

KNOWLEDGE-BASED CAPITAL IN A SET OF LATIN AMERICAN COUNTRIES: THE LA KLEMS-IADB PROJECT

Matilde Mas, University of Valencia and Ivie
Eva Benages, Ivie and University of Valencia

KNOWLEDGE-BASED CAPITAL IN A SET OF LATIN AMERICAN COUNTRIES: THE LA KLEMS-IADB PROJECT

Matilde Mas, University of Valencia and Ivie
Eva Benages, Ivie and University of Valencia

Abstract

This paper presents the framework and methodology for the economic valuation of the knowledge-based economy in five Latin American (LA) countries, namely Costa Rica, El Salvador, Mexico, Peru and the Dominican Republic, for which a brand new database (IADB-Ivie, 2020) has recently been released. It uses an alternative approach to measuring the knowledge intensity of economies as to those based on the aggregation of industries according to selected indicators such as research and development (R&D) expenditure or labor force skills. Instead, we follow an economic approach rooted in the growth accounting methodology, determining the contribution of each individual factor of production (capital and labor) according to the prices of the services it provides. This methodology will be applied to the above-mentioned LA countries, and to the United States and Spain which are used as benchmarks. Data are available to cover the period 1995–2016.

JEL classification: O33, O47

Keywords: Knowledge economy; Growth accounting; Capital services; Human capital.

1. Introduction

This paper provides an alternative approach for measuring the knowledge economy. It follows the growth accounting methodology as developed by Jorgenson and associates (1987, 1995, 2005), which is applied to a set of five Latin American countries, the US and Spain for the period 1995–2016.

Knowledge economy is the term loosely applied to describe an economy where a considerable share of production is based on accumulated knowledge. The knowledge economy has grown in importance in recent decades, as it is regarded as a source of economic growth and competitiveness in all developed economies, in contrast to more traditional economic activities. As a result, it has attracted increased attention from researchers, policy-makers, international institutions, etc. However, despite the frequent use of this term, there is no metric that accurately measures how much economic value stems from knowledge, and its effects on productivity, competitiveness and economic growth. The most widely used approach classifies productive activities into several categories according to technological intensity, usually on the basis of R&D expenditure or high-skilled labor¹ or, more recently, on the basis of the digitization degree (Calvino et al., 2018). Calculations are then made on the percentage that these activities represent in total employment or production.

There are three important limitations regarding these conventional measures of knowledge intensity. The first is that it focuses on the current creation of knowledge rather than how the productive system uses it, which is crucial to analyzing certain problems. The second is that it uses classifications of knowledge intensity in activities based on a single factor: R&D expenditure in the case of manufacturing, and human capital with higher education in services industries. Knowledge, however, is incorporated into production through various channels: qualified labor in general, some capital assets and intermediate inputs. The weight that each of these carries in industries is different, and, therefore, classifying

¹ See, for example, the definition of KIS (Knowledge Intensive Services) and HTech (High Technology Manufacturing) or KIA classification (Knowledge Intensive Activities), which are used by Eurostat (2013). OECD (2015) uses these classifications as well. See also Tradecan (Trade Competitive Analysis of Nations) methodology, which was developed in 1990 by the Economic Commission for Latin America and the Caribbean (ECLAC).

activities based on a single criterion could bias the results. The third major limitation is that the incorporation of knowledge varies from one country to another within the same industry. The reality is that knowledge is (more or less) present in all industries and not only in those defined as high or medium technology in the usual classifications, which in turn have different degrees of knowledge intensity by country.

Other studies examine the knowledge economy through a set of indicators which includes several profiles of the presence of knowledge in productive activities. In some cases, synthetic indices of the development of knowledge —both in the economic system and society— are elaborated, including multiple variables which are aggregated according to statistical criteria or ad hoc weights. However, many of these indices are usually partial² and have an ambiguous meaning, given that they are not derived from a metric based on clear definitions and evaluation criteria, nor on a precise structure of relationships between variables. In this sense, business accounting and the system of national accounts have advantages for the aggregation, which is based on the relative prices of goods or factors.

More recently, other researchers have assessed the part of the economy stemming from new technologies. For instance, Calvino et al. (2018) classify 36 ISIC revision 4 sectors according to the extent to which they have gone digital. They propose various indicators³, together with an overall summary indicator of the digital transformation in sectors encompassing all the dimensions considered. The International Monetary Fund (2018), the OECD (2014, 2019) and the Bureau of Economic Analysis (Barefoot et al., 2018) have also produced important research in this area using a range of different approaches to measure the *digital economy*. However, these methodologies are still under development and, to date, there is no widely accepted method to measure the *digital economy*.

² Some examples are the KEI and KAM indicators published by the World Bank (see Chen and Dahlman [2006] and World Bank [2008a, 2008b] for more details) or the Digital Economy and Society Index (DESI) developed by the European Commission (see more details at: <https://ec.europa.eu/digital-single-market/en/desi>). All of them take into account different economic and social dimensions to measure the development of the knowledge economy, but exclude some important areas, such as physical capital endowments, institutional characteristics of the labor markets, etc., which may be relevant.

³ The five indicators are: share of ICT investment; share of purchases of intermediate ICT goods and services; stock of robots per employee; share of ICT specialists in total employment; and share of turnover from online sales.

This paper explores whether it is possible to assess the intensity with which knowledge is used –not its generation or creation– within economies from a different perspective. It relies on a revised version of the growth accounting methodology developed by Pérez and Benages (2012) and applied to all the European countries included in the EU KLEMS database. Maudos et al. (2017) updated and expanded this methodology with an application to the Spanish regions for which KLEMS-type data is available. Mas, Hofman and Benages (2019a, 2019b) also applied the same methodology to a set of LA countries⁴.

This work departs from this previous research in two ways. First, it expands the definition, and thus the empirical measurement, of the knowledge-based economy. Second, it considers four LA countries (Costa Rica, El Salvador, Peru and the Dominican Republic) for which information has only recently become available (<http://laklems.net>)⁵, as well as Mexico, which is the leading LA country in KLEMS-type data. Spain and the US are included in the analysis as benchmarks. We took information for Spain and the US from EU KLEMS (<http://euklems.net/>), although when necessary, data on the US was also accessed from the Bureau of Labor Statistics (BLS) and the Bureau of Economic Analysis (BEA) to update and supplement this database. Spain's capital data are also supplemented with the BBVA Foundation-Ivie (2019) database on capital stock.

There are many questions we are interested in answering in this study such as: Is the value added generated by the factors of production incorporating knowledge high enough to speak of *knowledge economies*? What differences can we observe in the weight of knowledge among industries and among countries? What is the time evolution of knowledge intensity by industry and by economies? How wide is the gap between LA countries and the two benchmark countries? Do activities and countries converge in knowledge intensity?

To address these issues, the paper is structured as follows. Section 2 explores the methodological approach adopted in the context of related economic literature, while

⁴ Mas, Hofman, and Benages (2019a) revised and extended the methodology to a set of four LA countries, and Mas, Hofman and Benages (2019b) again applied it to the same four Latin American countries, plus the United States, and five European countries (France, Germany, Italy, Spain, and the United Kingdom).

⁵ See IADB-Ivie (2020) and Mas and Benages (2020).

section 3 revises the statistical data, its sources and coverage. Sections 4 and 5 present the results at the aggregate level and by industry, respectively. Finally, section 6 sets out the main conclusions.

2. Calculating knowledge intensity: methodological approach

The most widely used approach for measuring knowledge intensity in economies is based on classifying manufacturing industries according to technology intensity—measured by the weight of R&D expenditure in relation to gross domestic product (GDP)—and services industries according to the use of human capital—measured by the percentage of staff with higher education⁶. The first one, the weight of R&D, responds better to the objective of analyzing the intensity in which knowledge is created rather than how much knowledge is used. In fact, the classification of manufacturing according to technological intensity was conceived for another purpose: to assess the origin of exogenous technological progress and its role in growth and competitiveness. The focus on R&D activities is justified since technology-intensive companies and industries show a high innovative and commercial dynamism and are especially productive⁷.

It is clear that R&D activities play a key role in generating knowledge. This knowledge is incorporated in the capital assets used in the production process. Machinery and other capital goods are the key vehicles for the use of knowledge. These capital goods are previously produced incorporating the knowledge used in their own production process, and are almost always intensive in human capital and in the use of other machinery. The same can be said of some intermediate products, although the degree in which they incorporate knowledge varies to a greater extent than in the case of machinery.

Since our objective is to measure the weight of knowledge used in current production, we should not concentrate solely on the discoveries of today but rather on all the knowledge accumulated in capital assets throughout time. It is not a question of *measuring knowledge*

⁶ See Galindo-Rueda and Verger (2016), OECD (2015) and Eurostat (2013).

⁷ See Hatzichoronoglou (1997).

but rather which part of the economic value of production remunerates the knowledge accumulated in the used inputs.

The refinement provided by the concept of productive capital offers a greater precision for measuring capital services and allows us to approximate the accounting of knowledge incorporated in the capital stock. Other analytical and statistical improvements in the methodology for measuring assets and their productive services are a consequence of a greater accuracy in aggregation procedures, using Tornqvist indices⁸. On account of these developments, an improved analysis is now available using sources of growth as well as key variables to estimate the value of production of assets incorporating knowledge. Developments currently underway extend the capital assets to take into account the contribution of intangible assets, many of which are also the result of knowledge accumulated by companies and their organizations.⁹ A more accurate measurement of physical and human capital services better assesses the knowledge incorporated in the factors and reduces the weight of the Solow residual¹⁰. These advances in growth accounting illustrate that, when the contributions of productive factors are measured more precisely, incorporated knowledge is more relevant than total factor productivity when explaining improvements in labor productivity¹¹.

The methodological and statistical framework of advanced versions of *growth accounting* offers an appropriate scheme to build an *accounting of the use of knowledge in production*. We can consider that knowledge is incorporated into production through the use of different kinds of labor, capital, and intermediate inputs. However, to simplify the presentation of the methodology, and relate it to subsequent empirical findings, we only show the case in which the measurement of the product is GDP or gross value added (GVA),

⁸ See OECD (2001, 2009) and Jorgenson et al. (1987).

⁹ See Corrado et al. (2006), Marrano and Haskel (2006), Van Ark and Hulten (2007), Fukao et al. (2007), Marrano et al. (2007), Hulten (2008), Corrado et al. (2013, 2017). From our work's perspective, the services of intangible assets increase the value added generated but the income they yield could be allocated to the heart of the organizations, both to the owners of capital and labor. It is because these assets, by their nature, do not have an external market that determines their price. Therefore, their contribution can be considered to be accounted through the remuneration of other factors.

¹⁰ See Solow (1956, 1957).

¹¹ See Coremberg and Pérez (2010), Oulton (2016) and Pérez and Benages (2017) on how a more accurate measurement of productive factors impacts total factor productivity.

although the approach will be replicable in similar terms to the case of total production. Thus, we do not consider knowledge incorporated into intermediate inputs, but only content in primary inputs, labor and capital. Taking this into account, to assess the contribution of productive factors based on knowledge, first we have to identify which factors contain knowledge, measure the amount used in different activities, and value their services with appropriate prices.

From this point of view, knowledge intensity in an industry is defined as the value of the knowledge services used in relation to the value of its production. Thus, it can take any value in the interval $[0,1]$. Industries are therefore not classified into categories of greater or lesser intensity, avoiding the discontinuity caused by thresholds which arbitrarily separate some groups from others. However, certain arbitrariness is unavoidable when considering which assets include knowledge and which do not.

One possibility is to take a very restrictive approach and include only ICT and intangible capital (on the asset side) and only workers with the highest level of tertiary education (on the labor side) as knowledge-contributing factors. This is the approach followed in Mas, Hofman and Benages (2019a). Alternatively, we can also take a broader approach in which knowledge-based factors are understood to include not only high-skilled but also medium-skilled workers (higher and upper secondary education), and not only ICT but all types of machinery and equipment. Low-skilled workers and real estate capital are not considered to incorporate significant knowledge and so are excluded. This is the approach followed by Pérez and Benages (2012) and Mas, Hofman and Benages (2019b).

In this paper we consider both approaches in order to assess the accuracy and sensitivity of the results obtained in each case.

As already mentioned, the knowledge intensity of an industry can take any value in the interval $[0,1]$. One of the implications of this is that, unlike the conventional approach, knowledge intensity in an industry is not constant over time or among countries. Another implication is that the knowledge intensity of an economy is obtained from the knowledge intensity in each of its industries, as well as from the weight of value added of each branch of activity in the aggregate GVA.

Assuming that there are m types of labor and n types of capital and some of these provide knowledge services and others do not, let L_{ij} be the amount of labor of type i used in sector j ; K_{hj} the amount of capital of type h used in the same sector j ; P_{ij}^L is the unitary wage paid for the labor of type i in sector j ; and P_{hj}^K is the user cost of type h capital in sector j . Defining the value added in real terms produced by sector j as V_j and being P_j^V its price, the value added of sector j in nominal terms ($V_j P_j^V$) is distributed between the different inputs included in the production process so that,

$$V_j P_j^V = \sum_{i=1}^m L_{ij} * P_{ij}^L + \sum_{h=1}^n K_{hj} * P_{hj}^K \quad [1]$$

Let us assume that the price of the amount used for each type of labor depends on its productivity, and that the basis for differences in productivity is the human capital that each type contains. Under these hypotheses, wages can approximate the economic value of the amount of knowledge per unit of each type of labor. According to this criterion, we can consider that the type of labor that offers a lower wage (for workers with lower education levels) does not incorporate knowledge. While the other types of labor do incorporate knowledge, though at different rates according to the number of years or level of education. If we generalize to allow f type of low-skilled labor, the value of labor is decomposed into two parts, the second of which measures the value of human capital services:

$$\sum_{i=1}^m L_{ij} * P_{ij}^L = \sum_{i=1}^f L_{ij} * P_{ij}^L + \sum_{i=f+1}^m L_{ij} * P_{ij}^L \quad [2]$$

Thus, the value of knowledge incorporated through labor (knowledge-intensive labor, KIL) would be given by:

$$KIL_j = \sum_{i=f+1}^m L_{ij} * P_{ij}^L \quad [3]$$

The unit value of productive services providing different kinds of labor that incorporate knowledge is not the same. For example, the production services of workers with higher education are more intensive in knowledge than in the case of workers with upper secondary education. By multiplying the amount of each type of labor by its wages, knowledge intensity can be accurately calculated when the wages are a reflection of this intensity. This criterion implies that the value of knowledge that qualified workers have

does not depend only on the level of education achieved, but also on their experience and how it is used by the productive system in general, which is reflected in their wages.

In terms of capital, we assume that the productivity of each asset is reflected in its user cost, which is taken into account in the calculation of the productive capital. The differences in the user cost have become more relevant due to the growing importance of ICT investment, which was a key driving force behind the disaggregation of assets and the distinction between net and productive capital¹².

The capital user cost has three components: the financial opportunity cost or rate of return, the depreciation rate resulting from the service life of the corresponding asset, and earnings or losses of capital arising from variations in its price.

In the long-term, i.e., in the absence of price changes associated with the business cycle¹³, the component of the user cost that most differentiates certain assets from others is the depreciation rate, which, in general terms, depend on the average service life of the assets. The service life of machinery is shorter than housing or infrastructure, while that of ICT assets is shorter than the majority of machinery and transport equipment. It is widely accepted that the materials that make up the assets and, in particular the complexity and vulnerability to obsolescence (i.e., the technology incorporated) make the economic life shorter (and depreciation faster). Assets that contain more knowledge tend to have a shorter economic life and, thus, a more intense depreciation.

In the language of capital theory, more depreciation means greater user cost that should be offset by a greater flow per unit of time of the asset's productive services, because otherwise the decision to invest in it would not be justified ¹⁴.

We assume that the content of knowledge in assets increases proportionately with its user cost. We use as a starting point the hypothesis that assets with a lower user cost do not

¹² See OECD (2001, 2009).

¹³ See Schreyer (2009).

¹⁴ We follow the neoclassical approach under the standard assumptions of profit maximizing behaviour; competitive markets, in which factors are remunerated by their marginal product; and constant returns to scale.

incorporate knowledge in a significant way, while assets with a higher user cost do. Therefore, as aforementioned, we can assume that machinery and equipment do incorporate knowledge (although with the relative intensity reflected by their user cost, e.g., much higher in ICT assets) or we can follow a more restrictive view for capital which considers that only ICT and intangible assets incorporate knowledge in the production process.

The value added generated by physical capital is broken down into two broad categories: those that do not incorporate knowledge significantly (g assets) and those that do ($n-g$ assets):

$$\sum_{h=1}^n K_{hj} * P_{hj}^K = \sum_{h=1}^g K_{hj} * P_{hj}^K + \sum_{h=g+1}^n K_{hj} * P_{hj}^K \quad [4]$$

Then, the value of knowledge incorporated through physical assets (*knowledge-intensive capital, KIK*) would be given by:

$$KIK_j = \sum_{h=g+1}^n K_{hj} * P_{hj}^K \quad [5]$$

And the value of knowledge-intensive factors or value added based on knowledge (*knowledge-intensive value, KIV_j*) of activity j will therefore be:

$$KIV_j = KIL_j + KIK_j \quad [6]$$

The relative knowledge intensity (*%KIV_j*) of activity j is defined as

$$\%KIV_j = \frac{KIV_j}{V_j P_j^V} = [KIL_j + KIK_j] / V_j P_j^V \quad [7]$$

Given the knowledge content of each industry, the knowledge intensity of an economy depends on the weight of the various branches in the aggregate. If q industries exist, the knowledge intensity of the economy as a whole (*%KIV*) is defined as,

$$\%KIV = \sum_{j=1}^q \%KIV_j \left[V_j P_j^V / \sum_{j=1}^q V P_j^V \right] \quad [8]$$

The exercises carried out in this paper, using LA KLEMS data, adopt the two approaches (the restrictive and the broader one) to measuring the knowledge economy presented in this

section. That is, for labor we will consider high- and medium-skilled workers (higher and upper secondary education) as knowledge intensive and also only high-skilled workers, and for capital, we will compare the results obtained when considering ICT and machinery and equipment capital as knowledge-based assets with a more restrictive version which considers ICT capital as the only component of knowledge-based capital.

3. Statistical data: sources and coverage

The estimates of knowledge intensity following the methodology described above are mainly based on data from KLEMS databases: LA KLEMS for the five Latin American countries, EU KLEMS for Spain and the United States¹⁵. These databases contain information by industry on variables related to productivity and economic growth: value added, output, employment and skills, gross capital formation by assets and accumulated capital, capital and labor compensation, etc. At the moment, LA KLEMS data is available for the period 1990-2016, whereas EU KLEMS database covers the period 1995–2016, although the coverage varies depending on the country, the selected variable and its detail. That is why additional sources have been used to supplement the data for these countries. Taking all this into account, in this paper we will focus on the period 1995-2016, for which data is available for most of the countries considered.

The KLEMS databases offer all the variables needed to apply the methodology outlined in section 2: value added, capital compensation, and labor compensation by educational attainment level. However, there are particular problems concerning each variable that need to be solved before the described methodology can be applied. Regarding capital compensation, although previous releases of EU KLEMS included a disaggregation of capital compensation by asset, recent releases include only total compensation by industry. The same is true for LA KLEMS countries. We must therefore estimate the capital compensation for each asset. This estimation will be made following the KLEMS method (Timmer et al., 2007) and taking as a basis the information on gross fixed capital formation (GFCF) deflators, capital stock, and depreciation rates included in the KLEMS databases.

With regard to labor-related variables, in the case of EU KLEMS data it is necessary to link up labor input files from different EU KLEMS releases to construct long time series.

Labor data are classified by educational attainment, distinguishing between three levels: high, medium, and low. For our purposes, we have two options: 1) to consider that workers with high- and medium-education levels contribute knowledge to the production process,

¹⁵ It was necessary to use additional data sources (BEA, BLS, BBVA Foundation-Ivie, WIOD) in order to update and supplement the EU KLEMS database.

whereas the rest do not, or 2) to consider that only workers with high-education levels do. In the case of physical capital, KLEMS databases distinguish nine capital assets: three ICT assets and six non-ICT assets (see Table 1). However, information on intangible assets (R&D and other intellectual property products) that was included in the European System of National and Regional Accounts (ESA 2010) is not yet available for two LA countries: the Dominican Republic and El Salvador. Because of that, to make the data comparable, these intangible assets have not been considered when calculating knowledge-based GVA for the remaining countries; only the first seven assets shown in Table 1 are included in the estimation. As stated before, we can either classify ICT assets, transport equipment, and other machinery and equipment as knowledge-based capital assets, whereas residential and non-residential structures are considered to have lower knowledge intensity, or we can consider that only ICT assets are knowledge intensive, whereas the rest of assets are not.

Thus, we have two measures of knowledge-based GVA, on the one hand, a broader one that includes the remuneration of high- and medium-educated workers and ICT and machinery and equipment capital, and, on the other hand, a restrictive one that only includes the remuneration of high-educated workers and ICT assets.

Table 1. Capital assets considered for the estimation of knowledge-based GVA

KLEMS assets
ICT assets
Software
Computing equipment
Communication equipment
Non-ICT assets
Transport equipment
Machinery & Equipment (excluding ICT)
Non-residential structures
Residential structures
Research and development (R&D)
Other Intellectual Property Products

Source: Own elaboration.

As explained in section 2, knowledge intensity is measured at the sectoral level. However, the industry classification of the EU KLEMS database is different from that of LA KLEMS data. While the former has been updated according to the most recent industry classifications (ISIC Rev. 4/NACE Rev. 2), the LA KLEMS database still follows previous classifications (based on ISIC Rev. 3.1/NACE Rev. 1). For that reason, although greater industry detail is available for Spain and the United States, only nine individual industries are considered in this paper, in order to have a common industry classification for all the countries analyzed. Table 2 shows a list of these industries.

Table 2. Industry classification (available for all countries)

Agriculture, forestry, and fishing
Mining and quarrying
Manufacturing
Electricity, gas and water supply
Construction
Wholesale & retail trade; accommodation and food service
Transportation and communications
Financial, real estate and business services
Other services

Source: Own elaboration.

Table 3 provides an overview of the two sets of variables involved in the methodology presented in section 2 for Spain, the United States and the five Latin American countries. Capital and labor inputs are classified by capital assets and by types of labor according to the level of educational attainment.

Regarding capital input, Table 3 shows the composition of gross fixed capital formation (capital flows) in the countries considered. Due to its variability, the table shows the average structure for the whole period analyzed (1995–2016). As expected, the share of ICT investment over total investment is lower in the Latin American economies (around 5.4% on average) while in Spain and the United States it is more than twice the Latin American average. The United States has the highest share of ICT assets (18.9%).

In all the countries, residential and non-residential structures are by far the largest category of capital assets, reaching a high of 73.4% in the Dominican Republic, almost 25 percentage points above the country with the lowest share, the United States (49.9%). In general, real estate assets are more important in the Latin American countries and Spain than in the United States. Machinery and equipment (including transport equipment and cultivated assets) accounts for around 30% of total investment in Costa Rica, Mexico, Peru, and the United States, whereas its share is 10 percentage points lower in the Dominican Republic and Spain (22.7% and 23.5% respectively), and 10 percentage points higher in El Salvador (41.5%). The analysis of this structure is important because capital stock stems from the accumulation of GFCF flows. Therefore, the structure of capital stock and capital compensation in each country is determined, to a great extent, by GFCF characteristics.

As expected, due to its lower base level, ICT investment has experienced a higher rate of growth than non-ICT assets in all the countries over the period 1995–2016, the only exceptions being El Salvador. The difference between the two is especially marked in the United States (7.6% ICT vs. 1.2% non-ICT), Spain (8.7% ICT vs. 1% non-ICT) and Mexico (10% vs. 3.8%). It is worth highlighting the case of El Salvador, whose GFCF in ICT assets show the lowest growth rate over the years 1995–2016, 0.3%. Regarding non-ICT assets, the high growth rate in the Dominican Republic, above 7%, is worth noting. It seems that, in general, investment grows at a higher rate in countries that have lower points of departure in terms of accumulated stock, as is the case of the Latin American countries. The only exception is El Salvador.

Table 3 also shows information about labor (in terms of total hours worked), according to the level of educational attainment (part b of the table). The United States has the lowest share of unskilled labor. In fact, the labor structure in the US and Spain is biased towards more educated labor. Among LA KLEMS countries, Peru, Costa Rica and the Dominican Republic show the highest shares for high-skilled workers, above or around 25%, compared to nearly 40% in the case of the United States and Spain. The structure of labor differs among countries and these differences will play an important role in determining the intensity of the use of knowledge in the economy.

The general pattern since 1995 has been, as expected, a decrease in the share of the lower levels in favor of the other two in all the countries. In fact, only in Mexico, the Dominican Republic and slightly in Costa Rica has the amount of less qualified labor increased in absolute terms. In the majority of countries, in general, job creation is concentrated among workers with high or medium educational levels, who, according to the described methodology, are the main contributors to knowledge.

Table 3. Descriptive statistics

a) Gross fixed capital formation

a.1) GFCF structure by assets, average 1995-2016 (%)	Costa Rica	Dominican Republic	El Salvador	Mexico	Peru	Spain	US
ICT	8.00	3.91	6.78	5.50	2.82	10.87	18.87
Software	1.40	0.74	0.32	0.20	0.58	4.61	10.90
Computing equipment	5.17	0.96	4.47	2.27	1.44	2.47	3.89
Communication equipment	1.44	2.21	1.99	3.04	0.80	3.79	4.07
Non-ICT	92.00	96.09	93.22	94.50	97.18	89.13	81.13
Transport equipment	9.85	5.30	5.91	12.17	7.24	8.75	7.98
Machinery & Equipment (exclu. ICT)	22.86	16.67	34.24	14.19	25.65	14.28	23.25
Cultivated assets*	1.45	0.69	1.33	0.44	1.72	0.50	-
Non-residential structures	39.74	29.23	29.61	35.53	34.16	32.09	26.49
Residential structures	18.10	44.20	22.13	32.16	28.40	33.52	23.41
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00

a.2) GFCF. Average annual growth rates (1995-2016)	Costa Rica	Dominican Republic	El Salvador	Mexico	Peru	Spain	US
ICT	4.52	14.21	0.34	9.96	7.87	8.73	7.63
Software	20.31	19.72	6.75	5.35	6.68	5.92	7.33
Computing equipment	2.16	20.42	0.29	9.36	7.49	11.51	12.34
Communication equipment	9.19	12.11	-0.78	10.84	9.43	12.69	6.64
Non-ICT	4.44	7.21	0.43	3.79	4.85	1.02	1.21
Transport equipment	4.50	8.95	3.07	10.00	5.49	4.37	3.23
Machinery & Equipment (exclu. ICT)	3.27	7.48	-0.85	6.11	5.15	1.23	2.20
Cultivated assets	0.86	1.74	0.08	2.72	3.26	11.77	-
Non-residential structures	4.52	5.87	2.35	2.85	5.11	-0.23	0.20
Residential structures	6.09	8.37	-0.40	2.32	4.26	1.20	0.74
Total	4.45	7.31	0.42	4.00	4.92	1.79	2.06

Table 3. Descriptive statistics (cont.)

b) Labor

b.1) Labor share by level of education, 2016 (%)	Costa Rica	Dominican Republic	El Salvador	Mexico	Peru	Spain	US
High	24.11	25.91	12.63	13.40	31.68	39.68	38.55
Medium	40.07	35.01	48.68	46.54	44.48	23.93	53.93
Low	35.82	39.08	38.69	40.06	23.84	36.39	7.53
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00

b.2) Labor. Average annual growth rates (1995-2016)	Costa Rica	Dominican Republic	El Salvador	Mexico	Peru	Spain	US
High	4.00	3.37	1.95	1.63	3.82	4.30	2.73
Medium	3.00	3.67	2.17	3.02	2.56	3.41	-0.14
Low	0.40	2.01	-0.29	1.03	-2.14	-1.18	-1.05
Total	2.07	2.88	1.04	1.95	1.21	1.41	0.68

* Not available for US.

Source: BEA (2018), BBVA Foundation-Ivie (2019), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013) and own elaboration.

4. Knowledge intensity estimates. Aggregated results

This section presents the main aggregated results that can be obtained with the exercises proposed in section 2 for measuring the knowledge economy. Our objective is to replicate Mas, Hofman and Benages (2019b) (which corresponds to the broader approach described in section 2) but with two important departures. The first one is the consideration of a brand new database released in April, 2020 (<http://laktelems.net>), which incorporates four LA countries previously absent from the LA KLEMS database, namely Costa Rica, the Dominican Republic, El Salvador and Peru.¹⁶ In addition, Mexico is also now included; although it was already present, information for the country—provided by INEGI—has been revised to align it with the methodology and assumptions followed for the other four countries. The information for Spain and the US was also revised for the same reason. Secondly, this paper considers two alternative definitions, one more restrictive than the other, which allows us to check the sensitivity of the results to a more or less stringent definition of the knowledge economy.

We start with the knowledge economy's share of total GVA (as given by Equation [8]) for each individual country during the period considered. Panel a in figure 1 shows the profiles for share of knowledge-based GVA, defined as in the broad approach, while panel b shows the same share, but following the restrictive approach.

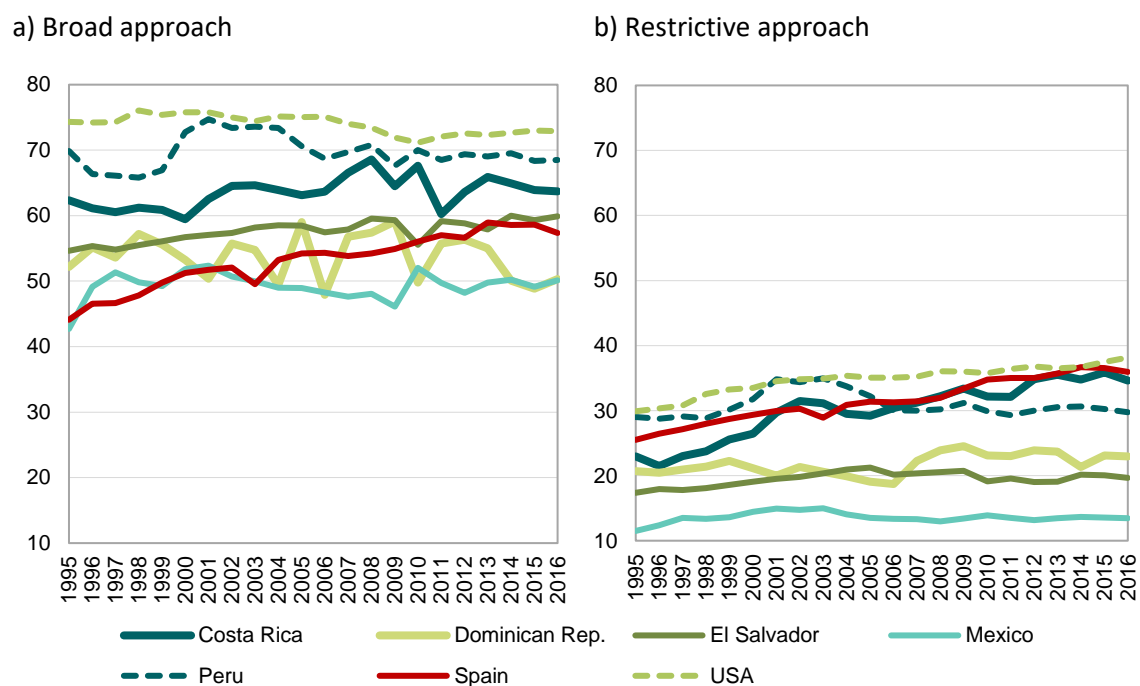
As expected, the United States presents the highest shares. On average, for the whole period 1995–2016, in the US the knowledge economy (broad approach) accounted for around 74% of total GVA, although it shows a downward trend. Among the LA countries, Peru has by far the highest share, averaging around 70%, followed by Costa Rica, with a share close to 65%, but with a more volatile profile. The remaining countries, including Spain, show lower shares (below 60%) during the whole period. Mexico and the Dominican Republic are the two countries with the lowest shares in 2016. The Dominican Republic even saw a reduction in knowledge share in its economy between 1995 and 2016.

The results of applying the restrictive approach show a quite different image of the situation in each country. Now knowledge-based GVA (considering only that generated by high-skilled workers and ICT assets) accounts for less than 40% of total GVA in all

¹⁶ IADB-Ivie (2020) and Mas and Benages (2020).

countries. The US still holds the leading position (38%), but this time Spain ranks second (36%). Among the LA countries, only Costa Rica shows similar shares, while the remaining countries report lower shares, especially Mexico, whose knowledge share is below 15%. In this case, all the countries show an upward trend between 1995 and 2016, a pattern that is more pronounced in the case of Costa Rica and Spain. However, the gap between LA countries and the most developed of the two benchmark countries (US) is higher in this case than in the broad approach: whereas in 2016 under the broad approach the LA average share accounts for 80% of the US knowledge-based GVA share, in the case of the restrictive approach it accounts for only 63%.

Figure 1. Knowledge-based GVA. International comparison, 1995-2016 (percentage over total GVA)



Source: BEA (2018), BBVA Foundation-Ivie (2019), LAKLEMS (2020), EUKLEMS (2019), WIOD (2013) and own elaboration.

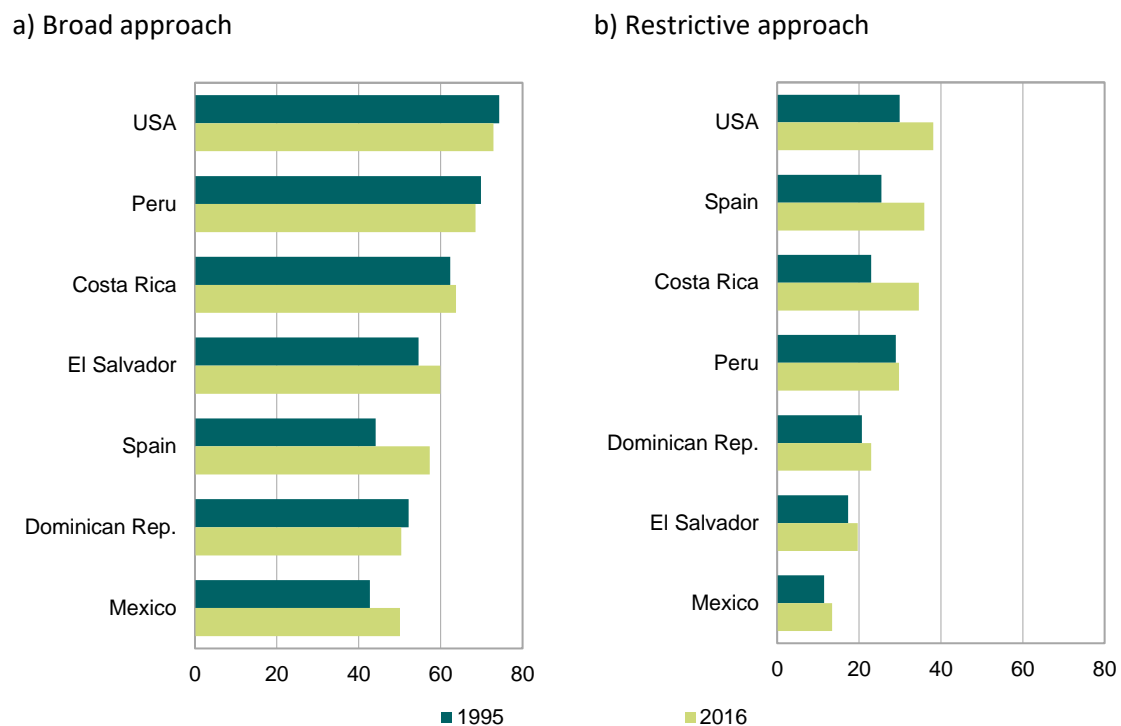
A comparison of the two approaches reveals two clusters of Latin American countries. Costa Rica and Peru follow a common pattern, showing a higher share of knowledge-based GVA which is more similar to that of the US or Spain. Mexico, the Dominican Republic and El Salvador form the second cluster, approaching a lower value of around 50-60% for the broad approach and around 15-25% for the restrictive approach. The change in values for Spain from panel a to panel b is worth highlighting; this change

suggests that the restrictive approach tends to favor the most developed countries, and may indicate that it is a more accurate approach when analyzing more advanced countries, whereas the broad approach seems to be more appropriate when comparing the situation of lagging countries.

Figure 2 summarizes the position of the seven countries, at the beginning and at the end of the period, in terms of the knowledge economy's share of total GVA. Panel a again reports the results according to the broad approach, and panel b, those for the restrictive approach. Panel a shows very little change in the order of the countries in 2016 compared to 1995. The same is seen when the restrictive approach is considered. Following the broad definition, the US, Peru and Costa Rica had the highest share in 1995 and 2016, with the US taking the lead. The countries that follow are El Salvador, Spain and the Dominican Republic, while Mexico takes the last place. It is worth noting that the distance between the leading country (US) and the country at the bottom of the ranking (Mexico) reached more than 30 percentage points in 1995, whereas this difference was around 20 percentage points in 2016, showing a certain convergence among LA countries and the US, one of the two benchmark countries in this analysis.

Some differences arise under the restrictive approach, that is, when the focus is on the more knowledge-intensive assets and workers (panel b of figure 2). The US remains in first position, but now Spain takes the second place, closely followed by Costa Rica. Peru falls to fourth position and the Dominican Republic now surpasses El Salvador, which lies in penultimate position; Mexico remains at the bottom. Interestingly, in 2016 the differences between the leader and the last country in the ranking are higher than in the case of the broad approach and these differences increased by 6.3 pp between 1995 and 2016, contrary to the results for the broad perspective. Thus, the benchmark countries show a higher intensity than the LA countries in the use of factors of production which are at the *core* of the knowledge economy (ICT and high-skilled workers), with the exception of Costa Rica. LA countries are still lagging behind in this area.

Figure 2. Knowledge-based GVA. International comparison, 1995 and 2016
(percentage over total GVA)



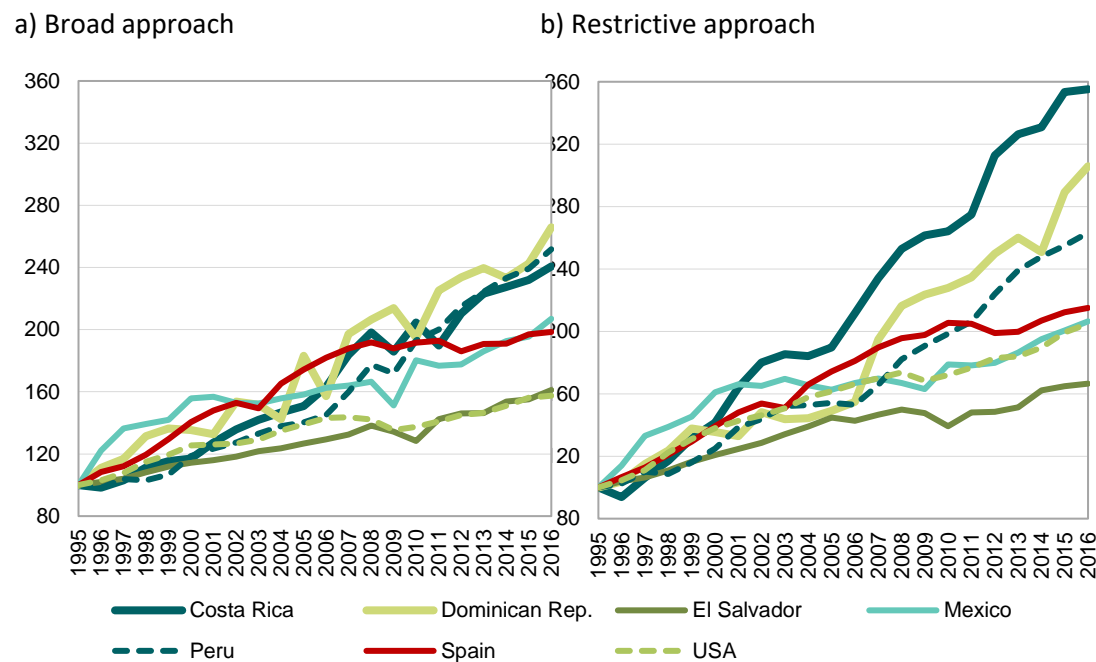
Note: Countries are ranked according to Knowledge-based GVA share in 2016.

Source: BEA (2018), BBVA Foundation-Ivie (2019), LAKLEMS (2020), EUKLEMS (2019), WIOD (2013) and own elaboration.

Figure 3 shows the dynamics of knowledge-based GVA, measured in real terms, over the 1995–2016 period in the seven countries considered. Panel a reflects the knowledge-based GVA according to the broad approach. Four Latin American countries show the fastest growth, with the Dominican Republic and Peru taking the lead, followed closely by Costa Rica. Now, the two benchmark countries, Spain, and especially the United States, followed a slower path, similar to that of El Salvador and Mexico, the least dynamic of the Latin American countries. Panel b reflects the more dynamic behavior of the knowledge-based GVA calculated following the restrictive definition. This means that the value generated by the most technological assets and the most educated workers has grown more intensively in all countries. This growth is particularly intense in Costa Rica, the Dominican Republic and Peru, but more modest in Spain, the US, El Salvador and especially in Mexico. Overall, figure 3 confirms that there was some convergence over the period, with the countries ranked lowest in 1995 growing faster

than the leaders. Mexico and El Salvador, are the exceptions to this general convergence behavior.

Figure 3. Real knowledge-based GVA. International comparison, 1995-2016 (1995=100)

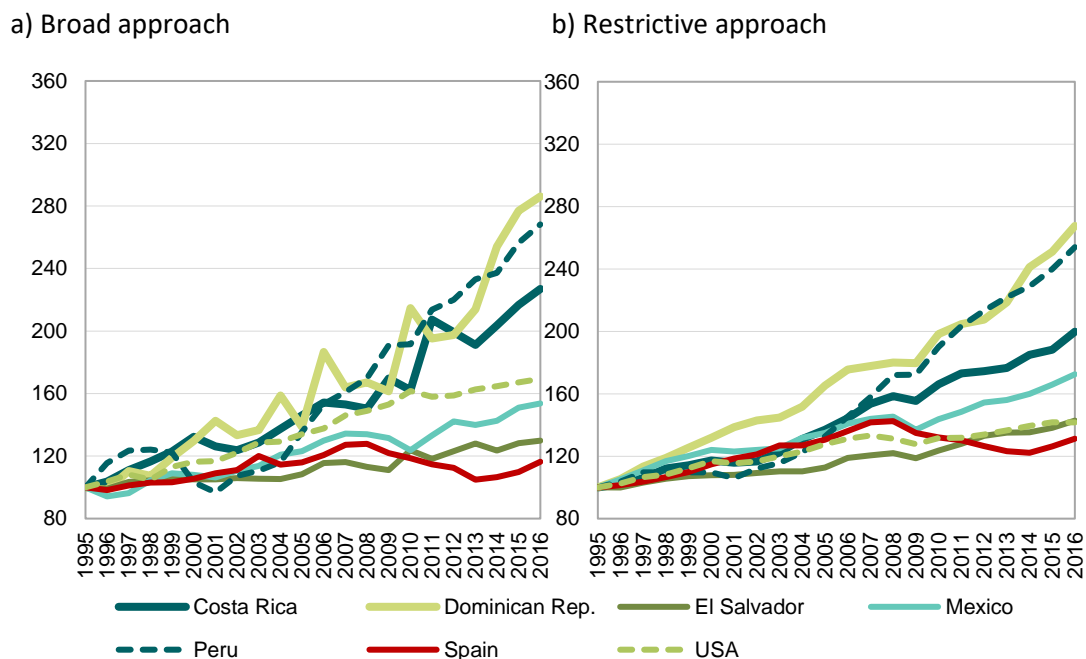


Source: BEA (2018), BBVA Foundation-Ivie (2019), LAKLEMS (2020), EUKLEMS (2019), WIOD (2013) and own elaboration.

The information provided by figure 4 qualifies the above conclusions. It shows the dynamics of non-knowledge GVA, also in real terms. Panel a refers to the broad approach and b to the restrictive approach. The first point of note when the information in panel a is compared with that in figure 3 is the much more dynamic behavior of the American countries in contrast to Spain, whose profile even declines between 2007 and 2013. Notably, the United States shows faster growth in the non-knowledge than in the knowledge economy, a pattern that is repeated for the Dominican Republic and Peru. The main difference when we analyze the non-knowledge GVA according to the restrictive definition (panel b) is the much more modest growth in the US, similar to that of Spain. In this case, there is no country where non-knowledge GVA grows more than knowledge-based GVA.

Overall, the picture from the two figures is of less dynamism in the US and Spain, in contrast to Costa Rica, the Dominican Republic and Peru, which showed more dynamic behavior.

Figure 4. Real non-knowledge GVA. International comparison, 1995-2016 (1995=100)



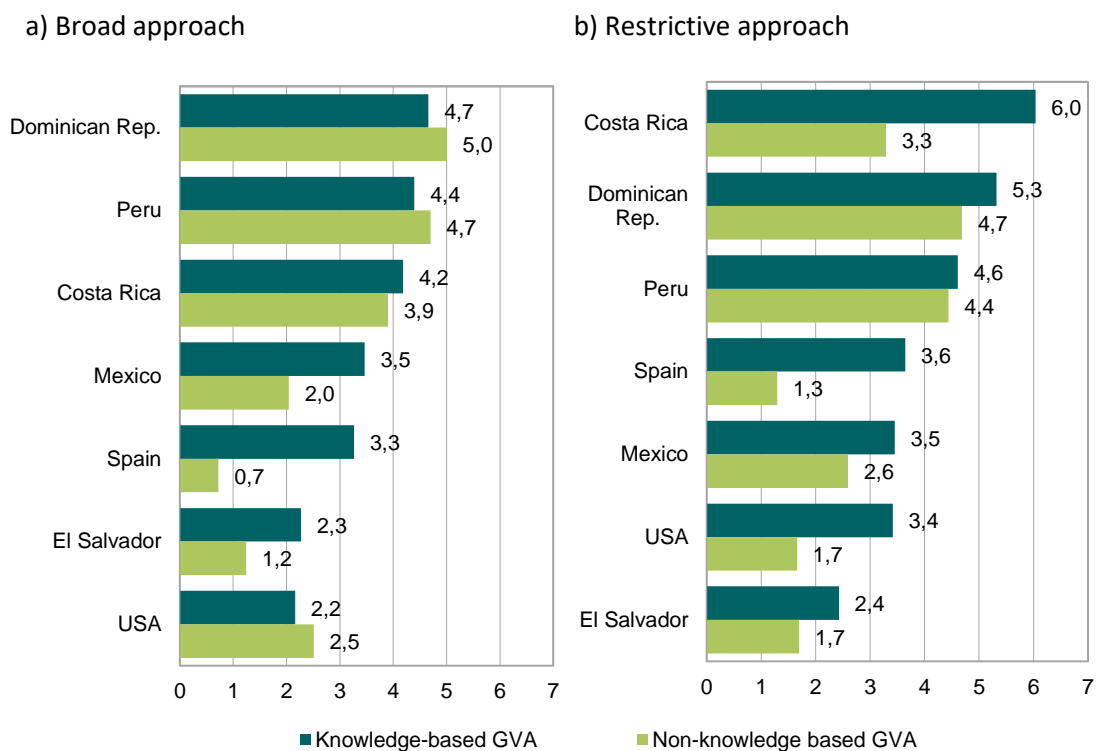
Source: BEA (2018), BBVA Foundation-Ivie (2019), LAKLEMS (2020), EUKLEMS (2019), WIOD (2013) and own elaboration.

A complementary way of observing the same phenomenon is provided by figure 5, which depicts the annual rates of growth of knowledge and non-knowledge GVA over the period 1995–2016 and considering both approaches. Three Latin American countries take first places in both aggregations: the Dominican Republic, Peru and Costa Rica. For the broad approach, the Dominican Republic takes the lead (4.7%), while in the case of the restrictive approach Costa Rica shows the highest growth rate (6%). Costa Rica stands out for its use of productive inputs with a higher knowledge content (high-skilled workers and ICT assets), as its position improves under the restrictive approach. This is also the case for the benchmark countries, US and Spain.

Figure 5 clearly shows the countries in which knowledge-based GVA grows more than non-knowledge GVA. This faster growth is seen in Costa Rica, Mexico, El Salvador and Spain according to the broad approach, and in all the countries according to the

restrictive approach, especially in Costa Rica and Spain. This result confirms the higher dynamism of the most technological assets and the most educated workers in generating value added.

Figure 5. Average growth rate of knowledge and non-knowledge GVA. International comparison, 1995-2016 (percentage)



Note: Countries are ranked according to knowledge GVA growth.

Source: BEA (2018), BBVA Foundation-Ivie (2019), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013) and own elaboration.

Figures 3, 4, and 5 provided the rates of growth of knowledge and non-knowledge-based GVA considered individually. Figure 6 combines this information with each component's share of total GVA, showing each one's contribution to total GVA growth. This information is provided for the whole period 1995–2016 (panel a) and also separately for the pre-recession (panel b) and post-recession (panel c) years. The results obtained following the two approaches are also distinguished.

Regardless of the period analyzed, Peru, the Dominican Republic, and Costa Rica have the highest rates of GVA growth and also the highest contribution of the knowledge economy (in percentage points). Mexico and El Salvador show more modest results,

especially when compared with the three Latin American leaders. The two benchmark countries, the United States and Spain, show even more modest growth for the whole period. However, their behavior was more positive in the expansion years (1995–2007) than in the years that followed. This is particularly true in the case of Spain, for which a sharp contrast in behavior is seen between the pre- and post-recession years. During the expansion years (panel b), the knowledge economy made an important contribution to growth. However, the consequences of the great recession after 2007 (panel c) were dramatic for Spain, which presented a negative average annual rate of growth for the whole 2007–2016 period. This country had negative contributions of the non-knowledge economy throughout those years, indicating that the non-knowledge part of the economy is more vulnerable to difficult times than its knowledge counterpart. This result may justify the importance of measuring and fostering the knowledge-based economy.

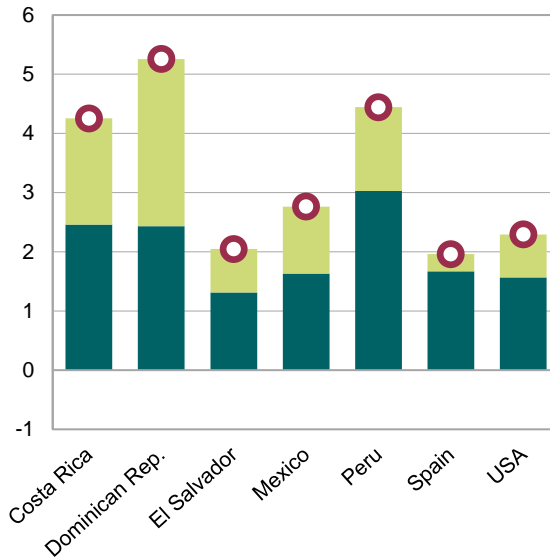
Regarding the differences between the broad and restrictive approaches, in almost all the countries and periods the contribution of knowledge-based GVA is higher than that of non-knowledge GVA under the broad approach. On the other hand, when we follow the restrictive definition, the contribution of knowledge-based GVA is only greater than, or similar to, that of non-knowledge GVA in Spain and the US, being smaller in the case of Latin American countries. As mentioned previously, LA countries are still lagging behind in terms of the most technological assets and the most educated workers' contribution to growth, at least in comparison to the US and Spain.

To conclude the presentation of aggregated results, figure 7 shows knowledge-based GVA per capita (expressed in 2010 US dollars PPP per person) at the beginning and end of the period. Regardless of the approach, the two benchmark countries lead the ranking, with the United States in first place. The five Latin American countries present lower values. Among them, and also regardless of the approach, Costa Rica leads the ranking and El Salvador is in last place. As can be seen, the gap between LA countries and the two benchmarks is significant. The knowledge-based GVA per capita in Costa Rica, the leading LA country in this respect, is 25% of the US value in 2016, regardless of the approach. In the case of El Salvador, which occupies the last place in the ranking, it is around 5–10%. It is worth noting that all seven countries experienced an improvement in this variable between 1995 and 2016 for both approaches.

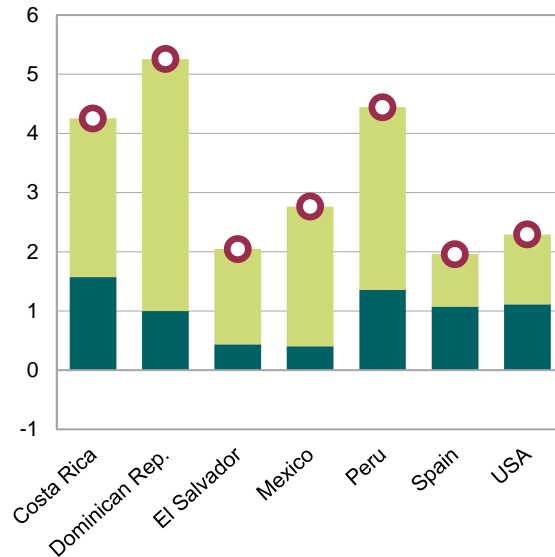
Figure 6. GVA annual growth rate: knowledge and non-knowledge contribution. International comparison, 1995-2016 (percentage)

a) 1995-2016

a.1) Broad approach

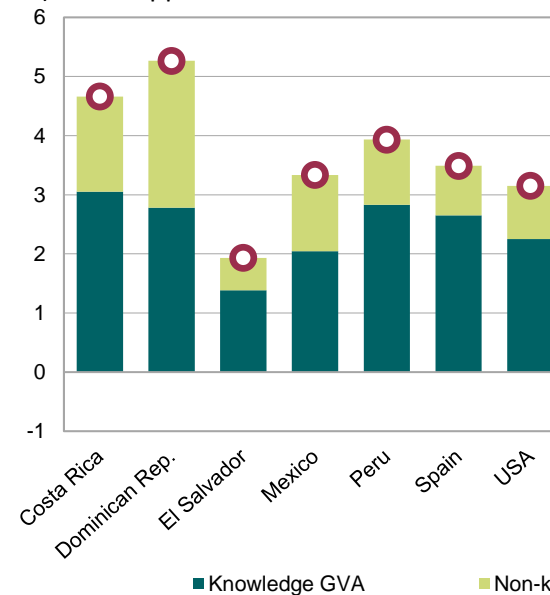


a.2) Restrictive approach

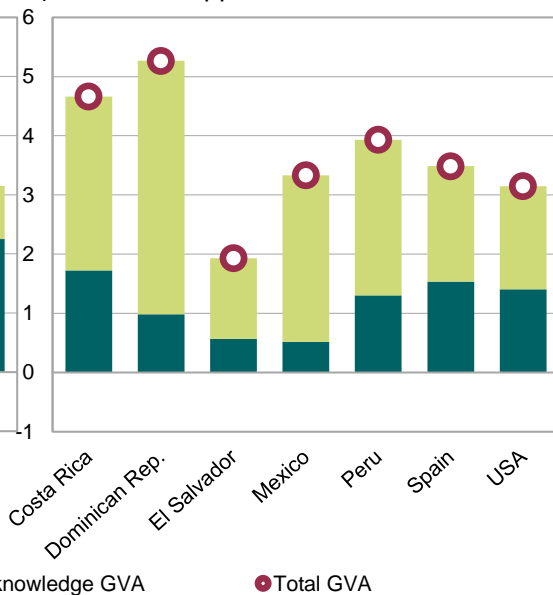


b) 1995-2007

b.1) Broad approach



b.2) Restrictive approach



■ Knowledge GVA

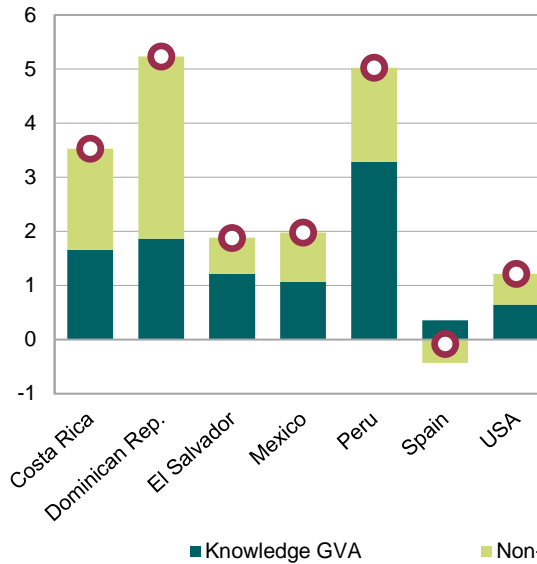
■ Non-knowledge GVA

● Total GVA

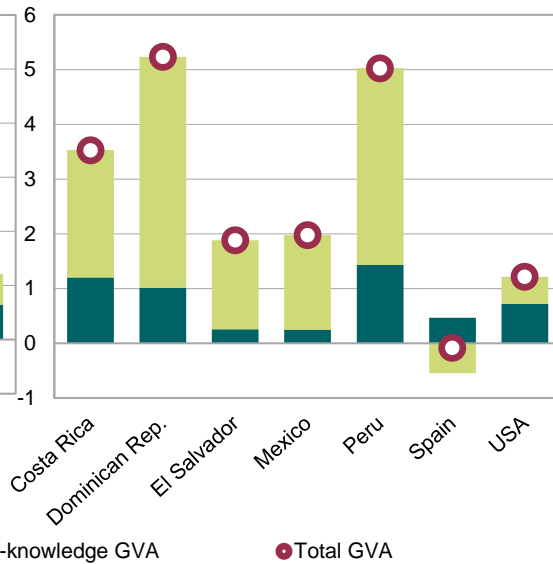
Figure 6. GVA annual growth rate: knowledge and non-knowledge contribution. International comparison, 1995-2016 (percentage) (cont.)

c) 2007-2016

c.1) Broad approach



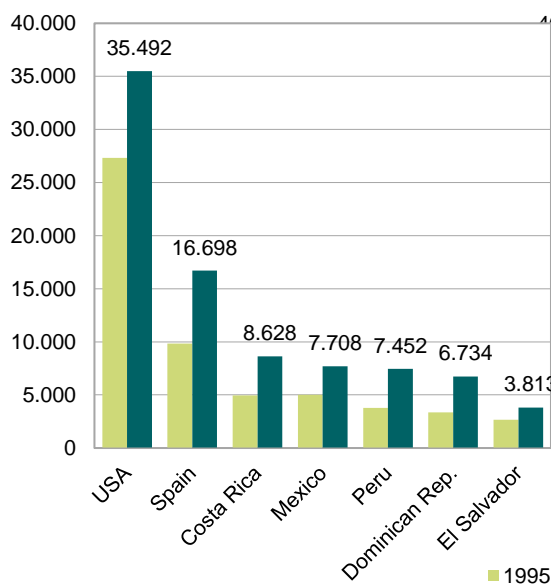
c.2) Restrictive approach



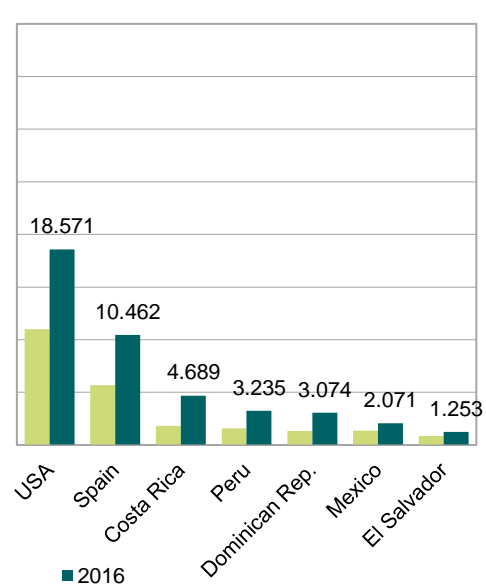
Source: BEA (2018), BBVA Foundation-Ivie (2019), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013) and own elaboration.

Figure 7. Knowledge-based GVA per capita, 1995 and 2016 (2010 US Dollars PPP per person)

a) Broad approach



b) Restrictive approach

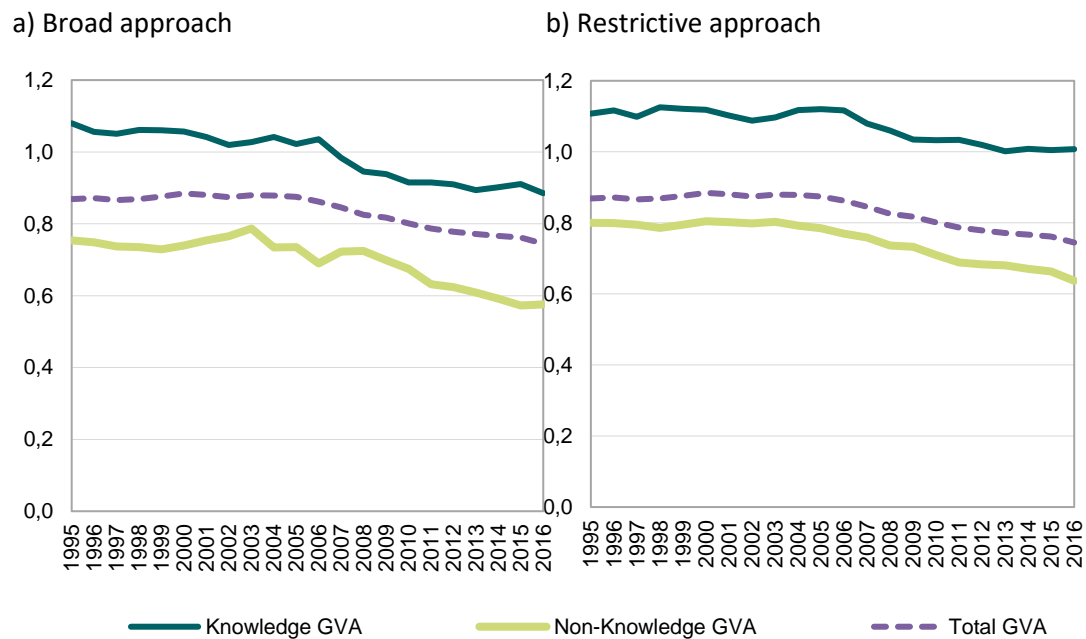


Note: Countries are ranked according to 2016.

Source: BEA (2018), BBVA Foundation-Ivie (2019), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013), World Bank (2020) and own elaboration.

The positive performance of the knowledge-based economy in all the countries and the strong growth trend shown by the less developed ones (namely the Latin American countries) resulted in a process of convergence between them. Figure 8 reflects this convergence, showing the coefficient of variation for knowledge-based, non-knowledge based, and total GVA per capita, considering all the countries analyzed. As can be seen, the differences among the seven countries are higher in the knowledge GVA than in total GVA and non-knowledge GVA, where the differences are lower. Additionally, the differences in the three variables declined throughout the period. Thus, there was convergence in knowledge-based GVA per capita, although convergence in non-knowledge GVA per capita was somewhat stronger.

Figure 8. Convergence in the knowledge and non-knowledge-based GVA per capita among countries. International comparison, 1995-2016 (coefficient of variation)

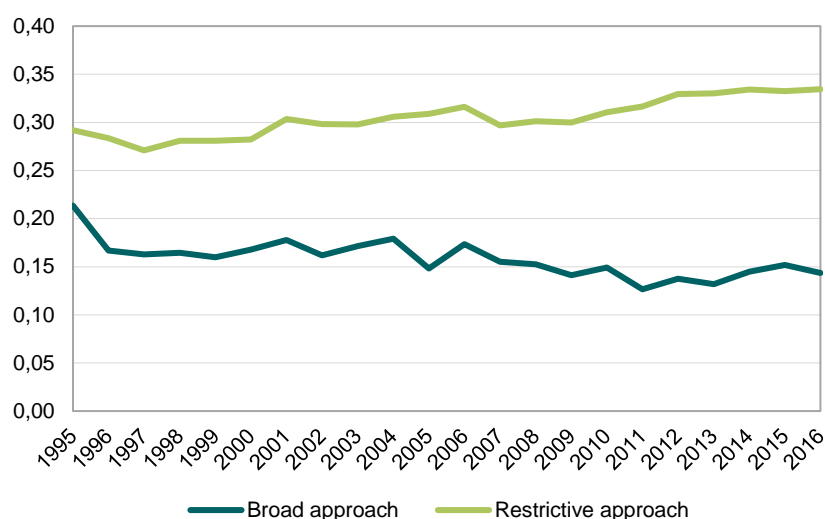


Source: BEA (2018), BBVA Foundation-Ivie (2019), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013), World Bank (2020) and own elaboration.

Figure 9 offers complementary information to analyze the convergence among countries by showing the coefficient of variation for the share of knowledge-based GVA out of total GVA, once again considering LA countries and both benchmarks. In this case, the differences among countries under the restricted approach are clearly higher, with a slight increase throughout the period 1995–2016. By contrast, there is convergence when the broader approach is considered. This result implies that in general, LA countries have advanced more in terms of the use of machinery and equipment and

medium-skilled workers than in terms of technologically advanced assets and most educated labor.

Figure 9. Convergence in the knowledge-based GVA share among countries. International comparison, 1995-2016 (coefficient of variation)



Source: BEA (2018), BBVA Foundation-Ivie (2019), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013), World Bank (2020) and own elaboration.

Taking as a point of departure these aggregated results, our contribution aims at deepening the characterization of the knowledge-based economy in Latin American countries and examining the evolution of the determinants of the knowledge intensity (capital and labor) in these countries over the years. To this end some additional analyses are performed in the following sections.

Disaggregation of knowledge-based GVA by source

As already explained in section 2, our approach to the knowledge-based economy assumes that knowledge is embedded in the two factors of production —labor and capital— and that the contribution of each individual asset is determined by the prices of the services it provides. Thus, it is useful to analyze the knowledge and non-knowledge compensation, as a percentage of GVA, of all the components considered, also distinguishing between ICT, non-ICT machinery and equipment and real estate capital, as well as between high, medium and low-skilled labor. In fact, we can easily move from the narrowest to the broadest definition of knowledge-based GVA by either

focusing solely on ICT capital and high-skilled labor compensation for the narrow definition, or by also including compensation corresponding to machinery and equipment and medium-skilled labor for the broader perspective.

Table 4 offers this information for the start and end of the period (1995 and 2016). ICT capital compensation has the lowest share in all countries, lying below 3% in LA countries. In the US and Spain it accounts for 4.3% and 4.1% in 2016, respectively, although this share was not very different in 1995. The decline in the prices of these assets may explain this behavior. Machinery and equipment compensation ranges between 7.4% in Spain and 18.3% in Peru in 2016. Two clusters can be identified: Spain, the US, Costa Rica and the Dominican Republic, which have lower shares, and the remaining LA countries, with higher shares for these assets. Real estate capital compensation has a large participation, standing out in the case of some Latin American countries such as the Dominican Republic and Mexico.

Regarding labor compensation, high-skilled workers play a more important role in the US and Spain than in LA countries, as their compensation accounts for more than 30% in both countries. These results are the combination of the weight of high-educated workers and the wages they receive. Among LA countries only Costa Rica shows a share above 30%, being the LA country with the most similar pattern to the US and Spain. At the other end, high-skilled labor compensation in Mexico only accounts for 11.1% of GVA. The good news is that in all countries the weight of the less educated workers' compensation decreased between 1995 and 2016, meaning that these economies now make more intensive use of knowledge.

In general, among the Latin American countries, Costa Rica and, at a certain distance, Peru, have the most similar GVA composition to that of Spain and the US. The Dominican Republic and Mexico stand out for their high share of real estate capital compensation, and El Salvador and Mexico are characterized by their lower weight of high-skilled labor compensation. In Mexico the capital share amounts to almost 60% of total GVA, with labor making up the remaining 40%, an income distribution that is more biased toward capital than in the rest of the countries.

Table 4. Knowledge and non-knowledge compensation over GVA by source. International comparison, 1995 and 2016 (percentage)

a) 1995

	Costa Rica	Dominican Rep.	El Salvador	Mexico	Peru	Spain	US
ICT capital compensation	2.08	1.33	1.20	0.96	0.65	3.70	4.06
Mach&Equipment capital compensation	19.41	15.20	12.50	13.15	18.21	8.35	11.97
Real estate capital compensation	14.65	26.88	22.53	48.67	9.66	24.28	21.56
Labor compensation. High-skilled	20.89	19.37	16.17	10.55	28.36	21.81	25.84
Labor compensation. Medium-skilled	19.98	16.27	24.77	18.06	22.66	10.25	32.47
Labor compensation. Low-skilled	23.00	20.94	22.84	8.62	20.47	31.61	4.10
Total GVA	100.00	100.00	100.00	100.00	100.00	100.00	100.00

b) 2016

	Costa Rica	Dominican Rep.	El Salvador	Mexico	Peru	Spain	US
ICT capital compensation	2.11	0.95	1.92	2.33	1.01	4.12	4.29
Mach&Equipment capital compensation	10.24	10.95	14.97	14.74	18.29	7.42	10.79
Real estate capital compensation	24.24	34.01	25.91	43.40	24.90	26.83	25.14
Labor compensation. High-skilled	32.53	22.03	17.76	11.13	28.74	31.82	33.87
Labor compensation. Medium-skilled	18.85	16.41	25.26	21.90	20.48	14.00	23.97
Labor compensation. Low-skilled	12.04	15.65	14.18	6.50	6.58	15.81	1.94
Total GVA	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Source: BEA (2018), BBVA Foundation-Ivie (2019), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013) and own elaboration.

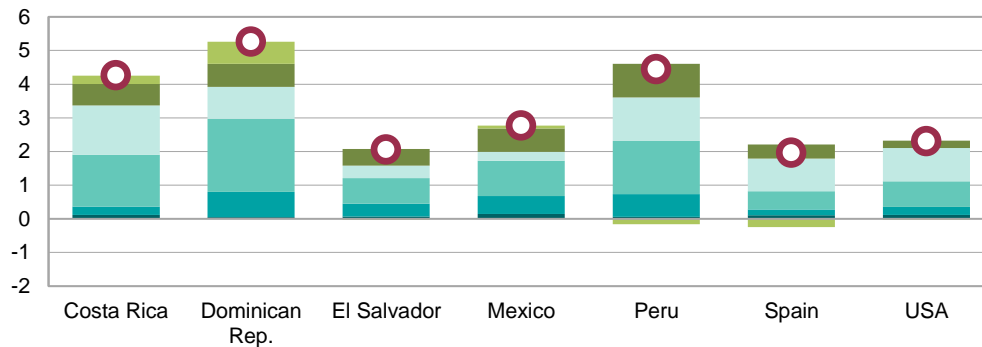
Figure 10 complements the information provided in Table 4, reporting the contribution of the six types of inputs to GVA growth in real terms. This information is provided for the whole period 1995–2016 (panel a) and also separately for the pre-recession (panel b) and post-recession (panel c) years. Focusing on the whole period (1995–2016) and starting with the most knowledge-intensive capital (ICT capital), Costa Rica, Mexico, the

US and Spain show the largest contributions. The most knowledge-intensive labor contribution (high-skilled labor) is remarkably high in Costa Rica, and also in Peru, but very low in Mexico and El Salvador. The Dominican Republic stands out for the highest contributions of real estate capital and low-skilled labor. The contribution of the latter is negative in the case of Spain, the United States, El Salvador and Peru.

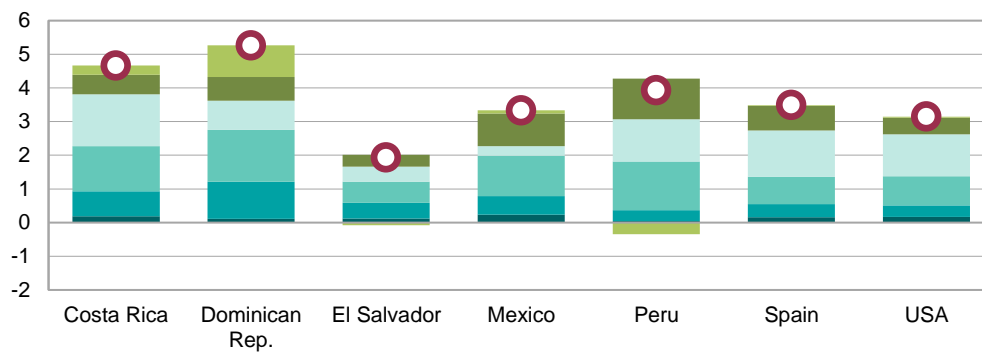
The results are more or less similar for the pre-recession period, but in the more recent years (2007–2016) there is a sharp contrast in behavior between the LA countries and Spain and the US, since the latter two were affected more seriously by the global economic crisis. Spain in particular presented a negative average annual rate of growth for the whole 2007–2016 period. In both countries, the contribution of real estate capital and low-skilled labor decreased in those years, indicating that the less knowledge-intensive part of the economy is more vulnerable to difficult times. Figure 11 aggregates the individual contribution to GVA growth of each input into knowledge and non-knowledge capital and labor according to the broad (panel a) and restrictive (panel c) approaches. The first conclusion to highlight is that in almost all the countries, knowledge-intensive labor made a higher contribution to GVA growth than knowledge-intensive capital. This is particularly true for the most developed countries, whose GVA growth stems mainly from knowledge-intensive labor. Second, the contribution of non-knowledge capital is much greater in Latin American countries, especially in Peru and the Dominican Republic. Third, in all the countries the contribution of non-knowledge-intensive capital was higher than its knowledge-intensive counterpart. However, in most countries (El Salvador, the Dominican Republic and Mexico being the exceptions in the case of the restrictive approach) the contribution of non-knowledge-intensive labor was lower than its knowledge-intensive counterpart.

Figure 10. Knowledge and non-knowledge inputs' contribution to annual real GVA growth rate. International comparison, 1995-2016 (percentage)

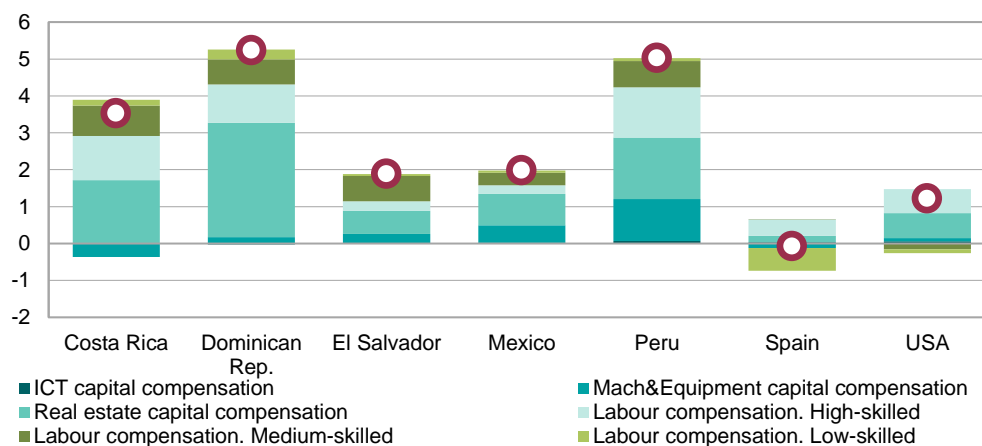
a) 1995-2016



b) 1995-2007



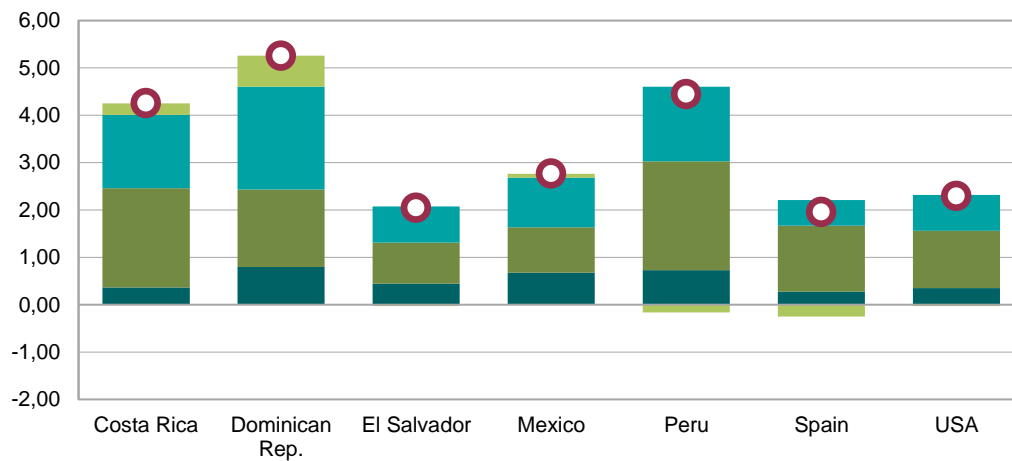
c) 2007-2016



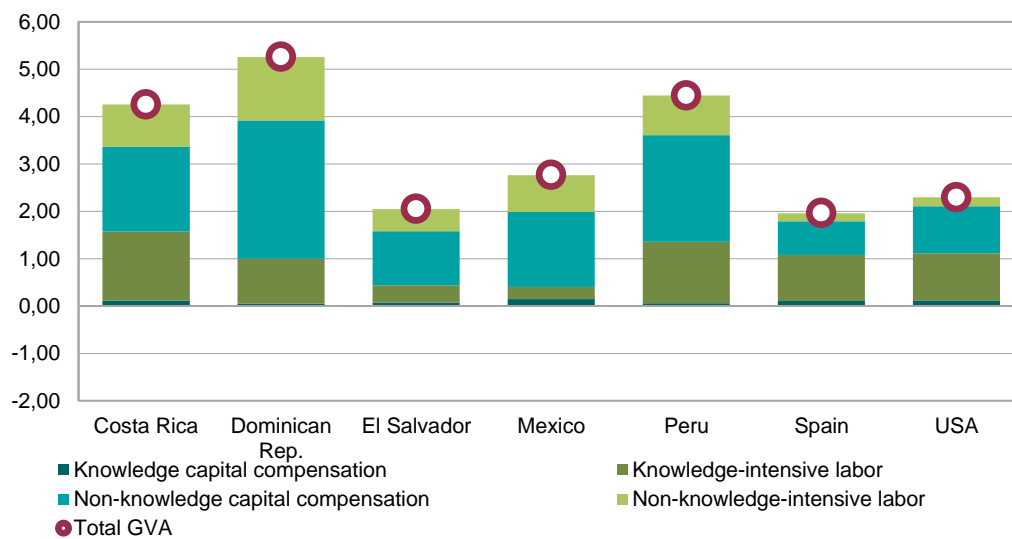
Source: BEA (2018), BBVA Foundation-Ivie (2019), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013) and own elaboration.

Figure 11. Knowledge and non-knowledge capital and labor contribution to annual real GVA growth rate. International comparison, 1995-2016 (percentage)

a) Broad approach



b) Restrictive approach



Source: BEA (2018), BBVA Foundation-Ivie (2019), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013) and own elaboration.

Comparison to traditional methods for measuring the knowledge economy

If we compare these aggregated results with those from other traditional methods, such as R&D intensity or tertiary education share, we find significant differences. As figure 12 shows, the order of countries changes when we take into account only R&D intensity (panel a) or the weight of the hours worked by high-skilled workers (panel b) to measure the knowledge economy. Regarding R&D intensity, Mexico is ranked first in 2016 (3.1% of GVA), followed by the US and Spain (3% and 1.4%, respectively). Costa Rica and Peru, which showed a better performance than Mexico under our approach, now appear in the last places with R&D intensities below 0.5% of their GVA. These differences are explained by the focus of our approach on the use of knowledge by the economic system, rather than on its generation or creation, which can be associated with R&D investment figures, but seems to be a partial measure of the knowledge intensity of an economy. Conversely, if we associate knowledge with the weight of the most educated workers, then the results are similar to those obtained throughout this section: the two countries used as benchmarks take the lead, followed by Peru, the Dominican Republic and Costa Rica, whereas Mexico and El Salvador are placed at the bottom. The conclusions that can be drawn from the method proposed in section 2 are therefore in line with those derived from the analysis of human capital but differ significantly from those based on the analysis of R&D intensities.

Figure 13 provides additional information following the OECD taxonomy on economic activities based on R&D intensity (see Galindo-Rueda and Verger, 2016)¹⁷. According to this taxonomy, GVA stemming from high R&D intensive activities (panel a) accounts for less than 5% of total GVA even in the benchmark countries: 3.3% in the US and 1.4% in Spain. In this case, Mexico again shows a good position, particularly compared with Spain, while Costa Rica falls further behind in the ranking. Although information is not available for the Dominican Republic, El Salvador and Peru, their situation is probably worse. If medium-high R&D activities are also considered (panel b of figure 11), the order of the countries for which information is available remains the same, although, as expected, the share of total GVA is higher (10.6% in the US, 8.7% in Mexico, 8.1% in Spain and 4.7% in Costa Rica). These shares are considerably lower than those of figure

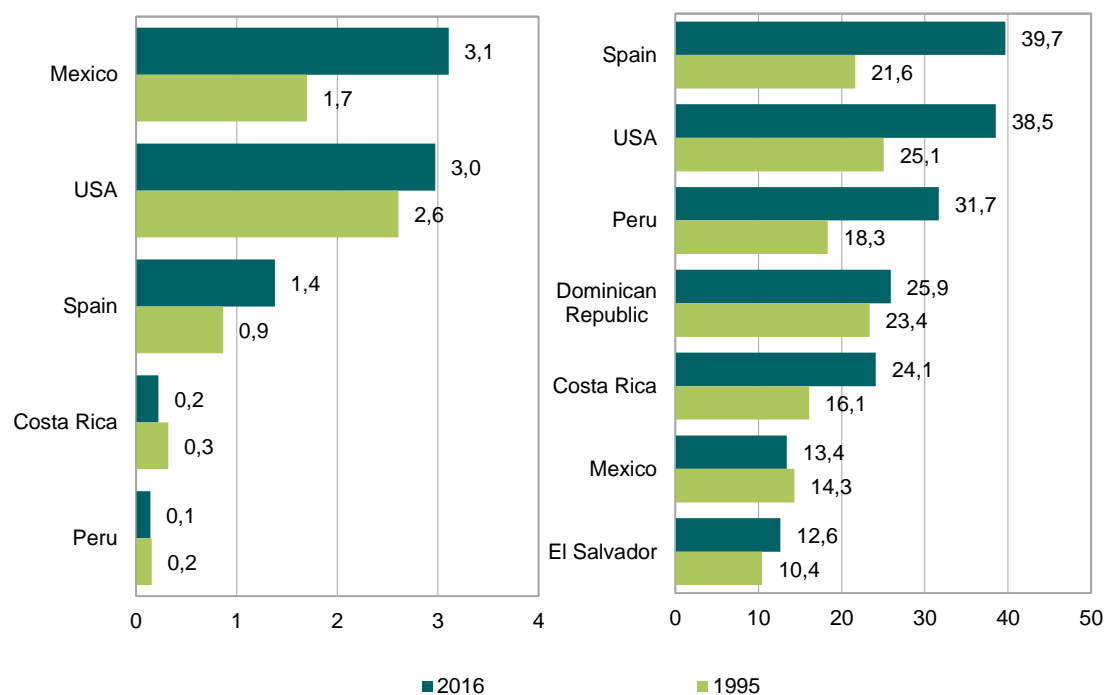
¹⁷ The OECD has also created a taxonomy of digital intensive sectors (see Calvino et al., 2018), but information about its share of GVA is only available for Spain and Mexico. According to this classification, in 2016 high digital intensive industries account for 19% in Spain and 17% in Mexico.

2, indicating that focusing on R&D expenditures provides only a partial image of the so-called knowledge economy. In addition, it is worth noting that the weight of these R&D intensive economic activities declined in the US, the leading country in this area, between 1995 and 2016. This may imply that it is not a good indicator to measure the spread of knowledge in the economy.

Figure 12. Traditional methods to measure the knowledge economy results. International comparison, 1995 and 2016 (percentage)

a) R&D intensity (percentage over GVA)

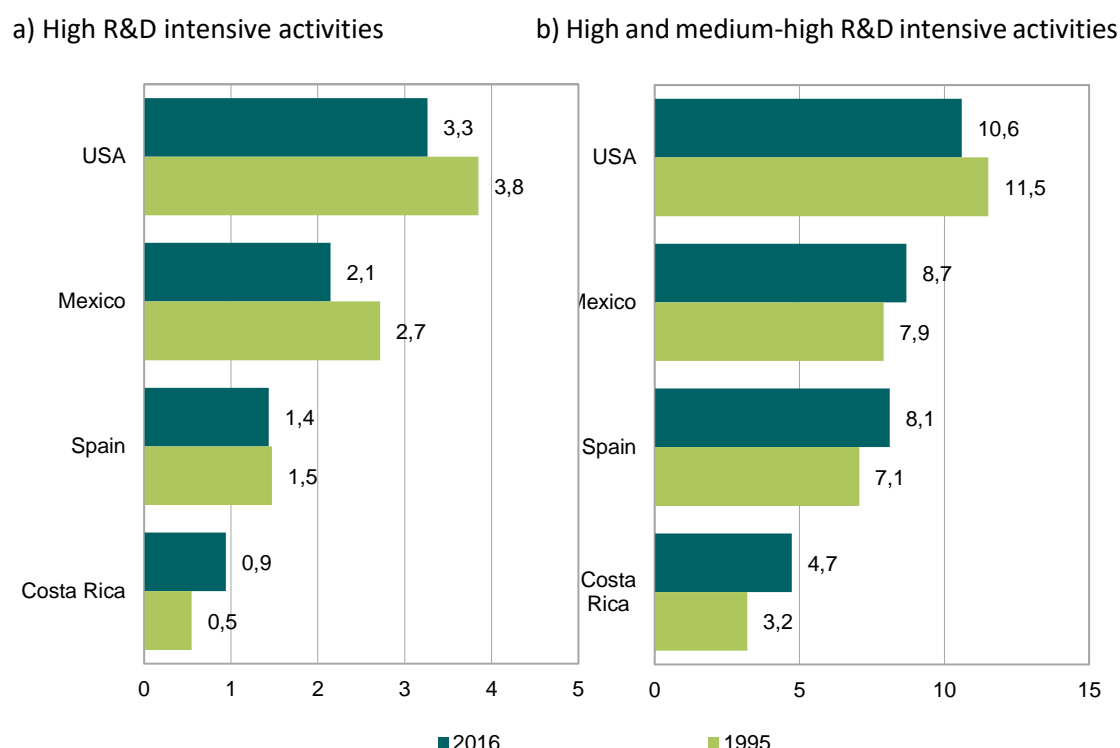
b) Hours worked by high-skilled workers (percentage over total hours)



Note: Countries are ranked according to 2016.

Source: BEA (2018), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013) and own elaboration.

Figure 13. High- and medium-high R&D intensive activities. International comparison, 1995 and 2016 (percentage over GVA)



Note: Countries are ranked according to 2016. Information for the Dominican Republic, El Salvador and Peru is not available. The first year available for the US is 1997. High R&D intensive activities (2-digit definition) comprises ISIC Rev. 4 21, 26 and 72. High- and medium-high intensive activities (2-digit definition) comprises ISIC-Rev 4 20-21, 26-28, 29-30, 58, 62-63 and 72.

Source: OECD (STAN database, 2019) and own elaboration.

5. Knowledge-based GVA by industry

A distinctive characteristic of the KLEMS methodology is the emphasis it puts on the importance of industry disaggregation. In fact, the results outlined until now come from the aggregation of industry data, as described in section 2 (see Equation [8]). Thus, it is worth analyzing the results regarding knowledge-based GVA and its composition from a sectoral perspective.

Figure 14 shows how the knowledge economy was distributed in 2016 among the nine sectors considered. Both definitions, broad and restrictive, are represented. In almost all countries, *Other services* (which includes Public administration, Education, Health, Social services, Arts, entertainment and recreation, and other services) absorbs the highest share of the knowledge economy, reaching up to 30% in the United States,

Spain, and Costa Rica under the broad approach, and above 40% under the restrictive approach. The second most important sector in the most developed countries is *Financial, real estate and business services*. *Manufacturing* takes second position in El Salvador and Mexico, and *Wholesale & retail trade, accommodation and food service* lies second in Peru and the Dominican Republic. Summing up, these four sectors absorb the highest share of the total knowledge economy, regardless of the approach, while the other five sectors have a much smaller share, especially *Agriculture, Mining and quarrying*, and *Electricity, gas and water supply*. It is worth noting that two sectors, *Other services* and, in some cases, *Financial, real estate and business services*, increase their share of total GVA when the restrictive approach is considered, whereas the opposite happens in the remaining sectors. That means that more ICT assets and high-skilled labor are concentrated in these two sectors than in other sectors of the economy.

Figure 14. Knowledge-based GVA by industry. Broad and restrictive approach, 2016.
Total GVA = 100 (percentage of total knowledge-based GVA)

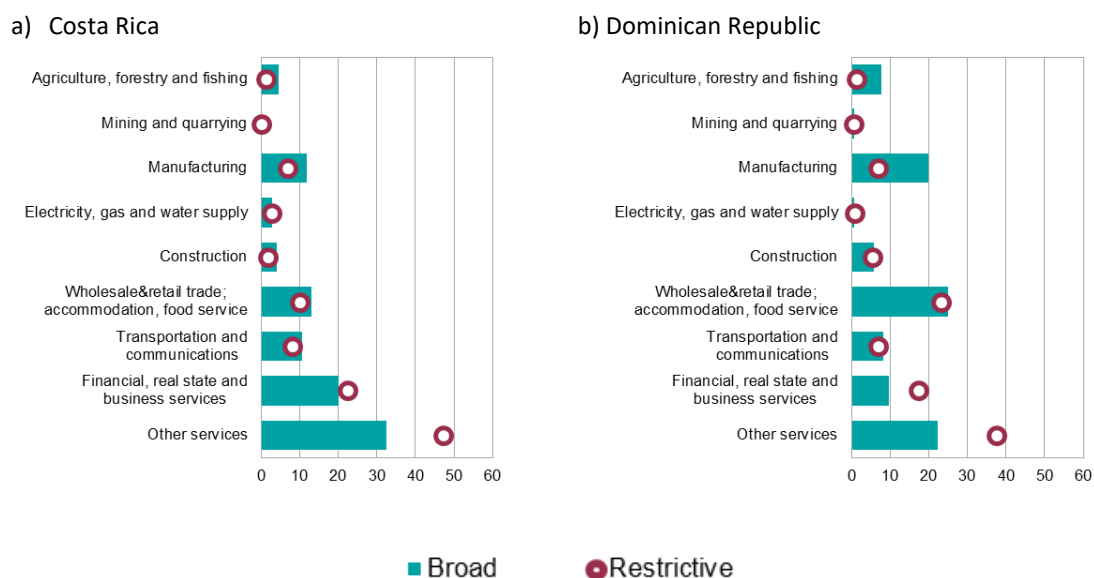
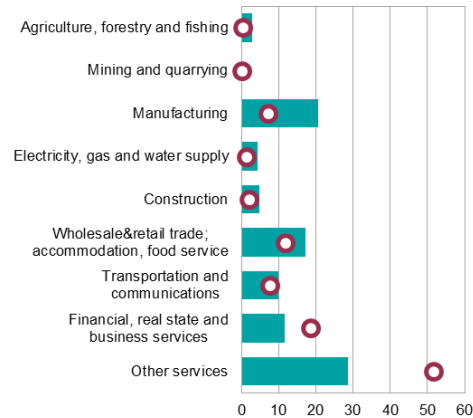
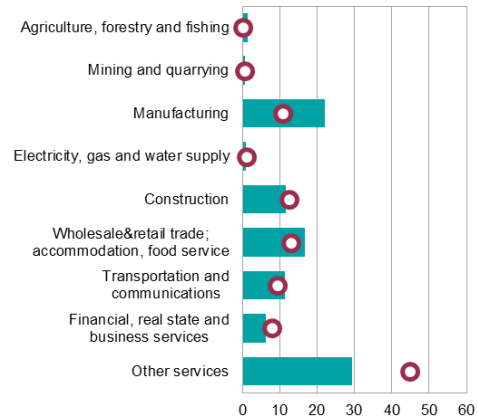


Figure 14. Knowledge-based GVA by industry. Broad and restrictive approach, 2016.
Total GVA = 100 (percentage of total knowledge-based GVA) (cont.)

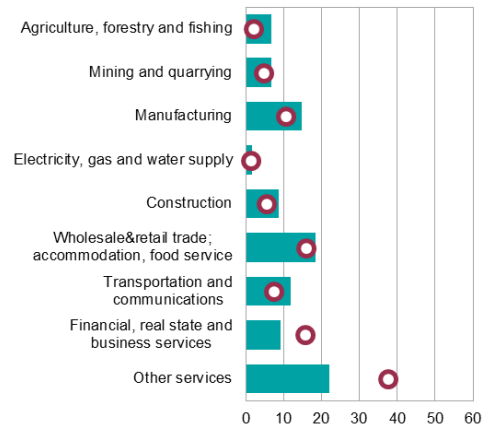
c) El Salvador



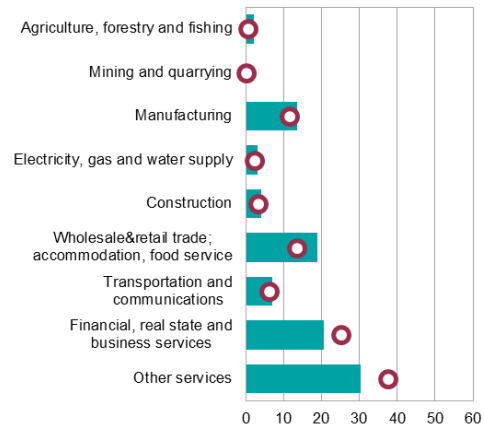
d) Mexico



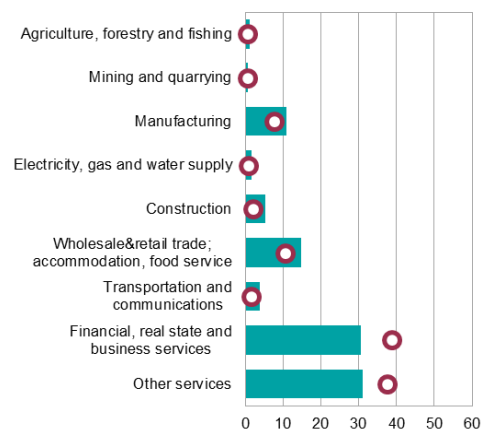
e) Peru



f) Spain



g) US



■ Broad ● Restrictive

Source: BEA (2018), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013) and own elaboration.

It is to be expected that the largest sectors of the economy should also absorb the largest shares of both the knowledge and the non-knowledge GVA, as we have seen. It is interesting, therefore, to consider the complementary view offered by figure 15, which reports the share of knowledge-based GVA within each industry (that is, assuming that the GVA for each industry takes a value of 100). The first point to note is that while there are striking differences between industries in some countries, in others the penetration of knowledge is more homogenous across all the sectors considered. Broadly speaking, it seems that the more developed a country is, the more evenly the knowledge economy is spread across all the sectors of the economy. The two benchmark countries, Spain and the United States, and also Costa Rica and Peru among LA countries, illustrate this observation.

Secondly, there are notable differences between countries in the ranking of sectors by knowledge content. Even so, *Mining and quarrying, Agriculture, forestry and fishing, and Electricity, gas and water supply* are the least knowledge-intensive sectors in most (though not all) of the countries. Also worth noting is the low knowledge intensity of one of the sectors that accounts for a large proportion of total knowledge-based GVA (see figure 14), namely *Financial, real estate and business services*.

On the other hand, the *Other services* industry, which includes Public administration, Health and Education, among others, has the highest knowledge intensity in all the countries, regardless of the selected approach, although it is especially striking under the restrictive approach. It is also interesting to note that *Manufacturing*, which is more R&D intensive, is not the most knowledge-intensive sector according to our approach. However, it holds a high position in the industry ranking. As explained in section 2, our approach focuses on the use of knowledge-intensive inputs and not on the R&D expenditure of each industry, which is the base of other knowledge-related measures.

Figure 16 provides complementary information related to the evolution of the use of knowledge-intensive inputs in each industry between 1995 and 2016. Spain, the US and Costa Rica show a better performance in all their industries than the remaining countries, since in most of them the weight of knowledge in the GVA has increased since 1995, although there are considerable differences between industries. On the other hand, the remaining countries show a worse performance, as the weight of knowledge inputs have decreased in many industries.

Altogether, it seems that the results in terms of growth of the knowledge-based GVA share are better when we consider the more restrictive approach, although there are significant differences between industries and countries.

Figure 15. Knowledge-based GDP by industry. Broad and restrictive approach, 2016.
Total industry = 100 (percentage of each industry's GVA)

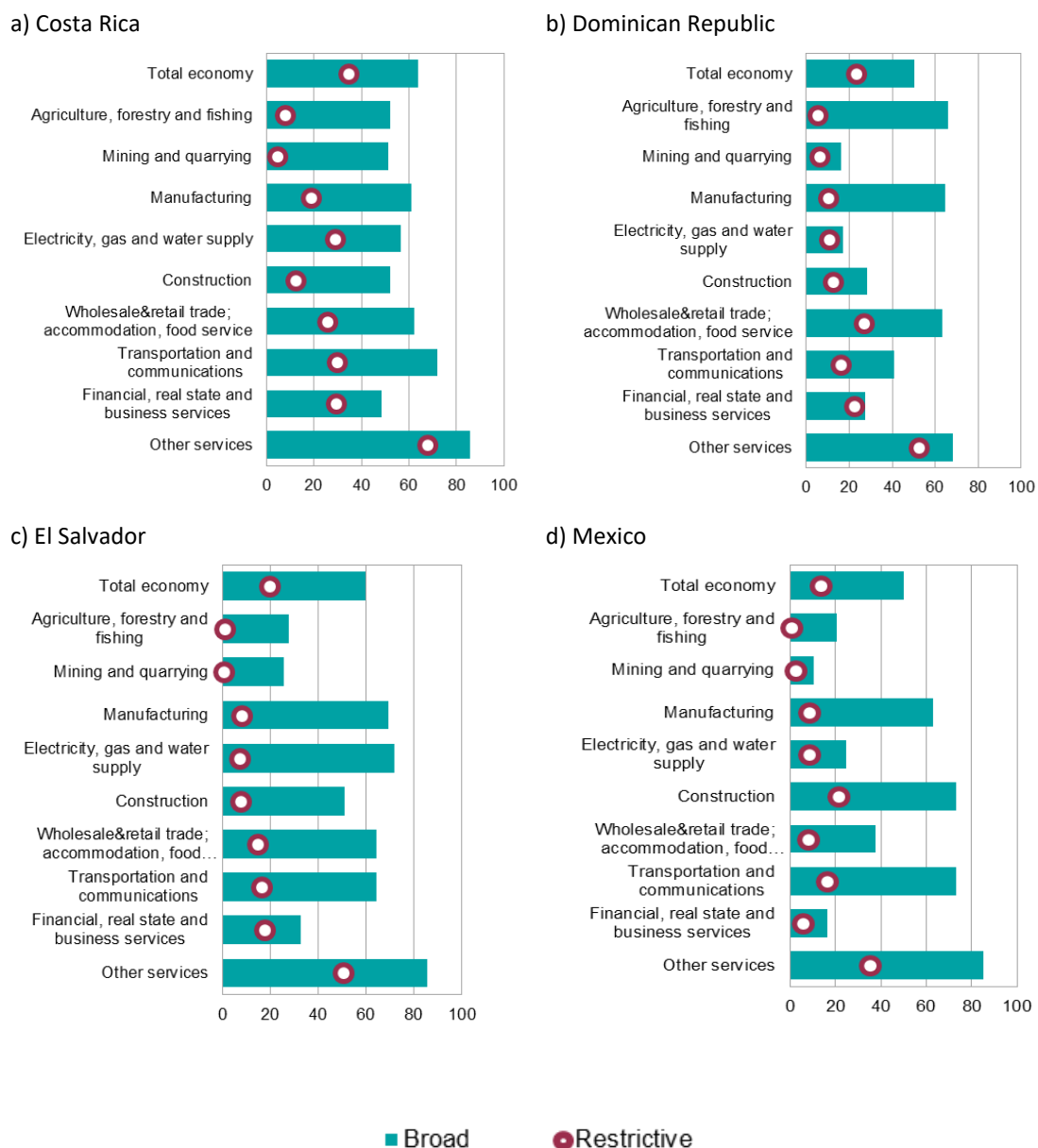
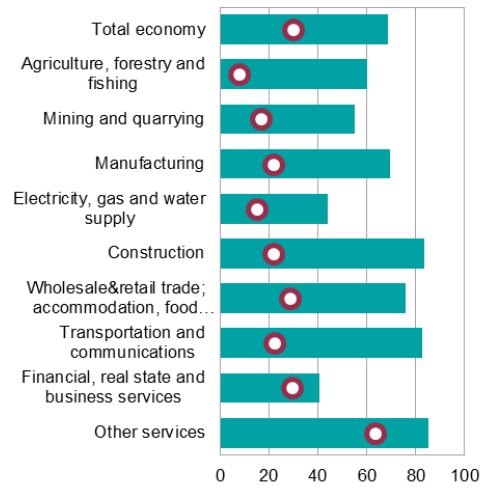
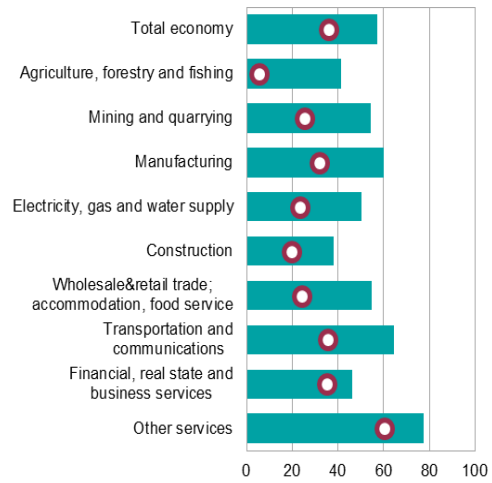


Figure 15. Knowledge-based GDP by industry. Broad and restrictive approach, 2016.
Total industry = 100 (percentage of each industry's GVA) (cont.)

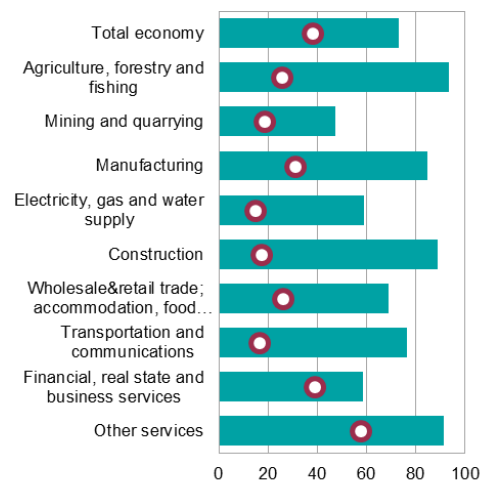
e) Peru



f) Spain



g) US

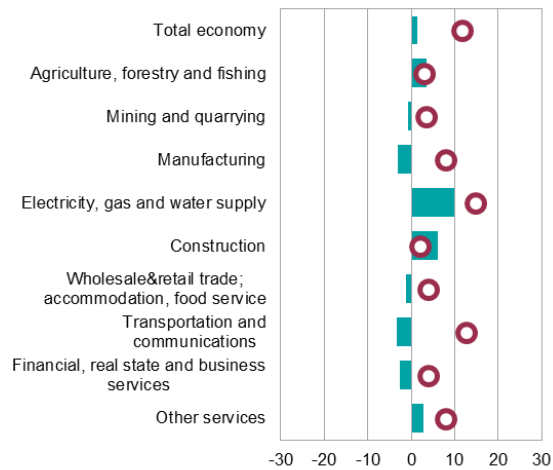


■ Broad ● Restrictive

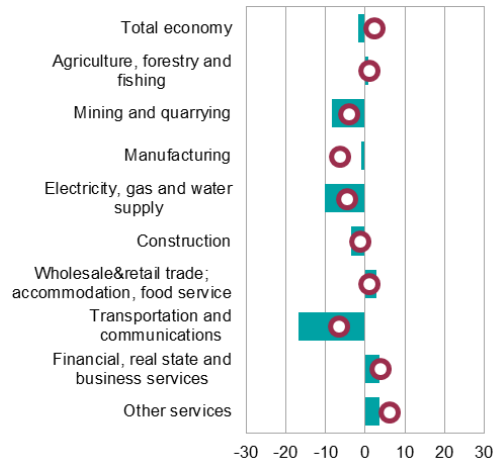
Source: BEA (2018), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013) and own elaboration.

Figure 16. Knowledge-based GDP by industry. Broad and restrictive approach. Difference 2016-1995 (percentage points)

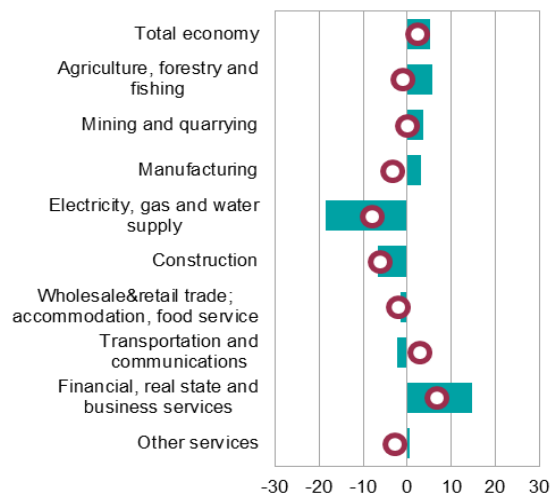
a) Costa Rica



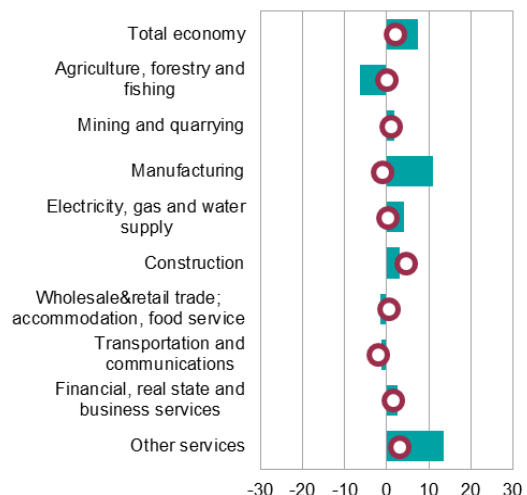
b) Dominican Republic



c) El Salvador



d) Mexico

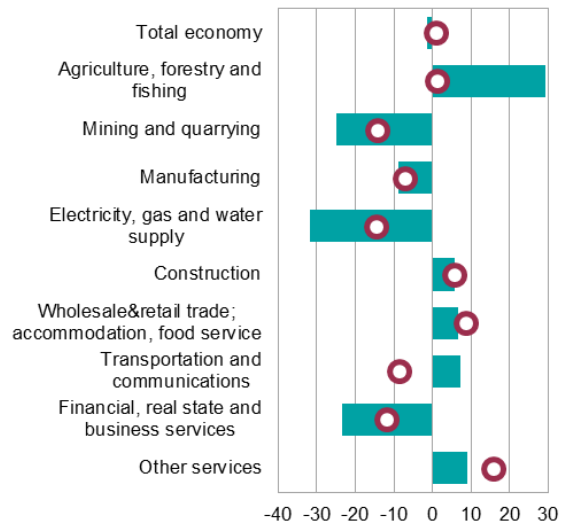


■ Broad

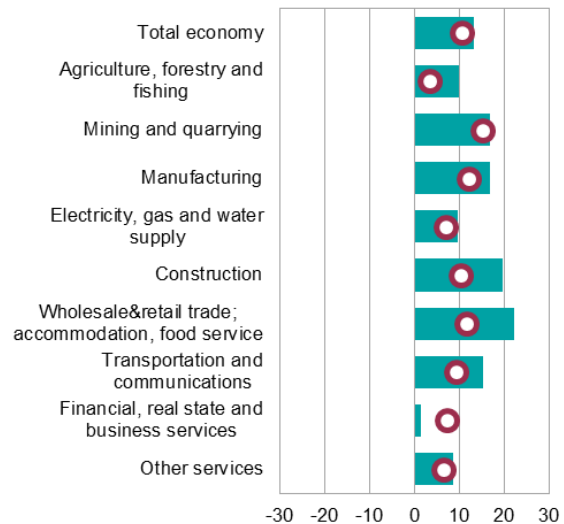
● Restrictive

Figure 16. Knowledge-based GDP by industry. Broad and restrictive approach. Difference 2016-1995 (percentage points) (cont.)

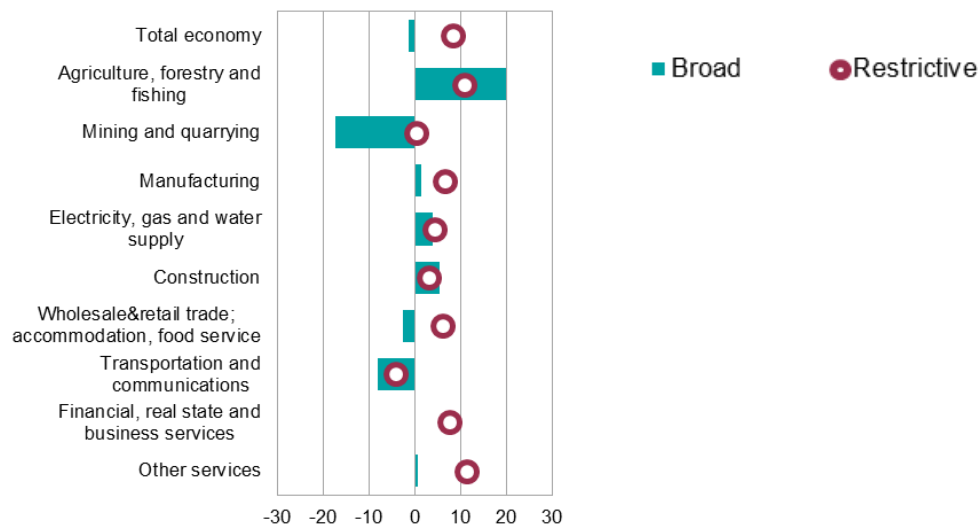
e) Peru



f) Spain



g) US



Source: BEA (2018), BBVA Foundation-Ivie (2019), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013) and own elaboration.

Knowledge-based GVA by industry and source

Table 5 completes the information from the sectoral perspective, offering the composition of GVA for each country and industry, considering all the components that were already identified in Table 4 for the whole economy. Using this information we can focus on the narrowest or broadest definition of knowledge-based GVA by aggregating the corresponding knowledge-intensive assets and labor considered under each definition. Table 5 confirms the large differences among countries and sectors, as it is very difficult to establish a common pattern among countries, and even among industries within the same country. However, we can state that in general, *Transport and communications* is the sector in which GVA relies more on ICT capital, although in the US this type of capital is more important in *Financial, real estate and business services*. By contrast, in Mexico the higher share of ICT capital compensation corresponds to *Construction*. In most countries, machinery and equipment capital compensation is concentrated in *Mining, Energy* and *Manufacturing* industries. Regarding labor, the higher shares of high-skilled labor compensation correspond to services sectors, such as *Other services* and *Financial, real estate and business services*, whereas low-skilled labor compensation accounts for a higher percentage of sectoral GVA in the case of *Agriculture, forestry and fishing*.

Table 5. Knowledge and non-knowledge compensation over GVA by industry. International comparison, 2016 (percentage of each industry's GVA)

	ICT capital compensation	Mach&Equipment capital compensation	Real estate capital compensation	Labor compensation. High-skilled	Labor compensation. Medium-skilled	Labor compensation. Low-skilled	GVA
Costa Rica							
Total economy	2.11	10.24	24.24	32.53	18.85	12.04	100.00
Agriculture, forestry and fishing	0.32	31.73	15.88	7.48	12.66	31.93	100.00
Mining and quarrying	0.32	41.12	41.28	4.27	5.69	7.32	100.00
Manufacturing	2.62	21.02	25.80	16.22	20.99	13.35	100.00
Electricity, gas and water supply	2.80	19.00	39.10	26.05	8.65	4.41	100.00
Construction	0.54	11.14	12.66	11.58	29.00	35.09	100.00
Wholesale&retail trade; accommodation, food service	0.41	7.33	23.24	25.04	29.40	14.58	100.00
Transportation and communications	6.54	19.91	16.98	23.30	22.34	10.94	100.00
Financial, real estate and business services	2.88	4.58	45.53	26.34	14.60	6.07	100.00
Other services	0.87	2.04	5.49	66.93	16.03	8.64	100.00
Dominican Republic							
Total economy	0.95	10.95	34.01	22.03	16.41	15.65	100.00
Agriculture, forestry and fishing	1.17	51.51	0.00	3.85	9.50	33.97	100.00
Mining and quarrying	1.63	5.22	79.68	4.56	4.76	4.15	100.00

	ICT capital compensation	Mach&Equipment capital compensation	Real estate capital compensation	Labor compensation. High-skilled	Labor compensation. Medium-skilled	Labor compensation. Low-skilled	GVA
Manufacturing	1.09	41.57	27.03	8.95	13.09	8.28	100.00
Electricity, gas and water supply	0.62	0.00	79.96	10.11	6.60	2.70	100.00
Construction	0.12	3.15	49.46	12.22	12.75	22.29	100.00
Wholesale&retail trade; accommodation, food service	0.15	0.40	7.33	26.61	36.13	29.39	100.00
Transportation and communications	5.15	8.66	40.65	10.89	16.30	18.36	100.00
Financial, real estate and business services	0.31	0.06	70.42	21.91	5.01	2.29	100.00
Other services	0.34	0.41	20.72	51.81	15.53	11.19	100.00
El Salvador							
Total economy	1.92	14.97	25.91	17.76	25.26	14.18	100.00
Agriculture, forestry and fishing	0.22	12.17	30.69	0.66	14.78	41.48	100.00
Mining and quarrying	0.31	4.83	14.54	0.00	20.40	59.92	100.00
Manufacturing	0.84	32.00	16.54	6.89	29.50	14.23	100.00
Electricity, gas and water supply	0.58	53.66	24.81	6.31	11.43	3.21	100.00
Construction	0.32	24.20	30.16	6.96	19.52	18.85	100.00
Wholesale&retail trade; accommodation, food service	2.36	7.86	13.14	11.97	42.21	22.46	100.00

	ICT capital compensation	Mach&Equipment capital compensation	Real estate capital compensation	Labor compensation. High-skilled	Labor compensation. Medium-skilled	Labor compensation. Low-skilled	GVA
Transportation and communications	10.16	29.91	27.95	6.13	18.30	7.55	100.00
Financial, real estate and business services	1.54	2.52	64.02	15.72	12.72	3.49	100.00
Other services	0.39	3.50	0.79	50.16	31.74	13.41	100.00
Mexico							
Total economy	2.33	14.74	43.40	11.13	21.90	6.50	100.00
Agriculture, forestry and fishing	0.13	10.72	64.34	0.47	9.10	15.25	100.00
Mining and quarrying	0.13	0.52	87.11	2.15	7.65	2.43	100.00
Manufacturing	2.22	30.57	31.63	6.15	24.25	5.18	100.00
Electricity, gas and water supply	0.18	1.11	73.98	8.14	15.45	1.14	100.00
Construction	5.99	37.78	10.26	15.23	14.25	16.49	100.00
Wholesale&retail trade; accommodation, food service	4.23	14.51	57.74	3.64	15.36	4.53	100.00
Transportation and communications	1.95	30.23	19.13	14.29	26.69	7.71	100.00
Financial, real estate and business services	1.53	1.40	83.02	4.13	9.55	0.37	100.00
Other services	0.44	1.00	3.64	34.60	49.00	11.32	100.00

	ICT capital compensation	Mach&Equipment capital compensation	Real estate capital compensation	Labor compensation. High-skilled	Labor compensation. Medium-skilled	Labor compensation. Low-skilled	GVA
Peru							
Total economy	1.01	18.29	24.90	28.74	20.48	6.58	100.00
Agriculture, forestry and fishing	0.13	27.46	9.78	7.42	25.26	29.94	100.00
Mining and quarrying	0.81	27.38	42.12	15.77	11.01	2.92	100.00
Manufacturing	0.96	27.73	26.72	20.59	20.31	3.68	100.00
Electricity, gas and water supply	1.01	23.28	54.36	14.03	5.86	1.46	100.00
Construction	0.99	31.31	8.92	20.81	30.22	7.76	100.00
Wholesale&retail trade; accommodation, food service	0.92	15.38	13.16	27.54	32.14	10.87	100.00
Transportation and communications	1.30	29.01	12.41	21.00	31.49	4.80	100.00
Financial, real estate and business services	1.23	5.04	58.99	28.30	5.91	0.53	100.00
Other services	1.24	4.75	11.55	61.97	17.22	3.27	100.00
Spain							
Total economy	4.12	7.42	26.83	31.82	14.00	15.81	100.00
Agriculture, forestry and fishing	0.21	29.48	40.53	5.29	6.34	18.16	100.00
Mining and quarrying	2.90	18.53	24.52	22.66	10.42	20.98	100.00
Manufacturing	3.82	14.17	20.52	28.08	13.94	19.46	100.00
Electricity, gas and water supply	8.12	21.20	41.65	15.10	5.95	7.98	100.00

	ICT capital compensation	Mach&Equipment capital compensation	Real estate capital compensation	Labor compensation. High-skilled	Labor compensation. Medium-skilled	Labor compensation. Low-skilled	GVA
Construction	0.33	5.05	36.74	19.54	13.16	25.18	100.00
Wholesale&retail trade; accommodation, food service	2.04	8.70	17.17	22.20	21.79	28.10	100.00
Transportation and communications	13.49	13.29	18.99	21.97	15.90	16.36	100.00
Financial, real estate and business services	5.52	2.26	46.84	29.63	8.80	6.94	100.00
Other services	2.80	2.01	11.41	57.35	15.18	11.24	100.00
United States							
Total economy	4.29	10.79	25.14	33.87	23.97	1.94	100.00
Agriculture, forestry and fishing	0.23	28.19	0.00	25.17	39.48	6.93	100.00
Mining and quarrying	1.17	11.49	50.94	17.41	17.30	1.69	100.00
Manufacturing	2.97	21.90	12.52	28.02	31.72	2.88	100.00
Electricity, gas and water supply	1.55	27.20	40.51	13.20	16.85	0.68	100.00
Construction	0.75	14.13	4.93	16.44	57.62	6.12	100.00
Wholesale&retail trade; accommodation, food service	4.01	12.73	27.65	21.79	30.47	3.36	100.00
Transportation and communications	2.15	20.75	20.49	14.23	39.09	3.29	100.00
Financial, real estate and business services	7.54	7.90	40.51	31.38	11.82	0.84	100.00
Other services	1.45	5.70	7.47	56.13	27.87	1.38	100.00

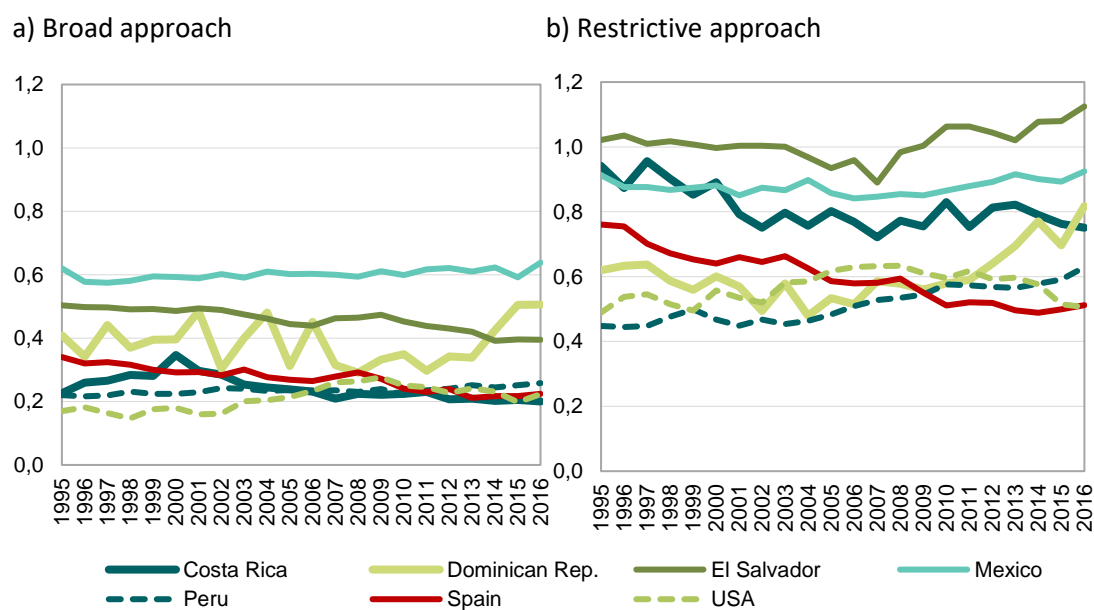
Source: BEA (2018), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013) and own elaboration.

Sectoral and countries convergence

Having confirmed the major differences between countries and sectors, it is interesting to analyze whether these differences increased or decreased over the period analyzed. One way to verify this is by computing the dispersion (as measured by the coefficient of variation) of the knowledge shares over GVA among sectors. Figure 17 provides this information and identifies Mexico as the country with the highest dispersion under the broad approach, whereas El Salvador leads when the restrictive approach is considered. On the other side, the US and Spain are the countries with the lowest dispersion, regardless of the approach, together with Costa Rica and Peru. This result confirms that the more developed economies have a more homogenous penetration of knowledge in the different sectors.

Figure 17 also shows no general pattern of convergence towards less dispersion between sectors (Spain and Costa Rica are the only exceptions under the restrictive approach) and that the dispersion among industries is higher when we consider the restrictive approach. This means that the differences among industries are larger in terms of ICT capital and high-skilled workers.

Figure 17. Convergence in the knowledge-based GVA share among industries. International comparison, 1995-2016 (coefficient of variation)

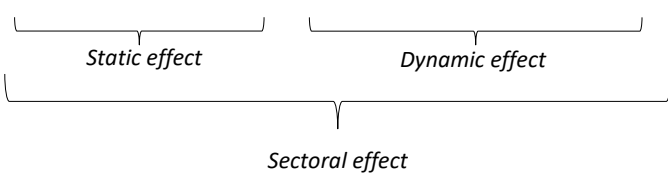


Source: BEA (2018), BBVA Foundation-Ivie (2019), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013) and own elaboration.

Finally, in relation to sectoral results it is interesting to use the shift-share technique to analyze the drivers of the knowledge-based economy's share of GVA (represented in figure 1) and the determinants of the differences among countries.

Shift-share analysis is widely used to decompose the changes in an aggregate variable over time into three components: within-industry effect, sectoral static effect, and sectoral dynamic effect. It thus allows us to explain the changes in the knowledge intensity of GVA (Y^K/Y) over a specific period of time (0 to T) as follows:

$$\frac{Y_T^K}{Y_T} - \frac{Y_0^K}{Y_0} = \underbrace{\sum_{j=1}^J \theta_{j0} \left(\frac{Y_{jT}^K}{Y_{jT}} - \frac{Y_{j0}^K}{Y_{j0}} \right)}_{\text{Within-industry effect}} + \underbrace{\sum_{j=1}^J (\theta_{jT} - \theta_{j0}) \frac{Y_{j0}^K}{Y_{j0}}}_{\text{Static effect}} + \underbrace{\sum_{j=1}^J (\theta_{jT} - \theta_{j0}) \left(\frac{Y_{jT}^K}{Y_{jT}} - \frac{Y_{j0}^K}{Y_{j0}} \right)}_{\text{Dynamic effect}} \quad [9]$$



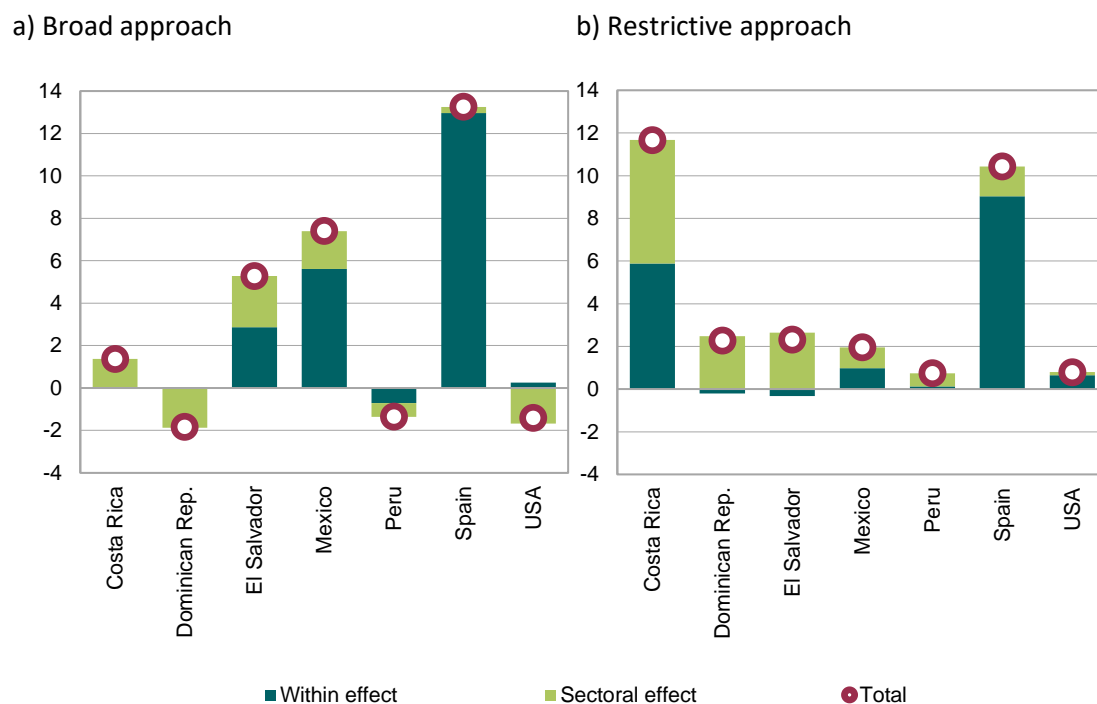
where $\frac{Y_T^K}{Y_T} - \frac{Y_0^K}{Y_0}$ is the change in knowledge intensity between years 0 and T, j is the industry, and θ_{jT} is the share of GVA in industry j in year T.

The within-industry effect shows the growth of knowledge intensity that would have occurred even without any structural change, i.e., due to the aggregate knowledge intensity gains (positive sign) or losses (negative sign) arising from internal improvements in knowledge intensity within each industry. The sectoral effect captures the consequences of the re-allocation of factors between sectors towards industries with a higher initial level of knowledge intensity (static effect) or with a higher rate of knowledge intensity growth (dynamic effect).

The main results are shown in figure 18 and can be summarized as follows. Under the broad approach (panel a), knowledge share increased between 1995 and 2016 in El Salvador, Mexico and Spain due to the within-industry effect. In Costa Rica, however, the sectoral effect was the main lever. In the remaining countries, there was a decline in this share caused mainly by the sectoral effect as well. Thus, it seems that the penetration of knowledge in all sectors of the economy is more relevant to becoming a knowledge-based economy than a sectoral change towards more advanced sectors, which tend to be more intensive in the use of knowledge. In addition, this sectoral change seems to have negative contributions, even in the US, one of the two benchmark countries.

Regarding the restrictive approach, since 1995 the weight of knowledge-based GVA increased in all the countries considered, although for different reasons. In Spain and the US this increase was mainly caused by the within-industry effect, whereas for the LA countries it was caused by the sectoral effect, with the exception of Costa Rica, where the within and the sectoral effects are of similar importance. Thus, as the US and Spain are the most advanced countries (with higher income per capita) and Costa Rica is the most advanced of the LA countries, the main conclusion to be drawn—from the perspective of designing public policies to improve an economy’s knowledge intensity—is that it is important to facilitate the penetration of knowledge-intensive assets (both capital and labor) in all sectors of the economy, since the structural change from less to more knowledge-intensive sectors does not seem to play a very important role.

Figure 18. Time shift-share analysis of the knowledge-based GVA share. Difference 1995-2016 (percentage points)



Source: BEA (2018), BBVA Foundation-Ivie (2019), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013) and own elaboration.

In addition to the time perspective, the shift-share technique can also be applied by interpreting subindex T in Equation [9] as the knowledge share in a given country and 0 as the knowledge share in the benchmark country. In this case, the within-industry effect, which is also known as the *country effect*, measures the difference that would

exist between a particular country and the benchmark if both had the same productive structure, that is, the same sectoral composition. The *sectoral effect* reflects the difference that would exist if knowledge was used with the same intensity as in the benchmark country in each industry and would therefore only be a consequence of the different weight of industries among countries.

Figure 19 shows the result of this exercise for 2016¹⁸, taking the US as benchmark. As stated in previous sections, the US is leader in terms of the knowledge-based GVA share. This explains why the difference between the US knowledge-based GVA share and that of other countries is always negative. As can be seen, the country effect is by far the most important determinant of the knowledge intensity differences between all countries and the US, regardless of the approach. Therefore, the different knowledge shares in each country's GVA can be primarily attributed to intra-industry differences among them, while the changing industry composition is less important. This means that the most important lever to reduce the differences from the leading country is the penetration of knowledge in all sectors of the economy, more than by a sectoral change towards a more similar sectoral structure to that of the benchmark country (in this case, the US). Thus, we obtain a similar conclusion to that arising from the time shift-share analysis (see figure 18). However, we must take into account that our sectoral classification detail is rather limited (9 individual sectors) and the sectoral effect may become more important when considering industries in greater detail.

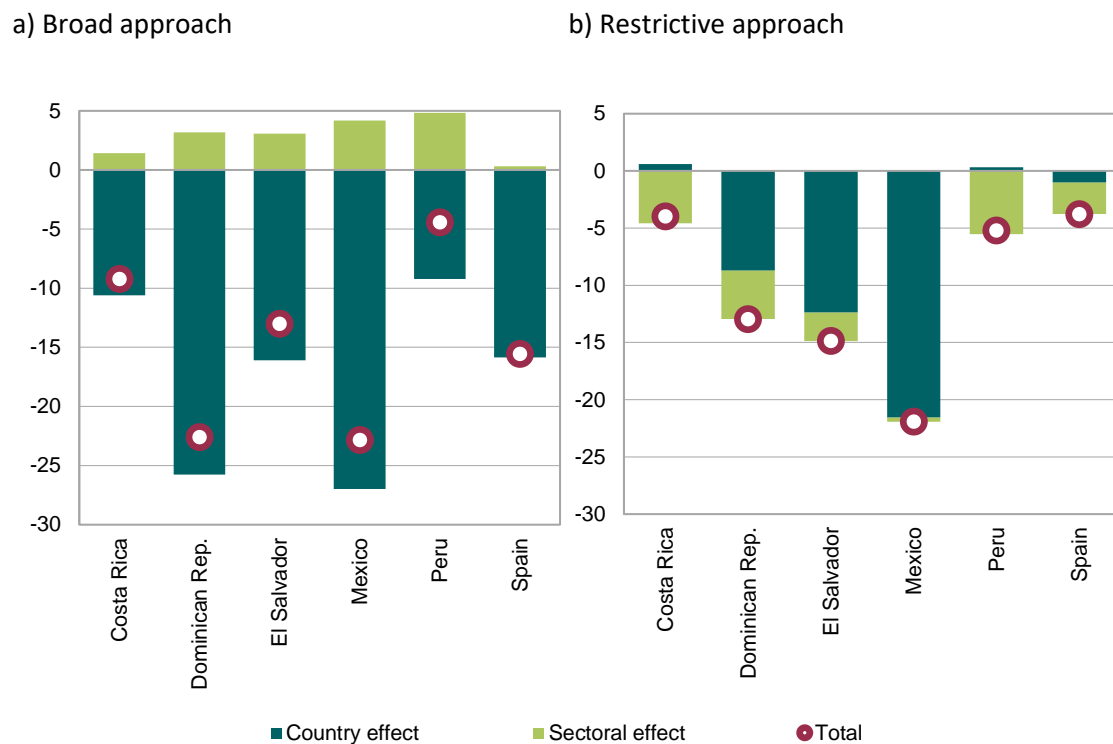
Comparison to traditional methods for measuring the knowledge economy by industry

To conclude the presentation of sectoral results, it is useful to compare them to results from more traditional measures of the knowledge economy, such as R&D intensity and the weight of high-skilled labor. Figure 20 shows this information, which can be contrasted with that offered in figure 15. As stated in the analysis of figure 12, it is clear that the gap between LA countries and the US in terms of R&D intensity is significant in all industries, except *Mining and quarrying* in Mexico, and this gap is even greater with our knowledge economy measure. This result is explained by the fact that our measure considers different factors according to their knowledge content and does not depend

¹⁸ The conclusions are the same if we apply this analysis to the previous years.

on a single magnitude such as R&D expenditure, which only takes into account the creation of new knowledge, but not its diffusion and use by the economic activities.

Figure 19. Shift-share analysis of the knowledge-based GVA share. Difference with benchmark country (United States), 2016 (percentage points)

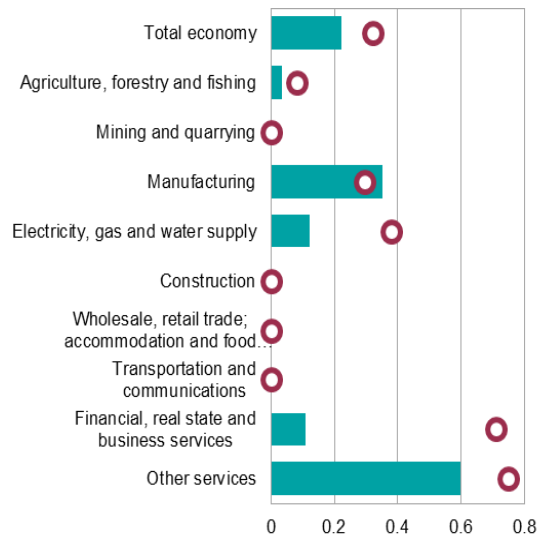


Source: BEA (2018), BBVA Foundation-Ivie (2019), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013) and own elaboration.

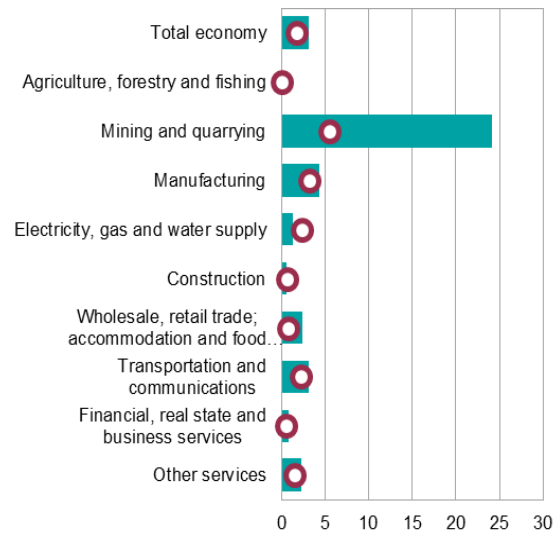
Regarding the differences among industries, *Manufacturing* is the sector with the highest R&D intensity in the benchmark countries. R&D intensity is also high in some advanced service sectors, such as *Other services*, a result that is also obtained under our approach. For the LA countries for which information is available, Costa Rica, Mexico and Peru, these results also hold, although *Manufacturing* falls behind *Other services* in Costa Rica and Peru, while in Mexico, the sector presenting the highest R&D intensity is *Mining and quarrying*, followed by *Manufacturing*.

Figure 20. R&D intensity by industry. International comparison, 1995 and 2016
(percentage of each industry's GVA). Total industry = 100

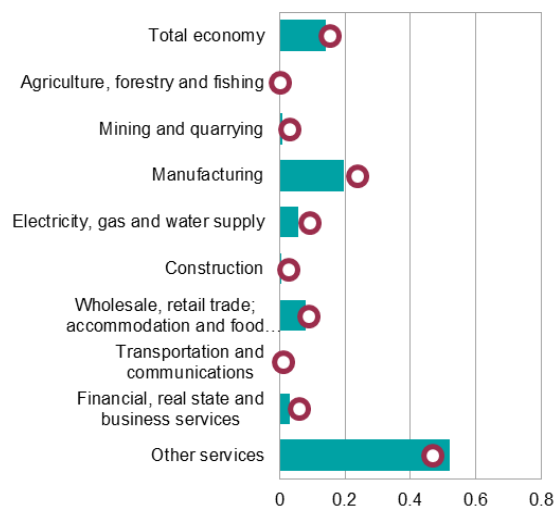
a) Costa Rica



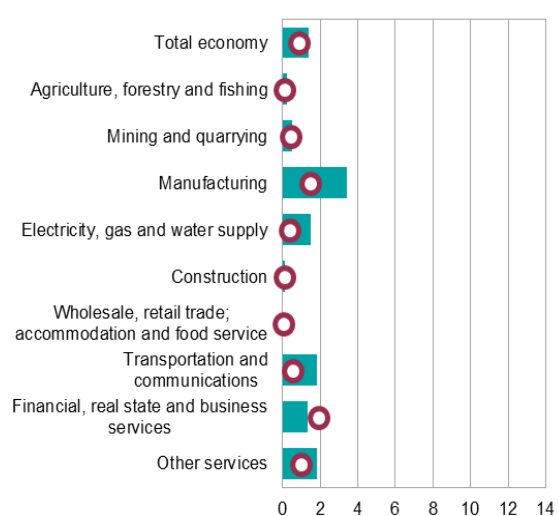
b) Mexico



c) Peru



d) Spain

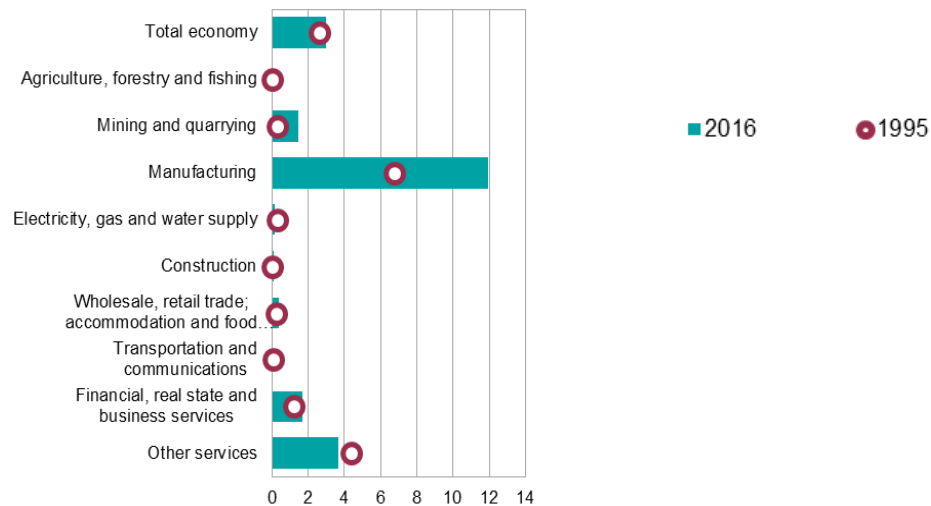


■ 2016

● 1995

Figure 20. R&D intensity by industry. International comparison, 1995 and 2016
(percentage of each industry's GVA). Total industry = 100 (cont.)

e) United States



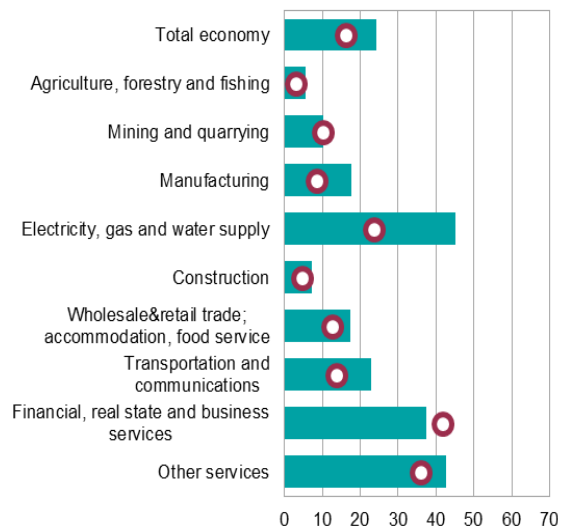
Note: Information is not available for Dominican Republic and El Salvador.

Source: BEA (2018), BBVA Foundation-Ivie (2019), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013) and own elaboration.

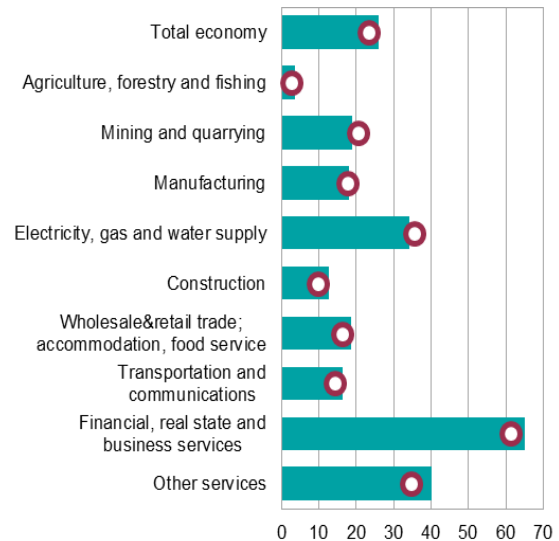
Figure 21 shows the results of analyzing the weight of hours worked by high-skilled workers by industry and country. In this case, and as we have already seen, the conclusions that can be drawn are more similar to those obtained with the methodology proposed here. The main differences stem from the fact that we consider not only the amount of hours worked by the most educated workers, but also their compensation (i.e., their wages) and we also take into account the compensation of capital assets, the other primary factor of production. However, once again we can see that there are some countries where the share of high-skilled workers is more homogeneous across all the sectors. This is the case of the benchmarks and two LA countries that also occupied an advanced position in our measure of knowledge-based economy, Costa Rica and Peru, and in this case, also the Dominican Republic. As labor compensation of educated workers is the main driver of our measure of knowledge GVA, this traditional approach, based on the share of high-skilled workers, offers conclusions that are more similar to those obtained throughout the paper than in the analysis of R&D intensity (see figure 20).

Figure 21. Hours worked by high-skilled workers by industry. International comparison, 1995 and 2016 (percentage of each industry's hours worked). Total industry = 100

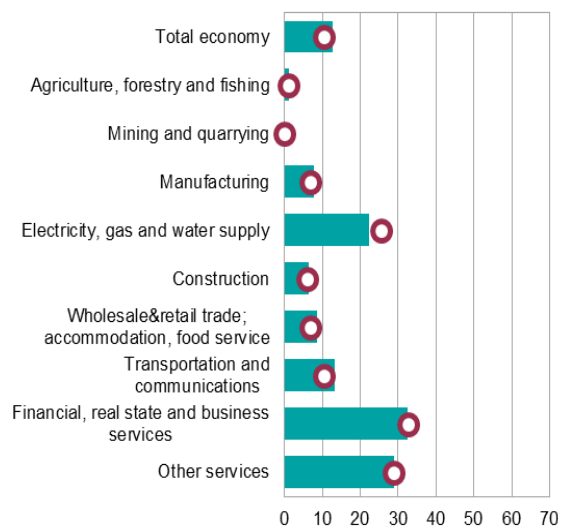
a) Costa Rica



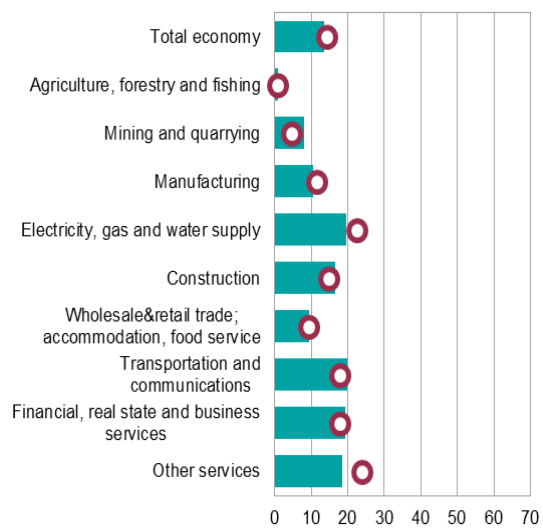
b) Dominican Republic



c) El Salvador



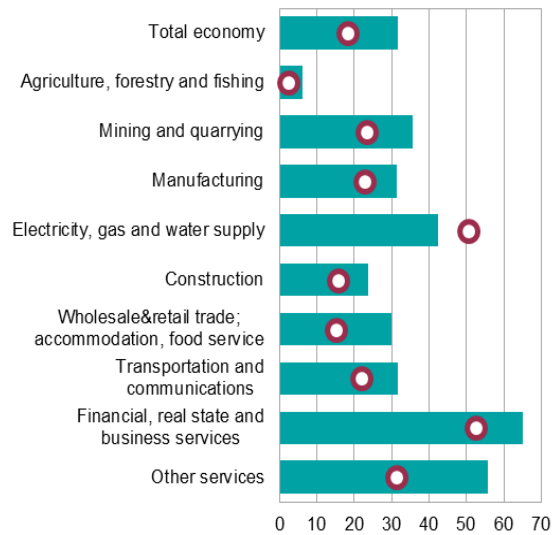
d) Mexico



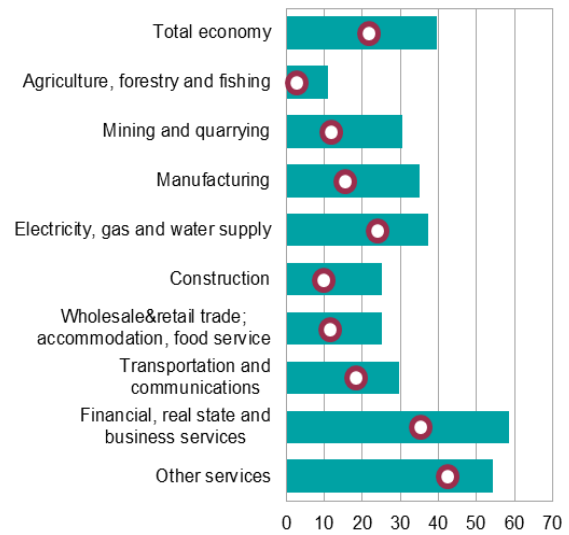
■ 2016 ● 1995

Figure 21. Hours worked by high-skilled workers by industry. International comparison, 1995 and 2016 (percentage of each industry's hours worked). Total industry = 100 (cont.)

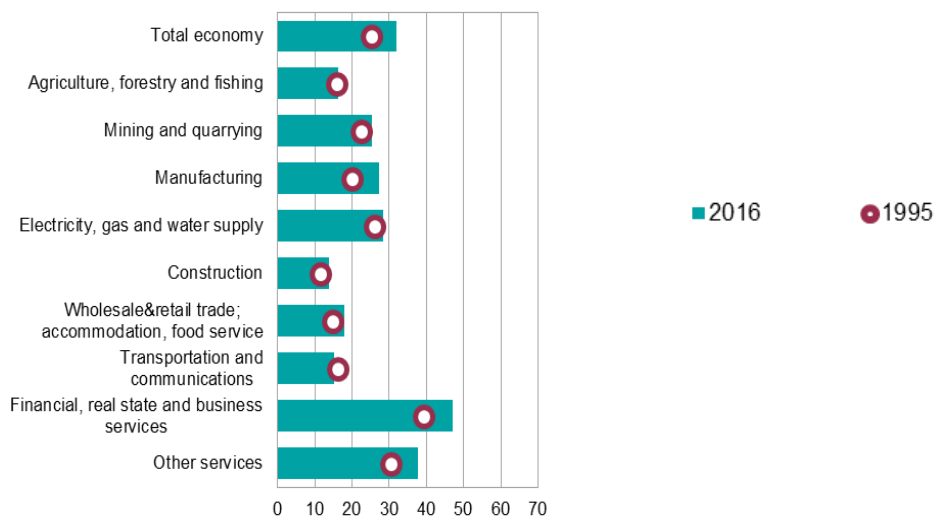
e) Peru



f) Spain



g) US



Note: For the United States the last available year is 2009.

Source: BEA (2018), BBVA Foundation-Ivie (2019), EU KLEMS (2019), LA KLEMS (2020), WIOD (2013) and own elaboration.

6. Conclusions

This paper proposes a methodology to compute the knowledge content of an economy based on more accurate and disaggregated measurements of human and physical capital services by branches of activity. To compute the size and composition of the knowledge economy, we use two definitions of knowledge-based inputs, one broader and one more restrictive. In the former, ICT and machinery and equipment assets are included as capital inputs and the highest and medium levels of educational attainment as labor inputs, and in the latter only ICT assets are included as knowledge-based capital and higher levels of educational attainment as knowledge-intensive labor. Once the knowledge-based inputs have been identified according to the two approaches, we quantify the portion of income that remunerates the services that these factors provide (capital and labor compensation, in KLEMS terminology) and, by extension, their contribution to GVA.

The methodology uses a new database for four Latin American countries for which this information was not previously available: Costa Rica, the Dominican Republic, El Salvador and Peru (IADB-Ivie, 2020). To those four LA countries we added already available information from Mexico after adjusting INEGI data to the same assumptions as the other four countries to ensure homogeneity. The results of the five countries are compared with those of the US and Spain, which are used as benchmarks. The period covered is 1995 to 2016, the latest year for which data are available for all the countries. The information comes from the most up-to-date releases of EU KLEMS and LA KLEMS. The main results can be summarized as follows.

First, the Latin American countries can be clustered in two groups. Costa Rica and Peru follow a common pattern, showing a higher share of knowledge-based GVA, more similar to that of the US or Spain, the benchmark countries. Mexico, the Dominican Republic and El Salvador form the second cluster.

Second, the US is the undisputed leader according to both the broad and the restrictive approaches. For the remaining countries, the comparison of the results from the two approaches suggests that the restricted approach tends to favor the most developed countries. The US, Spain, Costa Rica and Peru, in this order, occupy the first positions according to the restrictive approach, while under the broad approach, Spain occupies the fifth position after Peru, Costa Rica and El Salvador. Therefore, the use of the more

stringent definition provides a closer relation between a knowledge-based economy and its level of development, as measured by per capita income. We may therefore conclude that it is better to focus on the restrictive approach when we want to analyze advanced countries or the gap between less developed countries and benchmark countries. On the other hand, it may be more appropriate to focus on the broad approach when we are analyzing less developed countries.

Third, knowledge-based GVA calculated following the restrictive definition is more dynamic than under the broad definition, meaning that the value generated by the most technological assets and the most educated workers has grown more intensively in all countries.

Fourth, this growth was particularly intense in Costa Rica, the Dominican Republic and Peru, compared with more modest growth in El Salvador, Mexico, Spain and the US. Overall, this result suggests that there was some convergence over the period, with the countries ranked lowest in 1995 growing faster than the leaders. This convergence is confirmed by the evolution of the coefficient of variation of GVA and its components (knowledge and non-knowledge) per capita. Additionally, the differences among the seven countries are higher in the knowledge-based economy than in total GVA and the non-knowledge economy. However, we do not find convergence in terms of knowledge-based GVA share when we consider the restrictive approach.

Fifth, the behavior revealed in the US and Spain during the great recession years indicates that the non-knowledge part of the economy is more vulnerable to difficult times than its knowledge counterpart. Or put another way, the knowledge-based economy is more resilient to the consequences of negative shocks. This result justifies the usefulness of having an estimation of knowledge-based GVA that allows the design of appropriate public policies to foster its development.

Sixth, the disaggregation of knowledge-based GVA by sources shows that, generally speaking, among the Latin American countries, Costa Rica and, at a certain distance, Peru, have the most similar GVA composition to that of Spain and the US. The Dominican Republic and Mexico stand out for their high share of real estate capital compensation, and El Salvador and Mexico are characterized by the lower weight of their high-skilled labor.

Seventh, when our results are compared with other traditional measures, important differences arise that can be explained by the consideration of more than one single factor (as in the case of R&D intensity), by the fact that our objective is to measure the use of knowledge by the economic activities and not only knowledge generation, and by the consideration of the remunerations for the different factors of production in addition to their physical or absolute quantities. However, the conclusions drawn from the human capital analysis are more similar to those obtained when applying our approach than those from the analysis of R&D intensity.

Eighth, in almost all the countries, knowledge-intensive labor contributed more to GVA growth than knowledge-intensive capital. This is particularly true for the most developed countries. In most cases (El Salvador, the Dominican Republic and Mexico were the exceptions in the case of the restrictive approach) the contribution of non-knowledge-intensive labor was lower than its knowledge-intensive counterpart. Furthermore, the contribution of non-knowledge capital was much greater in Latin American countries, especially in Peru and the Dominican Republic.

Ninth, from the sectoral perspective, in almost all countries, the *Other services* (which includes Public administration, Education, Health, Social services, Arts, entertainment and recreation and other services) sector absorbs the highest share of the knowledge economy. The second most important sector in most developed countries is *Financial, real estate and business services*. *Manufacturing* takes second position in El Salvador and Mexico, and *Wholesale & retail trade, accommodation and food service* in Peru and the Dominican Republic. These four sectors absorb the highest share of the total knowledge economy, regardless of the approach, while the other five sectors have a much smaller share, especially *Agriculture, Mining and quarrying*, and *Electricity, gas and water supply*.

Tenth, broadly speaking, it seems that the more developed a country is, the more evenly the knowledge economy is spread across all the sectors of the economy. Spain and the United States, and also Costa Rica and Peru, illustrate this observation.

Eleventh, in general, the within-industry effect (i.e. the growth of knowledge intensity arising from internal improvements in knowledge intensity within each industry) is by far the most important determinant of the increase in the knowledge-based economy share under the broad approach. Considering the restrictive approach, however, the

sectoral effect is the main lever in the Dominican Republic, El Salvador and Peru, although in the US and Spain the main driver of the knowledge economy is the within-industry effect. Thus, the penetration of knowledge in all the sectors of the economy seems to be more relevant than sectoral change towards more advanced sectors in the case of the broad approach, whereas the within-industry effect seems to be more important under the restrictive approach, particularly for the more advanced countries, such as the US, Spain and Costa Rica.

Twelfth, when analyzing the gap between LA countries and the US, the country effect (i.e., the differences among countries arising from internal variations in the use of knowledge within the same industry) seems to be the main lever to reduce it, instead of fostering a change in sectoral specialization towards industries that are more intensive in the use of knowledge.

Finally, we should emphasize the usefulness of our conclusions in designing public policies to improve the workings of a knowledge-based economy and its growth. New policies could be defined to facilitate the penetration of knowledge-intensive assets (both capital and labor) in Latin American economic sectors, especially those with lower knowledge intensity. The comparison with the United States and Spain is a valuable benchmark as it offers two reference points to take into consideration.

References

- Aravena, C., Hofman, A.A., & Escobar, L.E. (2018). Fuentes del crecimiento económico y la productividad en América Latina y el Caribe, 1990-2013. *Economía Chilena*, Revista del Banco Central de Chile, Santiago.
- Barefoot, K., Curtis, D., Jolliff, W., Nicholson, J.R., Omohundro, R. (2018). Defining and Measuring the Digital Economy. Bureau of Economic Analysis, Washington. Available at: <https://www.bea.gov/sites/default/files/papers/defining-and-measuring-the-digital-economy.pdf>.
- BBVA Foundation-Ivie (2019). El stock y los servicios del capital en España y su distribución territorial y sectorial (1964-2017). Database available at: http://www.fbbva.es/TLFU/microsites/stock09/fbbva_stock08_index.html
- Bureau of Economic Analysis (BEA) (2018). Industry Economic Accounts. Available at: <https://www.bea.gov/data/economic-accounts/industry>.
- Bureau of Labour Statistics (BLS) (2018). Current Employment Statistics (CES). Available at: <https://www.bls.gov/ces/>
- Calvino, F., Criscuolo, C., Marcolin, L., and Squicciarini, M. (2018). A taxonomy of digital intensive sectors. OECD Science, Technology and Industry Working Papers. Available at: https://econpapers.repec.org/paper/oecstiaaa/2018_2f14-en.htm.
- Chen, D.H., & Dahlman, C.J. (2006). The Knowledge Economy, the KAM Methodology and World Bank Operations. Stock No. 37256. Washington DC: World Bank Institute.
- Coremberg, A., & Pérez, F. (Eds.) (2010). *Fuentes del crecimiento y productividad en Europa y América Latina*. Bilbao: BBVA Foundation.
- Corrado, C., Haskel, J., & Jona-Lasinio, C. (2017). Knowledge spillovers, ICT and productivity growth. *Oxford Bulletin of Economics and Statistics*, 79, 592-618, ISSN: 1468-0084, doi: 10.1111/obes.12171
- Corrado, C. Haskel, J., Jona-Lasinio, C., & Iommi, M. (2013). Innovation and intangible investment in Europe, Japan, and the United States. *Oxford Review of Economic Policy*, 29, 261-286, ISSN: 0266-903X, doi: 10.1093/oxrep/grt017
- Corrado, C., Hulten, C.R., & Sichel, D.E. (2006). Intangible capital and economic growth. NBER Working Paper No. 11948, Cambridge (MA): National Bureau of Economic Research.

- de Haan, M., & van Rooijen-Horsten, M. (2003). Knowledge Indicators Based on Satellite Accounts. Final Report for NESIS-Work Package 5.1, The Hague: Statistics Netherlands.
- EU KLEMS (2019). EU KLEMS Growth and Productivity Accounts. Available at: <https://euklems.eu/>
- Eurostat (2013). *Science, technology and innovation in Europe. 2013 Edition*. Luxembourg: Publications Office of the European Union. Available at: <http://ec.europa.eu/eurostat/data/database>
- Fukao, K., Hamagata, S., Miyagawa, T., & Tonogi, K. (2007). Intangible Investment in Japan: Measurement and Contribution to Economic Growth. RIETI Discussion Paper Series 07-E-034, Tokyo: Research Institute of Economy, Trade and Industry.
- Galindo-Rueda, F. and F. Verger (2016), "OECD Taxonomy of Economic Activities Based on R&D Intensity", OECD Science, Technology and Industry Working Papers, No. 2016/04, OECD Publishing, Paris, <https://doi.org/10.1787/5jlv73sqqp8r-en>.
- Hatzichoronoglou, T. (1997). Revision of the high-technology sector and product classification. STI Working Paper No. 59918, Paris: OECD.
- Hulten, C.R. (2008). Accounting for the Knowledge Economy. Economics Program Working Paper Series 08-13, New York: The Conference Board.
- Inter-American Development Bank (IADB) - Instituto Valenciano de Investigaciones Económicas (Ivie) (2020). Base de datos LAKLEMS (1990-2016) para República Dominicana, Costa Rica, México, Perú y El Salvador. April 2020. Available at: <http://laklems.net/>.
- International Monetary Fund (2018). *Measuring Digital Economy*. IMF Policy Papers. Available at: https://www.elibrary.imf.org/doc/IMF007/25936-9781498307369/25936-9781498307369/Other_formats/Source_PDF/25936-9781498308120.pdf.
- Jorgenson, D.W. (1995). *Productivity*. Volumen 1: *Postwar U.S. Economic Growth*. Cambridge (MA): MIT Press.
- Jorgenson, D.W., Gollop, F.M., & Fraumeni, B.M. (1987). *Productivity and U.S. Economic Growth*. Cambridge (MA): Harvard Economic Studies.
- Jorgenson, D.W., Ho, M.S., & Stiroh, K.J. (2005). *Productivity*. Volumen 3. *Information Technology and the American Growth Resurgence*. Cambridge (MA): MIT Press.

- López, A., Niembro, A., & Ramos, D. (2014). Latin America's competitive position in knowledge-intensive services trade. *CEPAL Review* 113, Santiago (Chile).
- López, A., & Ramos, D. (2013). ¿Pueden los servicios intensivos en conocimiento ser un nuevo motor de crecimiento en América Latina?. *Revista Iberoamericana de Ciencia, Tecnología y Sociedad*, 8(24). Buenos Aires: Centre for Studies in Science, Development and Higher Education.
- Mas, M., Hofman, A., & Benages, E. (2019a). Knowledge intensity in a set of Latin-American countries. *International Productivity Monitor*, Centre for the Study of Living Standards, num. 36, pages 204-233, Spring.
- Mas, M., Hofman, A., & Benages, E. (2019b). "Economic Valuation of Knowledge-Based Capital: An International Comparison", in *Measuring Economic Growth and Productivity. Foundations, KLEMS Production Models, and Extensions*, ed. B. M. Fraumeni (chapter 14), Amsterdam: Elsevier.
- Mas, M., & Benages, E. (2020). Crecimiento económico y productividad en América Latina. Metodología Base de datos LAKLEMS. Inter-American Development Bank. Abril 2020.
- Maudos, J., Benages, E., & Hernández, L. (2017). *El valor económico de las actividades basadas en el conocimiento en España y sus regiones*. Madrid: Ramón Areces Foundation, 139 pp. Available at:
http://sgfm.elcorteingles.es/SGFM/FRA/recursos/doc/Monografias/FRA/2039963963_552017125332.pdf
- Marrano, M.G., & Haskel, J. (2006). How Much Does the UK Invest in Intangible Assets?, Working Papers No. 578, London: Queen Mary, University of London.
- Marrano, M.G., Haskel, J., & Wallis, G. (2007). What happened to the Knowledge Economy? ICT, Intangible Investment and Britain's Productivity Record Revisited. Working Paper No. 603, London: Queen Mary, University of London.
- Organisation for Economic Co-operation and Development (OECD) (2018). Purchasing Power Parities (PPP) Statistics. Available at: <https://stats.oecd.org/>
- OECD (2019). *OECD Skills Outlook 2019: Thriving in a Digital World*, OECD Publishing, Paris. Available at: <https://doi.org/10.1787/e11c1c2d-en>
- OECD (2015). *OECD Science, Technology and Industry Scoreboard 2015: Innovation for Growth and Society*. Paris: OECD.

- OECD (2014). *Measuring the Digital Economy: A New Perspective*. Paris: OECD. Available at: <http://dx.doi.org/10.1787/9789264221796-en>
- OECD (2009). *Measuring Capital OECD Manual*. Paris: OECD.
- OECD (2001). *Measuring Capital OECD Manual*. Paris: OECD.
- Oulton, N. (2016). The Mystery of TFP. *International Productivity Monitor*, 31, 68-87.
- Pérez, F., & Benages, E. (2017). The Role of Capital Accumulation in the Evolution of Total Factor Productivity in Spain. *International Productivity Monitor*, 33, 24-50.
- Pérez, F., & Benages, E. (2012). *El PIB basado en el conocimiento: Importancia y contribución al crecimiento*. Valencia: ABACO. Available at: <http://www.observatorioabaco.es/buscador?informe=115>.
- Schreyer, P. (2009). User costs and bubbles in land markets. *Journal of Housing Economics*, 18, 267-272.
- Solow, R. (1957). Technical Change and the Aggregate Production Function. *Review of Economics and Statistics*, 39, 312-330.
- Solow, R. (1956). A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics*, 70(1), 65-94.
- Statistics Canada (2018). Multifactor Productivity Statistics. Available at: https://www150.statcan.gc.ca/n1/en/subjects/economic_accounts/productivity_accounts/multifactor_productivity
- Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R. and de Vries, G. J. (2015), "An Illustrated User Guide to the World Input–Output Database: the Case of Global Automotive Production", *Review of International Economics*, 23: 575–605.
- Timmer, M., van Moergastel, T., Stuivenwold, E., Ypma, G., O'Mahony, M., & Kangasniemi, M. (2007). EU KLEMS growth and productivity accounts, Version 1.0. Part I Methodology. Available at: http://euklems.net/data/EUKLEMS_Growth_and_Productivity_Accounts_Part_I_Methodology.pdf
- United Nations (2017). World Population Prospects 2017. Available at: <https://population.un.org/wpp/Download/Standard/Population/>

- Van Ark, B., & Hulten, C.R. (2007). *Innovation, Intangibles and Economic Growth: Towards A Comprehensive Accounting of the Knowledge Economy*. EPWP#07-02, New York: The Conference Board, December.
- Van Rooijen-Horsten, M., Tanriseven, M., & de Haan, M. (2008). *R&D Satellite Accounts in the Netherlands. A Progress Report*. The Hague: Statistics Netherlands.
- WIOD (2013). World Input-Output Database. Available at: <http://www.wiod.org/release13>.
- World Bank (2008a). *Measuring knowledge in the world's economies? Knowledge Assessment Methodology and Knowledge Economy Index*. Knowledge for Development Program. Washington, DC: The World Bank.
- World Bank (2008b). *Building knowledge economies. Advanced Strategies for Development*. Washington, DC: The World Bank.
- World KLEMS (2018). World KLEMS Data. Available at: <http://www.worldklems.net/data.htm>