THE DEMAND FOR HIGHER EDUCATION IN THE FACE OF TECHNOLOGICAL PROGRESS AND ARTIFICIAL INTELLIGENCE

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Abstract

This article explores the impact that technological change and artificial intelligence may have on the demand for university studies, using Spanish data. It begins with a retrospective analysis of the evolution of demand over the last three decades. Then, based on the academic literature that analyzes the degree of exposure of each occupation to technological change and the employability patterns of different university degrees, three indexes are developed for each degree: RTI index (Routine Task Intensity), index of exposure to Artificial Intelligence (AI) and index of software exposure. These indexes, based on the exposure to technological change of the different university degrees, are very informative in order to explain both the job prospects and the expected salary of their graduates. The indexes can be used to improve the design of university courses and also as indicators of which degrees are likely to be in greater demand in the future. Finally, using microdata from the Community of Madrid enrollment process, where students indicate their preferences, another indicator is designed to rank degrees according to unsatisfied demand.

Keywords: University, technological change, artificial intelligence and demand.

JEL classification: I20, I23, I29.

* The opinions and analyses are the responsibility of the authors and, therefore, do not necessarily coincide with those of the Federal Reserve Bank of St. Louis or the Federal Reserve System. José Ignacio Conde-Ruiz gratefully acknowledges the support of the Spanish Ministry of Science and Innovation research project PID2019-105499GB-I00. Juan José Ganuza gratefully acknowledges the support of the Barcelona School of Economics and the Spanish Ministry of Science and Innovation research project PID2020-115044GB-I00.

I. INTRODUCTION

We are witnessing one of the greatest transformations of the educational and productive systems in history. This is due to technological change, especially digitalization and artificial intelligence. New technologies will dramatically affect pedagogical tools and change the demand and supply of education, especially in universities.

This paper focuses on the latter dimension, exploring the demand for university studies in Spain in the context of technological change. The aim of the article is twofold: on the one hand, to obtain a picture of the current university system; on the other hand, to identify the potential problems and opportunities that technological change can generate, in order to extract recommendations for improving educational policies. In addition, following Conde-Ruiz *et al.* (2024b), a gender perspective is also mainstreamed in the analysis to show the current gaps that exist between men and women in higher education and the potential consequences for employability and salaries in the face of technological change.

The starting point is a descriptive analysis of the evolution of demand over the last three decades. The data show interesting aggregate results. Firstly, Spain is one of the European countries with the highest percentage of young people with a university degree. The figure is even more positive for women. Similarly to the countries around us, women in Spain are in the majority in university studies. In terms of fields of knowledge, there has been a decrease in the relative demand for engineering and architecture studies and an increase in studies related to health sciences.

Demand for higher education differs significantly between men and women. There are no significant differences in social sciences and humanities, but there is an important gap in engineering and architecture, where men are over-represented, and in health-related fields, where women are in the majority. In the case of the natural sciences, although there are no significant overall differences, when the degrees that make up this field are analyzed in detail, the previous pattern reappears: the proportion of women is higher in health-related sciences and lower in STEM fields (Science, Technology, Engineering and Mathematics). The main conclusion of this analysis shows, through a detailed study of one hundred university degrees, that there is no convergence in the demand for higher education studies between the two genders and that there has been no significant progress in reducing the gender gap in STEM studies over the last twenty years.

The second part of the article focuses on the study by Conde-Ruiz *et al.* (2024a), which analyzes the degree of exposure of university degrees to technological change. The methodology used by Conde-Ruiz *et al.* (2024a) consists in linking two sources of information that have not been previously analyzed together: the employability patterns of different university degrees and the degree of exposure of each occupation to technological change. The result of combining the correspondence between degrees and occupations with indexes of automation and exposure to software and artificial intelligence of different occupations, is a set of groundbreaking indexes that measure the degree of exposure of university degrees to technology.

In particular, university degrees can be ranked based on three occupational indexes: Routine Task Intensity (RTI), Artificial Intelligence Exposure Index and Software Exposure Index, which have very different interpretations. RTI measures the risk of an occupation being replaced by technology because there is a high percentage of routine tasks. By ranking college degrees using employability patterns and this routinization index, we can identify the occupations most threatened by technology. College degree rankings based on technology exposure indexes (either to software or artificial intelligence) have a different interpretation because they identify occupations that require technology integration, but this may be complementary to college education. For example, degrees with a high value of this index, such as Industrial Technology Engineering, Statistics or Mining and Energy Engineering, should reinforce in their curricula the methodological aspects that help to incorporate these technologies.

The article shows that these indexes can explain to a large extent the degree of employability of university degrees, as well as the expected wage differences. Nevertheless, Conde-Ruiz *et al.* (2024a) show, using the evolution of university entrance grades in the Community of Madrid, that demand is not responding to the potential threats that technological change poses to some university degrees. From a gender perspective, Conde-Ruiz *et al.* (2024b) show that women are overrepresented in those degrees that, according to the indexes developed by Conde-Ruiz *et al.* (2024a), are more threatened by technology.

Although we are talking about the demand for university studies, the reality is that the studies pursued are often conditioned by the supply of degrees. In other words, it is possible that a student wants to study a degree but they cannot do it because there are not enough places available. In this sense, we created an excess demand ratio from microdata from the Community of Madrid that contains information on where the student was admitted and also the complete profile of preferences (up to twelve options) in relation to the choice of degree. This indicator can be useful to identify where it is most necessary to increase university supply.

The article is divided into six sections. Section two presents the descriptive study of the evolution of the demand for university degrees over the period

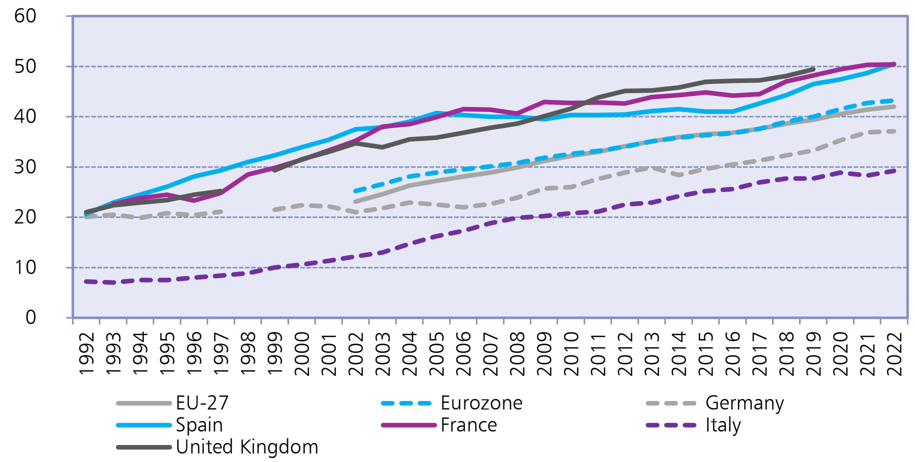
1985-2023. Section three presents the indexes we created to measure the level of exposure of university degrees to technological change. Section four uses the indexes of exposure to technological change to explain several labor market variables (the degree of labor market placement of the different degrees and their expected wage). Section five uses microdata on student preferences to analyze capacity constraints in the public supply of university degrees. Finally, section six presents conclusions and policy recommendations and thus concludes the article.

II. EVOLUTION OF THE DEMAND FOR UNIVERSITY DEGREES: 1985-2023

This section presents and analyzes how the demand for higher education has evolved over the past decades. The first question to be analyzed is how the percentage of young people between 25 and 34 years of age with a university degree has changed. Figure 1 shows the evolution of this indicator for Spain, the euro area average and various European countries. The first conclusion is that there is a general pattern in which the demand for university studies has increased steadily in all countries over the last three decades. In the case of Spain, the percentage of young people (25-34 years old) with tertiary education has risen from around 20% to 50%, placing it at the top of the list, along

FIGURE 1

PERCENTAGE OF POPULATION (25-34 YEARS OLD) WITH TERTIARY EDUCATION



Note: Tertiarty Education (ISCED 5-8) includes Higher Vocational Education.
Source: Eurostat.

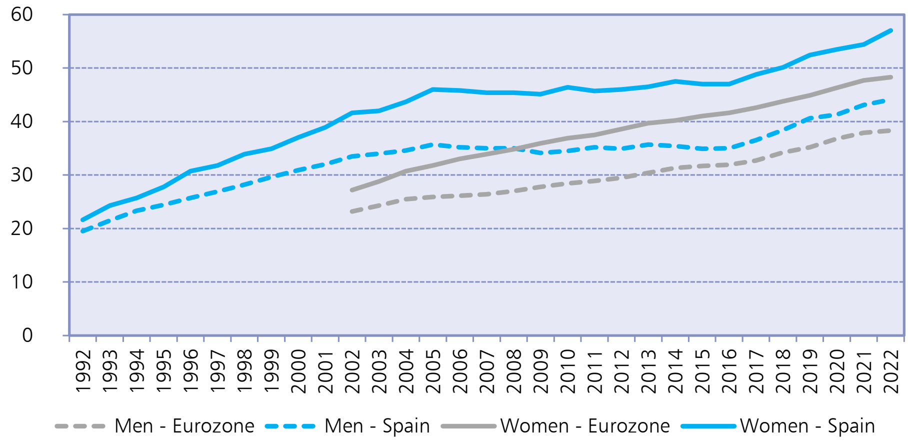
with France, amongst countries in our context and well above the euro area average, although it does not reach the levels of Luxembourg (64%) and Norway (60%) in Europe or Canada (73%) and South Korea (76%) in the world (OECD (2021)). It should be noted that university degrees also include third-cycle vocational degrees.

Spain has, therefore, a leading position within the Eurozone regarding the percentage of university students. This data is difficult to interpret. On the one hand, it can be seen as a source of competitive advantage for Spain, since general higher education can provide the tools to adapt to a changing labor demand, and this can be especially important in periods of technological uncertainty. But, on the other hand, this conclusion entails two important nuances. First, the alternative to a high rate of university graduates could also be high-quality vocational training with a high level of labor market insertion. This seems to be the case in Germany. On the other hand, if labor supply does not evolve in the same direction as its demand, and graduates do not find qualified jobs, overqualification may generate much dissatisfaction and friction in the labor market, instead of being a source of competitive advantage.

The difference in the evolution of the demand for university education by gender is also analyzed. Figure 2 shows the indicator of the percentage

FIGURE 2

PERCENTAGE OF POPULATION (25-34 YEARS OLD) WITH TERTIARY EDUCATION, BY GENDER



Note: Tertiarty Education (ISCED 5-8) includes Higher Vocational Education.
Source: Eurostat.

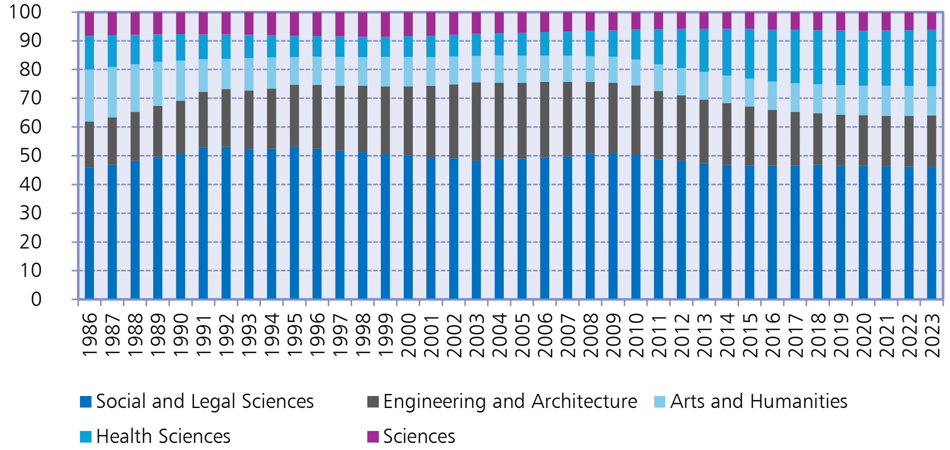
of people between 25 and 34 years of age with tertiary education out of the general population, for women and men. A positive gender gap is observed, *i.e.* there are more women at university than men. This gap occurred mainly in the 1990s, coinciding with the increase in university enrollment. This pattern is not exclusive to Spain and is also seen in the Eurozone countries. This result is also confirmed by the OECD reports (2021 and 2023), which indicate that a possible explanation could be that the benefit of obtaining a university degree in Spain is higher for women than for men. For example, in terms of employability, the difference between having a high school or university education is very small for a man (6% unemployment compared to 5%), while it is significant for a woman (dropping from 9% unemployment to 6%).

The specific demand for university degrees in Spain is discussed below. Figure 3 shows how the distribution of enrolled students by discipline of knowledge has changed.

The most in-demand degrees are in the area of social sciences, with a market share of close to 50 percent. The sciences and humanities have a smaller but almost stable market share over time. However, engineering and architecture greatly reduced their market share after the economic crisis

FIGURE 3

DISTRIBUTION OF ENROLLED STUDENTS (UNDERGRADUATE AND/OR 1ST AND 2ND CYCLE), BY DISCIPLINE OF EDUCATION



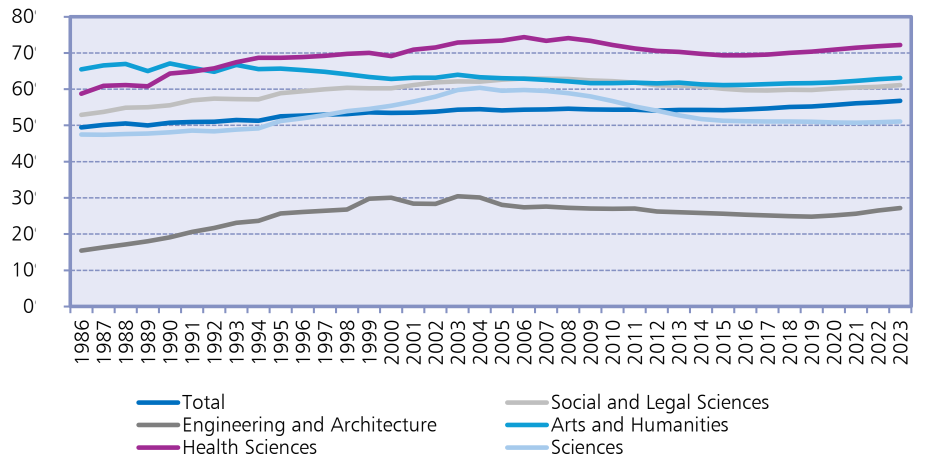
Source: Integrated University Information System, SIIU (General Secretariat of Universities).

and have not recovered it.[1] The space left by engineering has been taken over by health sciences. The increase in demand for health sciences can be explained both by the increase in demand associated with a higher level of development and also aging, as well as by the development of new disciplines associated with technological change.

Despite this, the demand changes by areas of knowledge and has evolved differently between the two genders. Figure 4 shows the evolution of female university students by disciplines of knowledge.

FIGURE 4

PROPORTION OF FEMALE STUDENTS OVER THE TOTAL NUMBER OF STUDENTS ENROLLED (UNDERGRADUATE AND/ OR 1ST AND 2ND CYCLE), BY BRANCH OF EDUCATION



Source: Integrated University Information System, SIIU (General Secretariat of Universities).

The most marked inequalities between genders are seen in health sciences, which are highly feminized areas of education, as well as in engineering and architecture, where the representation of women has been stagnant at below 30% since the late 1990s. The data seem to show that there are no significant gender differences in sciences, but reality is more complex. Table 1 shows the university degrees in the area of science knowledge ranked by the representation of women. The same initial pattern is seen here: women are overrepresented in degrees such as Biomedicine, that are close to the health sciences, while they are underrepresented in degrees such as Physics or Mathematics.

[1] This evidence follows Sofoklis and Megalokonomou (2019), who calculated the impact of unemployment on the demand for university studies with data from Greece. Job opportunities for engineers and especially architects were reduced in the economic crisis of 2008-2014 proportionally more than other professional profiles.

TABLE 1

PERCENTAGE OF WOMEN IN THE TOTAL UNDERGRADUATE ENROLLMENT (AREAS OF STUDY IN THE "SCIENCE" AREA)

Company	*2015-2016*	*2016-2017*	*2017-2018*	*2018-2019*	*2019-2020*	*2020-2021*	*2021-2022*	*2022-2023*
Geography and Land Use Planning	28	29	29	28	27	27	26	27
Physics	26	25	26	27	27	27	28	28
Mathematics	38	38	38	37	36	35	36	36
Geology	41	41	41	40	40	41	40	39
Statistics	43	43	45	45	46	46	46	45
Environmental Sciences	47	48	48	48	49	49	49	50
Chemistry	53	53	53	54	54	54	54	55
Marine Sciences	55	58	56	57	58	56	57	58
Biotechnology	60	60	61	61	61	62	62	63
Biology	62	62	62	62	62	62	63	63
Biochemistry	65	65	65	66	66	68	69	70
Biomedicine	77	76	75	75	76	76	77	79

Source: Integrated University Information System, SIIU (General Secretariat of Universities).

Table 1A in the Annex shows in detail the representation of women in one hundred university degrees.[2] The general conclusion is similar to Figure 4: women are overrepresented in degrees related to health, social work and teaching, which we could call the "care economy". In social sciences and humanities, although there are divergences in representation, these are generally smaller. Finally, in STEM degrees, with the exception of those degrees related to health, women are significantly underrepresented. To give a sample of this pattern, Table 2 show a selection, taken from the general analysis of all degrees, of the fifteen courses in which women are most represented and those fifteen in which they are least represented.

The gender gap for STEM studies is not a Spanish anomaly. The OECD report (2023) shows that, to a greater or lesser extent, this gap occurs in all developed countries. However, it is worrying that, despite efforts to promote STEM studies among girls and female teenagers, there has been no significant progress in the last two decades. Moreover, it is important to note that, as Hanushek *et al.* (2015) and Rebollo-Sanz and De la Rica (2022) show, given that the labor market values mathematics skills, this gap in STEM profiles may at least partly explain the gender wage gap. Moreover, as discussed in the next section, job opportunities in STEM studies are less threatened by technological

[2] "Field of study", in the taxonomy of the Integrated University Information System (SIIU).

TABLE 2

FIELDS OF STUDY WITH THE LOWEST AND HIGHEST PERCENTAGES OF WOMEN COMPARED TO THE TOTAL NUMBER OF STUDENTS ENROLLED IN UNDERGRADUATE PROGRAMS

Company	*2015-2016*	*2016-2017*	*2017-2018*	*2018-2019*	*2019-2020*	*2020-2021*	*2021-2022*	*2022-2023*
Automotive Engineering	8	7	6	6	5	4	5	5
Sports Management	8	7	6	6	5	4	5	5
Computer Engineering	10	10	11	10	11	11	12	12
Mechanical Engineering	13	13	13	13	14	14	14	14
Computing	12	12	12	12	13	13	14	14
Software and Application Development	11	11	12	12	12	13	14	14
Electrical Engineering	13	14	14	14	15	15	15	15
Industrial and Automatic Electronics Engineering	14	14	15	15	16	16	16	16
Electronics Engineering	16	17	17	17	17	17	18	19
Video Game Development	12	12	12	13	13	14	17	19
Other Engineering	14	13	14	14	15	17	17	20
Prevention and Occupational Safety	14	13	14	14	15	17	17	20
Naval and Oceanic Engineering	19	19	20	20	20	21	21	22
Physical Activity and Sports	19	19	20	20	20	21	21	22
Telecommunication Engineering	21	20	21	21	21	22	22	22
Modern and Applied Languages	78	79	79	79	79	80	80	78
Performing Arts	80	77	77	79	79	79	77	78
Biomedicine	77	76	75	75	76	76	77	79
Design	73	74	75	75	76	77	78	79
Translation and Interpreting	80	80	81	81	81	80	80	80
Conservation and Restoration	78	77	76	77	78	80	81	80
Nursing	78	77	76	77	78	80	81	80
Social Education	81	81	81	81	81	81	82	82
Social Work	81	81	81	81	81	81	82	82
Pedagogy	83	83	83	83	84	83	84	84
Occupational Therapy	83	83	83	83	84	83	84	84
Protocol and Events	88	89	89	88	86	86	87	88
Speech Therapy	88	89	89	88	86	86	87	88
Early Childhood Education	93	93	93	93	92	92	91	91
Gender Equality	90	87	87	80	95	95	95	96

Note: The fifteen fields of study with the lowest and highest percentage of women compared to the total number of students enrolled in the 2022-23 school year

Source: Integrated University Information System, SIIU (General Secretariat of Universities).

changes than those associated with other types of studies, so the wage premium for STEM studies may rise, and that is likely to increase the wage gap between men and women in the near future.

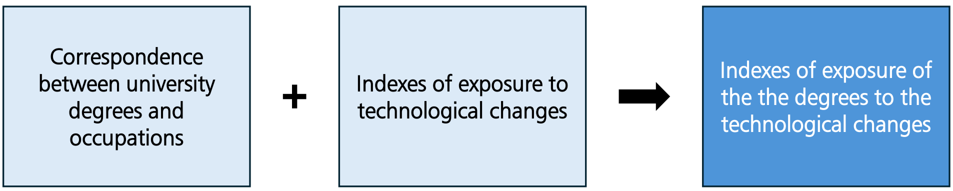
III. UNIVERSITY DEGREES IN THE FACE OF TECHNOLOGICAL CHANGE

This section analyzes the degree of exposure of university degrees to technological change. Two sources of information are used for this purpose. On the one hand, papers that assign indexes to the different occupations measuring how exposed those occupations are to technology. On the other hand, information on the occupations to which the different students access to depending on the degree studied.

In other words, in the first stage, each university degree is related to the different occupations. In a second stage, the information on the degree of exposure of each occupation to technological changes is used. Finally, each university degree is assigned an index of exposure to technology. Figure 5 shows, schematically, the calculation process for these indexes.

FIGURE 5

METHODOLOGY FOR OBTAINING THE EXPOSURE INDEXES OF UNIVERSITY DEGREES TO TECHNOLOGICAL CHANGES



Source: Created by the authors.

1. Correspondence Between University Degrees and Occupations

To obtain the correspondence between occupations and university degrees, data from the 2019 *Labor Market Insertion Survey of University Graduates (EILU,* in Spanish) are used. This statistical operation of the Spanish Statistics Agency aims to provide information on the employment situation of the group of university graduates, as well as the various aspects of their labor market insertion process (access to the labor market). In particular, it includes information on the cohort of graduates in the 2013-2014 academic year, with a sample of, approximately, 31,500 people (1st and 2nd cycle and graduates).

An important aspect is that it includes information on the occupation, using a two-digit CNO code,[3] in which the graduates of the different degree programs work (if applicable). From this information, it is possible to calculate the distribution of occupations for each university degree, that is, what percentage of the graduates of each degree program are working in a given occupation.[4]

2. Index of Exposure of the Occupations to Technological Changes and AI

The academic literature (see Dorn, 2015; Acemoglu and Restrepo, 2022; Autor, 2019; Autor and Dorn, 2013 and Conde-Ruiz and Ganuza, 2023, among others) tries to anticipate which occupations will be most affected by the new digital economy. To this end, they argue that technological change will not have a large differential impact on workers according to their levels of education, but rather according to the content of the tasks carried out in their occupations (Task Biased Technological Change). Thus, three types of tasks are distinguished: routine, abstract and manual tasks. Routine tasks involve the repetition of predetermined processes (as in car assembly lines or administrative tasks). Abstract tasks are those that involve problem solving, intuition, persuasion and leadership skills, as well as creativity. Manual (non-routine) tasks are those that require personal interactions, adaptability, visual recognition and language. It seems clear that routine tasks are easy to perform by automation technology, while abstract and manual tasks are much more difficult. The former because they are clearly complementary to technology and the latter because they are too expensive to be replaced by it. With this argument, a classification of the main tasks in each occupation is made. The most widely used database is O*NET (Occupational Information Network), which gives a direct correlation between tasks and occupations.

RTI (Routine Task Intensity) Index. Within this methodology, we used the synthetic measure of routine task intensity constructed by Lewandowski *et al.*

[3] Royal Decree 1591/2010, of November 26, 2010, approving the National Classification of Occupations 2011. https://www.boe.es/eli/es/rd/2010/11/26/1591

[4] The *Survey of Labor Market Insertion of University Graduates (EILU)* offers information on degrees at two CNO-11 digits. For example, economists would be included in code 28 "Professionals in social sciences: Economists; Sociologists, historians, psychologists and other professionals in social sciences (geographers, anthropologists, archaeologists, philosophers, professionals in political sciences...); Priests of different religions". See Conde-Ruiz *et al.* (2024a) for the complete list of EILU CNO-11 codes.

(2022) and Schotte *et al.* (2023).[5] A specificity of this approach is that, as opposed to O*NET-based analyses, it does not assume that the task content in a given country is identical to the contents used in the United States. Therefore, its main advantage is that it allows us to distinguish between differences in task content among workers who have the same occupation but live in different countries. This makes it possible to use the specific estimated data from Spain.

In particular, the authors construct country-specific metrics of routine task intensity at levels 1 and 2 of the ISCO-08[6] (International Standard Classification of Occupations) classification for several countries, based on data from three surveys (Lewandowski *et al.,* 2022). For those countries for which survey data are not available, an econometric estimation is used (Schotte *et al.,* 2023).

From the questions in the various surveys, they create a synthetic measure of the relative intensity of routine tasks according to the levels of routine cognitive, analytical non-routine cognitive and personal non-routine cognitive tasks, excluding manual tasks. Finally, the RTI is standardized from its average and standard deviation in the United States.

Thus, occupations with a higher content of non-routine tasks (analytical and personal) will have a lower value of this metric, while those occupations with a higher content of routine tasks (cognitive) will have a higher level. It is, therefore, a measure of the routine aspect of the occupation and thus of the ability to be replaced by technology.

Artificial Intelligence and Software Exposure Index. On the other hand, Webb (2020) identifies which tasks can be automated by a particular technology and constructs a metric of occupations' exposure to that technology based on information contained in their patent texts and their correlation to the tasks performed in different occupations. Specifically, occupation descriptions from O*NET and patent data from Google Patents Public Data are used. These indicators are available for the different occupations at 3-digit ISCO-08 from Albanesi *et al.* (2023).

The occupations least exposed to *software* would be those with a high manual component and which are not easy to "algorithmize", as well as those

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[5] A brief description of how the indexes is created can be found in the Annex.

[6] The ISCO-08 classification (International Standard Classification of Occupations) is the International Labor Organization's occupational classification system. It is structured into major groups (1 digit), major subgroups (2 digits), minor groups (3 digits) and unit groups (4 digits).

with a high interpersonal component. Artificial intelligence, on the other hand, affects different occupations, and by its very nature, it is not possible to know, *a priori,* the impact it may have or whether it will be positive or negative. All this makes the interpretation of these two indexes substantially more complex than the RTI.

In short, the routine task intensity (RTI) and technology exposure (artificial intelligence and software) indexes described above are available at a 2-digit and 3-digit disaggregation level, respectively, from ISCO-08. The correspondence between ISCO-08 and CNO-11 is not exact, which would entail that certain adjustments need to be made when calculating the indexes for occupations.[7]

To perform the analysis of the response of university degrees to technological changes we need indexes that measure the intensity of the latter, mainly based on the different types of tasks (routine/non-routine, manual/cognitive). However, as seen above, indexes along these lines have been calculated in the literature for different occupations, but not for degrees. This is partly because the linkage between tasks and occupations is straightforward from standardized international classifications (O*NET or ESCO, the multilingual European classification of skills, competencies, qualifications and occupations), while the correlation between both and degrees is in a very early process.[8]

Once all the occupations have been classified with each of the three indexes mentioned above (RTI, artificial intelligence exposure index and software exposure index), these indexes can be assigned to each university degree according to the occupations in which the students of each degree end up working. For each of the metrics, they are calculated as the weighted average of the indexes of the different occupations in which their graduates work, using as weights the distribution of occupations calculated from the data of the *Survey of Labor Market Insertion of University Graduates.*

As noted above, the RTI has a simple interpretation: the higher it is, the greater the risk that the occupation will be replaced by technology. Therefore, those degrees with a higher RTI run the same risk, as it would indicate that recent graduates in that degree would be being hired in occupations that are going to be threatened by technology.

7 For example, while when an ISCO group corresponds to several CNO groups, the value can be imputed to them, when a CNO group is composed of several ISCO groups, the arithmetic average has been calculated. On the other hand, the Albanesi *et al.* (2023) data are aggregated from 3 to 2 digits. Specifically, the 123 3-digit groups are aggregated into 40 2-digit groups, using the arithmetic average.

8 See, for example: https://esco.ec.europa.eu/en/about-esco/escopedia/escopedia/qualifications-and-esco

3. Ranking of University Degrees According to the three Technological Indexes by Occupations

Ranking According to the Routine Task Intensity Index. As noted above, the RTI index has a simple interpretation: the higher the RTI, the greater the risk of the occupation being replaced by technology. Therefore, those degrees with a higher RTI are at the same risk, as it would indicate that recent graduates in that degree would be being hired in occupations that are going to be threatened by technology.

First, we analyze the degrees with the lowest RTI, *i.e.,* those whose graduates work in occupations with lower technological risk. Table 3 shows the 15 degrees with the lowest RTI,[9] among which are mainly engineering of various types, mathematics, physics and architecture. In addition, Table 4 shows the 15 degrees with the highest RTI (those whose graduates work in occupations with high technological risk): Tourism, Management and Public Administration, Finance and Accounting or Nautical and Maritime Transport. However, some of the careers do not seem, *a priori,* to be related to occupations in which there is high routinization, such as Marine Sciences or Tourism, which would lead one to think that they may be capturing labor insertion into occupations in which this risk does exist, reflecting the phenomenon of over-qualification.

Ranking according to software or AI exposure rates. Tables 5 and 6 discuss degrees with low and high technology exposure indexes, respectively (all university degrees are in the Annex). It is relevant, in line with what has been

TABLE 3

DEGREES WITH LOW VALUES OF THE RTI INDEX

Computer Engineering
Computing
Software and Application Development and Multimedia Engineering
Mathematics
Aerospace Engineering
Telecommunication Engineering
Physics
Materials Engineering and Textile Engineering
Industrial Technology Engineering
Architecture and Urban Planning and Landscaping
Sound and Image Engineering
Electronics Engineering
Biomedical and Health Engineering
Power Engineering
Primary Education

Sources: Created by the authors with data from Schotte *et al.* (2023) and *Labor Market Insertion Survey of University Graduates 2019.*

[9] Table 2A in the Annex shows the complete list of degrees and the values of the three indexes.

TABLE 4

DEGREES WITH HIGH VALUES OF THE RTI INDEX

Information and Documentation
Marine Sciences
Modern and Applied Languages
Criminology
Humanities
Human Nutrition and Dietetics
Fine Arts
Labor Sciences
Geography
Horticultural and Landscape Engineering
Nautical and Maritime Transport
Art History
Finance and Accounting
Management and Public Administration
Tourism

Sources: Created by the authors with data from Schotte *et al.* (2023) and *Labor Market Insertion Survey of University Graduates 2019.*

described above, that those degrees more exposed to technology, based on these indexes, do not seem to be related to occupations with a high risk of being automated, but rather to occupations highly complementary to technology (engineering, architecture or statistics), which points to the need to acquire skills that allow this complementarity. As for the careers with the lowest exposure indexes, they are mostly in the fields of education and arts and humanities.

TABLE 5

DEGREES WITH LOW VALUES OF TECHNOLOGY EXPOSURE INDEXES

AI (Webb)	*Software (Webb)*
Early Childhood Education	Spanish Languages and Dialects
Primary Education	Primary Education
Spanish Languages and Dialects	Early Childhood Education
English Language	Literature
Pedagogy	Protocol and Events
Management and Public Administration	English Language
Literature	Music and Performing Arts
Music and Performing Arts	Pedagogy
Other Teachers	Translation and Interpretation
Classical Languages	Classical Languages
Other Foreign Languages	Other Foreign Languages
Archaeology	Archaeology
Finance and Accounting	Social Education
Modern and Applied Languages	Other Teachers
Protocol and Events	Management and Public Administration

Sources: Created by the authors with data from Albanesi *et al.* (2023) and *Labor Market Insertion Survey of University Graduates 2019.*

TABLE 6

DEGREES WITH HIGH VALUES OF TECHNOLOGY EXPOSURE INDEXES

AI (Webb)	*Software (Webb)*
Electronics Engineering	Statistics
Geomatics Engineering, Surveying and Mapping	Mining and Energy Engineering
Computing	Mechanical Engineering
Telecommunications Engineering	Industrial and Automatic Electronics Engineering
Computer Engineering	Aerospace Engineering
Industrial Chemical Engineering and Environmental Engineering	Food Science and Technology and Food Engineering
Civil Engineering	Power Engineering
Industrial and Automatic Electronics Engineering	Naval and Oceanic Engineering
Electrical Engineering	Telecommunication Engineering
Mechanical Engineering	Nautical and Maritime Transport
Power Engineering	Sound and Image Engineering
Naval and Oceanic Engineering	Electronics Engineering
Industrial Technology Engineering	Software and Application Development and Multimedia Engineering
Architecture and Urban Planning and Landscaping	Computer Engineering
Aerospace Engineering	Computing

Sources: Created by the authors with data from Albanesi *et al.* (2023) and *Labor Market Insertion Survey of University Graduates 2019.*

4. Discussion of the Results

The interpretation of the results obtained, as well as the economic policy implications that we can infer, are as follows: on the one hand, it is important to remember that the index assigned to each university degree has been created by looking at the occupations to which the students who have studied them have access and that, therefore, the information on the programs or contents of each degree has not been used; on the other hand, as will be seen below, the interpretation is very different depending on the index used.

The ranking of university degrees using the routinization index indicates that those careers with a lower index are training workers in occupations that, as they have a high percentage of routine tasks, will most likely be replaced by technology. As can be seen in Table 4, (or in Table 2A in the Annex, where all fields of study are shown), the careers most threatened by technology would be: History, Information and Documentation, Marine Sciences, Modern and Applied Languages, Criminology, Humanities, Human Nutrition and Dietetics, Fine Arts, Labor Sciences, Geography, Horticultural and Gardening Engineering, Nautical and Maritime Transportation, Art History, Finance and Accounting, Management and Public Administration, and Tourism. All these careers will certainly have to adapt their curricula to provide their students with training that will enable them to find occupations that are not at risk of automation. On the other hand, careers with a low routinization index are careers that are training workers in occupations with a low percentage of routine tasks and, therefore, have less risk of disappearing due to the advance of technology.

The ranking of university degrees using technology exposure indexes (either software or artificial intelligence) has a different interpretation. If they have a high index, it means that students taking these degrees enter occupations that are either exposed to software or exposed to artificial intelligence. For example, if we look at the software exposure index, the following university degrees have a high index: Industrial Technology Engineering, Statistics, Mining and Energy Engineering, Mechanical Engineering, Industrial Electronics and Automation Engineering, Aerospace Engineering, Food Science and Technology and Food Engineering, Energy Engineering, Naval and Ocean Engineering, Telecommunications Engineering, Nautical and Maritime Transport, Sound and Image Engineering, Electronics Engineering, Software and Applications Development and Multimedia Engineering, Computer Engineering and Computer Science.

If we look at the AI exposure index, the degrees with a high index would be: Software and Applications Development and Multimedia Engineering, Biomedical and Health Engineering, Electronics Engineering, Geomatics Engineering, Surveying and Cartography, Computer Science, Telecommunication Engineering, Computer Engineering, Industrial Chemical Engineering and Environmental Engineering, Civil Engineering, Industrial Electronic and Automatic Engineering, Electrical Engineering, Mechanical Engineering, Energy Engineering, Naval and Oceanic Engineering, Industrial Technologies Engineering, Architecture and Urban and Landscape Planning, and Aerospace Engineering. In this case, it is not necessarily negative to have a high index (software or artificial intelligence), as it will depend on whether such technology is complementary or substitutive to the student's competencies. For example, it seems clear that many engineers or architects use certain software to perform their tasks. The risk here is whether the functionalities of such software are complementary to the training being given to students or, on the contrary, substitutive. If university training is complementary to the advancement of technology, students pursuing such degrees are not at risk in terms of the occupations they will perform in the future. In any case, all careers with high rates of exposure to technology (software or artificial intelligence) should update their contents and curricula, paying special attention to technological progress.

IV. THE LABOR MARKET INSERTION OF UNIVERSITY GRADUATES AND THEIR EXPOSURE TO TECHNOLOGICAL CHANGES

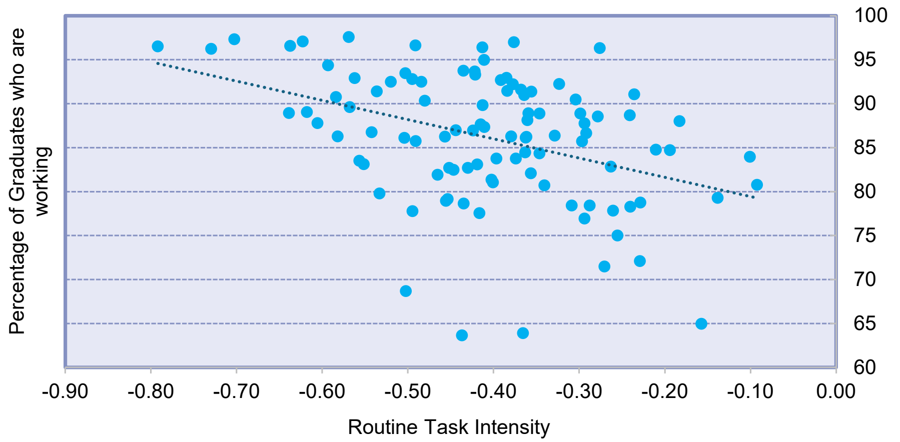
In this section we analyze the possible correlation between our indexes of intensity of routine tasks and exposure to technology (artificial intelligence and software) with certain characteristics of the degrees: the percentage of graduates who are working and the percentage of graduates affiliated to Social Security as employees who are in the top two quintiles of the contribution bases.[10]

1. Analysis of Labor Market Insertion

The following graphs show the relationship between the three indexes calculated for each university degree and their labor market insertion, measured as the percentage of graduates of each degree who are working. They show that the relationship is negative in the case of RTI, indicating that those degrees where students end up in occupations with a lower percentage of routine tasks have a higher percentage of graduates working. In the

FIGURE 6

LABOR MARKET INSERTION AND INTENSITY OF ROUTINE TASKS

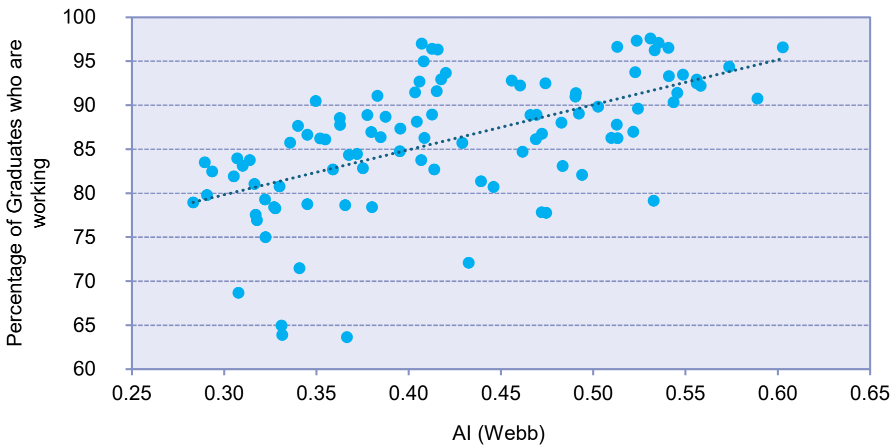


Sources: Schotte *et al.* (2023) and *Labor Market Insertions Survey of University Graduates 2019.*

[10] This metric is used as an approximation of the salary level.

FIGURE 7

LABOR MARKET INSERTION AND EXPOSURE TO ARTIFICAL INTELLIGENCE

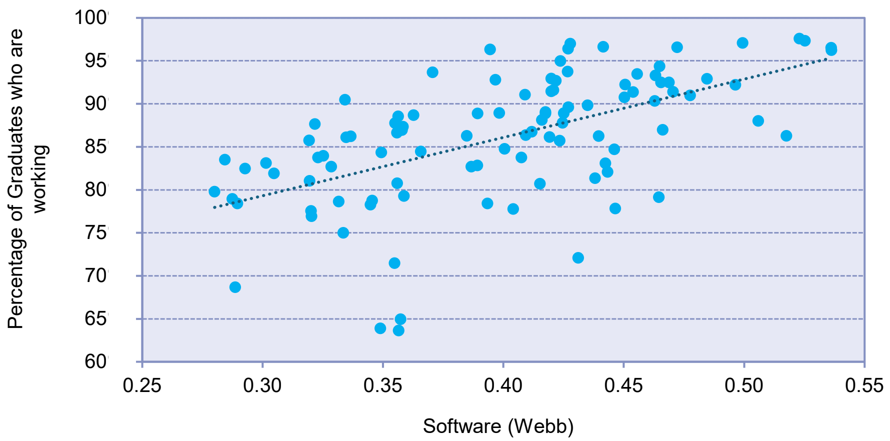


Sources: Albanesi *et al.* (2023) and *Labor Market Insertion Survey of University Graduates 2019.*

case of exposure to technology, the relationship is positive, indicating that those degrees with greater exposure to both software and AI have a higher percentage of graduates working.

FIGURE 8

LABOR MARKET INSERTION AND INTENSITY OF ROUTINE TASKS



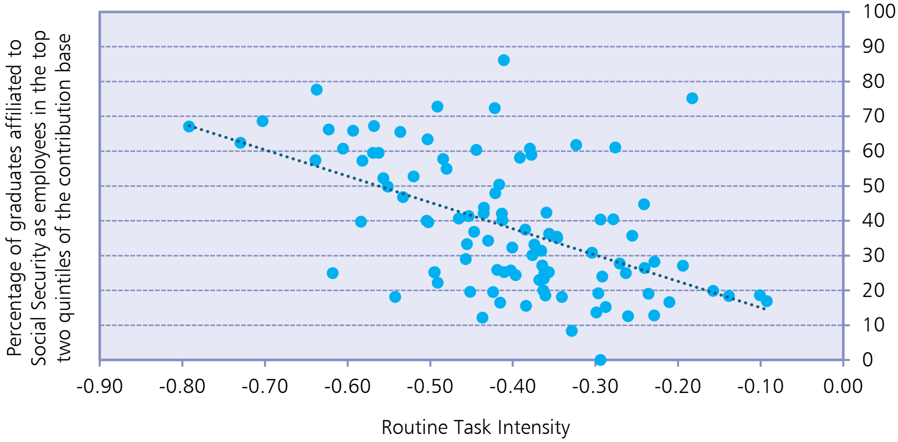
Sources: Albanesi *et al.* (2023) and *Labor Market Insertions Survey of University Graduates 2019.*

2. Analysis of Salaries Received by Employees

Finally, we show the relationship between the indexes and a metric related to salary, measured as the percentage of graduates of each degree, affiliated to

FIGURE 9

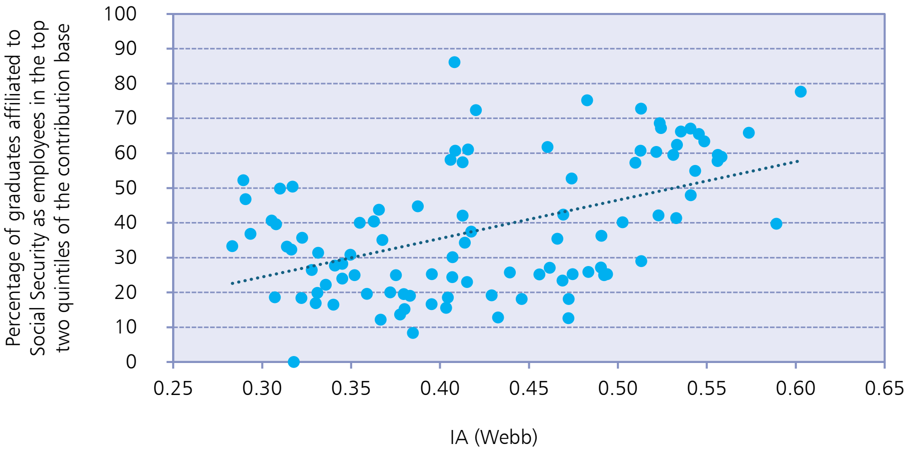
CONTRIBUTION BASE AND INTENSITY OF ROUTINE TASKS



Sources: Schotte *et al.* (2023) and *Labor Market Insertion Survey of University Graduates 2019.*

FIGURE 10

CONTRIBUTION BASE AND SOFTWARE EXPOSURE

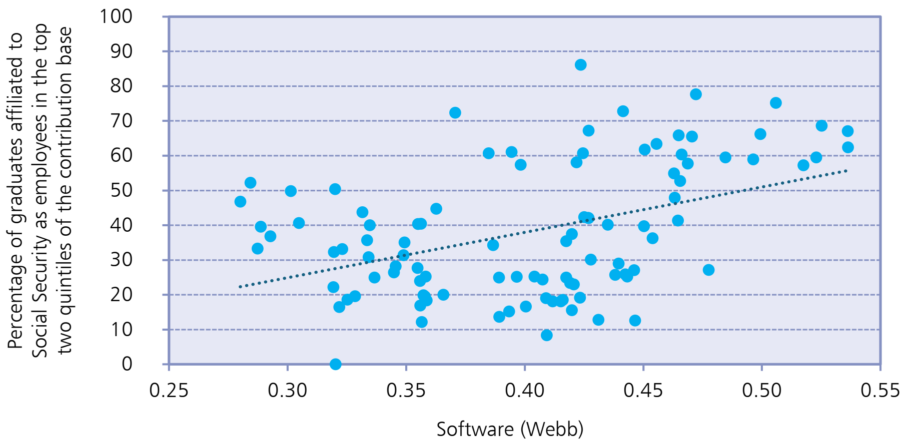


Sources: Albanesi *et al.* (2023) and *Labor Market Insertions Survey of University Graduates 2019.*

Social Security as employees, in the top two quintiles of the contribution bases. These show that the relationship is negative in the case of RTI, indicating that those degrees where their students end up working in occupations with less routine tasks have a higher percentage of graduates in the top quintiles, while in the case of exposure to technology, the relationship is positive, showing that those degrees with greater exposure have a higher percentage of graduates in these quintiles.

FIGURE 11

CONTRIBUTION BASE AND SOFTWARE EXPOSURE



Sources: Albanesi *et al.* (2023) and *Labor Market Insertions Survey of University Graduates 2019.*

3. Analysis of the Impact of the Exposure of University Degrees to Technological Changes on the Demand

Given the correlation between the indexes of the exposure of university degrees to technological changes and the labor market insertion, it would be expected that these indexes are a signal about the future evolution of the demand for university degrees. However, according to Conde-Ruiz *et al.* (2024b), the demand is not yet reacting to the potential exposure of degrees to technological changes. This article draws this conclusion after analyzing the correlation between the increase in the university entry grades and the number of enrollments between the years 2013-2014 (the year in which the participants in the survey finished university) and 2021-2022 (the last year available for university entry grades) and the different indexes that have been designed. The relationship between the indexes of the intensity of routine tasks and exposure to technology (artificial intelligence and software) with the variation of the entry grade is very weak and there seems to be no correlation between these indexes with the growth or decrease in the number of students over the period.

V. CAPACITY RESTRICTIONS IN THE PUBLIC PROVISION OF UNIVERSITY DEGREES

Finally, we constructed an excess demand ratio for the degrees from very detailed microdata on admissions in the universities of the single district of the Community of Madrid. The database contains information on the degree to which the student was admitted, the school year of admission (from 2013-2014 to 2021-2022), the university where the student was admitted, the university access itinerary and the complete profile of preferences (up to 12 options) in relation to the degree.[11]

The information offered by this database is richer than what can be obtained from the analysis of the number of admissions and the cut-off score of each degree because these variables are highly conditioned by the number of places available. For this same reason, the analysis of student preferences can be very useful for making decisions about which degrees should be invested in to increase the number of places. Using the data for the school year 2021-2022, we have carried out a first exploitation of the database to identify the capacity restrictions of the public provision of the universities by calculating the excess demand ratio. This ratio is defined as the quotient between the number of people who have chosen a degree as their first choice in the ranking and the number of students who have finally been admitted to this degree. Thus, the ratio indicates how many students would have wanted to study a certain degree for each student who has managed to do so. Given this definition, the ratio can be greater or less than one, with the degrees with a higher ratio having a higher unsatisfied demand.

Table 3A in the Annex shows this index for most of the 100 degrees analyzed above. Table 7 shows the 15 degrees with the highest excess demand ratio index. That is, the 15 degrees most in demand by students as their first choice with respect to the number of students admitted to it.

[11] Conde-Ruiz *et al.* (2024c) details the application system for university entrance in the Community of Madrid, where students have to indicate a ranking of their desired degrees. The article shows that, if students were acting rationally, these rankings should correspond to their true degree preferences. However, the same article analyzes whether there may be behavioral biases that lead students to eliminate unfeasible desired options from the rankings.

TABLE 7

DEGREES WITH HIGH VALUES OF THE EXCESS DEMAND INDICATOR

Career	*Excess Demand Ratio*
Biotechnology	3.41
Industrial Design and Product Development Engineering	3.19
Design	3.13
Medicine	2.68
Biochemistry	2.19
Veterinary Science	2.04
Industrial Organization Engineering and Nanotechnology	1.83
Criminology	1.66
Dentistry	1.50
Advertising and Public Relations	1.48
Physical Activity and Sports	1.45
Biomedical and Health Engineering	1.44
Aerospace Engineering	1.34
Physics	1.34
Architecture and Urban Planning and Landscaping	1.24

Note: The index is calculated as the ratio between the number of people admitted to a given degree program and the number of people who have made this their first choice in the ranking. It does not include double degrees or degrees from affiliated centers.

Source: Created by the authors with data admission microdata from the universities of the single district of the Community of Madrid.

For example, for each student enrolled in Biotechnology, there were more than three students who, although it was their first choice, were unable to take it. This is a preliminary analysis, so it would be interesting, in future research, to analyze the cross information between the degrees and to be able to generate more precise indicators, using, for example, in which degrees students who were not able to enroll in their first choice have ended up enrolling.

VI. CONCLUSIONS AND POLICY RECOMMENDATIONS

This article has analyzed the demand for university studies in an environment characterized by technological uncertainty and the irruption of artificial intelligence. Our analysis provides empirical results from which important policy recommendations can be drawn. Two main conclusions emerge from the descriptive analysis of demand in recent decades. The first relates to gender differences: women are overrepresented in health-related studies and, more generally, in all studies that can be included in the care economy, while they are underrepresented in science, engineering and architecture degrees. The low proportion of women in STEM fields is worrying because it has not changed in the last two decades and because, given the advantages of STEM studies in terms of job placement and future salaries, it may be behind the gender gaps observed in the labor market and may even tend to widen them. The second conclusion is that we should focus on quality rather than quantity: Spain is a relative leader in Europe in terms of the number of university students, so efforts should be focused on improving the quality of higher education and its interaction with the labor market.

To achieve this goal, it is important to understand how different university degrees and their job opportunities will be affected by technological changes and artificial intelligence. For this purpose, three indexes (Routine Task Intensity Index [RTI Index], Artificial Intelligence Exposure Index, and Software Exposure Index) have been constructed for each of the degrees, and they have shown to be very informative in explaining both the job opportunities of the various degrees and the expected salary of their graduates. These indexes allow us to discriminate between different programs and to rank them according to their level of exposure to technological changes, thus helping us to improve the design of programs in order to adapt them to the technological changes we are facing.

In particular, programs whose students work in jobs with a higher intensity of routine tasks (with a high percentage of these tasks) are the ones most at risk of having their job opportunities reduced by the replacement of new technologies and should be redesigned or, in the extreme, their provision reduced. On the other hand, programs whose students end up working in jobs with high rates of exposure to artificial intelligence and software have a very different interpretation: they are not necessarily threatened by technological change, but their curricula should be redesigned to take advantage of complementarities with technologies.

The methodology and the indexes obtained are a first step in understanding the degree of exposure of university degrees to technological changes, but it is important to be aware of the various limitations of our analysis. First, the indexes used to measure the threats and complementarities of different professions with technology may change in the coming years as technologies, especially artificial intelligence, evolve. On the other hand, university degrees are analyzed in aggregate and we do not take into account the university that teaches it or the characteristics of the students, or even their specialties. In other words, the employability pattern of a degree (and therefore, the indexes that could be obtained) may vary depending on the university that teaches it, the specialty that has been chosen or simply whether the degree has been taught in English.

Finally, the article also attempts to guide possible investments to expand university provision. To this end, the first step is to identify the degrees with the greatest unsatisfied demand. To this end, using microdata from the admissions process of the Community of Madrid where students reveal their preferences, those degrees where the ratio of excess demand is highest (the ratio between students who have chosen that degree as their first choice and students who have enrolled) are indicated. These degrees would, *a priori,* be candidates for investment to increase the number of places available.

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ANNEX

- *Routine Task Intensity Index (RTI)* (Lewandowski *et al.*, 2022; Lewandowski *et al.*, 2023)

This index is first calculated by Lewandowski *et al.* (2022) for 47 countries using three surveys: the OECD's Programme for the International Assessment of Adult Competencies (PIAAC), the World Bank's *Skills Toward Employment & Productivity (STEP) and the Chinese Urban Labor Survey (CULS).*

To make the index as consistent as possible with existing metrics in the literature, US PIAAC data are used to maximize consistency with Acemoglu and Autor's (2011) O*NET-based task metrics. In particular, questions harmonized in PIACC and STEP whose content is similar to the questions used by Acemoglu and Autor (2011) are first identified. Subsequently, the combinations of questions (and groups of questions) that most correlate with the O*NET-based occupation metrics for the U.S. No questions on physical tasks are used because there is only one question on this issue.

The non-routine cognitive analytical task metric is based on questions about problem solving, reading news, reading professional journals, problem solving, and programming. The non-routine cognitive interpersonal task metric is based on supervising others and making presentations. The routine cognitive task metric is based on (or lack of) ability to change the order of tasks, completing forms, and (or lack of) giving speeches or making presentations. For each item, values are considered (to be yes or no).

Each metric for each task is standardized so that the mean equal to 0 is the U.S. mean and the standard deviation 1 is the U.S. mean.

Finally, a synthetic measure of routine task intensity at the worker level is created as the difference of the logarithms of the routine cognitive task level and the mean of the analytical and personal non-routine tasks:

$$RTI = \text{In}\left(r_{cog}\right) - \text{In}\left(\frac{nr_{analytical} + nr_{personal}}{2}\right)$$

Subsequently, in Lewandowski *et al.* (2023), regression based RTI predictions are obtained for countries that do not have the necessary survey data (including Spain).

- *Indexes of Exposure to Technologies (AI and Software)* (Webb, 2020)

To assess the exposure of occupations to a given technology, Webb (2020) uses patent texts to identify what the technology can do and then quantify the extent to which each occupation involves performing similar tasks. For patents, he uses public data from Google Patents. In particular, the fields he uses are the title, abstract, and the Cooperative Patent Classification codes (which indicate the subject matter to which the patent relates).

TABLE 1A

PERCENTAGE OF WOMEN IN THE TOTAL UNDERGRADUATE ENROLLMENT

	2015-2016	*2016-2017*	*2017-2018*	*2018-2019*	*2019-2020*	*2020-2021*	*2021-2022*	*2022-2023*
Pedagogy	83	83	83	83	84	83	84	84
Early Childhood Education	93	93	93	93	92	92	91	91
Primary Education	67	67	68	67	68	68	67	69
Social Education	81	81	81	81	81	81	82	82
Audiovisual, Image and Multimedia	50	50	50	50	52	53	55	58
Design	73	74	75	75	76	77	78	79
Fine Arts	67	69	70	72	73	74	75	77
Art History	69	69	68	69	69	69	70	69
Conservation and Restoration	78	77	76	77	78	80	81	80
Performing Arts	80	77	77	79	79	79	77	78
Music	46	47	48	48	48	48	48	49
Religion and Theology	19	18	18	15	17	17	24	25
Archaeology	56	55	53	53	51	52	53	52
History	33	32	32	32	32	33	34	34
Philosophy	36	36	37	38	38	39	39	39
Humanities	60	61	61	61	62	63	63	62
English Language	73	73	73	74	74	74	75	75
Classical Languages	66	64	64	65	65	66	67	66
Other Foreign Languages	73	74	74	74	75	76	77	76
Translation and Interpreting	80	80	81	81	81	80	80	80
Spanish Languages and Dialects	71	71	71	71	71	72	72	73
Literature	70	71	71	71	71	72	74	78
Modern and Applied Languages	78	79	79	79	79	80	80	78
Economy	39	38	38	38	38	39	38	39
Public Policy and Management	41	39	39	39	41	42	44	46
International Relations	68	69	69	69	69	69	69	69
Psychology	74	74	75	75	76	76	77	77
Social and Cultural Anthropology	61	62	61	62	63	63	62	62

TABLE 1A *(continued)*

PERCENTAGE OF WOMEN IN THE TOTAL UNDERGRADUATE ENROLLMENT

	2015-2016	*2016-2017*	*2017-2018*	*2018-2019*	*2019-2020*	*2020-2021*	*2021-2022*	*2022-2023*
Criminology	59	60	60	60	61	61	60	60
Cultural Studies and Management	68	68	67	68	68	69	69	71
Geography	25	27	25	26	27	28	28	25
Gender Equality	90	87	87	80	95	95	95	96
Sociology	53	53	54	55	57	59	59	60
Other Social and Legal Sciences	48	43	47	42	50	52	51	52
Communication	57	58	60	61	61	62	62	63
Journalism	62	61	61	60	59	57	56	55
Information and Documentation	67	66	65	65	65	63	61	61
Financial and Actuarial	49	47	39	40	38	33	31	32
Finance and Accounting	50	50	49	48	48	47	46	46
Administration and Business	47	46	46	46	46	46	46	46
Labor Relations and Human Resources	62	62	62	62	63	64	64	65
Management and Public Administration	53	53	53	53	55	55	56	55
Marketing	51	52	52	52	53	53	53	55
Protocol and Events	88	89	89	88	86	86	87	88
Advertising and Public Relations	70	71	72	73	74	75	76	77
Trade	50	50	49	48	48	48	48	47
Law	55	56	56	57	57	58	59	60
Biology	62	62	62	62	62	62	63	63
Biochemistry	65	65	65	66	66	68	69	70
Biotechnology	60	60	61	61	61	62	62	63
Biomedicine	77	76	75	75	76	76	77	79
Environmental Sciences	47	48	48	48	49	49	49	50
Chemistry	53	53	53	54	54	54	54	55
Marine Sciences	55	58	56	57	58	56	57	58
Geography and Land Use Planning	28	29	29	28	27	27	26	27
Geology	41	41	41	40	40	41	40	39
Physics	26	25	26	27	27	27	28	28
Other Sciences	59	63	64	62	61	65	61	60
Mathematics	38	38	38	37	36	35	36	36
Statistics	43	43	45	45	46	46	46	45
Software and Application Development	11	11	12	12	12	13	14	14
Video Game Development	12	12	12	13	13	14	17	19
Multimedia Engineering	20	20	21	20	20	21	22	26
Computing	12	12	12	12	13	13	14	14
Industrial Chemical Engineering	47	46	46	47	47	47	47	47
Environmental Engineering	51	51	49	48	47	49	49	48

TABLE 1A *(continued)*

PERCENTAGE OF WOMEN IN THE TOTAL UNDERGRADUATE ENROLLMENT

	2015-2016	*2016-2017*	*2017-2018*	*2018-2019*	*2019-2020*	*2020-2021*	*2021-2022*	*2022-2023*
Power Engineering	29	28	28	27	27	26	26	26
Electrical Engineering	13	14	14	14	15	15	15	15
Computer Engineering	10	10	11	10	11	11	12	12
Sound and Image Engineering	25	25	27	26	28	29	30	30
Telecommunication Engineering	21	20	21	21	21	22	22	22
Industrial and Automatic Electronics Engineering	14	14	15	15	16	16	16	16
Electronics Engineering	16	17	17	17	17	17	18	19
Industrial Design and Product Development Engineering	47	47	47	47	48	49	50	51
Industrial Technology Engineering	23	23	24	24	24	25	26	26
Mechanical Engineering	13	13	13	13	14	14	14	14
Aerospace Engineering	23	23	24	24	25	25	26	26
Automotive Engineering	8	7	6	6	5	4	5	5
Naval and Oceanic Engineering	19	19	20	20	20	21	21	22
Industrial Organization Engineering	25	26	27	27	28	30	29	30
Nanotechnology	37	40	40	41	41	41	38	38
Other Engineering	14	13	14	14	15	17	17	20
Food Science and Technology	69	68	68	67	67	67	66	66
Oenology	50	50	51	51	51	50	49	47
Food Engineering	61	64	62	63	63	63	66	66
Materials Engineering	24	25	25	29	33	36	38	37
Textile Engineering	52	50	63	73	70	63	65	64
Mining and Energy Engineering	26	26	27	27	24	24	24	24
Architecture	49	49	50	50	52	53	55	57
Geomatics Engineering, Surveying and Mapping	31	31	29	28	28	26	29	26
Urban Planning and Landscaping	57	52	62	40	43	41	40	39
Technical Architecture	38	38	38	39	39	40	42	44
Civil Engineering	29	29	29	28	28	29	29	30
Agricultural and Agri-Food Engineering	36	36	34	33	33	33	33	33
Agricultural, Livestock and Rural Engineering	33	32	31	31	30	32	31	31
Horticultural and Landscape Engineering	31	39	26	27	16	21	23	23
Forestry and Forestry Engineering	26	27	25	25	26	26	28	27
Veterinary Science	72	73	74	75	76	77	77	78
Dentistry	59	60	61	62	63	63	65	66
Medicine	66	66	67	68	69	69	70	71

TABLE 1A *(continued)*

PERCENTAGE OF WOMEN IN THE TOTAL UNDERGRADUATE ENROLLMENT

	2015-2016	*2016-2017*	*2017-2018*	*2018-2019*	*2019-2020*	*2020-2021*	*2021-2022*	*2022-2023*
Nursing	80	80	81	81	81	82	82	82
Biomedical and Health Engineering	59	59	59	61	62	63	63	64
Optics and Optometry	72	73	73	74	74	74	76	76
Physiotherapy	49	48	48	48	47	47	48	48
Speech Therapy	90	91	91	91	91	91	90	91
Human Nutrition and Dietetics	74	73	73	73	72	73	73	72
Podiatry	67	67	65	67	68	71	73	74
Occupational Therapy	83	83	84	85	85	85	86	85
Pharmacy	70	70	70	71	71	71	72	72
Other Health Sciences	54	57	54	50	53	53	53	51
Social Work	82	82	82	82	83	83	84	84
Gastronomy and Culinary Arts	43	43	45	43	45	46	47	48
Hotel Management	65	65	66	68	63	63	66	64
Physical Activity and Sport	18	18	18	19	20	20	21	22
Sports Management	13	11	9	6	7	8	8	9
Tourism	67	67	67	67	67	67	67	66
Prevention and Occupational Safety	24	21	19	17	19	18	21	20
Military Education	10	12	13	15	21	27	29	28
Protection Of Property and Persons	18	19	23	26	27	29	28	26
Nautical and Maritime Transport	19	20	21	20	21	22	22	23
Ground Transportation Service	27	28	28	27	25	25	26	28
Air Transportation Services	33	30	29	27	29	31	31	34

Note: Fields of study without students enrolled in any of the courses are not included.

Source: Integrated University Information System (SIIU). General Secretariat of Universities.

TABLE 2A

ROUTINE TASK INTENSITY INDEX AND INDEX OF EXPOSURE TO TECHNOLOGIES. DEGREES

		Routine Task Intensity	*AI (Webb)*	*Software (Webb)*
11101	Pedagogy	-0.47	0.31	0.30
11201	Early Childhood Education	-0.46	0.28	0.29
11301	Primary Education	-0.56	0.29	0.28
11401	Other Teachers	-0.37	0.31	0.32
11901	Social Education	-0.42	0.34	0,32
21101	Audiovisual, Image and Multimedia	-0.40	0.41	0.41
21201	Design	-0.36	0.47	0.42
21301	Fine Arts	-0.23	0.43	0.43
21302	Art History	-0.16	0.33	0.36
21401	Conservation and Restoration	-0.44	0.37	0.36
21502	Music and Performing Arts	-0.55	0.31	0.30
22201	Archaeology	-0.29	0.32	0.32
22202	History	-0.27	0.34	0.35
22301	Philosophy	-0.37	0.33	0.35
22901	Humanities	-0.24	0.33	0.34
23101	English Language	-0.45	0.29	0.29
23102	Classical Languages	-0.40	0.32	0.32
23103	Other Foreign Languages	-0.42	0.32	0.32
23104	Translation and Interpreting	-0.49	0.34	0.32
23201	Spanish Languages and Dialects	-0.53	0.29	0.28
23202	Literature	-0.50	0.31	0.29
23901	Modern and Applied Languages	-0.26	0.32	0.33
31101	Economy	-0.29	0.36	0.36
31201	Public Policy and Management	-0.35	0.37	0.35
31202	International Relations	-0.43	0.41	0.39
31301	Psychology	-0.45	0.36	0.33
31401	Social and Cultural Anthropology and Culture Studies and Management	-0.50	0.35	0.33
31402	Criminology	-0.24	0.39	0.36
31404	Geography	-0.21	0.40	0.40
31406	Sociology and Gender Equality	-0.36	0.37	0.37
32101	Communication	-0.40	0.44	0.44
32102	Journalism	-0.42	0.38	0.36
32201	Information and Documentation	-0.26	0.38	0.39
41201	Financial and Actuarial	-0.42	0.42	0.37
41202	Finance and Accounting	-0.14	0.32	0.36
41301	Administration and Business	-0.28	0.36	0.36
41302	Labor Sciences	-0.23	0.35	0.35
41303	Management and Public Administration	-0.10	0.31	0.33

TABLE 2A *(continued)*

ROUTINE TASK INTENSITY INDEX AND INDEX OF EXPOSURE TO TECHNOLOGIES. DEGREES

		Routine Task Intensity	*AI (Webb)*	*Software (Webb)*
41401	Marketing	-0.38	0.41	0.38
41402	Protocol and Events	-0.31	0.33	0.29
41403	Advertising and Public Relations	-0.41	0.40	0.36
41601	Trade	-0.30	0.35	0.33
42101	Law	-0.44	0.37	0.33
51101	Biology	-0.34	0.45	0.42
51201	Biochemistry	-0.49	0.47	0.40
51202	Biotechnology	-0.54	0.47	0.41
51901	Biomedicine	-0.50	0.46	0.40
52101	Environmental Sciences	-0.30	0.43	0.42
53101	Chemistry	-0.42	0.48	0.44
53201	Marine Sciences	-0.26	0.47	0.45
53202	Geography and Land Management	-0.29	0.38	0.39
53203	Geology	-0.36	0.49	0.44
53301	Physics	-0.62	0.49	0.42
54101	Mathematics	-0.64	0.41	0.40
54201	Statistics	-0.52	0.47	0.47
61301	Software and Application Development and Multimedia Engineering	-0.70	0.52	0.53
61901	Computing	-0.73	0.53	0.54
71101	Industrial Chemical Engineering and Environmental Engineering	-0.42	0.54	0.46
71301	Power Engineering	-0.56	0.56	0.48
71302	Electrical Engineering	-0.50	0.55	0.46
71401	Computer Engineering	-0.79	0.54	0.54
71402	Sound and Image Engineering	-0.58	0.51	0.52
71403	Telecommunication Engineering	-0.62	0.54	0.50
71404	Industrial and Automatic Electronics Engineering	-0.54	0.55	0.47
71405	Electronics Engineering	-0.57	0.53	0.52
71501	Industrial Design and Product Development Engineering	-0.46	0.51	0.44
71502	Industrial Technology Engineering	-0.59	0.57	0.46
71503	Mechanical Engineering	-0.48	0.56	0.47
71601	Aerospace Engineering	-0.64	0.60	0.47
71603	Naval and Oceanic Engineering	-0.38	0.56	0.50
71901	Industrial Organization Engineering and Nanotechnology	-0.49	0.51	0.44

TABLE 2A *(continued)*

ROUTINE TASK INTENSITY INDEX AND INDEX OF EXPOSURE TO TECHNOLOGIES. DEGREES

		Routine Task Intensity	*AI (Webb)*	*Software (Webb)*
72101	Food Science and Technology and Food Engineering	-0.36	0.49	0.48
72102	Oenology	-0.44	0.52	0.43
72201	Materials Engineering and Textile Engineering	-0.61	0.51	0.42
72401	Mining and Energy Engineering	-0.44	0.52	0.47
73101	Architecture and Urban Planning and Landscaping	-0.58	0.59	0.45
73102	Geomatics Engineering, Surveying and Mapping	-0.45	0.53	0.46
73201	Technical Architecture	-0.41	0.50	0.43
73202	Civil Engineering	-0.48	0.54	0.46
81102	Agricultural and Agri-Food Engineering	-0.36	0.49	0.45
81103	Agricultural, Livestock and Rural Engineering	-0.36	0.47	0.43
81201	Horticultural and Landscape Engineering	-0.19	0.46	0.45
82101	Forestry and Forestry Engineering	-0.35	0.47	0.42
84101	Veterinary Science	-0.36	0.40	0.42
91101	Dentistry	-0.41	0.41	0.43
91201	Medicine	-0.41	0.41	0.42
91301	Nursing	-0.39	0.41	0.42
91401	Biomedical and Health Engineering	-0.57	0.52	0.43
91402	Optics and Optometry	-0.37	0.42	0.42
91501	Physiotherapy	-0.38	0.40	0.42
91502	Speech Therapy	-0.33	0.38	0.41
91503	Human Nutrition and Dietetics	-0.24	0.38	0.41
91504	Podiatry	-0.38	0.41	0.43
91505	Occupational Therapy	-0.30	0.38	0.39
91601	Pharmacy	-0.38	0.42	0.42
92301	Social Work	-0.36	0.35	0.34
101401	Physical Activity and Sport	-0.29	0.35	0.36
101501	Tourism	-0.09	0.33	0.36
104101	Nautical and Maritime Transport	-0.18	0.48	0.51
104103	Ground Transportation Services and Air Transportation Services	-0.32	0.46	0.45
109999	Services (Other Studies)	-0.28	0.42	0.39

Sources: Schotte *et al.* (2023) and Albanesi *et al.* (2023).

TABLE 3A

INDEX OF UNMET DEMAND. DEGREES

Career	*Excess Demand Ratio*
Biotechnology	3.41
Industrial Design and Product Development Engineering	3.19
Design	3.13
Medicine	2.68
Biochemistry	2.19
Veterinary Science	2.04
Industrial Organization Engineering and Nanotechnology	1.83
Criminology	1.66
Dentistry	1.50
Advertising and Public Relations	1.48
Physical Activity and Sports	1.45
Biomedical and Health Engineering	1.44
Aerospace Engineering	1.34
Physics	1.34
Architecture and Urban Planning and Landscaping	1.24
Mathematics	1.21
Protocol and Events	1.18
Translation and Interpreting	1.17
Industrial Technology Engineering	1.13
Psychology	1.12
Conservation and Restoration	1.09
Communication	1.06
Computing	1.04
Social Education	1.03
International Relations	1.01
Nursing	0.98
Mechanical Engineering	0.96
Administration and Business	0.92
Fine Arts	0.91
Marketing	0.91
Literature	0.88
Physiotherapy	0.83
Classical Languages	0.81
Primary Education	0.81
Archaeology	0.79
Spanish Languages and Dialects	0.76
Power Engineering	0.75
Law	0.74
Philosophy	0.73

TABLE 3A *(continued)*

INDEX OF UNMET DEMAND. DEGREES

Career	*Excess Demand Ratio*
Pharmacy	0.72
Biology	0.70
Finance and Accounting	0.69
English Language	0.68
Journalism	0.68
Human Nutrition and Dietetics	0.67
Industrial Chemical Engineering and Environmental Engineering	0.67
History	0.66
Art History	0.63
Social Work	0.63
Geography and Land Use Planning	0.57
Industrial and Automatic Electronics Engineering	0.56
Early Childhood Education	0.55
Sound and Image Engineering	0.55
Humanities	0.54
Economy	0.50
Electrical Engineering	0.50
Pedagogy	0.50
Trade	0.50
Telecommunication Engineering	0.50
Chemistry	0.50
Agricultural, Livestock and Rural Engineering	0.49
Labor Sciences	0.48
Policy and Public Management	0.47
Social and Cultural Anthropology and Cultural Studies and Management	0.46
Occupational Therapy	0.40
Financial and Actuarial	0.40
Naval and Oceanic Engineering	0.38
Materials Engineering and Textile Engineering	0.36
Forestry and Forestry Engineering	0.35
Geology	0.35
Tourism	0.33
Information and Documentation	0.32
Computer Engineering	0.30
Optics and Optometry	0.30
Sociology and Gender Equality	0.28
Management and Public Administration	0.28
Environmental Sciences	0.27
Geomatics Engineering, Surveying and Mapping	0.27

TABLE 3A *(continued)*

INDEX OF UNMET DEMAND. DEGREES

Career	*Excess Demand Ratio*
Civil Engineering	0.25
Food Science and Technology and Food Engineering	0.23
Podiatry	0.20
Speech Therapy	0.17
Technical Architecture	0.09

Note: The index is calculated as the ratio between the number of people admitted to a given degree program and the number of people who have made it their first choice in the ranking. It does not include double degrees or degrees from affiliated centers.

Source: Created by the authors with admission microdata from the universities of the Community of Madrid joint district.