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Regional Productivity Convergence in Peru

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Abstract

This paper examines whether labor productivity converged across Peru's regions ("departments") during 2002-12. Given the large differences in labor productivity across the regions of Peru, such convergence has the potential to raise aggregate productivity and incomes, and also reduce regional inequalities. The paper finds that labor productivity in the secondary sector (especially manufacturing) and the mining sector has converged across Peruvian departments. The paper does not find robust evidence for labor productivity convergence in agriculture and services. These patterns are consistent with recent cross-country evidence and with the hypothesis that productivity convergence is more likely in sectors with greater scope for market integration, because of the effects of competition and knowledge flows. The convergence in labor productivity within manufacturing and mining has been sufficient to lead to convergence in aggregate labor productivity across departments. But because services and agriculture continue to employ the majority of workers in Peru, aggregate convergence is slower than that within manufacturing. The paper also finds that poverty rates are not converging across departments. The limited impact of labor productivity convergence on poverty could be tied to the facts that not all sectors are experiencing productivity convergence, poorer people are employed in sectors where convergence has been slower (such as agriculture), and there is very little labor reallocation toward converging sectors (such as manufacturing).

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1. Introduction

Convergence in labor productivity and income levels across countries, and across regions within countries, is one of the central questions addressed by economic growth theory. Building on a large body of theoretical and empirical research, this paper examines the process of labor productivity convergence across Peru's regions (*departments*) in the recent decade.

With large differences in labor productivity across the regions of Peru, a process of sustained productivity catch-up by lagging regions has much potential to raise aggregate productivity and incomes, and also reduce regional inequalities. In theory, there are good reasons to expect such catch-up. A key reason why some economies lag behind others in output per worker is that they have less capital per worker. If there are diminishing returns to capital, lagging economies should have higher returns on investment, and hence grow faster than leading economies. This logic applies to countries, as well as to different regions within a country. Regions lagging behind in labor productivity could also be using less advanced technology than leading regions, as reflected in their lower Total Factor Productivity (TFP) levels.[1] The diffusion of better technology to less advanced regions can promote convergence, equalizing gaps in TFP. The flow of capital and labor across regions should also speed up convergence by helping equalize capital per worker, with capital moving to capital-poor regions, and labor moving to capital-rich regions.[2]

The empirical evidence on regional convergence is mixed. Per capita income and output tend to converge across US states and across Japanese prefectures (Sala-i-Martin, 1996; Barro and Sala-i-Martin, 1991). In contrast, per capita incomes appear to have diverged across Chinese provinces following the open door economic reforms of the late 1970s (Pedroni and Yao, 2006). Countries may experience periods of regional convergence as well as divergence. Studies on India, for instance, suggest that Indian states had been converging in the pre-1990s, only to start diverging during the 1990s (Cashin and Sahay, 1996; Sachs et al., 2002; Kalra and Sodsriwiboon, 2010). For Peru itself, a recent study argues that while regions converged between 1979 and 2008, the process has been weakening over time, and may have ceased after 2000 (Delgado and del Pozo, 2011).

The failure to uniformly find convergence across different settings – whether across or within countries – has led to the idea that convergence holds true, but only after accounting for differences in policies and institutions. Such "conditional convergence" finds support in the data.[3]

A recently proposed hypothesis is that the potential for convergence varies across sectors. In a large sample covering more than 100 countries, Rodrik (2013) finds that output per worker in the manufacturing sector has been converging unconditionally. A similar result was found for US states during the 1963 to 1989 period: inter-state convergence performance varied across sectors, with manufacturing accounting for the bulk of convergence (Bernard and Jones, 1996). Rodrik (2013) suggests that manufacturing has greater scope for catch-up because manufactured goods are traded and can be

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[1] Technology should be interpreted broadly to include production processes, information technology, logistical processes, firm organization and management.

[2] Since lagging regions have higher returns to capital (if the assumption of diminishing return holds true), well-functioning financial markets should redirect capital from high labor productivity regions to low labor productivity regions, helping equalize their gap in capital per worker. Labor, on the other hand, would be attracted to the leading regions because of their higher wages. The flow of labor towards high labor productivity regions would also serve to reduce the regional differences in capital per worker.

[3] Evidence on conditional convergence is reviewed in Durlauf et al., 2005

integrated into global production chains.[4] Global integration provides a channel for technological diffusion, and also imposes competitive pressure on lagging firms.

Starting with this hypothesis, this study uses data at the department–sector level to examine regional labor productivity convergence in different sectors in Peru during 2002-2012. Our main findings are supportive of the idea that there is productivity convergence in sectors with greater scope for national and global integration. Specifically, we find that labor productivity, measured as value added per worker, has converged unconditionally across Peruvian departments within the secondary sector (especially in manufacturing) and the mining sector. Our estimated rate of convergence within manufacturing is comparable to the corresponding cross-country estimate from Rodrik (2013).

There is weak evidence of labor productivity convergence within services in Peru. Furthermore, for agriculture, the estimated rate of the unconditional convergence is relatively low, and not statistically significant.

We find that the convergence in labor productivity within manufacturing and mining has been sizable enough to lead to convergence in aggregate departmental labor productivity. But this aggregate convergence is slower than that in manufacturing alone. The reason for this is that services and agriculture – within which convergence is either non-existent, or weak at best – continue to employ the majority of workers in Peru. As we show, while there is labor outflow from agriculture during this period, the bulk of it is apparently directed towards the services sector. Thus, the secondary sector continues to account for a relatively small share of employment (around 17%). This sectorial pattern of labor allocation is even stronger in lagging regions.

Convergence in regional GDP per capita and poverty rates is also examined. There is some evidence for convergence in GDP per capita, but this is not robust. In a period where output per worker is converging across regions, the much weaker convergence in output per capita suggests different rates of change in the ratio of the employed population to total population across regions.

More intriguingly, we find that poverty rates are not converging across departments. Why, when labor productivity is converging, do we find no evidence for poverty convergence? The literature offers a possible explanation. Loayza and Raddatz (2010) argue that the composition of growth matters for poverty reduction. Their evidence suggests that growth coming from labor-intensive sectors (such as agriculture, construction, and manufacturing) is most supportive of poverty reduction. Hence, it could be that the relatively weak productivity convergence in agriculture, combined with the lack of labor outflow from agriculture, is hindering poverty convergence. This is consistent with our results that even after conditioning on the growth in output per worker, there is no poverty convergence.

The limited impact of convergence in labor productivity within manufacturing and mining on poverty convergence can be explained with limited labor reallocation towards manufacturing. While going into the reasons behind such slow labor reallocation is beyond the scope of this study, it is important to note that this finding links our study to the literature on "structural transformation". The starting point of this literature is the stylized fact that as countries develop, there is a movement of labor out of agriculture and into manufacturing and services (Herrendorf et al., 2013). Understanding how this process is playing

[4] Productivity in farming, mining and certain industries may depend, to a large extent, on location-specific factors such as climate and soil quality. In such sectors, it is not obvious that labor productivity should converge across regions.

out in Peru and what constrains it is critical for policy aimed at promoting regional productivity convergence.[5]

It would also be useful to understand the relative roles of technology diffusion (or more broadly, TFP catchup) and capital accumulation in the labor productivity convergence that we find in manufacturing and mining. Limitations in the regional data set prevent us from analyzing these mechanisms in more detail. A companion paper to this study uses firm-level data to show that within industries, Peruvian firms are converging to the domestic frontier in labor productivity, even after adjusting for changes in capital per worker (Iacovone et al, 2015). This suggests that TFP convergence accounts for some part of the regional convergence in labor productivity.

The rest of this paper is organized as follows. Section 2 describes the data and presents summary statistics for departments, including the levels and rates of change in poverty, labor productivity and the geographic concentration of different sectors. Section 3 specifies the methodology used for measuring convergence. Section 4 presents the results, and Section 5 discusses the link to the issue of structural transformation. Section 6 concludes with a discussion of key takeaways for policy discussion and future research.

2. Data and Descriptive Statistics

2.1 The Data

Our primary data source on regional output during 2002-2012 is the Regional Information System for Decision Making (SIRTOD) maintained by INEI, Peru's Statistics Agency. For this period, the database provides department-level data at yearly frequency.[6] We use SIRTOD data on Value Added and GDP by industry and department (expressed in year 1994 constant new soles), and population by department.

Because of gaps in the regional and industry level employment estimates in SIRTOD, we complete this data using the employment information – also at regional and industry levels – found in the National Household Survey (ENAHO). ENAHO is also our source for data on poverty rates by department. The poverty rate is the percentage of population living below a specified threshold of income.

The definitions of the key variables in our study are as follows:

1. Value Added per worker = $\text{Value Added}_{i,j} / \text{Total employment}_{i,j}$
2. GDP per capita = $\text{Value Added}_{i} / \text{Total population}_{i}$
3. Poverty level = $\text{Population below income threshold}_{i} / \text{Total population}_{i}$

Here,
$i = \text{Department},\ j = \text{Industry}$

[5] We discuss this in more detail in Section 5.

[6] Departments of Lima and Callao are grouped into one region (Lima-Callao), following the classification used by INEI in the initial years of the sample (early 2000s).

2.2 Descriptive statistics

Annex A contains summary tables of the department- and sector-level data. Tables A1-A3 present the levels and growth rates of labor productivity during 2002-2012, by sector and department. Table A4 shows the rates of poverty, by department. Tables A5-A6 present information on the spatial concentration of different sectors across departments. Table A7 presents some other relevant department-level information, such as whether the department contains a port, a mine and a city with population of 500,000 or more, and the percent population residing in urban areas.

Table A1 shows that in both 2002 and 2012, the top one-third of departments in terms of labor productivity were: Moquegua, Lima-Callao, Pasco, Tacna, Arequipa, Ancash, Ica and Madre de Dios. In general, these departments have high labor productivity across the board. That is, they are also ranked high in terms of labor productivity within each main sector (Tables A1-A3).

This correlation is the strongest for agriculture: for instance, the top ten most productive regions are also in the top ten in agricultural labor productivity, with one exception. This is not surprising given the large share of agriculture in employment. While departments which rank high in overall labor productivity do tend to rank high on labor productivity in manufacturing, mining and services too, there are more exceptions compared to agriculture. Ayacucho, Cusco, Huancavelica, Piura, Junín and Amazonas are examples of departments with above median productivity in the secondary or tertiary sectors, but not in overall productivity, in 2012.

Tables A1-A3 also show that with the exception of mining, 2002-2012 was a period of rising labor productivity in Peru. Overall labor productivity grew annually at a rate of 3.7 percent. It grew by 4.7 percent per annum in agriculture, 2.8 percent per annum in manufacturing, and 3.1 percent per annum in services. Notably, labor productivity did not rise faster in manufacturing.

In 2002, the eight departments with the highest poverty rates (that is, the bottom one-third in terms of poverty) were Huancavelica, Huánuco, Amazonas, Puno, Apurimac, Cajamarca, Ayacucho, and Ucayali (Table A4). Largely, the same departments also had the highest poverty rates in 2012.

In general, departments with high poverty rates have low overall labor productivity. But a high-poverty region is not necessarily unproductive in all sectors, particularly mining, secondary and tertiary sectors. Huancavelica, Huánuco, Amazonas and Ayacucho have some of the highest poverty rates but have above-median labor productivity in manufacturing, mining or services.

Tables A5 and A6 examine the spatial concentration of the secondary and tertiary sectors in 2002 and 2012, respectively, at the department level. The tables present a simple measure of the geographic concentration of a sector j in a department i. This measure, also known as a "Location Quotient" for the sector-department pair, is the share of department i in sector j's employment (denoted by s_{ij}) divided by the share of department i in total employment (denoted by x_i). Aggregating the location quotients for sector j across all departments using the formula $\sum (s_{ij} - x_i)^2$ yields an overall geographic concentration index for sector j. The index measures the degree to which the geographic pattern of employment in the industry departs from the geographic pattern of overall employment, with higher values indicating a relatively more concentrated distribution of that sector's employment across departments.

As seen in Tables A5-A6, employment in both the secondary and the tertiary sectors is spatially concentrated relative to overall employment. However, their trends in the geographic concentration of employment are dissimilar, with the manufacturing sector becoming more concentrated, and the service sector more dispersed across departments in the last decade.[7] The manufacturing sector's geographic concentration index was 232 in 2002, and it increased to 317 in 2012. The service sector's index fell from around 234 to 97; this increased spatial dispersion occurred in all sub-sectors of services.

Table A7 presents other departmental information such as urbanization rates. The most urbanized departments – those with at least 80% urban share in population or containing a city with a population above half a million – are Arequipa, Ica, Lambayeque, La Libertad, Lima-Callao, Moquegua, Piura, Tacna and Tumbes. Ucayali, at 79% urban population, is also quite urbanized. The least urbanized—those with majority rural population – are Amazonas, Apurimac, Cajamarca, Huancavelica, and Huánuco. In general, the more urban departments are also more likely to have a port. The existence of mines is less correlated with urbanization at the department levels.

The tables indicate a pattern of positive correlation between urbanization, share of population above the poverty line, and the spatial concentration of manufacturing and services. The five least urbanized departments were all among the eight departments with the highest poverty rates in 2002 and 2012. Departments where the service sector Location Quotient (LQ) are the highest – namely Arequipa, Ica, Lambayeque, Lima-Callao, Madre de Dios, Moquegua, Tacna, Tumbes and Ucayali – are also among the most urbanized departments. Similarly, in 2012 manufacturing sector employment was concentrated in Arequipa, Ica, La Libertad, and Lima-Callao – all relatively urbanized departments.

The spatial concentration of the manufacturing sector across departments is also strongly correlated with the existence of ports. This relationship is weaker in the services sector: Madre de Dios, Tacna, and Ucayali have high service sector concentration but no port.

Labor productivity in the secondary and tertiary sectors is also correlated with their spatial concentration, as well as departmental urbanization and share of population above the poverty line. But this relationship is weaker. We have already mentioned that some departments are relatively productive in mining, secondary or tertiary sectors while having a high poverty rate. Similarly, while most of the departments with above median labor productivity in manufacturing are also those where this sector is spatially concentrated, there are some exceptions. For instance, Ancash, Tacna, Junín, Loreto and Piura have relatively high labor productivity in manufacturing, but their LQs for manufacturing were less than one in 2012. The most productive departments for the service sector (in 2002 and 2012) were Lima-Callao, Tacna, Arequipa, Ancash, Ica, Lambayeque, Huancavelica, Moquegua, and Junín. Amazonas and Pasco also saw improvements in their service sector labor productivity. Of these, Ancash, Junín, Amazonas and Pasco do not have high LQs in services. Thus, high labor productivity does not necessarily imply spatial concentration in services.

[7] We choose departments as the units for this spatial analysis for reasons of comparability with the department-level convergence analysis. We should note that the patterns in Tables A5-A6 could be different if spatial concentration were to be measured at a different level of spatial aggregation. For instance, it is possible that even though services are becoming more dispersed across departments, they are increasingly concentrating in urban areas within departments.

3. Methodology

3.1 Convergence in Labor Productivity and GDP per capita

In the literature, the most commonly applied test for convergence is to examine whether regions which are further away from the frontier in labor productivity are growing faster, where growth is measured over a long period of time to iron out the effects of cyclical shocks.[8] This test captures the process of catching up. Our main econometric specification implements this test through OLS regressions on department and industry (or, sector) level data.

Measuring labor productivity as value added per worker, we estimate the following regression which measures the association between initial level of labor productivity $y_{ijt-\tau}$ in department *j* and sector *i* and its (annualized) growth rate (in logs) over 2002-2012 . A positive β implies that departments with lower levels of initial labor productivity grew faster, converging to leading regions.

$$\Delta y_{ijt} = \alpha - \beta \ln y_{ijt-\tau} + \varepsilon_{ijt} \qquad (1)$$

For each of the three broad sectors (primary, secondary and tertiary sectors), we first estimate a standard convergence regression in which the relationship between growth and initial values of labor productivity for the sector as a whole is estimated across the 24 departments. Next, we estimate "pooled" convergence regressions for sub-sectors (or, industries) within each of the three sectors. For instance, the primary sector is split into three industries: agriculture, fishing and mining. This regression should have 64 (24 times 3) observations.[9] The pooled regressions assume that the rate of convergence is common across industries within the same broad sector. Industry fixed effects are included to account for industry-specific trends and industry-specific frontier levels of labor productivity.[10] Department fixed effects control for fixed department characteristics that might have a common effect on growth rates across industries. Since department fixed effects absorb department-level differences in policies and institutions, regressions with those fixed effects may be interpreted as conditional convergence regressions. These regressions identify within-department, cross-industry convergence by exploiting the fact that the distance to the frontier productivity level varies across industries within the same department. Thus, the pooled regression specification is

[8] In the growth and convergence literature, this is known as the concept of beta convergence. Convergence also means that the cross-sectional dispersion in productivity should be falling over time. This is known as sigma convergence. Even if lagging regions are growing faster, new shocks can increase the cross-sectional dispersion in productivity. Hence, beta convergence does not necessarily imply sigma convergence.

[9] In practice, the number of observations can be lower because of missing sub-sector observations.

[10] This is to account for the fact that in the standard derivation of the convergence equation, it is not the absolute initial level of productivity that matters for the effect of convergence on growth rates but rather, its distance from the steady-state (or frontier) value. When the regression is estimated for a single industry group with common frontier values across departments, it does not matter whether one uses the absolute initial level of productivity or its gap from the common frontier. When the regression includes multiple industries in the same department, the industry fixed effects adjust for any differences in the frontier value across industries.

$$\Delta y_{ijt} = \alpha - \beta \ln y_{ijt-\tau} + D_i + D_j + \varepsilon_{ijt} \qquad (2)$$

where:

Δy_{ijt} is the annualized growth rate of *y*

D_i, D_j are fixed effects by department and industry

For *i* department, *j* industry and *t* time period.

We also estimate a less flexible form of the "conditional convergence" equation, controlling for initial poverty levels but not including fully-flexible department dummies. This specification allows us to examine the association between initial poverty levels and productivity growth, which is useful because while regions with lower productivity also tend to be poorer, the relationship is not exact:

$$\Delta y_{ijt} = \alpha - \beta \ln y_{ijt-\tau} + \delta \ln Pov_{it-\tau} + \varepsilon_{ijt} \qquad (3)$$

Where

$\ln y_{ijt-\tau}$ is the log of the initial level of *y*

$\ln Pov_{it-\tau}$ is the log of the initial poverty rate

Similarly, in order to examine convergence of departments' GDP per capita, we estimate regressions with the same specifications as those in (1) and (3) but using total value added per population (our measure of GDP per capita) instead of labor productivity.

Regressions with single observations per department show classical OLS standard errors.[11] Whenever regressions with multiple observations per department are estimated (such as the convergence regressions disaggregated by sectors), we present standard errors adjusted for clustering of errors within departments. This accounts for potential correlation of shocks within departments.

3.2 Poverty convergence

Following Ravallion (2012), in order to examine if Peru's departments are reducing their gaps in terms of poverty levels, we regress the rate of change in department poverty rates on its initial levels of poverty. We also test if the speed of convergence depends on the growth rate of labor productivity in the department by including an interaction of the initial poverty level with the latter.

Specifically, the following equations are estimated using OLS:

- For unconditional convergence in poverty

[11] These results are consistent with specifications that use robust standard errors.

$$\Delta Pov_{it} = \alpha - \beta \ln Pov_{it-\tau} + \varepsilon_{it} \qquad (4)$$

- For differential convergence based on productivity growth:

$$\Delta Pov_{it} = \alpha - \beta \ln Pov_{it-\tau} + \delta \Delta y_{it} + \gamma (\ln Pov_{it-\tau} \text{ x } \Delta y_{it}) + \varepsilon_{it} \qquad (5)$$

Where:

ΔPov_{it} is the annualized growth rate of poverty

$\ln Pov_{it-\tau}$ is the log of the initial level of poverty

Δy_{it} is the annualized growth rate of VA per capita

$(\ln Pov_{it-\tau} \text{ x } \Delta y_{it})$is an interaction between initial poverty and VA p.c. growth

For *i* department and *t* time period.

3.3 Additional robustness checks

We test the robustness of our results to the following: dropping departments which are outliers in terms of productivity levels; using additional human capital, access to finance and infrastructure variables as controls to further examine conditional convergence; and splitting our study period into two five-year period to test for convergence over the pooled sub-periods.[12] These additional results are presented in Annex C.[13] Our main findings, discussed in Section 4, are robust to all of these additional tests, unless specifically mentioned otherwise.

4. Results

4.1 Convergence in the Primary Sector, but driven by mining industry

Figure 1 depicts the relationship between the growth rate of labor productivity in the primary sector during 2002-2012 and its initial level across the department of Peru.[14] The negative slope of the relationship indicates that departments whose labor productivity in the primary sector was lagging grew faster, catching up with the leading regions.

[12] We include conditioning variables one by one, and not jointly. With only 24 departments, there are limited degrees of freedom. Moreover, the conditioning variables tend to be correlated. This analysis does not intend to pinpoint exactly which conditions matters, but rather, to test robustness of conditional convergence to alternative conditioning variables.

[13] Since results without productivity outliers are very similar to those with the full sample, we do not include them in Annex C. These regression tables as well as others with more detailed analyses by subsector are available upon request.

[14] Annex B lists the names of the departments and their abbreviations, as used in the figures presented in this paper.

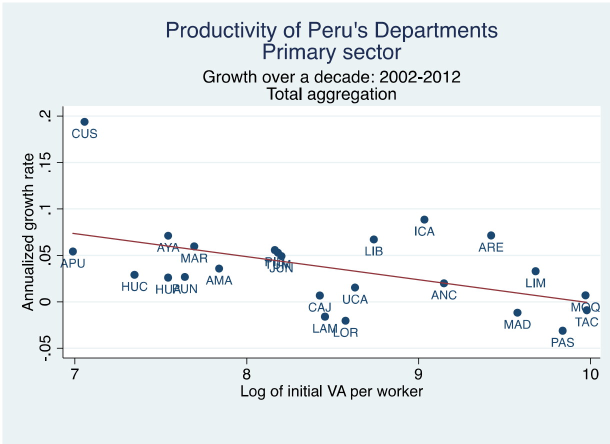

Figure 1: Initial labor productivity versus its growth rate in the primary sector

Table 1 presents the results from OLS estimation of the productivity convergence regressions for the primary sector. Column 1 aggregates all primary sub-sectors into one group and estimates the core unconditional convergence regression described in Equation (1). The (unconditional) convergence coefficient β is positive, with a value of 2.5%, and statistically significant.[15] This confirms that lagging departments have been growing faster over the study period. The estimate implies that the departments in the bottom 25% of productivity grew faster than the top 25% most productive departments by 5 percentage points per annum (that is, 2.5 times their difference in log of initial productivity, which is approximately 2.5 points).

Tables 1 and 2 present alternate specifications to demonstrate the robustness of this result. Columns 2-3 of **Table 1** estimate pooled convergence regressions after disaggregating the primary sector into agriculture + fishing (merged into one subsector) and mining, whereas Columns 4-5 repeat this after an even finer disaggregation into agriculture, fishing and mining (3 subsectors). The sectorial disaggregation permits us to condition on sub-sector and department fixed effects (shown in Columns 3 and 5). In **Table 2**, Columns 1-3 show results conditioning on initial poverty levels (as in Equation (3)). A notable pattern is that after conditioning on departmental poverty rates or fixed effects, convergence appears to be faster. This suggests that productivity convergence would have been even faster if departments were more "alike" – although it is not possible to pinpoint exactly which conditioning factors matter.

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[15] Recall that as defined in Equation (1), β is the negative of the coefficient on initial productivity.

Table 1: Labor productivity convergence regressions, Primary sector

	Primary sector							
	Total aggregation	Disaggregated by Agriculture + Fishing & Mining		Disaggregated by all sectors			Agriculture only	Mining only
	(1)	(2)	(3)	(4)	(5)		(6)	(7)
Dependent variable: Growth of VA per worker over a decade								
Log initial VA per worker	-0.025**	-0.030***	-0.050**	-0.030***	-0.056***		-0.008	-0.061***
	(0.009)	(0.006)	(0.022)	(0.006)	(0.016)		(0.011)	(0.016)
Constant	0.247***	0.296***		0.283***			0.102	0.649***
	(0.079)	(0.057)		(0.062)			(0.085)	(0.169)
Department FE	□	□	✓	□	✓	□	□	□
Industry FE	□	□	✓	□	✓	□	□	□
Observations	24	46	46	63	63		24	22
R-squared	0.246	0.296	0.714	0.227	0.584		0.025	0.437

Stardard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Labor productivity convergence regressions conditioning on initial poverty level, Primary sector

	Primary sector				
	Total aggregation	Disaggregated by Agriculture + Fishing & Mining	Disaggregated by all sectors	Agriculture only	Mining only
	(1)	(2)	(3)	(4)	(5)
Dependent variable: Growth of VA per worker over a decade					
Log initial VA per worker	-0.054***	-0.033***	-0.032***	-0.037***	-0.064***
	(0.010)	(0.006)	(0.007)	(0.012)	(0.015)
Log initial poverty level	-0.125***	-0.090**	-0.036	-0.097***	-0.122
	(0.032)	(0.035)	(0.040)	(0.029)	(0.074)
Constant	0.420***	0.274***	0.278***	0.276***	0.614***
	(0.076)	(0.051)	(0.061)	(0.087)	(0.164)
Observations	24	46	63	24	22
R-squared	0.565	0.364	0.236	0.363	0.508

Stardard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Upon further investigation, it is apparent that the unconditional convergence in the primary sector is driven by the mining industry. Figure 2 reveals that the relationship between the growth in labor productivity and its initial levels in agriculture has been essentially flat across Peru's departments.

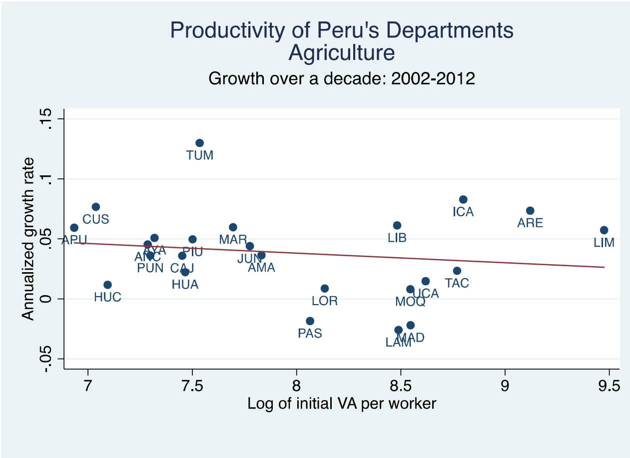

Figure 2: Initial labor productivity versus its growth rate in agriculture

This is confirmed through our regression analysis. **Table 1** presents convergence regressions estimated separately within agriculture (Column 6) and mining (Column 7). The mining sector has a high unconditional convergence coefficient of 6.1 percent, while the convergence coefficient for unconditional convergence in agriculture is statistically not significant.

There is some evidence of conditional convergence in agriculture. Controlling for initial poverty levels, there may have been convergence within agriculture (Column 4 of **Table 2**). Additional conditional convergence results presented in Annex C (Table C.8) are also suggestive of conditional convergence – specifically, conditional on measures of human capital and access to finance. If convergence in farm productivity is conditional on initial poverty rates or human capital levels, it cannot have been a driver of convergence in poverty across regions.

4.2 Convergence in manufacturing

Figure 3 shows that regions lagging behind in labor productivity in the secondary sector also grew the fastest during 2002-2012. The secondary sector employment in Peru is dominated by manufacturing industries. Hence, this result is very much in line with the cross-country finding by Rodrik (2013).

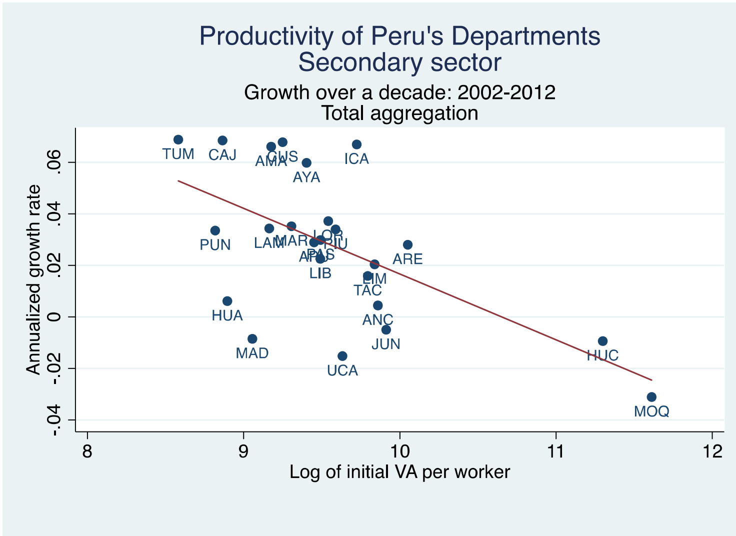

Figure 3: Initial labor productivity growth versus its growth rate in the secondary sector

Unconditional convergence in the secondary sector is confirmed by the regressions presented in Table 3. This table follows the same specification as Table 1 but it does so for the secondary sector. Column 1 presents convergence estimations for the aggregated secondary sector. Columns 2 and 4 present the same with data disaggregated into sub-sectors of manufacturing, water and electricity, and construction. In each case, the estimated convergence coefficient is positive and statistically significant. Also, convergence remains once controlling for initial poverty level (**Table 4**). However, as shown in Columns 4-5 of **Table 3** and Column 3 of **Table 4**, results are weaker for the most disaggregated specifications.

Table 3: Labor productivity convergence regressions, Secondary sector

	Secondary sector							
	Total aggregation	Disaggregated by Manufacturing & NonManufacturing		Disaggregated by all sectors			Manufacturing only	NonManuf. only
	(1)	(2)	(3)	(4)	(5)		(6)	(7)
Dependent variable: Growth of VA per worker over a decade								
Log initial VA per worker	-0.026***	-0.025***	-0.032	-0.018*	-0.035		-0.032***	-0.021*
	(0.007)	(0.006)	(0.019)	(0.010)	(0.030)		(0.007)	(0.010)
Constant	0.272***	0.262***		0.203**			0.326***	0.233**
	(0.068)	(0.058)		(0.097)			(0.062)	(0.100)
Department FE	□	□	✓	□	✓	□	□	□
Industry FE	□	□	✓	□	✓	□	□	□
Observations	24	48	48	72	72		24	24
R-squared	0.368	0.249	0.776	0.070	0.446		0.525	0.157

Stardard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Labor productivity convergence regressions conditioning on initial poverty level, Secondary sector

	Secondary sector				
	Total aggregation	Disaggregated by Manufacturing & NonManufacturing	Disaggregated by all sectors	Manufacturing only	NonManuf. only
	(1)	(2)	(3)	(4)	(5)
Dependent variable: Growth of VA per worker over a decade					
Log initial VA per worker	-0.026***	-0.026***	-0.017	-0.039***	-0.021*
	(0.008)	(0.006)	(0.011)	(0.007)	(0.011)
Log initial poverty level	-0.007	-0.011	0.016	-0.033*	-0.003
	(0.017)	(0.013)	(0.022)	(0.017)	(0.027)
Constant	0.275***	0.268***	0.201**	0.372***	0.233**
	(0.070)	(0.061)	(0.095)	(0.064)	(0.102)
Observations	24	48	72	24	24
R-squared	0.372	0.256	0.075	0.596	0.157

Stardard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

When we estimate separate regressions for manufacturing and non-manufacturing (the aggregation of water and electricity, and construction), we find some evidence that the convergence rate is higher within the group of manufacturing industries (3.2% versus 2.1%, Columns 6-7 of **Table 3**). The estimate implies that the departments in the bottom 25% of productivity in manufacturing grew faster than the top 25% most productive departments by 4.8 percentage points per annum (that is, 3.2 times their difference in log of initial productivity, which is approximately 1.5 points). **Table 4** shows very similar results once controlling for initial poverty. However, this point estimate of the manufacturing sector's convergence rate is sensitive to dropping outlier departments (Lima-Callao and Moquegua). The point estimate for manufacturing convergence drops to 2.3% after dropping these departments.

4.3 Absence of unconditional convergence in the tertiary sector

As shown in Figure 4, departments with low initial labor productivity in the tertiary sector did not experience faster growth in the same period. Indeed, this figure suggests that Peru's regions are diverging in terms of labor productivity in the tertiary sector.

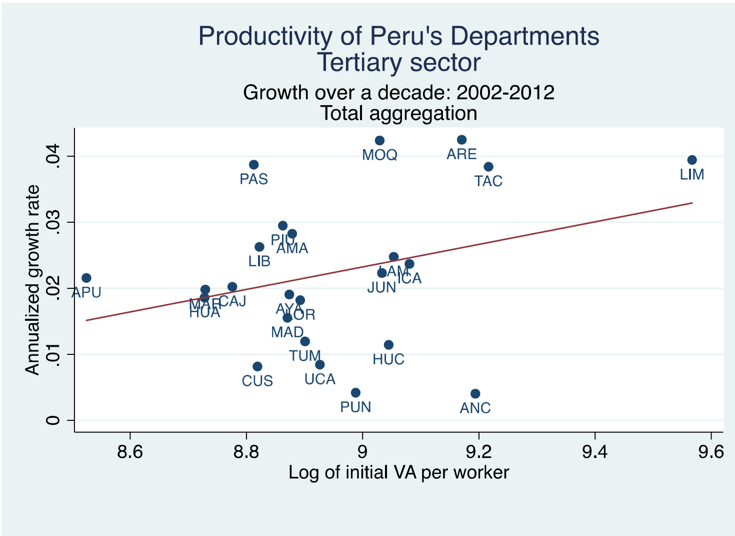

Figure 4: Initial labor productivity versus its growth rate in the tertiary sector

The regression analysis confirms this and shows that in the tertiary sector there is no statistically significant relationship between initial labor productivity and its subsequent growth; that is, there is no evidence for either convergence or divergence.

As seen in the first column of Table 5, for the tertiary sector as a whole, the convergence regression suggests that labor productivity has been diverging. But this is not robust to dropping the region of Lima-Callao, an outlier in terms of initial labor productivity and its growth rate. Columns 2-3 show sensitivity to disaggregating labor productivity by sub-sectors within the tertiary sector and estimating pooled convergence regressions.[16] When we estimate convergence regressions for each sub-sector individually, the restaurant and hotel industry shows evidence of convergence, while other sub-sectors are neither converging nor diverging.

Additional robustness checks presented in **Table 6** (conditioning for initial poverty levels) and Annex C confirm the absence of convergence. Notably, we do not find evidence of conditional convergence in the tertiary sector, no matter what the conditioning variable.

[16] The sub-sectors are commerce, hotels and restaurants, transport and communications, government services and a residual category of "other services".

Table 5: Labor productivity convergence regressions, Tertiary sector

	Tertiary sector		
	Total aggregation	Disaggregated by all sectors	
	(1)	(2)	(3)
Dependent variable: Growth of VA per worker over a decade			
Log initial VA per worker	0.017	0.005	-0.022***
	(0.011)	(0.004)	(0.008)
Constant	-0.130	-0.023	
	(0.101)	(0.036)	
Department FE	□	□	✓
Industry FE	□	□	✓
Observations	24	120	120
R-squared	0.094	0.008	0.686

Stardard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Labor productivity convergence regressions conditioning on initial poverty level, Tertiary sector

	Tertiary sector	
	Total aggregation	Disaggregated by all sectors
	(1)	(2)
Dependent variable: Growth of VA per worker over a decade		
Log initial VA per worker	-0.002	0.002
	(0.013)	(0.004)
Log initial poverty level	-0.021**	-0.024***
	(0.009)	(0.008)
Constant	0.024	-0.012
	(0.113)	(0.032)
Observations	24	120
R-squared	0.285	0.083

Stardard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

4.4 Convergence in overall labor productivity

We now combine the three broad sectors (primary, secondary and tertiary) and examine if regional labor productivity convergence within some industries (manufacturing and mining) has been sufficient for convergence in overall regional labor productivity. As Figure 5 suggests, this is indeed the case: department with lower levels of labor productivity in 2002, on average, experienced faster rates of growth.

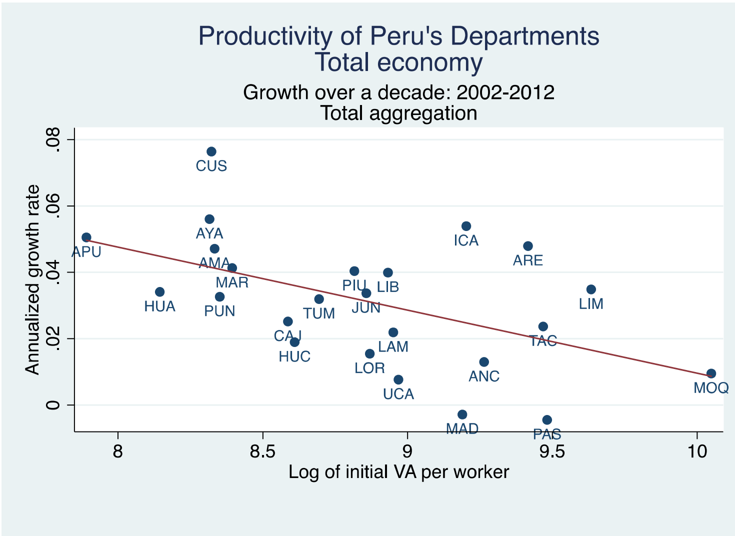

Figure 5: Relationship between initial labor productivity and its growth across Peru's departments

The results of our convergence regressions presented in **Table 7** confirm that initially lagging departments, in terms of labor productivity, have been catching up in the subsequent decade. This result is robust to estimating pooled convergence regressions for all sub-sectors of the economy and conditioning on department fixed effects and initial poverty levels (**Table 8**). The rate of convergence is 1.9 percent; this is slower than the one for either manufacturing or mining and is driven by the fact that labor productivity in other sub-sectors (i.e. agriculture, services) is not converging robustly. As shown earlier, while agriculture is converging, the rate is low, and statistically significant only in the conditional convergence specifications. In the tertiary sector, only the restaurant and hotels industry exhibits evidence of convergence.

Table 7: Labor productivity convergence regressions, All sectors

	Overall				
	Total aggregation	Disaggregated by Primary, Secondary & Tertiary		Disaggregated by all sectors	
	(1)	(2)	(3)	(4)	(5)
Dependent variable: Growth of VA per worker over a decade					
Log initial VA per worker	-0.019***	-0.019***	-0.030**	-0.020***	-0.048***
	(0.007)	(0.006)	(0.011)	(0.005)	(0.013)
Constant	0.199***	0.197***		0.201***	
	(0.060)	(0.057)		(0.049)	
Department FE	□	□	✓	□	✓
Industry FE	□	□	✓	□	✓
Observations	24	72	72	255	255
R-squared	0.266	0.215	0.792	0.106	0.386

Stardard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Labor productivity convergence regressions conditioning on initial poverty level, All sectors

	Overall		
	Total aggregation	Disaggregated by Primary, Secondary & Tertiary	Disaggregated by all sectors
	(1)	(2)	(3)
Dependent variable: Growth of VA per worker over a decade			
Log initial VA per worker	-0.040***	-0.023***	-0.020***
	(0.008)	(0.007)	(0.006)
Log initial poverty level	-0.051***	-0.031***	-0.014
	(0.014)	(0.011)	(0.012)
Constant	0.360***	0.220***	0.200***
	(0.066)	(0.060)	(0.049)
Observations	24	72	255
R-squared	0.541	0.283	0.110

Stardard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

4.5 Convergence in department GDP (value added) per capita

Value added per capita also appears to be converging across Peru's departments. Table 9 presents the regression results. The convergence in output per capita is not surprising in light of the convergence in output per worker. However, the estimated rate of convergence is lower, and less statistically significant. Also, this finding is sensitive to the choice of initial year (whether 2001 or 2002). How do we interpret this result? It is possible that changes in the ratio of the employed population to total population vary across departments in such a way as to increase the variance in output per capita growth rates and dampen the effect of the convergence in labor productivity. Specifically, our interpretation is that some of the regions experiencing a faster (resp., slower) increase in labor productivity are also experiencing a relative decline (resp., increase) in the ratio of the employed population to total population.

Table 9: Value added per capita convergence regressions

	(1)	(2)
Dependent variable: Growth of VA per capita over a decade		
Log initial VA per capita	-0.016**	-0.040***
	(0.007)	(0.009)
Log initial poverty level		-0.053***
		(0.015)
Constant	0.176***	0.334***
	(0.057)	(0.063)
Observations	24	24
R-squared	0.199	0.505

Stardard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

4.6 Persisting regional gap in poverty rates

As shown below in Figure 6: Relationship between initial poverty rate and its growth across departments, the last decade saw continued poverty reduction across Peru's department, with negative growth in the poverty rate in all departments. In most departments, the rate of poverty fell annually at a rate of around 5%. However, many of the departments with the highest initial poverty rates experienced the slowest rate of the decline in poverty. Accordingly, the regional gaps in poverty rates seem to be persisting.

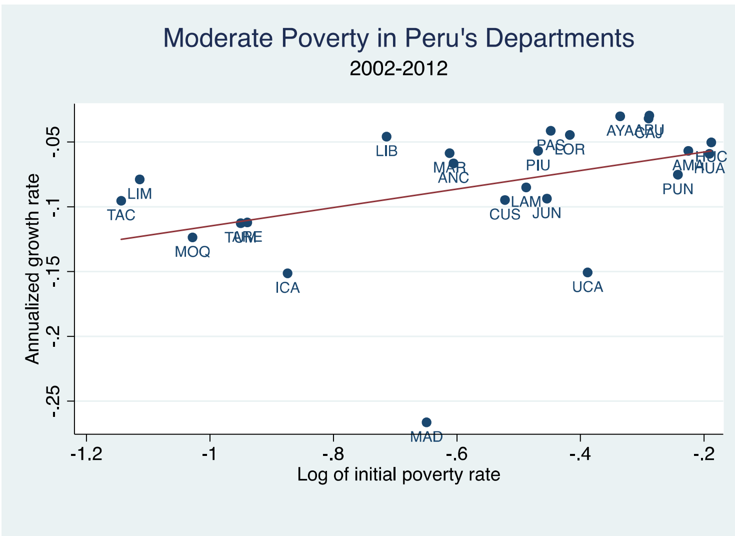

Figure 6: Relationship between initial poverty rate and its growth across departments

The lack of a catch-up in terms of poverty reduction is confirmed by the regression results reported in **Table 10**. If anything, the relationship between the initial rate of poverty and its subsequent growth rate across Peru's departments is positive.

This finding is at odds with the convergence in labor productivity, although there could be many explanations for this difference. One possibility is that even though low productivity regions are poorer on average, the relationship is not exact. This is consistent with the descriptive statistics presented in Section 2.2, where we noted that not all high poverty regions have low labor productivity in all sectors. Hence, there may be some regions with a large fraction of their populations below the poverty line, but with medium to high average labor productivity. As we have just seen, such regions have experienced relatively slow growth in labor productivity.

However, even this does not offer a full explanation for the absence of poverty convergence. If it were so, then conditional on initial poverty, departments with faster growth in labor productivity would have experienced faster poverty reductions. We examine this by including an interaction of the labor productivity growth rate and the initial poverty rate in the poverty convergence regressions, and find no evidence of a significant interaction effect (Column 2 in Table 10).

Table 10: Poverty convergence regressions

	(1)	(2)
Dependent variable: Growth of percentage of population living in poverty over a decade		
Log initial poverty level	0.072**	0.052
	(0.034)	(0.079)
VA per worker: Annualized gr. rate		0.108
		(2.550)
Log initial poverty level x VA per worker: Ann. gr. rate		1.075
		(4.227)
Constant	-0.043*	-0.078
	(0.022)	(0.049)
Observations	24	24
R-squared	0.167	0.245

Stardard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

A more likely reason for the persistence of the poverty gap between regions is related to the fact that not all industries are converging in labor productivity. It is possible that industries converging in labor productivity are less relevant to poverty reduction because they employ fewer low skilled workers, have weaker supply chain linkages to industries likely to employ low-skilled workers, and/or are less likely to produce goods that have a large share in the consumption basket of the poor. This would be in line with the findings of Loayza and Raddatz (2010) who argue that the composition of growth matters for poverty reduction. Their evidence suggests that growth coming from labor-intensive sectors (such as agriculture, construction, and manufacturing) is most supportive of poverty reduction. Hence, it could be that the relatively weak productivity convergence in agriculture and services is hindering poverty convergence.

5. Are workers moving into sectors that are catching up in labor productivity?

The impact of convergence in select sectors on convergence in overall labor productivity and poverty could, in potential, be higher if those sectors account for a growing share of employment. However, sectorial employment shares are shifting slowly, and not in a direction that particularly favors converging sectors. As seen in Figure 7, the tertiary sector – within which labor productivity has not been converging – as increased its share of total employment from around 52% to 58% between 2002 and 2012. The sector showing the most robust convergence – the secondary sector – has increased its share by a smaller amount, and it continues to have a small share of total employment (up from 14% to 17%). Meanwhile, the primary sector – another sector where there is convergence, especially in mining – has reduced its share in employment, offsetting the effect of the small rise in the secondary sector's share.

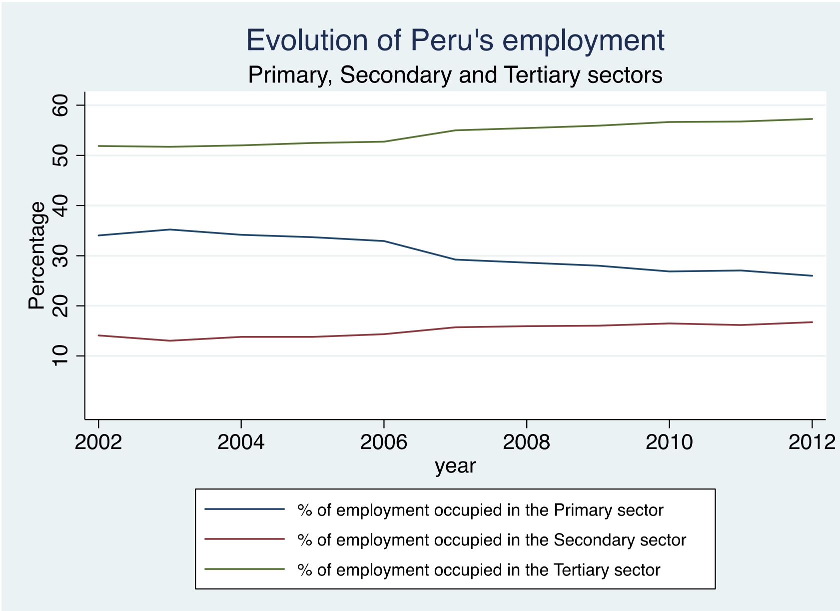

Figure 7: Employment shares by sector, all Peru

Even within the secondary sector, faster converging industries are growing slower in terms of employment share. As described in Section 4, convergence in labor productivity is notably faster in manufacturing, compared to other secondary sector industries such as construction, water and electricity. But it is the latter group that largely accounts for the rise in the share of the secondary sector in total employment.

Figure 8 compares sectorial employment shares across departments in the top and bottom half of the labor productivity distribution. Departments with low labor productivity tend to have more employment in the primary sector, and less in the secondary sector. While they are experiencing a faster shift in employment away from agriculture, this employment appears to be shifting to the tertiary sector. These patterns further dampen the potential impact of the convergence in manufacturing sector labor productivity.

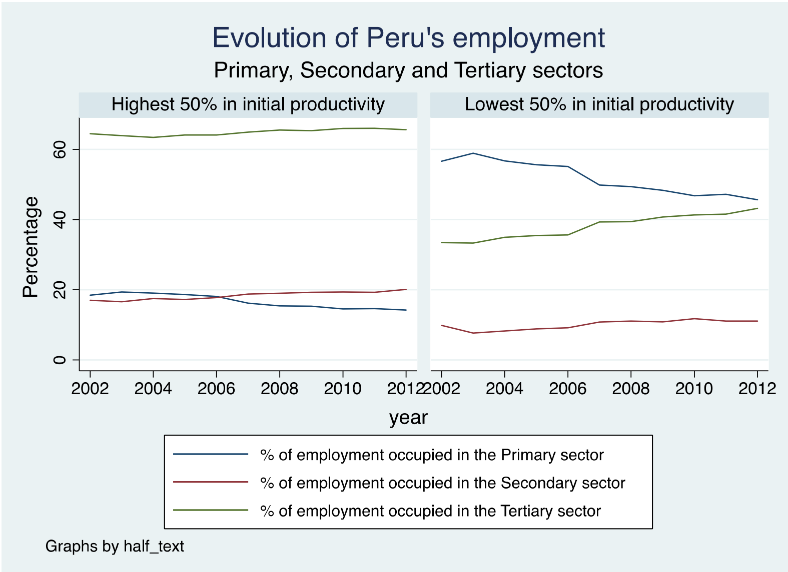

Figure 8: Employment shares across high and low productivity departments

Slow inter-sectorial labor reallocation could be limiting the impact of productivity convergence on poverty convergence. Evidence from the US, where convergence in regional incomes between the North and the South coincided with a narrowing of regional differences in the employment share in agriculture, supports this view (Caselli and Coleman, 2001).[17]

Investigating the reasons behind this slow reallocation is beyond the scope of this paper. Possible factors may be identified in the literature on structural transformation, which employs multi-sector growth models to examine the movement of labor out of agriculture and into manufacturing and services in the course of economic development (Herrendorf et al., 2013). This literature highlights the role of productivity and demand-related mechanisms. As agricultural productivity rises, it becomes possible to "release" workers from agriculture while still meeting the demand for food. Workers released from agriculture move into sectors where labor demand is rising, due to rising product demand or rising labor productivity.[18] As a country gets richer due to an overall rise in productivity, demand shifts in favor of services and manufacturing, also pulling workers out of agriculture.[19]

We note that the share of the tertiary and secondary sectors in employment is increasing in Peru (Figure 7), as broadly predicted by models of structural transformation. Further, the persistently low labor share

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[17] Caselli and Coleman (2001) explain that the South of the US had specialized in agriculture because of a comparative advantage in growing crops. With growing incomes, as demand and hence employment shifted towards manufacturing, and as inter-sectorial labor mobility barriers fell due to better education, the South was able to catch up with the North.

[18] The relationship between sectorial labor productivity and labor demand is not unidirectional, and depends on factors such as cross-elasticities of demand across sectors and tradability. Rising labor productivity should increase labor demand in tradable sectors. This relationship is more complicated in non-traded sectors.

[19] An *aggregate* (economy-wide) labor reallocation away from agriculture occurs, but not necessarily to the same extent within every region in a country. This is because of inter-regional trade and regional specialization. For instance, regions inherently advantaged in agriculture would continue to have a relatively larger proportion of employment (and value added) in agriculture.

of the manufacturing sector may, at first, seem to be at odds with the convergence of labor productivity in this sector, but the two patterns are not necessarily inconsistent. Multi-sector growth models show that it is productivity difference *across sectors* that matters to inter-sectorial labor reallocation, and not convergence within sectors. As discussed in Section 2.2, labor productivity may have grown faster in the service sector during the study period.

6. Conclusion

Our study reveals a positive trend of productivity convergence across the regions of Peru, and as such, suggests that regional gaps in incomes and poverty levels are falling over time. But as this convergence is largely driven by manufacturing and mining, it raises some interrelated research and policy questions about what is needed to improve the speed and sustainability of this process.

The majority of Peru's employment is in sectors within which labor productivity is not converging across regions. Manufacturing is a driver of convergence, but it still accounts for less than 20% of employment, and this share is even lower in lagging regions. Models of structural transformation could provide a useful framework for thinking about potential constraints to labor reallocation towards manufacturing. Broadly, such multi-sector models explain why policy makers should not look at sectors and markets in isolation. For example, to the extent that agricultural products are not traded, it is difficult to release labor from agriculture without raising agricultural productivity.

Moving more workers to manufacturing can only work up to a point. Can we use the lessons from manufacturing to think about productivity convergence in other sectors? More research is needed to understand this process. At best, we have some points of departure. Rodrik (2013) suggests that trade and contestability of markets promote convergence through competition and knowledge flows. Not surprisingly, Peru's manufacturing sector is concentrated in departments with ports. Thus, market integration in agriculture and services could help to expand the process of convergence beyond manufacturing and mining. But since many services are not tradable, this alone is probably not the answer. Policies to strengthen competition in the market for services and supply-side policies to promote technology diffusion could help.

Finally, we caution against using these findings as supportive of regional development policies that promote industrial location in less developed regions. This paper is about spatial patterns in productivity, and not in the size of different sectors. Economic geography suggests that due to agglomeration economies, some geographic concentration of industries may be optimal for productivity. Indeed, department-level spatial concentration in Peru's manufacturing sector seems to have increased during our study period, even as department-level productivity gaps are narrowing. Greater labor mobility across departments, together with greater spatial equity in the provision of social services such as health and education is also critical for spatial equity in the long run.

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ANNEX A: Summary Statistics and Other Descriptive Tables

Table A1: Labor Productivity in Peru (2002-2012), Main sectors

	Overall			Primary sector			Secondary sector			Tertiary sector		
	Levels		Annualized growth rate	Levels		Annualized growth rate	Levels		Annualized growth rate	Levels		Annualized growth rate
	2002	2012		2002	2012		2002	2012		2002	2012	
Department												
Apurímac	2,673	4,375	5.1	1,084	1,836	5.4	12,718	16,913	2.9	5,038	6,235	2.2
Huánuco	3,444	4,816	3.4	1,887	2,440	2.6	7,300	7,758	0.6	6,174	7,422	1.9
Ayacucho	4,089	7,053	5.6	1,887	3,752	7.1	12,123	21,663	6.0	7,143	8,627	1.9
Cusco	4,117	8,595	7.6	1,160	6,823	19.4	10,398	20,034	6.8	6,762	7,334	0.8
Amazonas	4,162	6,596	4.7	2,538	3,607	3.6	9,666	18,323	6.6	7,179	9,485	2.8
Puno	4,236	5,840	3.3	2,080	2,708	2.7	6,755	9,391	3.3	8,007	8,348	0.4
San Martín	4,422	6,627	4.1	2,196	3,920	6.0	11,005	15,548	3.5	6,181	7,521	2.0
Cajamarca	5,360	6,873	2.5	4,561	4,877	0.7	7,081	13,728	6.8	6,476	7,912	2.0
Huancavelica	5,487	6,620	1.9	1,552	2,066	2.9	80,749	73,450	-0.9	8,475	9,495	1.1
Tumbes	5,969	8,174	3.2	3,573	5,982	5.3	5,334	10,375	6.9	7,339	8,264	1.2
Piura	6,743	10,018	4.0	3,510	6,036	5.6	14,598	20,379	3.4	7,064	9,446	2.9
Junín	7,027	9,788	3.4	3,649	5,897	4.9	20,183	19,196	-0.5	8,378	10,446	2.2
Loreto	7,112	8,291	1.5	5,299	4,312	-2.0	13,926	20,057	3.7	7,278	8,716	1.8
La Libertad	7,573	11,201	4.0	6,246	11,956	6.7	13,240	16,541	2.3	6,785	8,793	2.6
Lambayeque	7,714	9,580	2.2	4,701	3,999	-1.6	9,548	13,377	3.4	8,549	10,917	2.5
Ucayali	7,852	8,476	0.8	5,598	6,519	1.5	15,254	13,084	-1.5	7,529	8,187	0.8
Madre de Dios	9,792	9,517	-0.3	14,404	12,801	-1.2	8,568	7,864	-0.9	7,120	8,306	1.6
Ica	9,925	16,780	5.4	8,385	19,574	8.8	16,713	31,937	6.7	8,783	11,100	2.4
Áncash	10,556	12,011	1.3	9,395	11,444	2.0	19,140	20,001	0.4	9,838	10,243	0.4
Arequipa	12,284	19,617	4.8	12,357	24,632	7.1	23,176	30,544	2.8	9,610	14,571	4.2
Tacna	12,944	16,356	2.4	21,558	19,676	-0.9	17,935	20,993	1.6	10,064	14,670	3.8
Pasco	13,121	12,546	-0.4	18,735	13,649	-3.1	13,259	17,789	3.0	6,720	9,824	3.9
Lima-Callao	15,277	21,519	3.5	16,009	22,136	3.3	18,740	22,933	2.0	14,286	21,030	3.9
Moquegua	23,131	25,426	1.0	21,402	22,928	0.7	110,416	80,482	-3.1	8,345	12,638	4.2
National level	**9,583**	**13,836**	**3.7**	**4,947**	**7,340**	**4.0**	**16,504**	**21,262**	**2.6**	**10,743**	**14,610**	**3.1**

Productivity is measured as Value added per worker in New Soles at 1994 prices.
Gray fill indicates values above the median.
Source: SIRTOD and ENAHO.

Table A2: Labor Productivity in Peru (2002-2012), Primary sector

	Overall			Primary sector			Agriculture			Mining		
	Levels		Annualized growth rate	Levels		Annualized growth rate	Levels		Annualized growth rate	Levels		Annualized growth rate
	2002	2012		2002	2012		2002	2012		2002	2012	
Department												
Apurímac	2,673	4,375	5.1	1,084	1,836	5.4	1,027	1,827	5.9	46,026	2,275	-26.0
Huánuco	3,444	4,816	3.4	1,887	2,440	2.6	1,747	2,177	2.2	47,357	30,972	-4.2
Ayacucho	4,089	7,053	5.6	1,887	3,752	7.1	1,508	2,475	5.1	32,413	71,203	8.2
Cusco	4,117	8,595	7.6	1,160	6,823	19.4	1,139	2,384	7.7	5,033	142,741	39.7
Amazonas	4,162	6,596	4.7	2,538	3,607	3.6	2,520	3,603	3.6	-	4,445	-
Puno	4,236	5,840	3.3	2,080	2,708	2.7	1,479	2,108	3.6	19,154	11,792	-4.7
San Martín	4,422	6,627	4.1	2,196	3,920	6.0	2,199	3,927	6.0	-	108	-
Cajamarca	5,360	6,873	2.5	4,561	4,877	0.7	1,723	2,451	3.6	359,437	77,905	-14.2
Huancavelica	5,487	6,620	1.9	1,552	2,066	2.9	1,205	1,354	1.2	24,200	26,167	0.8
Tumbes	5,969	8,174	3.2	3,573	5,982	5.3	1,874	6,356	13.0	1,226	14,002	27.6
Piura	6,743	10,018	4.0	3,510	6,036	5.6	1,811	2,939	5.0	135,320	47,251	-10.0
Junín	7,027	9,788	3.4	3,649	5,897	4.9	2,383	3,663	4.4	24,818	33,991	3.2
Loreto	7,112	8,291	1.5	5,299	4,312	-2.0	3,412	3,719	0.9	123,670	36,708	-11.4
La Libertad	7,573	11,201	4.0	6,246	11,956	6.7	4,827	8,744	6.1	107,921	53,273	-6.8
Lambayeque	7,714	9,580	2.2	4,701	3,999	-1.6	4,860	3,737	-2.6	-	21,661	-
Ucayali	7,852	8,476	0.8	5,598	6,519	1.5	5,535	6,406	1.5	19,701	16,939	-1.5
Madre de Dios	9,792	9,517	-0.3	14,404	12,801	-1.2	5,149	4,124	-2.2	45,571	47,195	0.4
Ica	9,925	16,780	5.4	8,385	19,574	8.8	6,630	14,695	8.3	24,862	80,864	12.5
Áncash	10,556	12,011	1.3	9,395	11,444	2.0	1,460	2,275	4.5	824,757	369,062	-7.7
Arequipa	12,284	19,617	4.8	12,357	24,632	7.1	9,139	18,582	7.4	74,468	49,776	-3.9
Tacna	12,944	16,356	2.4	21,558	19,676	-0.9	6,435	8,109	2.3	124,010	158,323	2.5
Pasco	13,121	12,546	-0.4	18,735	13,649	-3.1	3,180	2,640	-1.8	204,658	106,720	-6.3
Lima-Callao	15,277	21,519	3.5	16,009	22,136	3.3	13,026	22,726	5.7	124,105	18,447	-17.4
Moquegua	23,131	25,426	1.0	21,402	22,928	0.7	5,144	5,572	0.8	279,924	187,839	-3.9
National level	**9,583**	**13,836**	**3.7**	**4,947**	**7,340**	**4.0**	**2,912**	**4,629**	**4.7**	**98,822**	**55,320**	**-5.6**

Productivity is measured as Value added per worker in New Soles at 1994 prices.
Gray fill indicates values above the median.
Source: SIRTOD and ENAHO.

Table A3: Labor Productivity in Peru (2002-2012), Secondary sector

	Overall			Secondary sector			Manufacturing			Non-manufacturing		
	Levels		Annualized growth rate	Levels		Annualized growth rate	Levels		Annualized growth rate	Levels		Annualized growth rate
	2002	2012		2002	2012		2002	2012		2002	2012	
Department												
Apurímac	2,673	4,375	5.1	12,718	16,913	2.9	11,094	12,114	0.9	14,907	20,634	3.3
Huánuco	3,444	4,816	3.4	7,300	7,758	0.6	8,895	10,915	2.1	3,957	4,823	2.0
Ayacucho	4,089	7,053	5.6	12,123	21,663	6.0	11,950	13,747	1.4	12,415	28,782	8.8
Cusco	4,117	8,595	7.6	10,398	20,034	6.8	8,889	11,030	2.2	13,551	30,705	8.5
Amazonas	4,162	6,596	4.7	9,666	18,323	6.6	11,452	13,241	1.5	5,802	23,902	15.2
Puno	4,236	5,840	3.3	6,755	9,391	3.3	5,831	7,822	3.0	9,618	12,107	2.3
San Martín	4,422	6,627	4.1	11,005	15,548	3.5	12,722	18,793	4.0	8,779	12,449	3.6
Cajamarca	5,360	6,873	2.5	7,081	13,728	6.8	5,215	11,200	7.9	15,538	18,245	1.6
Huancavelica	5,487	6,620	1.9	80,749	73,450	-0.9	8,738	10,216	1.6	186,112	143,783	-2.5
Tumbes	5,969	8,174	3.2	5,334	10,375	6.9	4,361	6,891	4.7	6,527	13,594	7.6
Piura	6,743	10,018	4.0	14,598	20,379	3.4	14,112	22,051	4.6	16,073	18,073	1.2
Junín	7,027	9,788	3.4	20,183	19,196	-0.5	16,985	13,719	-2.1	26,501	28,046	0.6
Loreto	7,112	8,291	1.5	13,926	20,057	3.7	14,363	20,879	3.8	13,186	19,147	3.8
La Libertad	7,573	11,201	4.0	13,240	16,541	2.3	12,334	17,768	3.7	17,113	14,325	-1.8
Lambayeque	7,714	9,580	2.2	9,548	13,377	3.4	9,112	11,954	2.8	10,617	15,558	3.9
Ucayali	7,852	8,476	0.8	15,254	13,084	-1.5	13,616	10,555	-2.5	19,787	17,916	-1.0
Madre de Dios	9,792	9,517	-0.3	8,568	7,864	-0.9	9,904	10,901	1.0	6,537	5,591	-1.6
Ica	9,925	16,780	5.4	16,713	31,937	6.7	16,274	30,732	6.6	18,413	33,669	6.2
Áncash	10,556	12,011	1.3	19,140	20,001	0.4	18,131	18,145	0.0	21,087	22,623	0.7
Arequipa	12,284	19,617	4.8	23,176	30,544	2.8	24,508	26,634	0.8	20,879	36,529	5.8
Tacna	12,944	16,356	2.4	17,935	20,993	1.6	17,962	22,137	2.1	17,904	19,985	1.1
Pasco	13,121	12,546	-0.4	13,259	17,789	3.0	8,363	9,764	1.6	18,160	23,983	2.8
Lima-Callao	15,277	21,519	3.5	18,740	22,933	2.0	18,882	24,098	2.5	18,376	20,599	1.1
Moquegua	23,131	25,426	1.0	110,416	80,482	-3.1	199,958	81,731	-8.6	50,770	79,449	4.6
National level	**9,583**	**13,836**	**3.7**	**16,504**	**21,262**	**2.6**	**15,818**	**20,843**	**2.8**	**18,213**	**21,958**	**1.9**

Productivity is measured as Value added per worker in New Soles at 1994 prices.

Gray fill indicates values above the median.

Source: SIRTOD and ENAHO.

Table A4: Poverty Rates, 2002 and 2012

	Poverty		
	% of population		
	Levels		Annualized growth rate
	2002	**2012**	
Department			
Tacna	31.9	11.7	-9.5
Lima-Callao	32.8	14.4	-7.9
Moquegua	35.8	9.6	-12.4
Tumbes	38.7	11.7	-11.3
Arequipa	39.1	11.9	-11.2
Ica	41.7	8.1	-15.1
La Libertad	49.0	30.6	-4.6
Madre de Dios	52.2	2.4	-26.6
San Martín	54.2	29.6	-5.9
Áncash	54.6	27.4	-6.6
Cusco	59.3	21.9	-9.5
Lambayeque	61.4	25.2	-8.5
Piura	62.6	34.9	-5.7
Junín	63.5	23.7	-9.4
Pasco	63.9	41.9	-4.1
Loreto	65.9	41.8	-4.5
Ucayali	67.8	13.2	-15.1
Ayacucho	71.5	52.6	-3.0
Cajamarca	74.9	54.2	-3.2
Apurímac	74.9	55.5	-3.0
Puno	78.5	35.9	-7.5
Amazonas	79.8	44.5	-5.7
Huánuco	82.6	44.9	-5.9
Huancavelica	82.9	49.5	-5.0
National level	**52.3**	**25.8**	**-6.8**

Gray fill indicates values above the median.
Source: ENAHO.

Table A5: Spatial concentration indexes in the secondary and tertiary sectors, 2002

	Secondary sector				Overall tertiary sector	Tertiary sector				
	Manufacturing	Non-Manufacturing	Electricity & Water	Construction		Commerce	Restaurants & Hotels	Transport & Communication	Government services	Other services
Concentration index: s_{ij}/x_i										
Amazonas	0.39	0.45	1.07	0.39	0.51	0.50	0.58	0.50	0.75	0.28
Áncash	0.67	0.87	2.16	0.76	0.71	0.80	0.62	0.58	0.86	0.55
Apurímac	0.24	0.45	0.00	0.49	0.53	0.56	0.49	0.26	1.03	0.23
Arequipa	0.97	1.40	0.82	1.45	1.22	1.15	1.58	1.28	1.24	1.14
Ayacucho	0.40	0.60	0.21	0.63	0.56	0.59	0.47	0.48	0.92	0.31
Cajamarca	1.06	0.58	0.30	0.61	0.47	0.50	0.35	0.40	0.66	0.37
Cusco	0.71	0.84	0.30	0.89	0.68	0.64	0.64	0.69	0.84	0.63
Huancavelica	0.20	0.34	0.57	0.32	0.34	0.39	0.40	0.10	0.54	0.20
Huánuco	0.39	0.46	0.37	0.47	0.56	0.65	0.50	0.57	0.69	0.35
Ica	1.25	0.80	1.03	0.78	1.08	1.27	0.84	1.32	0.99	0.89
Junín	0.61	0.76	1.65	0.69	0.76	0.91	0.79	0.78	0.73	0.56
La Libertad	1.23	0.72	0.00	0.78	0.94	1.10	0.84	0.96	0.80	0.87
Lambayeque	1.06	1.08	0.71	1.11	1.14	1.40	0.64	1.30	1.10	0.97
Lima and Callao	1.45	1.41	1.21	1.43	1.44	1.30	1.51	1.44	1.23	1.77
Loreto	0.59	0.87	3.19	0.67	0.97	1.11	0.90	0.68	1.25	0.70
Madre de Dios	0.50	0.82	1.30	0.78	1.09	1.06	1.42	1.51	1.29	0.63
Moquegua	0.40	1.49	1.93	1.45	1.06	0.85	0.95	1.44	1.46	0.87
Pasco	0.41	1.01	1.98	0.93	0.83	0.94	0.94	0.52	1.05	0.57
Piura	0.98	0.80	1.40	0.75	0.97	1.07	0.96	0.91	0.94	0.88
Puno	0.89	0.71	0.49	0.73	0.52	0.53	0.60	0.61	0.65	0.34
San Martín	0.47	0.90	0.42	0.94	0.72	0.68	0.71	0.72	0.87	0.65
Tacna	0.63	1.37	1.75	1.34	1.37	1.37	1.68	1.31	1.57	1.11
Tumbes	0.80	1.62	0.70	1.70	1.09	1.12	0.75	1.29	1.27	0.96
Ucayali	0.89	0.80	1.19	0.77	1.07	1.12	1.14	1.61	1.05	0.76
Overall concentration index: $\Sigma(s_{ij} - x_i)^2$										
	232.48	**194.56**	**209.62**	**210.48**	**223.69**	**119.03**	**310.45**	**236.71**	**69.05**	**654.52**

i = Department; *j* = Substector of industry

s_{ij} = 100*(Employment$_{ij}$/Employment$_j$)

x_i = 100*(Total employment$_i$/Total employment)

Gray fill indicates indexes with values above 1.

Note: Concentration indexes with respect to total overall employment.

Source: ENAHO.

Table A6: Spatial concentration indices in the secondary and tertiary sectors, 2012

Source: ENAHO

	Secondary sector				Overall tertiary sector	Tertiary sector				
	Manufacturing	**Non-Manufacturing**	**Electricity & Water**	**Construction**		**Commerce**	**Restaurants & Hotels**	**Transport & Communication**	**Government services**	**Other services**
Concentration index: s_{ij}/x_i										
Amazonas	0.40	0.61	0.50	0.61	0.54	0.49	0.59	0.50	0.76	0.37
Áncash	0.77	0.91	0.33	0.95	0.89	0.94	1.01	0.89	1.00	0.64
Apurímac	0.28	0.60	0.62	0.60	0.61	0.65	0.67	0.38	0.90	0.34
Arequipa	1.22	1.32	2.26	1.26	1.09	1.02	1.24	1.16	1.18	0.96
Ayacucho	0.38	0.70	0.56	0.71	0.65	0.67	0.83	0.55	0.83	0.38
Cajamarca	0.66	0.61	0.39	0.63	0.60	0.65	0.40	0.53	0.88	0.38
Cusco	0.59	0.83	0.38	0.86	0.88	0.89	0.99	0.54	1.30	0.58
Huancavelica	0.19	0.28	0.00	0.30	0.45	0.52	0.48	0.21	0.65	0.25
Huánuco	0.41	0.73	0.51	0.75	0.67	0.63	0.79	0.73	0.80	0.47
Ica	1.06	1.22	1.21	1.22	1.05	1.16	1.08	1.21	0.95	0.86
Junín	0.75	0.77	0.75	0.77	0.84	0.87	0.96	0.69	0.78	0.91
La Libertad	1.23	1.13	1.58	1.10	0.92	0.92	1.06	0.91	0.72	1.08
Lambayeque	0.86	0.94	1.05	0.93	1.06	1.20	1.09	1.35	0.85	0.82
Lima and Callao	1.49	1.24	1.26	1.24	1.27	1.18	1.12	1.33	1.13	1.60
Loreto	0.47	0.70	0.42	0.72	1.00	1.00	1.27	1.03	1.03	0.78
Madre de Dios	0.39	0.86	0.51	0.88	1.09	1.01	1.58	1.05	1.21	0.87
Moquegua	0.63	1.27	1.24	1.27	1.00	0.74	0.98	0.71	1.67	0.90
Pasco	0.44	0.95	0.74	0.96	0.70	0.75	0.57	0.61	0.94	0.51
Piura	0.82	0.98	0.87	0.99	0.96	1.11	1.09	0.90	0.80	0.84
Puno	0.80	0.77	0.70	0.77	0.70	0.91	0.60	0.62	0.80	0.35
San Martín	0.45	0.78	1.30	0.75	0.77	0.79	0.76	0.65	1.02	0.56
Tacna	0.64	1.20	1.32	1.19	1.22	1.23	1.27	1.22	1.63	0.77
Tumbes	0.57	1.02	0.95	1.03	1.26	1.24	1.41	1.85	1.22	0.88
Ucayali	0.92	0.80	0.74	0.80	1.04	1.06	1.42	1.29	0.94	0.76
Overall concentration index: $\Sigma(s_{ij} - x_i)^2$										
	316.76	**81.03**	**159.44**	**78.43**	**96.88**	**47.71**	**36.19**	**150.99**	**31.30**	**466.31**

i = Department; *j* = Substector of industry

s_{ij} = 100*(Employment$_{ij}$/Employment$_j$)

x_i = 100*(Total employment$_i$/Total employment)

Gray fill indicates indexes with values above 1.

Note: Concentration indexes with respect to total overall employment.

Source: ENAHO.

Table A7: Regions of Peru that have ports, mines and medium/large cities

	Port	Mine	Cities over 500,000 inhabitants	% of urban population (est. 2015)
Amazonas				45
Ancash	✓	✓	□	61
Apurimac	□	✓	□	40
Arequipa	✓	✓	✓	90
Ayacucho	□	✓	□	54
Cajamarca	□	✓	□	35
Cusco	□	✓	□	56
Huancavelica	□	✓	□	23
Huanuco	□	✓	□	39
Ica	✓	✓	□	92
Junin	□	✓	□	66
La Libertad	✓	□	✓	78
Lambayeque	✓	✓	✓	82
Lima-Callao	✓	✓	✓	98
Loreto	✓	□	□	67
Madre de Dios	□	□	□	79
Moquegua	✓	✓	□	80
Pasco	□	✓	□	65
Piura	✓	✓	✓	77
Puno	□	✓	□	54
San Martín	□	□	□	65
Tacna	□	✓	□	87
Tumbes	✓	□	□	95
Ucayali	□	□	□	79

Sources: Information on ports and population: INEI; on mining: Ernst & Young, "Peru's mining & metals investment guide 2014-2015".

ANNEX B: List of Departments and their abbreviations

Department	Abbreviation	Department	Abbreviation
Amazonas	AMA	Lambayeque	LAM
Ancash	ANC	Lima-Callao	LIM
Apurimac	APU	Loreto	LOR
Arequipa	ARE	Madre de Dios	MAD
Ayacucho	AYA	Moquegua	MOQ
Cajamarca	CAJ	Pasco	PAS
Cusco	CUS	Piura	PIU
Huancavelica	HUC	Puno	PUN
Huanuco	HUA	San Martin	MAR
Ica	ICA	Tacna	TAC
Junin	JUN	Tumbes	TUM
La Libertad	LIB	Ucayali	UCA

ANNEX C: Results from additional specifications

Table C.1. Five-year specifications: Labor productivity convergence regressions, Primary sector

	Primary sector							
	Total aggregation	Disaggregated by Agriculture + Fishing & Mining		Disaggregated by all sectors			Agriculture only	Mining only
	(1)	(2)	(3)	(4)	(5)		(6)	(7)
Dependent variable: Growth of VA per worker over a decade								
Log initial VA per worker	-0.022**	-0.027***	-0.049	-0.027***	-0.056***		-0.004	-0.054***
	(0.008)	(0.006)	(0.029)	(0.006)	(0.018)		(0.010)	(0.017)
Constant	0.223***	0.271***		0.246***			0.073	0.575***
	(0.071)	(0.057)		(0.061)			(0.083)	(0.184)
Department FE	□	□	✓	□	✓	□	□	□
Industry FE	□	□	✓	□	✓	□	□	□
Observations	48	93	93	130	130		48	45
R-squared	0.131	0.128	0.398	0.083	0.321		0.004	0.19

Stardard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Table C.2. Five-year specifications: Labor productivity convergence regressions, Secondary sector

	Secondary sector							
	Total aggregation	Disaggregated by Manufacturing & NonManufacturing		Disaggregated by all sectors			Manufacturing only	NonManuf. only
	(1)	(2)	(3)	(4)	(5)		(6)	(7)
Dependent variable: Growth of VA per worker over a decade								
Log initial VA per worker	-0.027***	-0.030***	-0.059**	-0.029**	-0.104**		-0.036***	-0.030**
	(0.009)	(0.007)	(0.028)	(0.011)	(0.050)		(0.009)	(0.014)
Constant	0.283***	0.318***		0.328***			0.365***	0.327**
	(0.086)	(0.073)		(0.106)			(0.082)	(0.135)
Department FE	□	□	✓	□	✓	□	□	□
Industry FE	□	□	✓	□	✓	□	□	□
Observations	48	96	96	143	143		48	48
R-squared	0.161	0.122	0.423	0.052	0.285		0.281	0.093

Stardard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Table C.3. Five-year specifications: Labor productivity convergence regressions, Tertiary sector

	Tertiary sector		
	Total aggregation	Disaggregated by all sectors	
	(1)	(2)	(3)
Dependent variable: Growth of VA per worker over a decade			
Log initial VA per worker	0.019	0.000	-0.048***
	(0.014)	(0.004)	(0.010)
Constant	-0.149	0.023	
	(0.123)	(0.035)	
Department FE	□	□	✓
Industry FE	□	□	✓
Observations	48	240	240
R-squared	0.041	0	0.352

Stardard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Table C.4. Five-year specifications: Labor productivity convergence regressions, All sectors

	Overall				
	Total aggregation	Disaggregated by Primary, Secondary & Tertiary		Disaggregated by all sectors	
	(1)	(2)	(3)	(4)	(5)
Dependent variable: Growth of VA per worker over a decade					
Log initial VA per worker	-0.016**	-0.017***	-0.031***	-0.019***	-0.061***
	(0.007)	(0.006)	(0.010)	(0.005)	(0.015)
Constant	0.176***	0.186***		0.200***	
	(0.060)	(0.054)		(0.047)	
Department FE	□	□	✓	□	✓
Industry FE	□	□	✓	□	✓
Observations	48	144	144	513	513
R-squared	0.111	0.104	0.572	0.039	0.212

Stardard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Table C.5. Five-year specifications: Value added per capita convergence regressions

	(1)	(2)
Dependent variable: Growth of VA per capita over a decade		
Log initial VA per capita	-0.014**	- 0.024***
	(0.006)	(0.008)
Log initial poverty level		-0.017*
		(0.009)
Constant	0.156***	0.230***
	(0.046)	(0.058)
Observations	48	48
R-squared	0.113	0.184

Stardard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Table C.6. Five-year specifications: Poverty convergence regressions

	(1)	(2)
Dependent variable: Growth of percentage of population living in poverty over a decade		
Log initial poverty level	0.064***	0.109***
	(0.017)	(0.024)
VA per worker: Annualized gr. rate		2.576***
		(0.856)
Log initial poverty level x VA per worker: Ann. gr. rate		-3.610**
		(1.573)
Constant	-0.035**	-0.025
	(0.015)	(0.020)
Observations	48	48
R-squared	0.245	0.407

Stardard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Table C.7. Specifications with additional control variables: Labor productivity convergence regressions, Primary sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Human capital					Access to finance	Government	Infrastructure				Health
Control variables	Avg. years of schooling	Working-age population	Working-age pop. w/ elementary education	Working-age pop. w/ non-university higher education	Working-age pop. w/ university higher education	Bank deposits per capita	Tax collected per capita	Electric capacity per capita	HHs w/ access to water network	HHs w/ access to electricity network	HHs w/ landline telephone	HHs affiliated to a public health institution
Level	% of pop. 15 yrs and older	% of tot. pop.	% of working-age pop.	% of working-age pop.	% of working-age pop.	New soles in logs	New soles in logs	Log of MW/pop.	% of total HHs	% of total HHs	% of total HHs	% of total HHs
Dependent variable: Growth of VA per worker over a decade												
Primary sector: Total aggregation												
Log initial VA per worker	-0.048***	-0.039***	-0.048***	-0.043***	-0.044***	-0.051***	-0.047***	-0.026**	-0.036***	-0.042***	-0.040***	-0.057***
	(0.010)	(0.010)	(0.012)	(0.011)	(0.009)	(0.011)	(0.010)	(0.010)	(0.009)	(0.011)	(0.010)	(0.013)
Initial value of control var	0.034***	0.006**	-0.002**	0.009**	0.007***	0.033***	0.025***	0.002	0.002***	0.001**	0.003**	0.006***
	(0.011)	(0.002)	(0.001)	(0.004)	(0.002)	(0.010)	(0.008)	(0.007)	(0.000)	(0.001)	(0.001)	(0.002)
Constant	0.142*	-0.035	0.540***	0.315***	0.357***	0.509***	0.326***	0.279**	0.253***	0.318***	0.344***	0.420***
	(0.073)	(0.130)	(0.129)	(0.075)	(0.071)	(0.102)	(0.070)	(0.129)	(0.067)	(0.077)	(0.082)	(0.085)
Observations	24	24	24	24	24	24	24	24	24	24	24	24
R-squared	0.501	0.428	0.440	0.426	0.528	0.508	0.497	0.250	0.478	0.412	0.411	0.495
Primary sector: Disaggregated by Agriculture + Fishing & Mining												
Log initial VA per worker	-0.033***	-0.032***	-0.033***	-0.032***	-0.033***	-0.033***	-0.033***	-0.031***	-0.032***	-0.032***	-0.032***	-0.033***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Initial value of control var	0.024**	0.005**	-0.002**	0.006	0.005**	0.018	0.014	0.006	0.001**	0.001*	0.001	0.003
	(0.010)	(0.002)	(0.001)	(0.005)	(0.003)	(0.013)	(0.010)	(0.009)	(0.000)	(0.000)	(0.001)	(0.002)
Constant	0.111	-0.028	0.391***	0.261***	0.281***	0.346***	0.260***	0.360***	0.256***	0.259***	0.296***	0.274***
	(0.089)	(0.137)	(0.075)	(0.068)	(0.056)	(0.070)	(0.062)	(0.122)	(0.055)	(0.052)	(0.058)	(0.059)
Observations	46	46	46	46	46	46	46	46	46	46	46	46
R-squared	0.340	0.335	0.341	0.320	0.339	0.325	0.322	0.302	0.317	0.322	0.306	0.325
Primary sector: Disaggregated by all sectors												
Log initial VA per worker	-0.032***	-0.032***	-0.032***	-0.032***	-0.032***	-0.033***	-0.033***	-0.031***	-0.031***	-0.031***	-0.032***	-0.031***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)
Initial value of control var	0.012	0.003	-0.001	0.004	0.003	0.013	0.010	0.003	0.000	0.000	0.001	0.001
	(0.009)	(0.002)	(0.001)	(0.004)	(0.002)	(0.008)	(0.007)	(0.008)	(0.001)	(0.000)	(0.001)	(0.002)
Constant	0.194**	0.084	0.323***	0.264***	0.278***	0.322***	0.257***	0.309***	0.271***	0.271***	0.284***	0.278***
	(0.078)	(0.126)	(0.084)	(0.066)	(0.061)	(0.076)	(0.060)	(0.108)	(0.065)	(0.059)	(0.064)	(0.062)
Observations	63	63	63	63	63	63	63	63	63	63	63	63
R-squared	0.236	0.240	0.233	0.235	0.236	0.240	0.239	0.228	0.230	0.230	0.232	0.229

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table C.8. Specifications with additional control variables: Labor productivity convergence regressions, Agriculture and Mining

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Human capital					Access to finance	Government	Infrastructure				Health
Control variables	Avg. years of schooling	Working-age population	Working-age pop. w/ elementary education	Working-age pop. w/ non-university higher education	Working-age pop. w/ university higher education	Bank deposits per capita	Tax collected per capita	Electric capacity per capita	HHs w/ access to water network	HHs w/ access to electricity network	HHs w/ landline telephone	HHs affiliated to a public health institution
Level	% of pop. 15 yrs and older	% of tot. pop.	% of working-age pop.	% of working-age pop.	% of working-age pop.	New soles in logs	New soles in logs	Log of MW/pop.	% of total HHs	% of total HHs	% of total HHs	% of total HHs
Dependent variable: Growth of VA per worker over a decade												
Agriculture only												
Log initial VA per worker	-0.035**	-0.029**	-0.035**	-0.037**	-0.026*	-0.030*	-0.036**	-0.007	-0.015	-0.027*	-0.037**	-0.030*
	(0.014)	(0.012)	(0.016)	(0.013)	(0.013)	(0.015)	(0.016)	(0.011)	(0.011)	(0.014)	(0.015)	(0.017)
Initial value of control var	0.028**	0.006**	-0.002**	0.010***	0.005**	0.020*	0.021**	-0.002	0.001*	0.001*	0.003**	0.003
	(0.011)	(0.002)	(0.001)	(0.003)	(0.002)	(0.011)	(0.009)	(0.006)	(0.000)	(0.000)	(0.001)	(0.002)
Constant	0.075	-0.131	0.399**	0.242**	0.208**	0.302**	0.237**	0.077	0.107	0.195**	0.294**	0.229*
	(0.077)	(0.112)	(0.163)	(0.086)	(0.093)	(0.134)	(0.098)	(0.117)	(0.080)	(0.093)	(0.107)	(0.112)
Observations	24	24	24	24	24	24	24	24	24	24	24	24
R-squared	0.253	0.290	0.193	0.324	0.200	0.165	0.219	0.030	0.177	0.178	0.256	0.137
Mining only												
Log initial VA per worker	-0.063***	-0.062***	-0.062***	-0.062***	-0.065***	-0.068***	-0.066***	-0.065***	-0.065***	-0.062***	-0.063***	-0.066***
	(0.015)	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Initial value of control var	0.029	0.006	-0.002	0.004	0.007	0.029	0.020	0.019	0.001	0.001	0.001	0.005
	(0.025)	(0.006)	(0.002)	(0.009)	(0.006)	(0.024)	(0.019)	(0.018)	(0.001)	(0.001)	(0.003)	(0.004)
Constant	0.415	0.286	0.753***	0.617***	0.636***	0.756***	0.618***	0.859***	0.607***	0.603***	0.654***	0.628***
	(0.263)	(0.411)	(0.188)	(0.183)	(0.166)	(0.188)	(0.172)	(0.261)	(0.174)	(0.182)	(0.174)	(0.168)
Observations	22	22	22	22	22	22	22	22	22	22	22	22
R-squared	0.474	0.464	0.477	0.445	0.484	0.479	0.466	0.468	0.466	0.454	0.441	0.477

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table C.9. Specifications with additional control variables: Labor productivity convergence regressions, Secondary sector

	Human capital					Access to finance	Government	Infrastructure				Health
Control variables	Avg. years of schooling	Working-age population	Working-age pop. w/ elementary education	Working-age pop. w/ non-university higher education	Working-age pop. w/ university higher education	Bank deposits per capita	Tax collected per capita	Electric capacity per capita	HHs w/ access to water network	HHs w/ access to electricity network	HHs w/ landline telephone	HHs affiliated to a public health institution
Level	% of pop. 15 yrs and older	% of tot. pop.	% of working-age pop.	% of working-age pop.	% of working-age pop.	New soles in logs	New soles in logs	Log of MW/pop.	% of total HHs	% of total HHs	% of total HHs	% of total HHs
Dependent variable: Growth of VA per worker over a decade												
Secondary sector: Total aggregation												
Log initial VA per worker	-0.025***	-0.026***	-0.025***	-0.025***	-0.026***	-0.025***	-0.025***	-0.019	-0.027***	-0.025***	-0.025***	-0.028***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.011)	(0.007)	(0.007)	(0.007)	(0.008)
Initial value of control var	-0.001	-0.000	0.000	-0.001	0.001	-0.001	-0.002	-0.005	0.000	-0.000	-0.000	0.001
	(0.006)	(0.001)	(0.000)	(0.002)	(0.001)	(0.005)	(0.004)	(0.006)	(0.000)	(0.000)	(0.001)	(0.001)
Constant	0.275***	0.280**	0.256***	0.269***	0.275***	0.267***	0.274***	0.161	0.274***	0.272***	0.271***	0.282***
	(0.078)	(0.110)	(0.075)	(0.070)	(0.070)	(0.072)	(0.070)	(0.153)	(0.069)	(0.070)	(0.070)	(0.069)
Observations	24	24	24	24	24	24	24	24	24	24	24	24
R-squared	0.368	0.368	0.376	0.372	0.377	0.370	0.373	0.387	0.388	0.376	0.368	0.396
Secondary sector: Disaggregated by Manufacturing & NonManufacturing												
Log initial VA per worker	-0.025***	-0.025***	-0.024***	-0.025***	-0.026***	-0.025***	-0.024***	-0.021**	-0.027***	-0.024***	-0.025***	-0.028***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.008)	(0.007)	(0.006)	(0.006)	(0.007)
Initial value of control var	0.001	0.001	0.000	0.000	0.001	-0.000	-0.001	-0.004	0.000	-0.000	0.000	0.001
	(0.005)	(0.001)	(0.000)	(0.002)	(0.001)	(0.003)	(0.003)	(0.004)	(0.000)	(0.000)	(0.000)	(0.001)
Constant	0.259***	0.220***	0.255***	0.262***	0.266***	0.261***	0.263***	0.189*	0.265***	0.262***	0.263***	0.274***
	(0.075)	(0.072)	(0.057)	(0.059)	(0.058)	(0.052)	(0.059)	(0.104)	(0.063)	(0.058)	(0.057)	(0.068)
Observations	48	48	48	48	48	48	48	48	48	48	48	48
R-squared	0.250	0.254	0.250	0.249	0.256	0.249	0.251	0.259	0.267	0.250	0.250	0.283
Secondary sector: Disaggregated by all sectors												
Log initial VA per worker	-0.017	-0.016	-0.017	-0.015	-0.017	-0.016	-0.016	-0.023*	-0.017	-0.017	-0.017	-0.018
	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
Initial value of control var	-0.004	-0.002	0.000	-0.003	-0.000	-0.005	-0.005	0.009*	-0.000	-0.000	-0.000	0.001
	(0.008)	(0.001)	(0.001)	(0.003)	(0.002)	(0.007)	(0.006)	(0.005)	(0.001)	(0.000)	(0.001)	(0.001)
Constant	0.230***	0.353***	0.180	0.207**	0.202*	0.181	0.210**	0.331**	0.205**	0.205**	0.201*	0.202*
	(0.082)	(0.090)	(0.118)	(0.088)	(0.098)	(0.110)	(0.088)	(0.153)	(0.093)	(0.092)	(0.098)	(0.099)
Observations	72	72	72	72	72	72	72	72	72	72	72	72
R-squared	0.073	0.090	0.074	0.085	0.070	0.076	0.078	0.094	0.071	0.071	0.072	0.072

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.10. Specifications with additional control variables: Labor productivity convergence regressions, Manufacturing and NonManufacturing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Human capital					Access to finance	Government	Infrastructure				Health
Control variables	Avg. years of schooling	Working-age population	Working-age pop. w/ elementary education	Working-age pop. w/ non-university higher education	Working-age pop. w/ university higher education	Bank deposits per capita	Tax collected per capita	Electric capacity per capita	HHs w/ access to water network	HHs w/ access to electricity network	HHs w/ landline telephone	HHs affiliated to a public health institution
Level	% of pop. 15 yrs and older	% of tot. pop.	% of working-age pop.	% of working-age pop.	% of working-age pop.	New soles in logs	New soles in logs	Log of MW/pop.	% of total HHs	% of total HHs	% of total HHs	% of total HHs
Dependent variable: Growth of VA per worker over a decade												
Manufacturing only												
Log initial VA per worker	-0.035***	-0.037***	-0.035***	-0.038***	-0.036***	-0.038***	-0.038***	-0.030***	-0.036***	-0.034***	-0.037***	-0.042***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Initial value of control var	0.005	0.002	-0.000	0.002	0.002	0.008	0.007*	-0.003	0.000	0.000	0.001	0.002**
	(0.006)	(0.001)	(0.000)	(0.002)	(0.001)	(0.005)	(0.004)	(0.004)	(0.000)	(0.000)	(0.001)	(0.001)
Constant	0.307***	0.254***	0.359***	0.357***	0.343***	0.390***	0.343***	0.281**	0.341***	0.331***	0.360***	0.382***
	(0.065)	(0.084)	(0.078)	(0.068)	(0.063)	(0.074)	(0.061)	(0.099)	(0.065)	(0.065)	(0.063)	(0.062)
Observations	24	24	24	24	24	24	24	24	24	24	24	24
R-squared	0.544	0.558	0.536	0.552	0.561	0.572	0.584	0.533	0.543	0.528	0.583	0.621
NonManufacturing only												
Log initial VA per worker	-0.021*	-0.020*	-0.021*	-0.021*	-0.021*	-0.021*	-0.020*	-0.014	-0.023**	-0.021*	-0.020*	-0.022**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.017)	(0.010)	(0.011)	(0.011)	(0.010)
Initial value of control var	-0.001	0.001	0.000	-0.000	0.000	-0.004	-0.006	-0.005	0.000	-0.000	-0.000	0.001
	(0.009)	(0.002)	(0.001)	(0.003)	(0.002)	(0.008)	(0.006)	(0.010)	(0.000)	(0.000)	(0.001)	(0.001)
Constant	0.240*	0.166	0.220*	0.235**	0.233**	0.227**	0.252**	0.117	0.222**	0.237**	0.234**	0.227**
	(0.121)	(0.192)	(0.107)	(0.103)	(0.102)	(0.102)	(0.101)	(0.238)	(0.100)	(0.103)	(0.101)	(0.100)
Observations	24	24	24	24	24	24	24	24	24	24	24	24
R-squared	0.157	0.164	0.163	0.157	0.158	0.165	0.195	0.168	0.195	0.158	0.167	0.189

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table C.11. Specifications with additional control variables: Labor productivity convergence regressions, Tertiary sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Human capital					Access to finance	Government	Infrastructure				Health
Control variables	Avg. years of schooling	Working-age population	Working-age pop. w/ elementary education	Working-age pop. w/ non-university higher education	Working-age pop. w/ university higher education	Bank deposits per capita	Tax collected per capita	Electric capacity per capita	HHs w/ access to water network	HHs w/ access to electricity network	HHs w/ landline telephone	HHs affiliated to a public health institution
Level	% of pop. 15 yrs and older	% of tot. pop.	% of working-age pop.	% of working-age pop.	% of working-age pop.	New soles in logs	New soles in logs	Log of MW/pop.	% of total HHs	% of total HHs	% of total HHs	% of total HHs
Dependent variable: Growth of VA per worker over a decade												
Tertiary sector: Total aggregation												
Log initial VA per worker	-0.001	0.007	0.003	0.003	-0.005	-0.006	0.001	0.019	0.007	0.002	-0.008	-0.014
	(0.014)	(0.012)	(0.015)	(0.013)	(0.014)	(0.014)	(0.015)	(0.013)	(0.012)	(0.013)	(0.017)	(0.010)
Initial value of control var	0.006*	0.001*	-0.000	0.002*	0.002**	0.007**	0.004	-0.001	0.000*	0.000*	0.001*	0.002***
	(0.003)	(0.001)	(0.000)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.022	-0.120	0.006	-0.018	0.050	0.089	-0.005	-0.151	-0.056	-0.014	0.086	0.119
	(0.111)	(0.096)	(0.138)	(0.114)	(0.118)	(0.128)	(0.125)	(0.129)	(0.102)	(0.113)	(0.147)	(0.090)
Observations	24	24	24	24	24	24	24	24	24	24	24	24
R-squared	0.229	0.224	0.173	0.220	0.294	0.297	0.194	0.097	0.239	0.231	0.232	0.560
Tertiary sector: Disaggregated by all sectors												
Log initial VA per worker	0.002	0.003	0.003	0.003	0.002	0.001	0.002	0.004	0.003	0.003	0.002	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Initial value of control var	0.007**	0.002***	-0.000**	0.002**	0.002***	0.008***	0.005***	0.002	0.000**	0.000**	0.001***	0.002***
	(0.003)	(0.001)	(0.000)	(0.001)	(0.000)	(0.002)	(0.002)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.057	-0.124**	0.016	-0.024	-0.008	0.018	-0.021	-0.002	-0.032	-0.022	-0.004	-0.015
	(0.035)	(0.054)	(0.036)	(0.034)	(0.031)	(0.031)	(0.032)	(0.043)	(0.037)	(0.031)	(0.031)	(0.030)
Observations	120	120	120	120	120	120	120	120	120	120	120	120
R-squared	0.061	0.080	0.049	0.061	0.082	0.097	0.068	0.015	0.062	0.064	0.049	0.123

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table C.12. Specifications with additional control variables: Labor productivity convergence regressions, All sectors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Human capital					Access to finance	Government	Infrastructure				Health
Control variables	Avg. years of schooling	Working-age population	Working-age pop. w/ elementary education	Working-age pop. w/ non-university higher education	Working-age pop. w/ university higher education	Bank deposits per capita	Tax collected per capita	Electric capacity per capita	HHs w/ access to water network	HHs w/ access to electricity network	HHs w/ landline telephone	HHs affiliated to a public health institution
Level	% of pop. 15 yrs and older	% of tot. pop.	% of working-age pop.	% of working-age pop.	% of working-age pop.	New soles in logs	New soles in logs	Log of MW/pop.	% of total HHs	% of total HHs	% of total HHs	% of total HHs
Dependent variable: Growth of VA per worker over a decade												
Overall: Total aggregation												
Log initial VA per worker	-0.038***	-0.029***	-0.034***	-0.035***	-0.035***	-0.040***	-0.036***	-0.016*	-0.029***	-0.032***	-0.034***	-0.052***
	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)	(0.008)	(0.008)	(0.009)	(0.006)	(0.009)	(0.007)	(0.008)
Initial value of control var	0.015***	0.002**	-0.001**	0.004***	0.003***	0.015***	0.010***	-0.002	0.001***	0.001**	0.001***	0.004***
	(0.005)	(0.001)	(0.000)	(0.002)	(0.001)	(0.004)	(0.004)	(0.004)	(0.000)	(0.000)	(0.000)	(0.001)
Constant	0.234***	0.124*	0.372***	0.303***	0.316***	0.408***	0.304***	0.156	0.247***	0.283***	0.314***	0.436***
	(0.051)	(0.061)	(0.096)	(0.063)	(0.055)	(0.076)	(0.063)	(0.097)	(0.050)	(0.067)	(0.063)	(0.066)
Observations	24	24	24	24	24	24	24	24	24	24	24	24
R-squared	0.520	0.443	0.402	0.472	0.580	0.541	0.476	0.277	0.548	0.405	0.494	0.644
Overall: Disaggregated by Primary, Secondary & Tertiary												
Log initial VA per worker	-0.022***	-0.021***	-0.021***	-0.022***	-0.023***	-0.022***	-0.022***	-0.018**	-0.022***	-0.021***	-0.022***	-0.024***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Initial value of control var	0.008**	0.002**	-0.000	0.002*	0.002**	0.007**	0.006*	-0.001	0.001***	0.000	0.001**	0.002***
	(0.004)	(0.001)	(0.000)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)	(0.001)
Constant	0.155***	0.098	0.238***	0.203***	0.216***	0.238***	0.200***	0.184**	0.192***	0.202***	0.215***	0.220***
	(0.051)	(0.058)	(0.067)	(0.058)	(0.059)	(0.070)	(0.056)	(0.085)	(0.055)	(0.057)	(0.059)	(0.060)
Observations	72	72	72	72	72	72	72	72	72	72	72	72
R-squared	0.264	0.258	0.239	0.246	0.301	0.261	0.255	0.216	0.301	0.242	0.256	0.287
Overall: Disaggregated by all sectors												
Log initial VA per worker	-0.020***	-0.020***	-0.020***	-0.020***	-0.021***	-0.021***	-0.020***	-0.020***	-0.020***	-0.020***	-0.020***	-0.021***
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
Initial value of control var	0.005	0.001	-0.000	0.001	0.001	0.005	0.003	0.004	0.000	0.000	0.000	0.001*
	(0.003)	(0.001)	(0.000)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)	(0.001)
Constant	0.167***	0.149***	0.217***	0.197***	0.200***	0.216***	0.194***	0.241***	0.194***	0.195***	0.202***	0.196***
	(0.044)	(0.042)	(0.057)	(0.048)	(0.049)	(0.056)	(0.047)	(0.071)	(0.048)	(0.047)	(0.050)	(0.049)
Observations	255	255	255	255	255	255	255	255	255	255	255	255
R-squared	0.110	0.108	0.108	0.107	0.112	0.111	0.109	0.111	0.108	0.109	0.109	0.112

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1