



SPAIN

SELECTED ISSUES

November 2018

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November 2, 2018

Approved By
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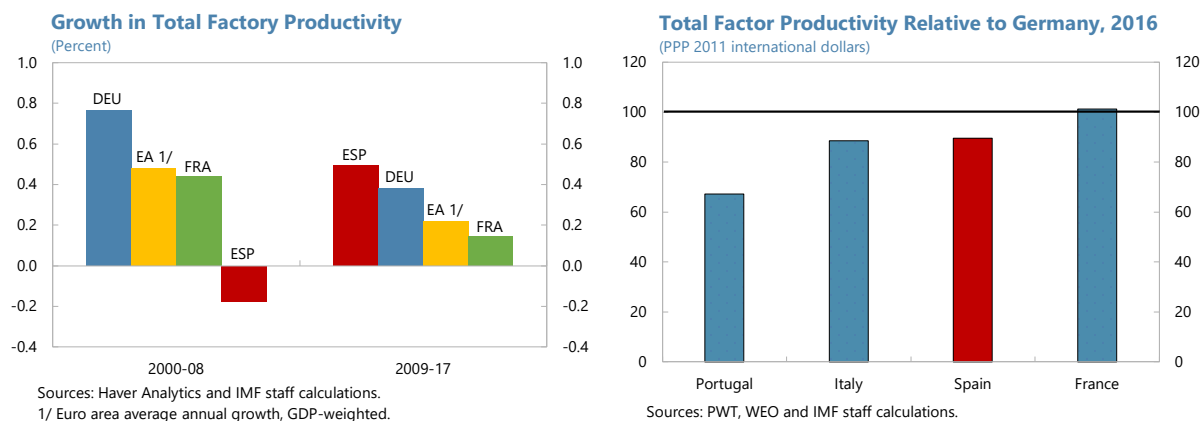
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DIFFERENCES IN REGIONAL PRODUCTIVITY: WHAT IS BEHIND IT?^{1, 2}

Recent studies of income convergence among Spanish regions suggest that the convergence has been slow since 1980 reflecting persistent regional disparities in total factor productivity. Our empirical analysis—employing stochastic frontier models—finds that, among other factors, differences in regions' skills mismatch and technology absorption capacity could be behind the disparities. A benchmarking exercise demonstrates significant potential growth benefits from policy measures that would bring regions closer to the frontier.

A. Introduction

1. Despite improved post-crisis productivity growth, Spain's productivity is still considerably below that of advanced European peers. The latest estimates suggest that Spain's productivity gap relative to Germany is above 10 percent. In addition, the evolution of Spain's total factor productivity (TFP) before and after the Global Financial Crisis differs considerably from the experience of other advanced economies. Most advanced economies recorded strong productivity growth pre-crisis, which then slowed down considerably post-crisis. In the case of Spain, average productivity growth was negative at 0.2 percent before the crisis and turned positive afterwards—on average growing by 0.5 percent per year.



2. This paper explores differences in productivity across Spanish regions and attempts to identify potential factors that might be behind these differences. This angle has not been studied much yet in the literature. Employing stochastic frontier analysis, the paper estimates a production frontier for Spanish regions and the distance of each region from the frontier. Then it

¹ Prepared by Ara Stepanyan. Tingyun Chen provided excellent research assistance.

² This paper has benefited from comments by the Bank of Spain, Ministry of Economy and Business of Spain, and participants in the seminar organized by the Bank of Spain in September 2018.

tries to identify the role of structural factors for the distance from the frontier. Through a benchmarking exercise, it also demonstrates potential in GDP gains from bring regions closer to the frontier.

3. The paper is organized as follows. Section II summarizes the existing literature on income convergence among Spanish regions, Section III provides some stylized facts about structural differences of Spanish regions, Section IV lays out the methodology, Section V describes the empirical analysis, and Section VI concludes.

B. Literature Review

4. Most studies focusing on income convergence among Spanish regions found evidence of strong convergence during 1950–70, which slowed down considerably afterwards. Mas and others (1995) in their analysis of Spanish regions demonstrate that convergence happened mostly in the period of 1955–79. This was driven by a reduction in the share of agriculture sector in regional economies and a narrowing of infrastructure gaps helped by increased public investments. However, they highlight that the rate of convergence decelerated considerably during 1980s with persistent regional differences in unemployment rates being a force against convergence. De la Fuente (2002a, 2002b) analyzes the periods of 1965–75 with strong convergence and 1975–95 with convergence stagnation. In the first period, he finds that equalization of education levels, internal migration, and closing infrastructure gaps across regions supported the rapid convergence in labor productivity and income per capita. For the second period, he argues that a sharp decline in the internal migration rate and inability of regional economies to absorb labor freed up from the agriculture sector contributed to the slowdown in the convergence in employment rates and per capita income across regions.

5. Studies that cover recent periods highlight a lack of convergence. Puente (2017) concludes that the differences among Spanish regions are similar to European peers, but the initial differences among regions in terms of income per capita have persisted for the last 30 years. He shows that on the one hand, labor productivity contributed to the convergence of income per capita across regions, but on the other hand, the divergence in unemployment rates, with poorer regions recording higher levels, widened the difference between regions. Puente argues that capital accumulation was the main driver for convergence in labor productivity across Spanish regions, while TFP did not play a role in this process. Garrido-Yserte and Mancha-Navarro (2010) mention that regional differences in GDP per capita are primarily due to regional disparities in employment rather than differences in regional productivity. The European Commission's 2018 country report also acknowledges that regional disparities in income per capita are not larger than those observed in other advanced European countries. The report shows that differences in employment rates across Spanish regions are behind disparities in GDP per capita across regions.

C. Stylized Facts

6. Differences in total factor productivity across Spanish regions contribute to regional disparities in income per capita. Spanish regions exhibit considerable differences in income per capita (Figure 1). In 2016, the richest region generated twice as much GDP per capita as the poorest region. This reflects a significant variation in labor productivity across regions. In particular, employees in the most productive region produced 50 percent more output than employees in the least productive region. The disparities in labor productivity in turn could be caused either by differences in capital intensity of regions (capital-to-labor ratio) or differences in TFP. The data show that the capital stock per employee is distributed quite evenly across regions, but TFP varies considerably. The difference between the region with the highest and the lowest TFP was about 60 percent in 2016 (Figure 1).

7. Total factor productivity disparities could reflect different structures of regional economies. Economists have long argued that the manufacturing sector is the main driver for innovation. Thus, countries with a large share of the manufacturing sector were found to be more productive (Pisano and Shih, 2009). The literature also points to the increasing role of the services sector, particularly financial and business services, for an acceleration of productivity growth since the 2000s (Corrado, Lengermann, and Bartelsman, 2007). The economic structure of Spanish regions is very diverse. Based on data from 2016, the services sector dominates in all regions, but it varies from 60 to 85 percent of GDP across regions. The variation is particularly large for financial and information technology and communication (ITC) services (Figure 2). The difference between the regions with the highest and lowest shares of financial services in GDP is twofold, while in the case of ITC services the difference is fivefold. However, it is worth noting that the Community of Madrid, which has the highest share of GDP for both of these sub-sectors, is an outlier. The heterogeneity among regions is also considerable as regards the relative importance of the manufacturing and agriculture sectors. Some regions derive one quarter of their GDP from manufacturing, while in other regions manufacturing has only a share of 3 percent. Similarly, in some regions agriculture contributes to more than 6 percent of GDP, while in other regions its contribution is negligible. The construction had a largely similar share across regions in 2016. Productivity differences among sectors could contribute to TFP disparities across regions. Therefore, in the empirical analysis, we use the share of each sector in GDP to control for the impact of differences in sectoral productivity on aggregate TFP.

8. Regions also differ in terms of other structural characteristics, potentially contributing to regional TFP differences as well.

- McGowan and Andrews (2015) argue that skill mismatch generates inefficient resource allocation weighing on productivity. In Spain, about 40 percent of Spain's labor force has at most lower secondary education—one of the highest shares among Euro Area countries, and the dispersion across regions is wide, ranging from 25–50 percent (Figure 3). This translates into a significant mismatch between skills supply and demand with a fivefold difference in the skills mismatch index between the best and the worst matched regions. The skills mismatch index captures the difference between skills demand represented by the share of workers with

different level of education in employment and skills supply measures by the share of people with different level of education in the labor force.

- Moreover, research and development (R&D) activities are widely acknowledged as the main direct source of technological progress, and indirectly they increase a country's capacity to absorb technology (Griffith, Redding, and Van Reenen, 2003). Engaging actively in research and development facilitates the understanding and assimilation of discoveries by others. Thus, we use R&D spending to capture regions' innovation and technology absorption capacity. Spain spends less on research and development (R&D) compared with peers. Most of the Spanish regions spend below the country's average (relative to the economy) with the top four regions responsible for more than half of the overall R&D spending.³ However, there could be an economic rationale for some regions to specialize in R&D activities depending, for example, on their proximity to universities and scientific parks. At the same time, R&D spending efficiency varies widely (Figure 3). When measured by the number of new patents per money spent on R&D, ten out of 17 regions have R&D efficiencies below the regional average. Five regions achieved above average efficiency despite spending less than the regional average.
- And finally, foreign direct investment (FDI) is an important channel of technology diffusion, which facilitates the adoption of innovations generated globally. The success of Spanish regions in attracting FDI varies considerably. In 2016, the top four regions received more than 70 percent of the overall FDI attracted by the country.

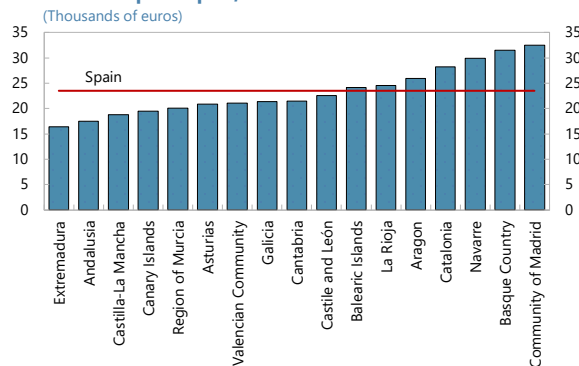
9. Regulatory requirements and procedures for doing business vary considerably across regions as well, which could be another factor causing regional differences in total factor productivity. Economic regulation has considerable influence on decisions to invest in physical and human capital, including intellectual property, as well as on the level of competition (Swedish Agency for Growth Policy Analysis, 2010). Requirements and procedures to start a business are not unified across Spanish regions. As a result, for example the time required to start a business ranges between 14 to 20.5 days and between 63 to 248 days for starting an industrial SME. The divergence is similar when dealing with construction permits, getting electricity, or registering property (Figure 3).

³ Interpreting regional data on R&D spending requires caution because of a potential bias in the data towards regions that host headquarters of firms that conduct R&D.

Figure 1. Spain: Regional Differences in Income and Production Factors

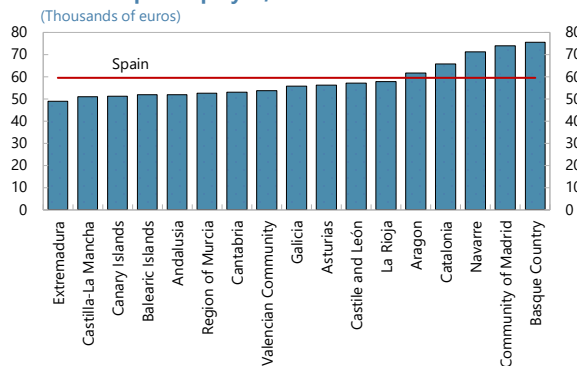
Regional differences in income per capita are considerable.

Real GDP per Capita, 2016



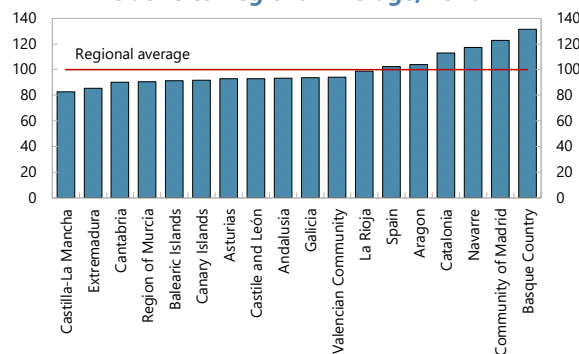
They are driven by regional disparities in labor productivity...

Real GDP per Employee, 2016



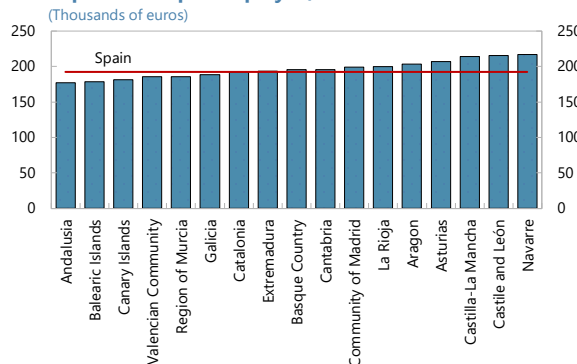
...that resulted from differences in total factor productivity,...

TFP Relative to Regional Average, 2016



...while the capital stock per employee is relatively evenly distributed.

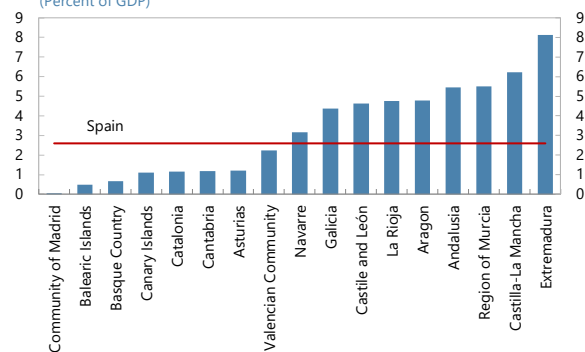
Capital Stock per Employee, 2016



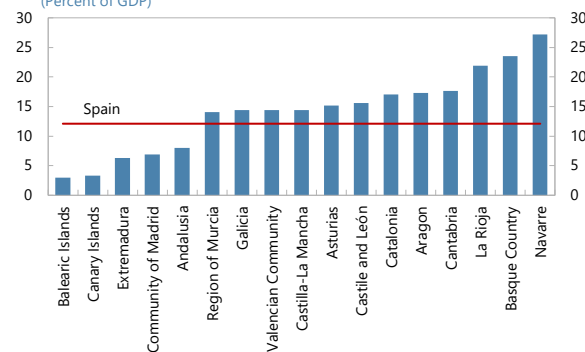
Sources: Fundación BBVA, INE, Instituto Valenciano de Investigaciones Económicas and IMF staff calculations.

Figure 2. Spain: GDP Structure of Spain Regions

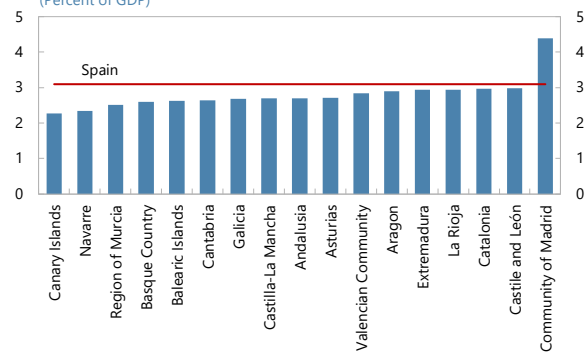
Share of Agriculture in Regional Real GDP, 2016
(Percent of GDP)



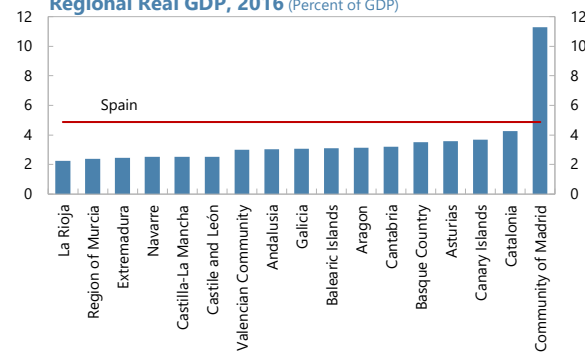
Share of Manufacturing in Regional Real GDP, 2016
(Percent of GDP)



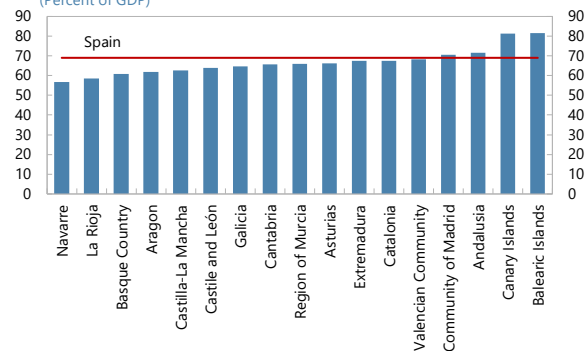
Share of Financial Activities in Regional Real GDP, 2016
(Percent of GDP)



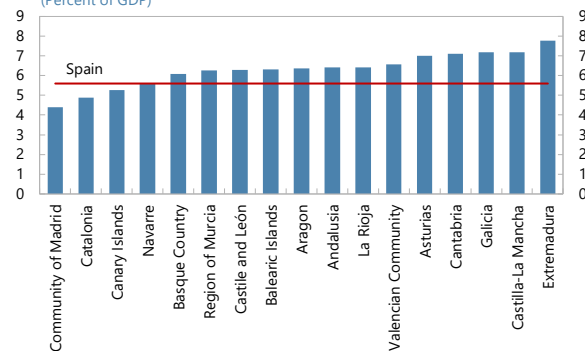
Share of Information and Communication in Regional Real GDP, 2016
(Percent of GDP)



Share of Other Services in Regional Real GDP, 2016
(Percent of GDP)



Share of Construction in Regional Real GDP, 2016
(Percent of GDP)



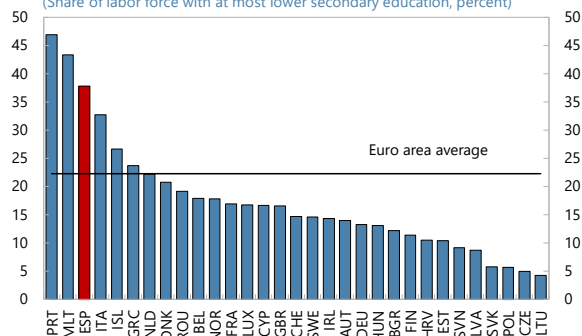
Sources: INE and IMF staff calculations.

Figure 3. Spain: Structural Differences of Spanish Regions

Spain's share of low skilled in the labor force is one of the highest among EU countries.

Share of Low Skilled in Labor Force, 2016

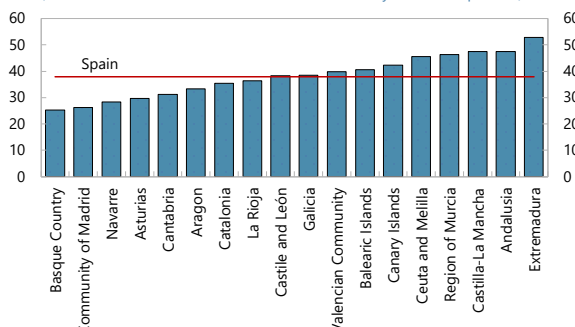
(Share of labor force with at most lower secondary education, percent)



Considerable variations in education levels across Spanish regions...

Share of Low Skilled Labor Force, 2016

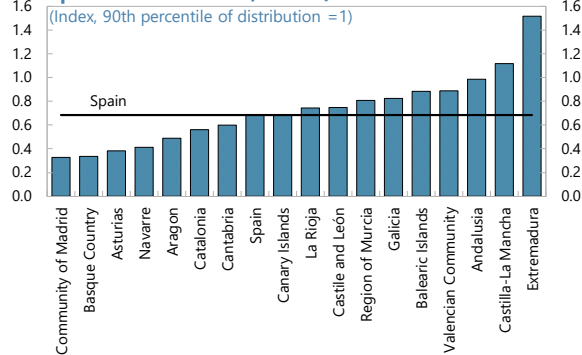
(Share of labor force with at most lower secondary education, percent)



... translate into a significant variation in the mismatch between skills demand and supply.

Spain: Skill Mismatch, 2016 1/

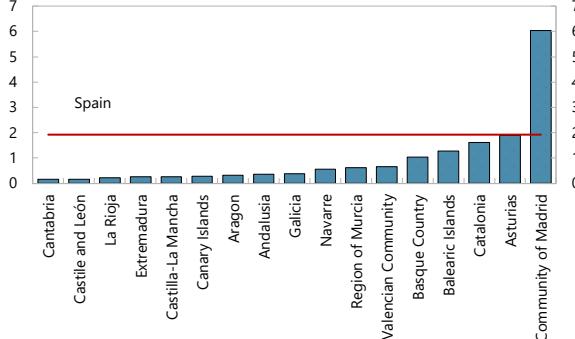
(Index, 90th percentile of distribution = 1)



A few regions receive the lion's share of the country's foreign direct investments.

Foreign Direct Investments, 2000-16

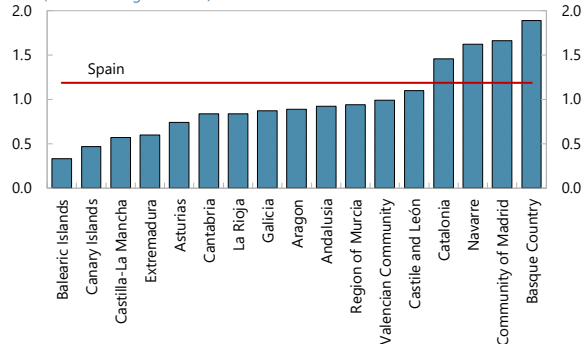
(Percent of regional GDP)



R&D spending is also concentrated in a few regions...

R&D Expenditure, 2016

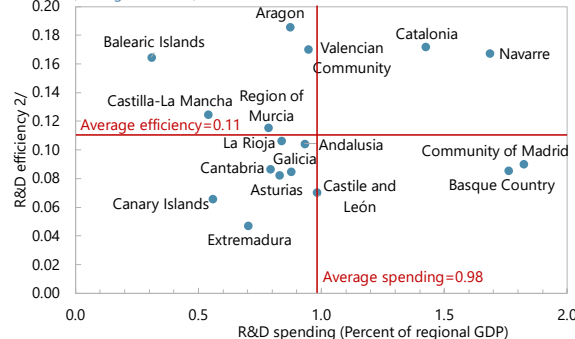
(Percent of regional GDP)



...with the efficiency of R&D spending varying considerably.

Spain: R&D Spending and Efficiency 2/

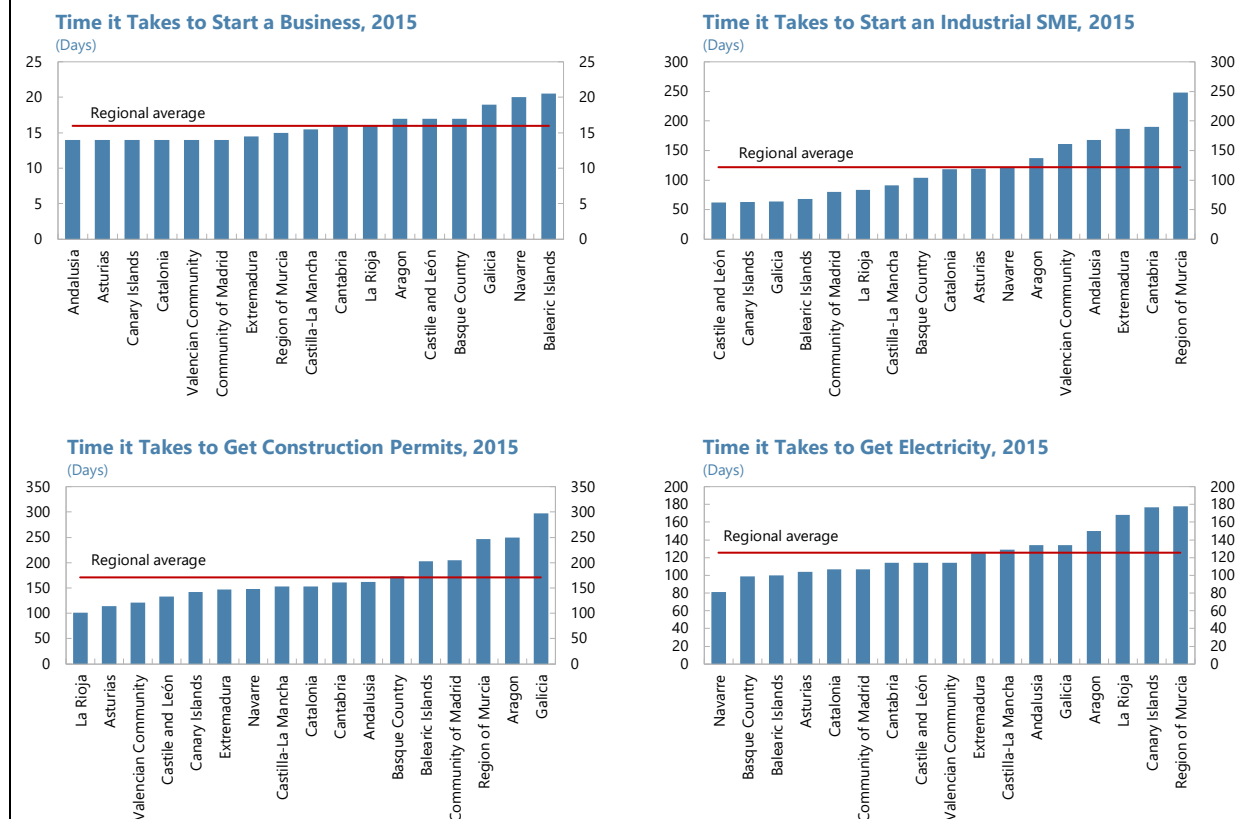
(Average, 2000-12)



Sources: Eurostat; INE; OECD; and IMF staff calculations.

1/ The skills mismatch index captures the difference between skills demand represented by the share of workers with different level of education in employment and skills supply measures represented by the share of people with different levels of education in the labor force.

2/ R&D efficiency is measured by the number of new patents per money spent on R&D.

Figure 3. Spain: Structural Differences of Spanish Regions (concluded)

Sources: World Bank, Doing Business in Spain 2015 and IMF staff calculations.

D. Methodology and Data

10. Stochastic frontier models are used to analyze efficiency of economic agents, regions, or countries. The intuition behind stochastic frontier models is that frontier technology provides the maximum output that can be achieved by any economic agent with a given level of inputs. The distance of individual agents from the frontier reflects their inefficiency. Stochastic frontier models are characterized by composite errors that are composed of idiosyncratic disturbances (to capture measurement errors and other noise) and one-sided disturbance, which represents inefficiency. In this paper we use a stochastic frontier panel-data model proposed by Battese and Coelli (1995) to estimate the contributions of technological progress and country-specific technical efficiency to TFP growth. The advantage of panel-data stochastic frontier models is that they allow to estimate time-variant inefficiency, which is more realistic than the outcomes of cross-sectional stochastic frontier models that assume constant inefficiency over time. The disadvantage is that it is quite data demanding and estimating fixed-effects models become challenging. Stochastic frontier models could be described by the following equations:

$$y_{i,t} = a + x_{i,t}\beta + \varepsilon_{i,t} \quad (1)$$

$$\varepsilon_{i,t} = v_{i,t} - u_{i,t} \quad (2)$$

$$v_{i,t} \sim N(0, \sigma_v^2) \quad (3)$$

$$u_{i,t} = z_{i,t}\delta + w_{i,t} \quad (4)$$

11. Where $y_{i,t}$ is the output of region i at time t , $x_{i,t}$ is a vector of production function inputs (in our case capital K, and human capital augmented labor LHC) and a time trend representing technological change, $\varepsilon_{i,t}$ is the composed error term, $v_{i,t}$ is assumed to be an iid random error, independently distributed of the $u_{i,t}$. The $u_{i,t}$ are non-negative random variables, associated with technical inefficiency of production, which are assumed to be independently distributed, such that it is obtained by truncation (at zero) of the normal distribution with mean $z_{i,t}\delta$, and variance, σ_u^2 . $z_{i,t}$ is a vector of explanatory variables associated with technical inefficiency of the production of country i , at time t . δ is an $(m \times 1)$ vector of unknown coefficients. $w_{i,t}$ is defined by the truncation of the normal distribution with zero mean and variance σ_u^2 , such that the point of truncation is $z_{i,t}\delta$ i.e., $w_{i,t} \geq z_{i,t}\delta$. This assumption ensures non-negativity of $u_{i,t}$. All parameters of the stochastic frontier model, including those to capture the impact of structural variables on technical inefficiency, are simultaneously estimated with a maximum likelihood method.

12. Kumbakhar and Lovell (2000) demonstrate that a change in TFP, which is defined as output growth not explained by input growth, can be expressed as:

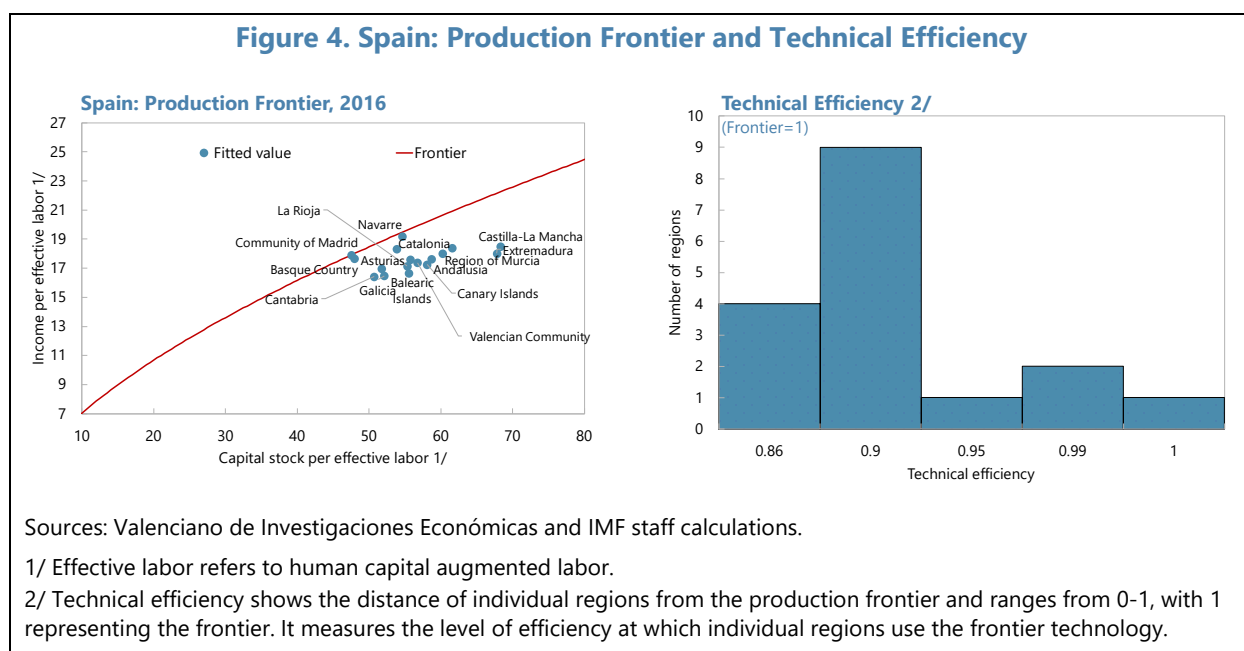
$$\Delta TFP = \Delta TP + \Delta TE + (\epsilon - 1) \left[\frac{\epsilon_{lhc}}{\epsilon} \Delta LHC + \frac{\epsilon_k}{\epsilon} \Delta K \right] \quad (5)$$

Where, ΔTP is technological change, which is represented by the coefficient of the time trend in equation (1) of the production frontier. ΔTE is change in technical efficiency. ϵ_{lhc} and ϵ_k are output elasticities with respect to human capital augmented labor and capital respectively. $\epsilon = \epsilon_{lhc} + \epsilon_k$ represents the return to scale. In the case of constant returns to scale, $\epsilon = 1$ and factor accumulation do not have any impact on TFP growth.

13. Stochastic frontier analysis is employed to estimate the production frontier for Spanish regions and identify structural factors that could explain the distance from the frontier. The analysis covers 17 Spanish regions over the period 2000–16. The choice of the period covered in the analysis was constraint by the lack of data of some structural variables before 2000. Regional data on GDP, capital stock, employment, and education attainment of the employed are from INE and Instituto Valenciano de Investigaciones Económicas. Structural data by regions used to identify technical inefficiency are from INE and OECD. Unfortunately, time series data are not available for regional regulatory variables. The World Bank's Doing Business Report provides estimates only for one year. Therefore, these indicators are not used in the regressions. We used the approach by Estevao and Tsounta (2011) to construct skills mismatch index for all regions (see Annex I for more details).

E. Empirical Analysis

14. Many regions are far from the estimated production frontier. Estimated GDP shares of capital and human capital augmented labor in the production function are 60 and 40 percent, respectively. While it suggests a lower share for labor than in the earlier literature, it is in line with the recent global evidence of declining labor shares. These estimates are used to construct a production frontier for Spain, which demonstrates the maximum output per effective labor (labor augmented by human capital) that could be obtained in Spain with any given level of capital per effective labor (Figure 4). Plotting regions relative to the frontier shows a considerable gap to the production frontier for most regions (Figure 4). Out of 17 regions, only three regions are close to the production frontier. There are regions with a largely similar level of capital per effective labor but substantially different output per effective labor. This indicates inefficiencies in regions. Our estimated technical efficiency, which measures the distance from the frontier, suggests that twelve regions use available technologies only at 81–90 percent efficiency (Figure 4).

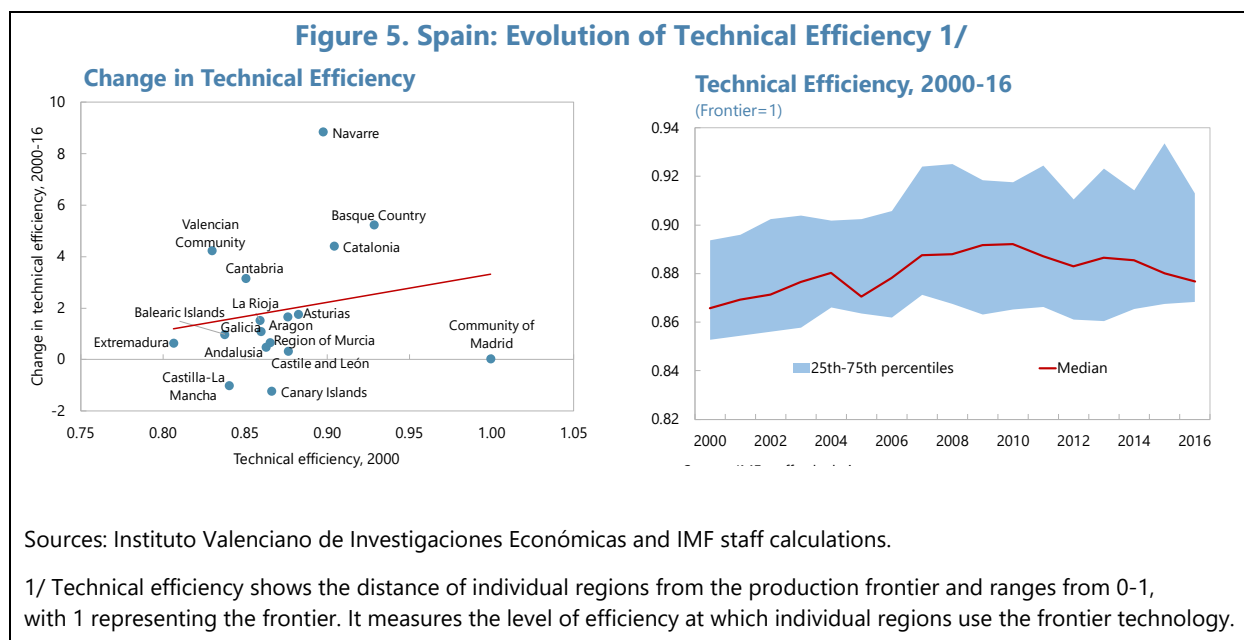


15. Spain's production frontier regressed over time, though after the crisis this process slowed down. According to our estimation, Spain's production frontier moved inwards by about 1 percent per year on average since 2000 (Table 1). However, when the sample is shortened to cover only the post-crisis period, the negative coefficient of the time trend, which represents technological progress, decreases substantially in absolute terms. This suggests that the inward move of the production frontier has slowed. Similarly, the coefficient of an interaction term between the post-crisis dummy and time trend is positive and statistically significant implying a slowdown in the post-crisis inward shift of the production frontier. The inward move in the production frontier may appear puzzling, since the usual expectation is that technology progresses over time. However, this pattern is consistent with the negative productivity growth observed before the crisis, which was associated with a shift towards less productive activities. A countercyclical behavior in aggregate TFP could have also been generated by differences in productivity among workers with the same level of

education as well as the concentration of job creation and destruction on low-productive workers along the economic cycle.⁴ However, it is possible that on a more disaggregated level (firm or sector) this pattern would not necessarily hold.

16. Inefficient use of available technologies by most of the regions—owing in part to skills mismatch and low innovative capacities—contributed to the productivity variation. Our empirical analysis suggests that the distance from the frontier, which is measured by the estimated technical inefficiency, tends to be higher in regions with elevated skills mismatch and lower in regions with higher foreign direct investment and research and development spending relative to GDP (Table 1). Specialization of some regions in R&D activities could well be economically justified. However, high technical inefficiency in regions with low spending on R&D might suggest that technology diffusion is limited from regions specialized in R&D activities to the rest of the country. The structure of the economy and education level of the labor force also demonstrate statistically significant associations with the technical efficiency when included in the analysis alone. However, these indicators become insignificant when we control for skills mismatch and the FDI-to-GDP ratio (Table 1). Some of these factors may capture the effects of regulatory or institutional differences among regions, which are not controlled for in our analysis due to the lack of data.

17. Technical efficiency generally improved over time, though with no signs of convergence across regions. While most of the regions have improved their technical efficiency compared with 2000, low efficient regions did not converge to the high efficient ones. The regions that recorded the largest gains in efficiency were already closer to the production frontier in the beginning of the sample (Figure 5). The median technical efficiency improved before the crisis but deteriorated slightly afterwards. At the same time, the dispersion among regions widened somewhat after the crisis.



⁴ Overestimation of capital accumulation during the pre-crisis boom years could be another possible factor generating inward move in the production frontier.

Table 1. Stochastic Frontier Analysis

Variables	Sample: 2000–16	Sample: 2000–16	Sample: 2008–16	Sample: 2000–16	Sample: 2000–16	Sample: 2000–16
	Parameters (1)	Parameters (2)	Parameters (3)	Parameters (4)	Parameters (6)	Parameters (5)
Production Function						
Capital	0.606*** (0.04)	0.593*** (0.04)	0.581*** (0.06)	0.499*** (0.05)	0.236*** (0.05)	0.108** (0.04)
Human capital augmented labor	0.405*** (0.04)	0.422*** (0.04)	0.433*** (0.06)	0.517*** (0.05)	0.750*** (0.05)	0.881*** (0.04)
Time trend	-0.0126*** (0.001)	-0.0153*** (0.002)	-0.00573*** (0.002)	-0.0108*** (0.001)	-0.00488*** (0.001)	-0.00491*** (0.001)
Post-crisis dummy interacted with time trend		0.0007*** (0.00)				
Intercept	3.805*** (0.45)	4.042*** (0.47)	3.758*** (0.64)	4.820*** (0.47)	7.837 (124.8)	8.770*** (0.45)
Inefficiency component						
Skill mismatch	0.0778*** (0.015)	0.0826*** (0.015)	0.0321 (0.020)	0.0761*** (0.021)		
Foreign direct investments to GDP	-0.00976** (0.004)	-0.00891** (0.004)	-0.00882** (0.004)	-0.0459*** (0.010)		
R&D spending to GDP	-0.0702*** (0.010)	-0.0600*** (0.010)	-0.108*** (0.012)			
Labor force with at most secondary education				0.117 (0.087)		0.798*** (0.256)
Share of agriculture in GDP				0.002 (0.002)	0.0184*** (0.002)	
Intercept	0.138*** (0.028)	0.123 (0.108)	0.234*** (0.041)	-0.0243 (0.027)	0.405 (124.8)	-0.427*** (0.141)
Number of observations	272	272	153	272	252	287

Standard errors are in parentheses. *** (**) (*) Denotes significance at 1% (5%) (10%) level.

18. Closing the distance to the frontier could yield significant gains. For example, if below average performing regions improved their efficiency up to the average, overall GDP would be 1.4 percent higher. In a scenario that assumes all regions are closing half of their distance to the production frontier, GDP would increase by 4 percent. About 80 percent of these gains could come from lowering the skills mismatch and increasing R&D spending to enhance regions innovation and technology absorption capacity. Gains from lowering skills mismatch and increasing R&D activities would be similar in size under the assumption that below average performing regions improve up to the regional average. In the scenario in which regions close half of the gap with the frontier, the gains from better innovation and technology absorption capacity are almost twice as large as the gains from a lower skills mismatch.⁵

⁵ GDP gains from reducing the skills mismatch in the laggard regions to the regional average are estimated at 0.6 percent. In a more ambitious scenario in which half of the distance to the best performing region is reduced, GDP could be 1.2 percent higher. As regards R&D spending, overall GDP could be 0.5 percent higher if the regions with below average spending bring it to the regional average. Closing half of the R&D spending gap with the best performer could create potential gains of 2.2 percent.

F. Conclusion and Policy Recommendations

19. Regional income disparities—driven by differences in TFP and unemployment—while not large compared with European peers, have been persistent in recent years. Most of the studies that looked at the income convergence of Spanish regions point to a fast convergence during 1950–70s with subsequent slowdown during 1980s. We document that the convergence largely stalled since 2000. The rapid convergence of early years lowered regional income differences to levels observed in other advanced European countries. While the pace of capital accumulation continued to converge over the past two decades, diverging labor market outcomes offset its impact on regional income disparities contributing to the persistence in income per capita differences across regions.

20. The main findings of the stochastic frontier analysis of Spanish regions suggest:

- The economy's overall productivity frontier moved inward overtime, but this trend has slowed down after the crisis. The inward shift of the production frontier could be one of the explanations for the negative TFP growth observed before the crisis.
- Most of the regions use available technologies inefficiently. While overtime most regions improved their efficiency, those initially closer to the frontier recorded larger gains.
- High skill mismatch and low capacity to innovate and absorb technologies are potential factors preventing regions from using available technologies efficiently. This has contributed to the existing TFP disparities among regions.

21. Policy options to lower regional disparities and raise TFP include:

- Policies to reduce school drop-out rates will be critical to address significant skills gaps that prevent many people from finding employment. At the same time, increasing labor market relevance of tertiary education through better cooperation between private sector and universities could help to reduce skills mismatch at the higher education end. Given the large regional differences in education outcomes, systematic exchanges of best practices and peer review among regions could contribute to reducing these differences (see European Commission, Country Report Spain 2018).
- Active labor market policies (ALMP) at the regional level could also work toward addressing skills mismatch and education outcomes. Particularly, the focus on well-targeted training, for which spending has been lower than in other EU countries, could be enhanced. The Spanish Activation for Employment Strategy 2017-2020 that focuses on results-oriented funding system and impact evaluation has a potential to enhance the efficiency of regional ALMPs.

- A better coordination between different levels of government, including for the design, implementation, and evaluation of research and innovation policies, could improve the efficiency of R&D spending. Understanding and addressing factors that hold back the uptake of R&D incentives and business-science cooperation could strengthen the government's efforts to enhance regions' innovative capacity.
- Improving the business environment would help regions to attract more FDI, thereby accelerating their acquisition and adoption of innovations generated globally.

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Annex I. Skills Mismatch Index

1. The skills mismatch index captures the difference between skill supply and demand. We use the framework presented in Estevao and Tsounta (2011) to compile a skills mismatch index. Skills demand is represented by the share of workers with different levels of education in employment. Skills supply is measured by the share of people with different levels of education in the labor force. The skills mismatch index for each region i at time t is constructed using the following formula:

$$\text{Skills mismatch index}_{i,t} = \sum_{j=1}^3 (S_{i,j,t} - M_{i,j,t})^2 \quad (1)$$

in which j is the skill level (low, medium, high); $S_{i,j,t}$ is the percentage of the population with skill level j at time t in region i (skill level supply), and $M_{i,j,t}$ is the percentage of employees with skill level j at time t in region i (skill level demand).

2. Data on educational attainment of the labor force and employment by education are from the National Statistics Institute. Skill supply is constructed by using the share of people with less than primary, primary and lower secondary education in labor force as low-skilled, the share of upper secondary and post-secondary non-tertiary education as medium-skilled, and share of tertiary education as high-skilled. The demand for low-skilled is approximated by the share of employees with less than primary, primary and lower secondary education in employment, for medium-skilled by the share of employees with upper secondary and post-secondary non-tertiary education and for high-skilled by the share of employees with tertiary education.