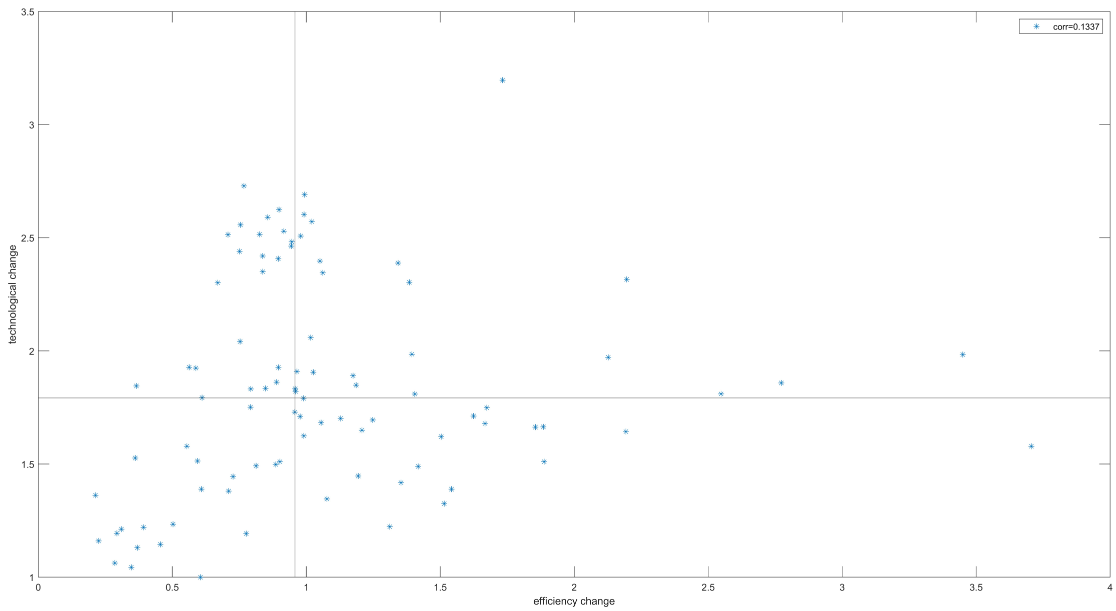


Efficiency change presents an average larger than one but a median smaller than unity. This means that some countries with better performances have pulled up the

[11]We do not add hats on the estimated indexes in Table 3 to improve readability, but each time we provide results it is for estimated concepts.

overall performance. In fact, a bit more than 40% of the countries present an efficiency decrease. One mode is noticed for efficiency change while two modes are observed for technological change. This is confirmed by the $p-$values of the Silverman's tests. This implies that a group of countries has pushed up the production possibilities while others are lagging behind. To better understand these patterns, we cross efficiency and technological changes in Figure 4. There, we draw the medians of each dimension to identify four groups. Moreover, we provide in Table 4 the best and worst 10 performers.[12]

Figure 4: Efficiency and technological change scatter plot



First, there is no clear connection between efficiency and technological changes as the correlation coefficient is rather small at 0.13. This is explained by the fact that we find countries in each of the four groups. The best performers are those in the upper-right as they are pushing the technology and benefit from positive efficiency change. Worse performers lie in the lower left. The most innovative countries are European, and we find several African countries amongst the poorer performances. We also note that countries with high positive efficiency changes can be called followers as they do not innovate directly, but rather benefit from innovations made by others.

[12]Countries are given in decreasing order in Table 4.

Table 4: Efficiency and technological changes

top	$\nabla e(k_b, k_c)$	$\nabla tech(k_b, k_c)$
top 10 +	Thailand, Indonesia, Bolivia, Argentina, Tunisia, Singapore, Romania, Malta, Korea, Botswana	Denmark, Belgium, Switzerland, Austria, France, Spain, Cyprus, Italy, Luxembourg, Ireland
top 10 −	Congo, Myanmar, Rwanda, Burkina Faso, Malawi, Mozambique, Bangladesh, Barbados, Mali, Chad	Venezuela, Mozambique Rwanda, Mali, Tanzania, Myanmar, Ethiopia, Burkina Faso, Malawi, Chad

3.2 Resource capacity constraint

Previous investigations, while pointing out several interesting patterns, are rather standard as they do not consider the resource capacity constraint. To do so, we have to compare how countries generate labor productivity by taking the resource constraint into account, and when ignoring such constraints. The former is captured by our (in)efficiency measurement defined before. The latter can be obtained by computing (in)efficiency when capital per worker is ignored. By taking a simple ratio between both concepts, we measure to what extent resource capacity represents a constraint.[13] It is given for country i at time t as follows:

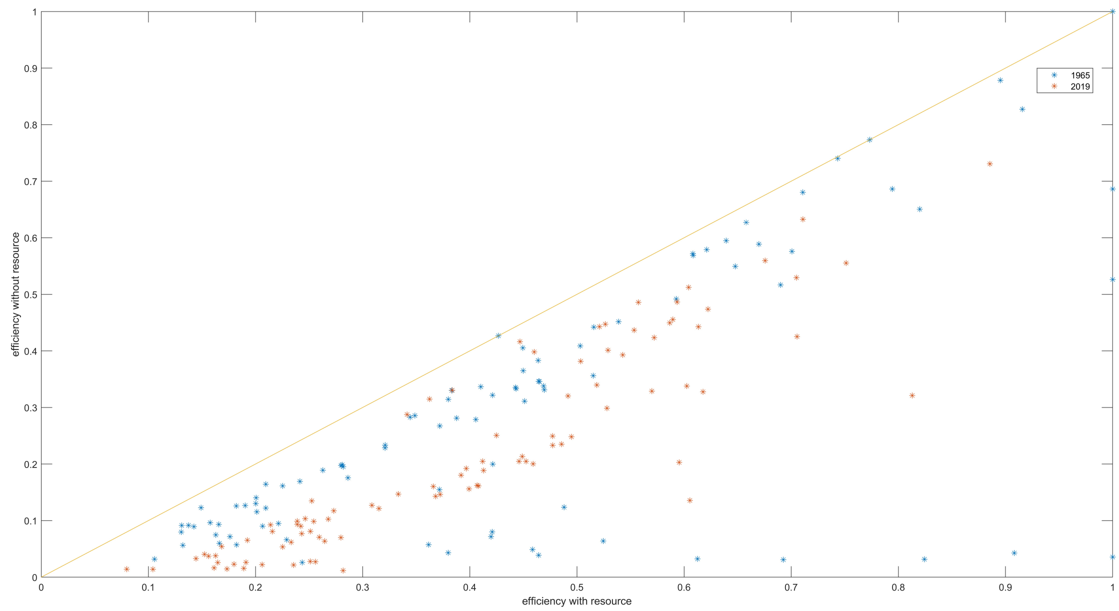
$$r_t(k_{it}) = \frac{e_t(1)}{e_t(k_{it})}. \tag{8}$$

$e_t(k_{it})$ is the (in)efficiency measurement as defined before in Section 3.1. $e_t(1)$ exactly captures the (in)efficiency behaviour without resource constraint. By taking the ratio between both, we measure how resource capacity, here capital per worker, impacts the labor productivity performance. As there is no natural ranking between $e_t(k_{it})$ and $e_t(1)$, the ratio $r_t(k_{it})$ is unbounded. When it is greater than one, it reflects that capital per worker is not used in an optimal manner. Therefore, labor productivity could be increased without requesting more resources. When $r_t(y_t, k_t)$ is smaller than one, it is the opposite situation: more capital per worker is needed to raise labor productivity. Indeed, in that case, ignoring the resource variations reveals more potential labor productivity improvements. In other words, economic growth is

[13] Another option is to use a difference: $e_t(1) - e_t(k_{it})$. The ratio is preferred for several reasons such as it is unit-free, easy to interpret, and to measure over time.

limited by resources, i.e. there is under-investment. In our empirical case, we expect to see the latter case only. At this point, we highlight that a related ratio has been used before by Cherchye et al. (2019), Perelman and Walheer (2020) , Aparicio et al. (2022), Mwaku et al. (2024), and Nsabiman et al. (2024). We cross (in)efficiency with ($e_t(k_{it})$) and without ($e_t(1)$) resources in Figure 5.

Figure 5: Efficiency with and without resources



The diagonal line captures the benchmark case, i.e. when (in)efficiency with and without resources are equal. Above the diagonal, $r_t(k_{it}) > 1$, resources can be used in a better way; and below the diagonal, $r_t(k_{it}) < 1$, more resources are needed. All observations lie below the diagonal for both time periods. That is, under-investment is observed. We may interpret this finding as the need for additional resources to meet sufficient and stable economic growth, i.e. the notion of a steady state (Fernald and Jones, 2014; Jones, 2016).

As done before for the efficiency measurement, we can define two indexes for the resource ratio. The first one captures the change in the resource constraint over time, and the second one the resource environment effect:

$$\nabla rc(k_{ib}, k_{ic}) = \frac{r_c(k_{ic})}{r_b(k_{ib})}, \tag{9}$$

$$\nabla renv(k_{ib}, k_{ic}) = \left[\frac{r_b(k_{ib})}{r_c(k_{ib})} \times \frac{r_b(k_{ic})}{r_c(k_{ic})}\right]^{1/2}. \tag{10}$$

Both concepts follow closely the indexes defined before for the efficiency measurements in (6) and (7). The only difference is that they are here defined for the resource capacity constraint measurement. Note that (10) again involves counterfactual concepts. $\nabla rc(k_{ib}, k_{ic})$ tells us how the resource constraint has evolved over time. A value larger than unity implies that under-investment impact has decreased between b and c. When the index is smaller than one, we observe a greater impact.

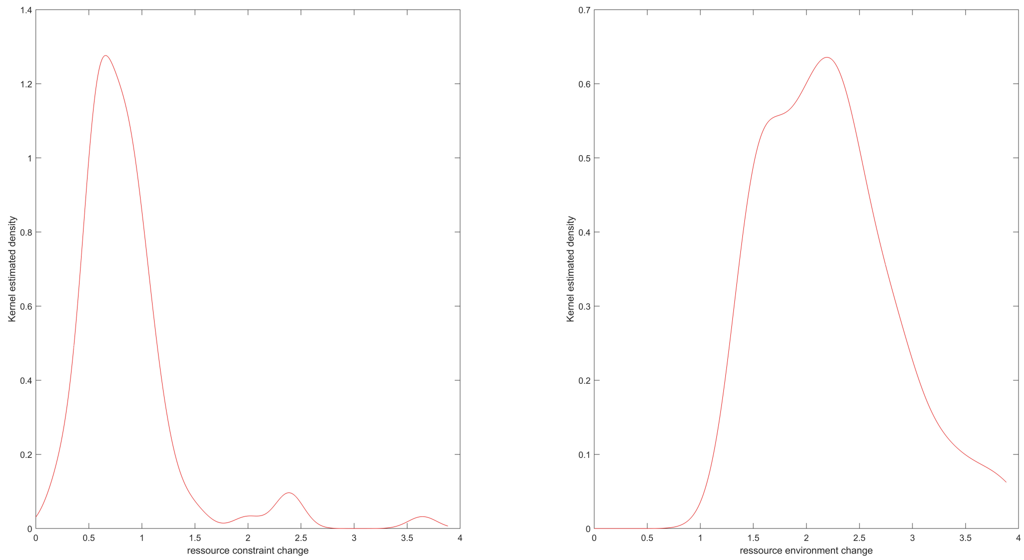
$\nabla renv(k_{ib}, k_{ic})$ represents the resource environment change. To better understand what this change means, let us compare the two factors of the first fraction in (10). When $r_b(k_{ib}) < r_c(k_{ib})$, it implies that the resource constraint is larger for countries in period b when the technology is the one at period c. That is, resource constraint is more important in period c than in b. There is a less favorable environment in c in that case. When $r_b(k_{ib}) > r_c(k_{ib})$, the opposite situation prevails: there is a more favourable environment in c. A value of one represents the status quo. As a similar comparison holds true for $r_b(k_{ic})$ and $r_c(k_{ic})$, we conclude that $\nabla renv(k_{ib}, k_{ic}) > 1$ means that the resource environment has improved between b and c. When it is smaller than one, it is the opposite situation. Distributions for both indexes are provided in Figure 6. In Table 5, we give descriptive statistics for both indexes.

Table 5: Resource constraint and resource environment change statistical tests

statistics	$\nabla rc(k_b, k_c)$	$\nabla renv(k_b, k_c)$
min	0.20	1.43
mean	0.92	2.22
median	0.79	2.19
max	6.68	3.88
more than one mode	0.02	0.48

The resource constraint change is, on average, smaller than unity revealing the growing importance of under-investment over time. This being said the distribution of the resource constraint change highlights three groups of countries. One with very high resource constraint change in the [3.2 – 4] interval, a second in the [1.8–2.5] in-

Figure 6: Resource constraint and resource environment change



terval, and a last one with an average of around 0.75. This reveals that the increasing importance of under-investment is not a rule in the world. Next, the resource environment has, on average, increased showing that the resource environment is more and more favourable in the world over time (the minimum value is 1.43). Note that this does not imply that all countries have benefited similarly from such a more favourable environment. We do not find statistical evidence of multi-modes for the resource environment change even though Figure 6 shows a small bump. Finally, we note that the resource environment has more importantly increased than technological change (Table 3).

As done before for the efficiency and technological changes, we cross the resource constraint change and the resource environment effect in Figure 7 and give the best and worst top performers in Table 6. A first observation is that the resource constraint and resource environment changes are slightly positively related. The Pearson correlation coefficient is close to 0.30 and significant. This means that countries with positive resource constraint changes are those that have a more favourable resource environment. Graphically, we see four distinct groups of countries. More developed countries are those with smaller resource environment changes. However, this does not mean that the resource environment is less favourable over time in these countries as all resource environment changes are positive (Table 5). Countries with higher resource environment changes are less developed. This is also true for those with lesser resource constraint changes, but countries are different in both groups. This means that under-investment is more severe in less developed countries. Finally, we find mostly African and Asian countries is the best resource constraint change group.

Figure 7: Resource constraint and resource environment change scatter plot

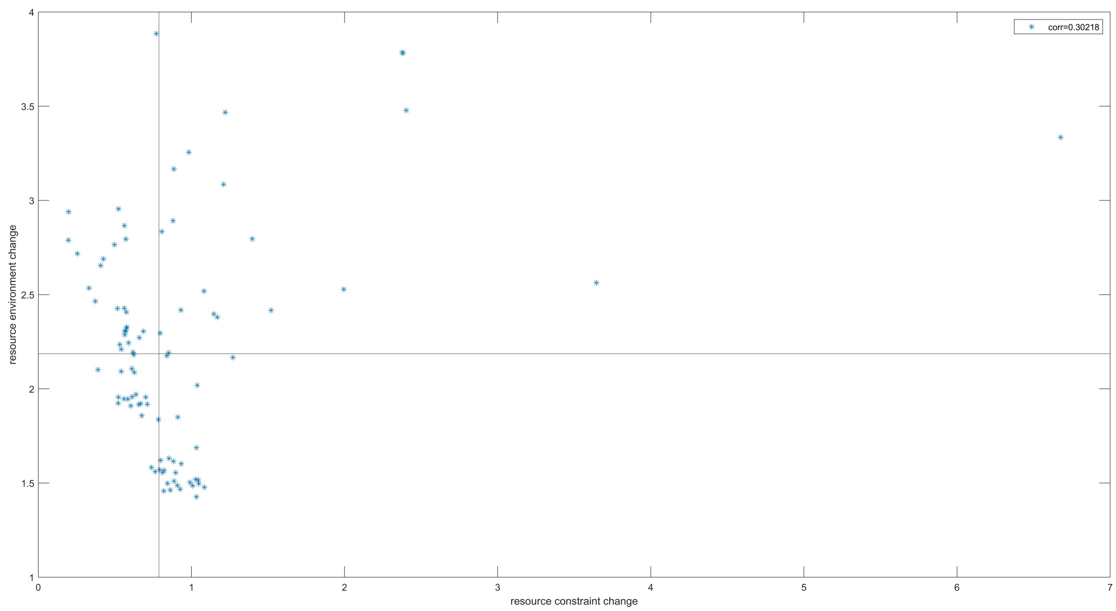


Table 6: Resource constraint and resource environment changes

group	$\nabla rc(k_b, k_c)$	$\nabla renv(k_b, k_c)$
top 10 +	Mozambique, Taiwan, Bangladesh, Botswana, Egypt, Rwanda, Mali, Burkina Faso, China, Myanmar	Congo, Uganda, Malawi, Tanzania, Myanmar, Mozambique, Burkina Faso, Rwanda, Mali, Ethiopia
top 10 −	Zimbabwe, Madagascar, Niger, Senegal, Ghana, Zambia, Bolivia, Venezuela, Kenya, Nigeria	Italy, Luxembourg, Cyprus, Belgium, Ireland, Greece, France, Spain, Switzerland, Austria

3.3 Path-dependence and moderator effect

Our previous investigation highlighted the existence of under-investment in the world. At the same time, $\beta-$convergence seems to be true (Figure 1). A follow-up question is how under-investment impacts $\beta-$convergence ? Under-investment in resources may act as a constraint preventing the economic growth convergence from happening. That is, under-investment has a moderator effect on labor productivity convergence. While moderator effects have been studied before (Forte and Moura, 2013; Teixeira and Queirós, 2016; Sainz-Fernandez et al., 2018; Dada and Abanikanda, 2022), this is not the case for under-investment. Moreover, another important aspect is whether and how the moderator effect of under-investment varies when combined with efficiency, technological, or resource environment change. Answering such questions is another added value of our empirical investigation.

At the same time, under-investment may present a second undesirable feature: path-dependence. Such notion of path dependence can be traced back to David (1985) where it is defined as 'important influences upon the eventual outcome [that] can be exerted by temporally remote events'. In economics, this term was widely used to describe the phenomenon in which future paths of a system are based on its current or past states (Eliasson, 1989; Redding, 2002; Dutt, 2009; Bellaïche, 2010; Harada, 2010; Aghion et al., 2016; He and Walheer, 2020), but not in the under-investment context.

If both features are combined, this may lead to a vicious circle from which it is difficult to get out. Intuitively, this would mean that countries with worse performances, i.e. smaller initial labor productivity value, tend to be more impacted by under-investment, whilst under-investment prevents $\beta-$convergence from occurring. When repeating such phenomena over time, we obtain the virtuous circle.

In the following, we use the same definitions, yet adapt to our context. First, we look at how initial output per worker is linked to the efficiency, technological, resource constraint, and resource environment changes. The rationale behind such exercise is to verify whether countries with worse initial conditions have benefited more from efficiency increases and technological and environment advancements, and are less affected by the resource capacity constraint. Next, to study the role of the different dimensions in the $\beta-$convergence process, we augment the regression equation in (1) by including additional factors: indexes and interaction terms. Such interaction effects exactly capture the moderation effects. Formally, the regression equations to test for the path-dependence existence and the moderator effect are given as follows:

$$\nabla z(k_{ib}, k_{ic}) = \alpha + \beta y_{ib} + u_i, \quad (11)$$

$$ln(y_{ic}/y_{ib}) = \alpha + \beta y_{ib} + \gamma_1 \nabla rc(k_{ib}, k_{ic}) + \gamma_2 \nabla z(k_{ib}, k_{ic}) + \phi_1 y_{ib} \times \nabla rc(k_{ib}, k_{ic}) + \phi_2 y_{ib} \times \nabla z(k_{ib}, k_{ic}) + u_i, \quad (12)$$

where $\nabla z(k_{ib}, k_{ic}) = \{\nabla rc(k_{ib}, k_{ic}), \nabla e(k_{ib}, k_{ic}), \nabla tech(k_{ib}, k_{ic}), \nabla renv(k_{ib}, k_{ic})\}$.

Table 7 gives the slope coefficients of the GLS regressions of the path-dependence.[14] In Appendix B, Figure 9 shows the scatter plots and the GLS fitted regression lines. A positive slope coefficient for the regression with the output per worker in 1965 in (11) implies path-dependence. We see that only technological change presents a path-dependence pattern. Countries with larger initial labor productivity are those pushing the technological frontier over time, i.e. they are more innovative. Such findings are coherent with other recent investigations (Redding, 2002; Aghion et al., 2016). Next, efficiency change has benefited countries in need. A similar finding holds for the resource constraint and resource environment changes. This means worse initial performers have less resource constraint and a better resource environment over time. In terms of amplitude, the resource environment presents the largest impact as it has the greater slope coefficients.

Table 7: Path dependence slope coefficients

statistics	Output per worker 1965
$\nabla e(k_b, k_c)$	-0.0011*
$\nabla tech(k_b, k_c)$	0.0023*
$\nabla rc(k_b, k_c)$	-0.0012*
$\nabla renv(k_b, k_c)$	-0.0031*

Next, results for the moderator effects in (12) are given in Table 8. There, we also give the R^2 and $p-$value of the Fisher test for the global significant level. It is required to verify the significance level of the coefficient ϕ to conclude the existence of a moderator effect. Next, the value of ϕ has to be checked: if ϕ is negative (positive), it means that the variable supports (plays against) convergence (as β is found to be negative, see Table 2). Finally, to understand the strength of the moderator effect, we can compare the values of the coefficients.

[14]The symbol '*' means that the coefficient is significant at the 1% level in all following Tables.

Table 8: Moderator effects

statistics	$\nabla rc(k_b, k_c)$	$\nabla rc(k_b, k_c)$ combined with		
		$\nabla renv(k_b, k_c)$	$\nabla e(k_b, k_c)$	$\nabla tech(k_b, k_c)$
α	349.87	1079.2*	546.7*	-309.45
β	-0.0339*	-0.0058*	-0.00234*	-0.0061*
γ_1	219.53	435.57*	456.98*	314.12
γ_2		235.71	315.15*	464.44*
ϕ_1	0.0366*	0.0187*	0.00439*	0.0087*
ϕ_2		-0.0931*	-0.0123	-0.0047*
R^2	0.2438	0.5212	0.5324	0.6511
$F - stat$	0.0000	0.0000	0.0000	0.0000

A moderator effect to economic growth convergence is found for under-investment. We see that countries where under-investment decreases, i.e. greater $\nabla rc(k_b, k_c)$, are more likely to diverge over time. This means that under-investment is a brake on economic growth convergence. However, these results are contrasted when we take another dimension into account. When combined with technological or resource environment change, the story is different. Both dimensions present a negative coefficient meaning that they support $\beta-$convergence. It implies that it is possible to counter the moderator effect of under-investment if technological or resource environment changes are positive and high enough. As technological change presents path-dependence (see Table 8), it is probably simpler to set a more favourable environment. Policy-makers have an important role to play here. Finally, we note that no significant results are found when combined with efficiency change.

All in all, our results indicate that path dependence is not observed for the resource constraint and that $\beta-$convergence is possible when technological or resource environment change is positive and high enough.

4 Sensitivity tests

As the results might be sensitive to the empirical specification, we run several sensitivity tests to verify their robustness. First, we partition countries into two groups in light of their technological change value. Next, we do the same using their resource environment change value. Our second sensitivity test consists of removing observations during the oil and financial crisis. Finally, we verify how our results change when considering $\sigma-$convergence, i.e. a gradual reduction in dispersion.[15]

Overall, our additional analyses support our previous findings while highlighting some additional interesting features. One, different patterns are found in each group. Second, crises are found to have an impact on the moderator effects. Third, $\sigma-$divergence, which is reduced by the moderator effects, is observed.

4.1 Groups

As highlighted before in Figures 1(a), 3, and 6, distribution picks are observed. We may interpret this finding as the existence of groups of countries in the world; each group with its own growth regimes. Several researchers have studied group or club convergence (Azariadis and Drazen 1990; Durlauf and Johnson 1995; Bernard and Durlauf, 1996; Galor 1996).[16] In brief, convergence of countries within a technology regime or club is possible, but overall convergence is prevented by a certain club factor. In our context, this would imply that the resource constraint impact is different in each group. Our aim is not to confirm the club convergence hypothesis, but rather to verify how our results change when we partition countries into groups based on our previous empirical observations. In light of the distribution picks in Figures 3 and 6, we define two groups using technological change (cut-off at 1.83) and two groups using resource environmental change (cut-off at 1.74). The cut-offs correspond to the distribution modes.

Results for both grouping procedures are given in Tables 9 and 10 in Appendix C. For path-dependence, previous results are confirmed: only technological change presents such a phenomenon. This is true regardless of the grouping procedure. Next, $\beta-$convergence is found in each group but the impact of each dimension varies across groups. In the more technologically advanced group, under-investment does not present a moderator effect. This is true whether it is taken alone or combined

[15] Another sensitivity test is to redo the analysis for periods covered in previous research (e.g. Kumar and Russell, 2002; Henderson and Russell, 2005; Badunenko et al., 2008; Badunenko et al., 2014; Filippetti and Peyrache, 2015; Walheer, 2016, 2021, 2023; AlKathiri, 2022) to see how our new concept of resource capacity constraint challenges their conclusion. It is also a way to verify that our results are not driven by considering the updated sample. We redo our analysis considering the samples in Kumar and Russell (2002) and Henderson and Russell (2005), and we find similar findings. Given the space constraint, the additional results are not presented here but are available upon request.

[16] Club convergence has received a certain attention in the literature. As it is not the goal of this paper to go into detail we refer to Walheer (2022) for an overview.

with another dimension. Efficiency and technology change both present a moderator effect in that group. Such effect is negative meaning that both dimensions support $\beta-$convergence in the group. We do not find a moderator effect of under-investment for the group with the most favourable resource environment. However, technological and resource environment change both have a moderator effect encouraging $\beta-$convergence.

Next, for the group less technologically advanced and the one with a less favourable resource environment, there is a moderator effect of under-investment. As found before in Section 3.3, under-investment is a brake on economic growth convergence. Again, this result is counterbalanced by the other dimensions. As technology and resource environment changes have both a moderator effect in favour of $\beta-$convergence, it is, in principle, possible to counterbalance the moderator effect of under-investment. Finally, we highlight that this time, efficiency change also has a role to play in both groups.

4.2 Crisis

A fair criticism of our previous analysis is its sensitivity to extreme values. During the 1965–2019 period, the world faced several crises that clearly impacted the countries' performances. An advantage of our estimation method is to include all available information. However, a drawback is that it is sensible to potential issues (as those explained in Section 3.1) but also to extreme data as it might be the case for crises. We remove four time periods from our estimation: the oil crisis 1974–1977, the oil crisis 1989–1992, and the financial crisis 2008-2011.[17]

In Appendix D, we provide the distributions for the four indexes (Figure 9), the path dependence regressions (Table 11), and the moderator effect regressions (Table 12). First, distributions are similar to those obtained previously in Figures 3 and 4 when all periods are used to estimate the potential outputs. The picks (modes) are, in fact, more visible, when crises are removed. Next, path-dependence is again only found for technological change. Note that coefficients are smaller than before (compared to Table 8). Finally, $\beta-$convergence is found and a moderator effect for under-investment is observed. This effect can be countered by technological advancement, a more favourable resource environment, or positive efficiency change. All in

[17]Another option is to adopt a median regression. We obtain simialr results.

all, our previous results are confirmed.

4.3 $\sigma-$convergence

Besides $\beta-$convergence, which is probably the most popular definition of convergence, $\sigma-$convergence has received certain attention in the economic literature (Dalgaard and Vastrup, 2001; Young et al., 2008; Egger and Pfaffermayr, 2009; Rapacki and Próchniak, 2009; Kong et al., 2019). The basic idea is to verify how labor productivity variability changes over time. If such variability decreases, it means that differentiation between countries decreases over time. That is, there is a convergence as countries are more and more similar. In practice, labor productivity variability is measured by its standard deviation. Contrary to $\beta-$convergence, the regression equation for $\sigma-$convergence depends on time and not on individuals. This has two implications for our indexes. First, they have to be computed at each time period. Second, they have to be aggregated annually. Finally, as indexes capture change with respect to a base period, we have to take the initial labor productivity variability into account. All in all, we have the following equation:

$$\begin{aligned}\sigma(y_t)/\sigma(y_b) =& \alpha + \beta t + \gamma_1 \nabla rc(k_b, k_t) + \gamma_2 \nabla z(k_b, k_t) \\ & + \phi_1 t \times rc(k_b, k_t) + \phi_2 t \times \nabla z(k_b, k_t) + u_t. \end{aligned} \tag{13}$$

$\nabla z(k_b, k_t)$ is an aggregated index built on the $\nabla z_r(k_{ib}, k_{it})$'s at time t (the same holds true for $\nabla rc(k_b, k_c)$). We recall here that $\nabla z(k_{ib}, k_{it})$ represents one of our four indexes (see (11) and (12)). Also, we note that $\nabla z(k_{ib}, k_{it})$ is the index with a current time period t and a base period b. To aggregate indexes, it is, generally, not advised to take the arithmetic average, it is rather, better, to use a weighted sum. In particular, we follow the well-known procedure explained in Zelenyuk (2006) and Walheer (2018). In brief, relative output-labor ratios are utilized to define aggregated potential outputs that are, then, used to obtain the aggregated indexes.

Variabilities of labor productivity and capital-labor ratio are shown in Figure 11 in Appendix E. Both are given with respect to their initial value. We see that capital-labor ratio follows a much more stable trend than labor productivity. Labor productivity is only larger is the [2005–2008] interval and in 2018–2019. Note that the gap between both variabilities reduces over time. Results for the moderator effects are given in Table 13. $\sigma-$divergence is found as the slope coefficient is positive.

Divergence is strengthened by under-investment as it presents a moderator effect with a positive coefficient. Such a process is braked by technological change only. The coefficient for efficiency and resource environment changes are both insignificant.

5 Conclusion

Using a non-parametric intuitive approach and a tailored database, we investigate how resource capacity impacts economic growth convergence. We distinguish two main channels: path-dependence and moderator effect. Under-investment in resources may act as a constraint preventing the economic growth convergence from happening. At the same time, countries with lower performances may have larger under-investment over time. If both features are combined, this may lead to a virtuous circle from which it is difficult to get out.

Our results reveal the growing importance of under-investment over time, but not for all countries. Next, the resource environment has, on average, increased showing that the resource environment is more and more favourable in the world. Also, our empirical exercise indicates that path dependence is not observed for the resource constraint but there is a moderator effect. However, $\beta-$convergence is possible by promoting technological advances or creating a more favourable resource environment.

We run several sensitivity tests to verify the robustness of our results. First, we partition countries into two groups in light of their technological change value and their resource environment change. Next, we remove potential extreme observations. Finally, we verify how our results change when considering $\sigma-$convergence, i.e. a gradual reduction in dispersion. Overall, our additional analyses support our previous findings while highlighting some additional interesting features for each group.

Finally, we want to mention some potential paths for further research using the concept of resource capacity. A first extension is to include other resources such as human capital and energy; and distinguish between private and public resources. Next, the pollution process can be included to capture the negative effect of economic growth. Finally, technology heterogeneity can be taken into account as it may be argued that countries (or groups of countries) have access to different technologies.

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Appendix A

When assuming that the production function is quasi-concave, continuous, strictly increasing, and satisfies constant returns-to-scale. The reconstructed technology for the production process $\langle Y_t, K_t, L_t \rangle$ is defined as follows (Charnes et al., 1978):

$$T_t = \left((Y_t, K_t, L_t) \;\middle|\; \begin{array}{c} Y_t \leq \sum_{\tau=1}^{t} \sum_{j=1}^{n} \mu_{j\tau} Y_{j\tau}, \\ K_t \geq \sum_{\tau=1}^{t} \sum_{j=1}^{n} \mu_{j\tau} K_{j\tau}, \\ L_t \geq \sum_{\tau=1}^{t} \sum_{j=1}^{n} \mu_{j\tau} L_{j\tau}, \\ \mu_{j\tau} \geq 0 \; \forall j, \forall \tau. \end{array} \right). \tag{14}$$

As constant returns-to-scale is assumed, we can multiply each side of the inequalities by $L_{j\tau}/L_t$:

$$T_t = \left((Y_t, K_t, L_t) \;\middle|\; \begin{array}{c} \frac{L_{j\tau}}{L_t} Y_t \leq \sum_{\tau=1}^{t} \sum_{j=1}^{n} \mu_{j\tau} Y_{j\tau} \frac{L_{j\tau}}{L_t}, \\ \frac{L_{j\tau}}{L_t} K_t \geq \sum_{\tau=1}^{t} \sum_{j=1}^{n} \mu_{j\tau} K_{j\tau} \frac{L_{j\tau}}{L_t}, \\ \frac{L_{j\tau}}{L_t} L_t \geq \sum_{\tau=1}^{t} \sum_{j=1}^{n} \mu_{j\tau} L_{j\tau} \frac{L_{j\tau}}{L_t}, \\ \frac{L_{j\tau}}{L_t} \mu_{j\tau} \geq 0 \; \forall j, \forall \tau. \end{array} \right). \tag{15}$$

By reorganizing the terms in each inequality, we obtain:

$$T_t = \left((Y_t, K_t, L_t) \;\middle|\; \begin{array}{c} \frac{Y_t}{L_t} \leq \sum_{\tau=1}^{t} \sum_{j=1}^{n} \left(\mu_{j\tau} \frac{L_{j\tau}}{L_t} \right) \frac{Y_{j\tau}}{L_{j\tau}}, \\ \frac{K_t}{L_t} \geq \sum_{\tau=1}^{t} \sum_{j=1}^{n} \left(\mu_{j\tau} \frac{L_{j\tau}}{L_t} \right) \frac{K_{j\tau}}{L_{j\tau}}, \\ \frac{L_t}{L_t} \geq \sum_{\tau=1}^{t} \sum_{j=1}^{n} \left(\mu_{j\tau} \frac{L_{j\tau}}{L_t} \right) \frac{L_{j\tau}}{L_{j\tau}}, \\ \frac{L_{j\tau}}{L_t} \mu_{j\tau} \geq 0 \; \forall j, \forall \tau. \end{array} \right). \tag{16}$$

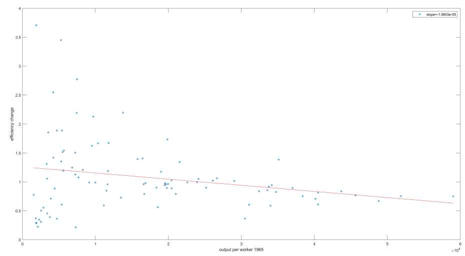
By defining labor productivity as $y_t = Y_t/L_t$, capital-labor ratio as $k_t = K_t/L_t$, and new multipliers by $\lambda_{j\tau} = \mu_{j\tau} \times L_{j\tau}/L_t$, we obtain:

$$T_t = \left((y_t, k_t, 1) \;\middle|\; \begin{array}{c} y_t \leq \sum_{\tau=1}^{t} \sum_{j=1}^{n} \lambda_{j\tau} y_{j\tau}, \\ k_t \geq \sum_{\tau=1}^{t} \sum_{j=1}^{n} \lambda_{j\tau} k_{j\tau}, \\ 1 \geq \sum_{\tau=1}^{t} \sum_{j=1}^{n} \lambda_{j\tau} 1, \\ \lambda_{j\tau} \geq 0 \; \forall j, \forall \tau. \end{array} \right). \tag{17}$$

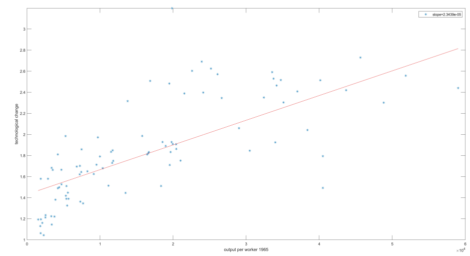
This last formation shows that the production process can be expressed as $\langle y_t, k_t, 1 \rangle$, and that non-decreasing returns is found (Banker et al., 2004).

Appendix B

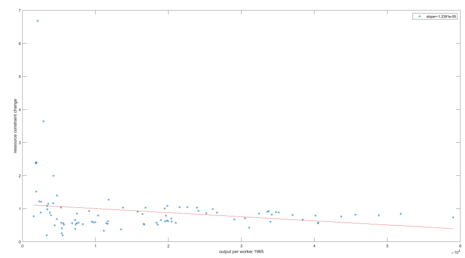
Figure 8: Path-dependence



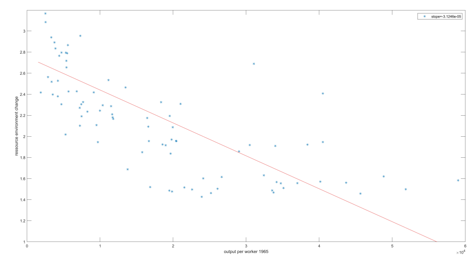
(a) Efficiency change



(b) Technological change



(c) Resource constraint



(d) Resource environment

Appendix C

Table 9: Path dependence slope coefficients per grouping

statistics	Output per worker 1965
grouping 1: $\nabla tech(k_b, k_c) > 1.83$	
$\nabla e(k_b, k_c)$	-0.00003*
$\nabla tech(k_b, k_c)$	0.00001*
$\nabla rc(k_b, k_c)$	-0.00001*
$\nabla renv(k_b, k_c)$	-0.00009*
grouping 1: $\nabla tech(k_b, k_c) < 1.83$	
$\nabla e(k_b, k_c)$	-0.00008*
$\nabla tech(k_b, k_c)$	0.000009*
$\nabla rc(k_b, k_c)$	-0.00003*
$\nabla renv(k_b, k_c)$	-0.00003*
grouping 2: $\nabla renv(k_b, k_c) > 1.74$	
$\nabla e(k_b, k_c)$	-0.00003*
$\nabla tech(k_b, k_c)$	0.00001*
$\nabla rc(k_b, k_c)$	-0.00002*
$\nabla renv(k_b, k_c)$	-0.00001*
grouping 2: $\nabla renv(k_b, k_c) < 1.74$	
$\nabla e(k_b, k_c)$	-0.000004*
$\nabla tech(k_b, k_c)$	0.000004*
$\nabla rc(k_b, k_c)$	-0.00004*
$\nabla renv(k_b, k_c)$	-0.00003*

Table 10: Moderator effects per grouping

statistics	$\beta-$conv.	$\nabla rc(k_b, k_c)$	$\nabla rc(k_b, k_c)$ combined with $\nabla renv(k_b, k_c)$	$\nabla e(k_b, k_c)$	$\nabla tech(k_b, k_c)$
grouping 1: $\nabla tech(k_b, k_c) > 1.83$					
α	521.98*	425.21*	457.64*	546.87*	435.98*
β	-0.00645*	-0.00479*	-0.00548*	-0.00987*	-0.00435*
γ_1		365.89	548.98*	345.87	567.98*
γ_2			126.99*	234.98*	543.34
ϕ_1		-0.00214	-0.00312	0.00871	-0.0113
ϕ_2			-0.00235	-0.00134*	-0.00235*
R^2	0.6363	0.4686	0.6545	0.4538	0.5698
$F-stat$	0.000	0.000	0.000	0.000	0.000
grouping 1: $\nabla tech(k_b, k_c) < 1.83$					
α	435.23*	245.98*	3254.68*	456.97	345.78*
β	-0.00526*	-0.00325*	-0.00429*	-0.00234*	-0.00436*
γ_1		234.58*	358.98	348.76	457.76
γ_2			465.98*	567.45*	345.78
ϕ_1		0.00128*	0.00365*	0.00456*	0.00345*
ϕ_2			-0.00124*	-0.00345*	-0.00234*
R^2	0.5487	0.4563	0.6358	0.4987	0.5514
$F-stat$	0.000	0.000	0.000	0.000	0.000
grouping 2: $\nabla renv(k_b, k_c) > 1.74$					
α	548.71*	458.55*	498.65*	654.87	567.87*
β	-0.00457*	-0.00215*	-0.00124*	-0.00324*	-0.00187*
γ_1		321.58*	231.98*	298.76	546.87*
γ_2			412.87*	345.87*	287.65
ϕ_1		-0.00362	0.00321	-0.00298	-0.00199
ϕ_2			-0.00128*	-0.00187	-0.00217*
R^2	0.4599	0.5987	0.5547	0.4989	0.6120
$F-stat$	0.000	0.000	0.000	0.000	0.000
grouping 2: $\nabla renv(k_b, k_c) < 1.74$					
α	426.50	* 546.98*	645.66*	765.87*	645.66
β	-0.00312*	-0.00214*	-0.00148*	-0.00287*	-0.00189*
γ_1		562.32*	421.65*	438.77*	398.65*
γ_2			512.98	198.76	165.88*
ϕ_1		0.00131*	0.00148*	0.00234*	0.00187*
ϕ_2			-0.00124*	-0.00176*	-0.00273*
R^2	0.4587	0.5698	0.6247	0.6547	0.6344
$F-stat$	0.000	0.000	0.000	0.000	0.000

Appendix D

Figure 9: Efficiency and technological changes without crisis

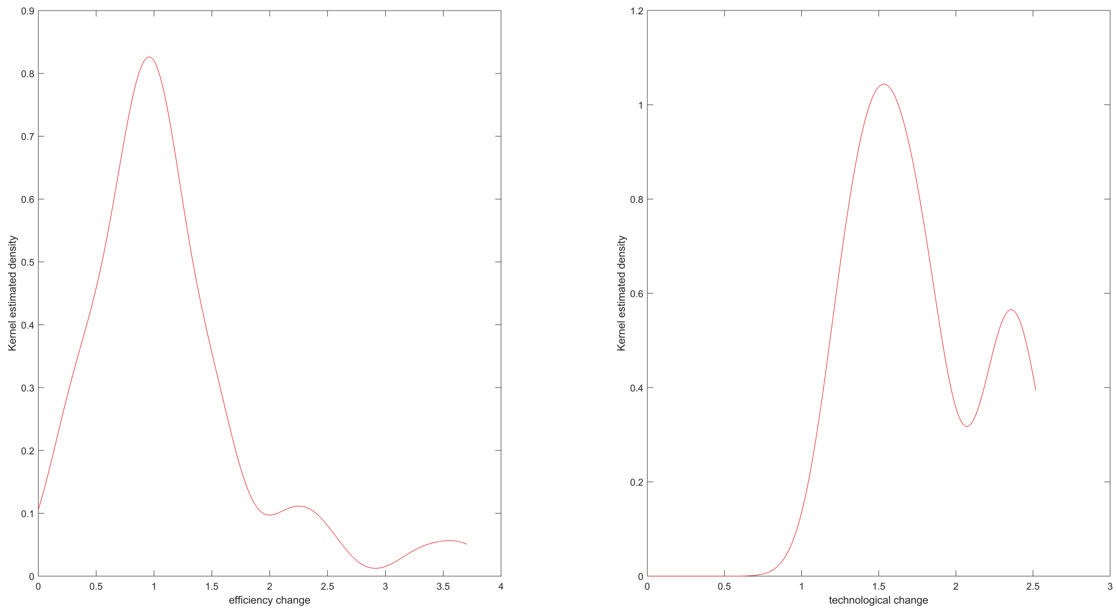


Table 11: Path dependence slope coefficients without crisis

statistics	Output per worker 1965
$\nabla e(k_b, k_c)$	-0.00001*
$\nabla tech(k_b, k_c)$	0.00002*
$\nabla rc(k_b, k_c)$	-0.00002*
$\nabla renv(k_b, k_c)$	-0.00002*

Figure 10: Resource constraint and resource environment change without crisis

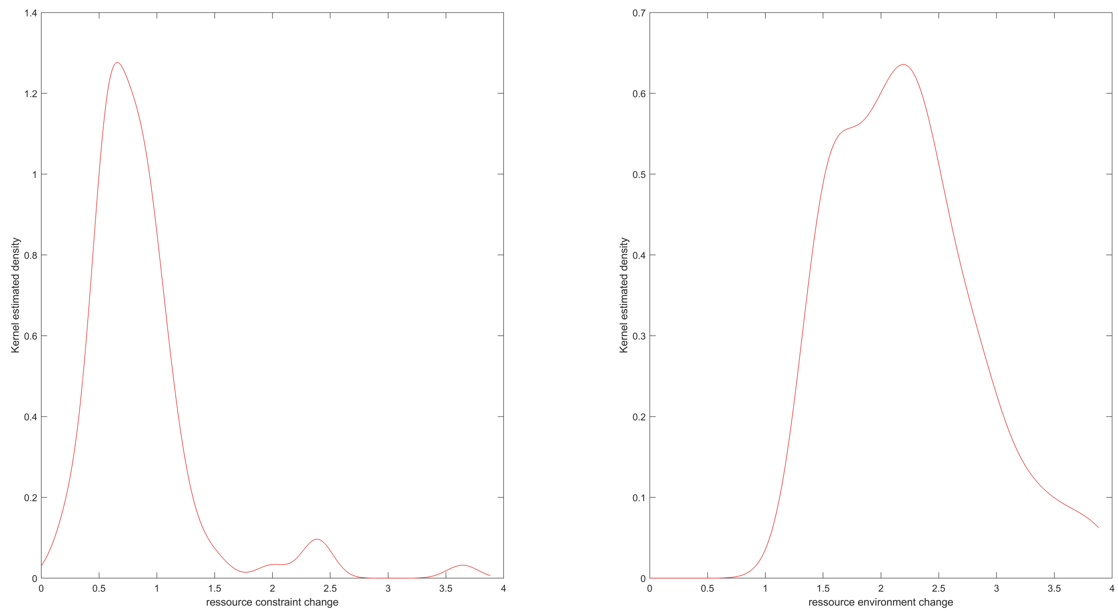


Table 12: Moderator effects without crisis

statistics	$\beta-$conv.	$\nabla rc(k_b,k_c)$	$\nabla rc(k_b,k_c)$ combined with		
			$\nabla renv(k_b,k_c)$	$\nabla e(k_b,k_c)$	$\nabla tech(k_b,k_c)$
α	370.62*	-131.53*	-408.41	243.98*	324.98
β	-0.0063*	-0.0008*	-0.0159*	-0.0065*	-0.00987*
γ_1		380.36*	562.67*	345.98	345.87*
γ_2			421.65*	347.98*	234.87*
ϕ_1		0.0013*	0.0345*	0.00234*	0.00176*
ϕ_2			-0.00421*	-0.00387*	-0.00248*
R^2	0.4517	0.6234	0.7125	0.6845	0.6285
$F-stat$	0.0000	0.0000	0.0000	0.0000	0.0000

Appendix E

Figure 11: Variability

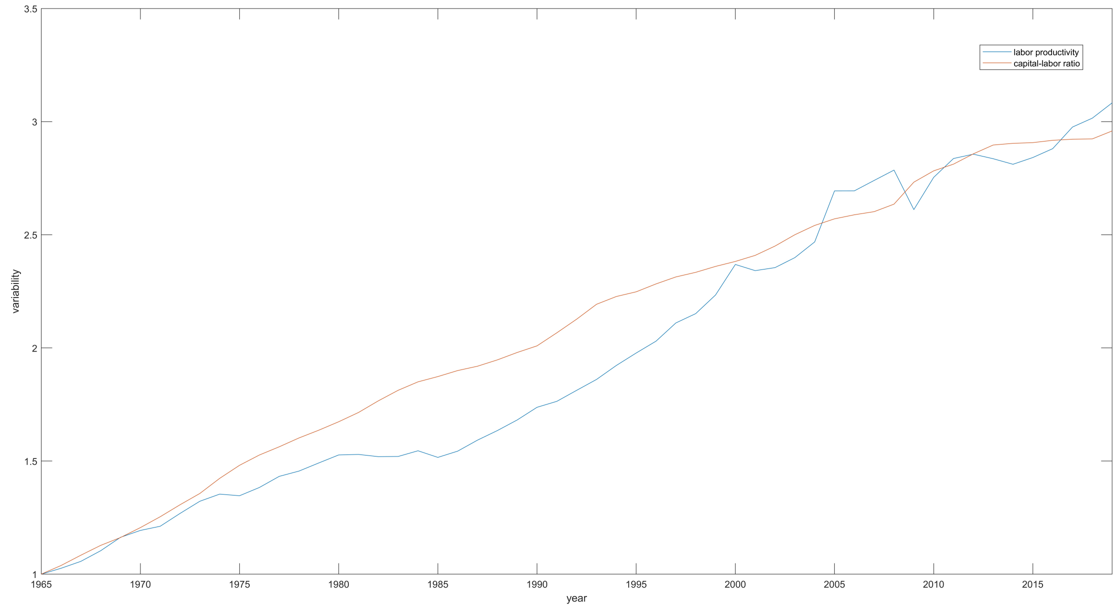


Table 13: Moderator effects for $\sigma-$convergence

statistics	$\sigma-$conv.	$\nabla rc(k_b, k_c)$	$\nabla rc(k_b, k_c)$ combined with		
			$\nabla renv(k_b, k_c)$	$\nabla e(k_b, k_c)$	$\nabla tech(k_b, k_c)$
α	-77.88*	413.94	341.71*	182.87*	292.87*
β	0.0345*	0.0568*	0.0457*	0.0324*	0.0456*
γ_1		0.02073*	0.0185*	0.0587	-0.0979
γ_2			23.98	40.97*	34.76
ϕ_1		0.2359*	0.0158*	0.0487*	0.0398*
ϕ_2			-0.0265	0.0987*	-0.0643*
R^2	0.9245	0.9187	0.9356	0.9412	0.9545
$F - stat$	0.000	0.000	0.000	0.000	0.000