Do old and new labour market risks overlap?
Automation, offshorability, and non-standard employment

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Abstract:

This article analyses whether automation and offshorability risks overlap with non-standard employment. The research uses data from Spain, as this is a country with one of the highest temporary employment rates across the world since the 1990s. In general, the analysis shows that automation risks affect more to those with non-standard work arrangements. However, higher educational level is crucial to be much less exposed to automation risks, irrespective of the type of contract or the working time. Conversely, the offshorability risk does not overlap with non-standard employment, and has the opposite relationship with the educational level. The results suggest that specific training policies attending to those with lower educational levels in non-standard employment would be advisable to protect these workers against automation risks.

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1. Introduction

There is a wide social worry about the employment impacts of the current technological change. Probably, the most prominent concern is about the risk of automation of a huge amount of jobs. There are different available estimations about the future employment destruction related to automation. The highest estimation corresponds to Frey and Osborne (2017), who present calculations that almost half of all jobs in the United States (US) have a high risk of being replaced and lost by automation. Other authors decrease these numbers until 14 per cent in the European Union (Pouliakas, 2018) or the OECD (Nedelkoska and Quintini, 2018) or even 9 per cent for the OECD (Arntz et al, 2016).

Offshorability is another risk closely related to automation risks. Usually, the approach to the displacement of some activities or occupations to other countries is understood as exclusively related to globalisation. Although some firms move offshore as a whole, technological change allows fissuring the workplace and even an occupation in their different tasks (Weil, 2014). However, as Blinder and Krueger (2013) remark not only are offshorable jobs divisible in simple and routinizable tasks, but also a wide variety of complex tasks involving high levels of skill and human judgement thanks to the new information and communication technologies. In fact, for the case of the US, Blinder and Krueger (2013) estimate that around 25 per cent of US jobs are offshorable.

Recently, there is an increasing interest in the relationship between offshoring and the occupational tasks characteristics (Püschel, 2015), but with disparate results. Goos et al. (2009) analyse different types of tasks and offshorability, although their measure of offshorability – consisting of news reports – is not related to labour demand outcomes. Becker et al. (2013) use micro-data from German firms to analyse the relationship of offshoring on the composition of labour demand, and they find a small effect of offshore firm activity on tasks composition at the firm level, increasing the share of non-routine and interactive tasks in the wage-bill of firms. On the other hand, Baumgarten et al (2013) find that offshoring has a substantial negative effect on wages, and this negative effect differs by task type. In fact, a higher degree of interactivity and, especially, non-routine tasks protect workers against the negative wage impact of offshoring, which is not strictly coincident with the results obtained by Becker et al (2013). Anyway, Becker et al (2013) and Baumgarten et al (2013) do not use any measure of offshorability risk (as Blinder and Krueger, 2013) but a realized offshoring of part of the firms' activities.

Both risks – automation and offshorability – have potential to eliminate and deeply transform many jobs in the next future across the world. However, we do not know exactly if these 'new' labour market risks will affect to the same workers suffering the 'old' risk of precariousness linked to non-standard employment relationships.

Why is this important? The standard employment relationship remains as the core of Western labour markets, mainly because of its implicit function for co-ordination and risk allocation in labour markets (Adam and Deakin, 2014). Nevertheless, since the 1970s different non-standard work arrangements have expanded in developed countries, with significant differences across countries and time. The increase of the numbers of workers in non-standard work has reinforced labour market segmentation, leading in some countries to greater employment volatility and negative consequences on economic stability (ILO, 2016; Toharia, 2005). Some authors as Standing (2011) even consider that there is a distinctive group of workers – the 'precariat' – detached from the core of the labour market suffering lower wages and worse working conditions in a permanent way. The specific form of non-standard employment depends on national differences in institutions and the evolution of national Labour Law. Anyway, a widely accepted manner to define non-standard employment as employment arrangements deviating from the standard employment relationship in four ways (ILO, 2016): temporary employment (i.e. not open-ended); part-time or, in general, normal working hours below the full-time standard in the country or the industry, including on-call work; temporary agency work or any other form of multi-party employment relationship; bogus or dependent self-employment.

The most visible relationship between non-standard employment and the current technological change has become from digital platforms. A lot of recent attention from the media and social researchers, especially lawyers, has focused on the rise of the use of dependent self-employment in the gig economy (ILO, 2008; Eurofound, 2018). The operation of some digital platforms allowing an easy and cheap outsourcing of small tasks has created a new 'mixed' terrain between salaried and self-employed workers. However, even the gig economy based on the local economy heavily rests on the legal figure of independent contractors or self-employment, while these workers do not have control over their working conditions nor their payment or working schedule. The expansion of this type of dependent self-employment is, many times, an increase in precariousness, because of their lower protection levels as these workers assume business risks related to the business cycle and they do not enjoy the common protection of workers' rights. Nevertheless, these workers are a small fraction of total employment. For example, Katz and Krueger (2016) estimate that these workers are around 0.5 per cent of total employment in the US, and Groen and Maselli (2016) estimate that for the European Union they are around 0.05 per cent.[1] At least nowadays, this is not the main link between 'old' risks as non-standard employment and 'new' risks related to technological change and offshoring.

There is a literature on the effects of automation and offshorability, focusing on aggregates outcomes as polarisation of wages (Autor et al 2006, 2008) or productivity or the labour share (Autor and Salomons, 2018), and a nascent branch about the impacts on individual unemployment spells and post-unemployment effects on job quality (Schmidpeter and Winter-Ebmer, 2018).

However, up to our knowledge, there is no systematic empirical evidence jointly analysing the 'new' risks related to technological change and offshoring and the 'old' risk of non-standard employment. The two most prominent estimations of automation risks (Frey and Osborne, 2017, and Arntz et al., 2016) do not even include variables related to contract type in their analyses. Nedelkoska and Quintini (2018) compare the median risk of automation by contract type, showing that the lowest risk corresponds to open-ended contracts (0.46), although for fixed-term contracts the risk is almost the same (0.47). Temporary agency contracts and training contracts have the highest risk of automation by contract type (0.56). In Pouliakas (2018), the descriptive information shows that 15.5

[1] The most recent estimation of electronically mediated work published by the US Bureau of Labor Statistics is 1.0 per cent of total employment in May 2017, using a new and specific questionnaire on contingent work. See Current Population Survey staff (2018).

per cent of workers with fixed-term or temporary agency contracts face a high risk of automation (above 0.7), while those with open-ended contracts facing the same level of risk are 13.5 per cent. On the other hand, there is evidence of actual offshoring on wages by contract type. Görg and Görlich (2015) find that offshoring core activities in manufacturing industries reduces wages of temporary workers, and Lee and Lee (2015) find that offshoring has different impacts on wages of temporary workers, a small positive one when offshoring to OECD countries and a negative one in case of non-OECD countries. However, we have not found evidence about the offshorability risk by contract type. Therefore, our article may provide interesting information to understand whether there is an overlap of both risks (i.e. a higher automation risk for non-standard employment), as the limited available information points to. In addition, we will provide novel information whether there is an overlap of the offshorability risk and non-standard employment, or not.

Our analysis will increase the knowledge of the performance of labour markets with new results showing a rich and complex relationship between new and old risks. However, our analysis is also interesting from a social and economic policy perspective. In fact, developing an effective social protection for non-standard employment to alleviate workers' insecurities and precariousness remains as a challenge in many countries (ILO, 2016; chapter 6). If workers with non-standard work arrangements are also affected by a systematic high risk of automation and offshorability, the challenges for social protection will be very different respect to a balanced distribution of the new risks by contract type.

In this article, the empirical analysis uses data from Spain. The Spanish case is interesting because this country has had a very high temporary employment rate since the mid-1980s (Toharia and Malo, 2000; Toharia, 2005). In fact, labour market segmentation by contract type has been a prominent feature of the Spanish labour market. The temporary employment rate was above 30 per cent in the second part of the 1990s and the first part of the 2000s, almost reaching 35 per cent in 2006. Only with the great recession, this rate decreased to around 25 per cent because of a huge employment adjustment based on these workers (García-Serrano and Malo, 2013). Temporary contracts are used across all industries and sectors, with different micro and macro negative side effects, from precariousness to low training and productivity, putting the quality of jobs at the center of the labour market policy debate (ILO, 2014). Recently, there was also an increase in the use of part-time contracts (López-Mourelo and Malo, 2015) and the self-employment rate has reached 16.5 per cent, which is above de average 15 per cent for the Euro area (OECD, 2018).

Therefore, in Spain the expansion of non-standard employment developed before the current widespread of new technologies and a distinction of 'old' risks (associated to non-standard employment) and 'new' risks (linked to the expected impact of automation and offshorability) makes sense. The main database is the Labour Force Survey (LFS), from 2011 to 2017, which follows the Eurostat methodology and the international ILO definitions for all concepts related to employment, unemployment and inactivity. We will use a definition of non-standard employment based on the information provided by the LFS, mainly temporary and part-time, although we will also present an analysis for self-employment. For the automation and offshorability risks we use different sources. Following the international literature, we use two different definitions: one based on occupations (Frey and Osborne, 2017) and other based on tasks (Torrejón, 2018). The first one is an adaptation from the US case, while the second one has been obtained from Spanish data sources including information on tasks. We use both definitions because Frey and Osborne (2017) provide higher estimates for how many workers are under a high risk of automation (conventionally, a risk above 0.7), while task-based approaches provide much lower estimate of workers affected by a high risk of automation. For the offshorability risk, we use one of the indicators provided by Blinder and Krueger (2013), which is based on experts' opinions and according to the authors is more reliable than other two indicators they define using subjective information from interviewees.

The remainder of the article is as follows. In the next section, we describe the data with some detail. In the third section, we present the empirical analysis of the distribution of the different risks of automation and offshorability by the different categories on non-standard employment.

2. Data

The data used in this article consist of an adaptation of automation risk indicators estimated by Frey and Osborne (2017) and Torrejón (2017), and the offshorability risk indicator provided by Blind and Krueger (2013) to the micro-data of the Spanish LFS from 2011-2017. We will explain the basic characteristics of all these indicators and how we have combined this information with the LFS.

2.1 Automation risks: occupational and task approaches.

The seminal work on automation risk and its impact on employment is Frey and Osborne (2017)[2]. They apply an occupations-based approach. Thanks to interviews with experts, they identified the current engineering bottlenecks that machine learning and mobile robotics developers face. This was the basic information to define the automation or automation risk of a core group of 70 occupations. The objective was distinguishing what occupations were composed by all tasks potentially automatable and what occupations were composed by tasks not fully automatable. For the description of occupation, Frey and Osborne (2017) used the O*NET (the US occupational classification). Thanks to the basic information for the core 70 occupations analysed by the expert, Frey and Osborne (2017) predict the probability of automation for all 702 occupations available in the O*NET[3], and analyse the expected impacts of automation on the US labour market.

The main result from Frey and Osborne (2017) was that 47 per cent of all US employees were exposed to a high risk of automation, where 'high' was defined as a risk from 0.7 to 1. Another distinctive feature of their prediction was the U-shaped distribution of employment by automation risk: most of workers were at the tails of the automation risk (33 per cent below an automation risk of 0.3 and 17 per cent above a risk of 0.7), while

[2] The working paper version of their article was released in 2013. In fact, a huge part of the literature following or discussing their methodology is previous to the published version of 2017. All key aspects discussed here are the same in both versions.

[3] Their estimation uses a Gaussian process classifier. See Frey and Osborne (2107) for the technical details.

relatively few workers were exposed to a medium level risk (19 per cent of employment between 0.3 and 0.7 probability of automation). [4]

We have used the estimated probabilities by Frey and Osborne (2017) for our first indicator of automation risk. We have imputed the corresponding automation risk estimated by Frey and Osborne (2017) to the 3-digit occupational classification of the Spanish LFS[5]. To transform their original estimations based on the US occupational classification we have used the official crosswalks to the International Standard Classification of Occupations for 2011 (ISCO-2011).[6]

Soon, other authors developed a task-based approach in order to check the prediction that almost half of total employment was affected by an automation of 0.7 or above. Arntz et al. (2016, 2017), Nedelkoska and Quintini (2018) and Pouliakas (2018) are examples of this approach at international level. All of them provide much lower estimates of employment affected by a high risk of automation (from 12 to 14 per cent), and the distribution of employment by automation risk is not U-shaped but rather an inverted U with relatively few people at the extremes of the risk distribution.

The task approach rests on the availability of a survey with detailed information on tasks, and the total risk correspond to the individual and it is the average of the automation risk attributed to each task. The main component of the automation risk is an indicator of tasks routinisation. The attribution of a specific automation risk to an occupation depends on individualised information. This is the reason we have used a second indicator of automation risk based on the tasks indicators proposed in the European Jobs Monitor (Fernández-Macías et al., 2016) and operationalised for the Spanish case by Torrejón (2018). In short, his methodology uses the three main tasks' indicators defined and standardised by the European Jobs Monitor (routinisation, social interactivity, and creativity). The automation risk is the weighted sum of the above three tasks' indicators, where the weights are estimated through a principal components analysis (Torrejón, 2018). The estimation of this automation risk indicator is at 2-digit ISCO level, therefore we will have less variation than for the automation risk based on occupations.

2.2 Offshorability risk

The offshorability risk is obtained from Blind and Krueger (2013). These authors estimate three different indicators for this risk using a specific survey with detailed information about this topic. Two of the indictors are based on subjective information and a the third one on an expert opinion about what jobs are more offshorable. The analysis of Blind and Krueger (2013) concludes that the last indicator based on experts' opinions is more reliable than the others and this is the reason we use it in our research.

[4] See Figure 3 from Frey and Osborne (2017; page 267)
[5] The 3-digit level is the maximum in the LFS micro-data files available for researchers.
[6] This is the reason our analysis begins in 2011. We tried to make a link with the previous version of the ISCO, but the data showed a clear break.

We have obtained the offshorability risk from the original micro-data of the survey[7] for the US Standard Occupational Classification (SOC-2000 at 6-digit level) and we have used the official crosswalk to the ISCO to obtain the offshorability risk for our occupational classification at 3-digit level. The original questionnaire offered 5 options for the coders going from not offshorable to offshorable with minor or no difficulty.[8] For the US case 67.5 per cent corresponded to not offshorable occupations. Because of this huge concentration of cases we have defined two categories: 0, not offshorable, and 1, offshorable. This second group merges all the possibilities from high to minor difficulty for offshoring. As we transform the original information based on a 6-digit classification into another with 3-digit, we have some 3-digit occupations merging more 2 or more 6-digit occupational categories. In these cases, we have allocated the average. The result is a variable ranging from 0 to 1, that we can interpret as the offshorability risk. However, we have many cases with 0 risk of offshorability, 64.9 per cent, which is close to the 67.5 per cent obtained for the US original survey.[9]

2.3 Non-standard employment definitions

Finally, in the LFS we have used the closest operational definition to the main four categories of non-standard employment established by the ILO (2016): temporary employment; part-time employment; contractual arrangements involving multiple parties (typically, agency workers); and disguised employment (mainly dependent self-employment). The use of these four categories presents the following peculiarities in our data:

- Our group of workers with temporary contracts will include temporary agency workers. In Spain, the most part of temporary contracts are direct hires by the firms and the proportion of agency workers is relatively low in terms of the stock of employment (Amuedo-Dorantes et al 2008).

- Part-time contracts refer to workers with a working day below the normal in their industry or firm. Therefore, in the Spanish LFS, part-time does not refer to a specific threshold in terms of working hours, but to the normal in the immediate context of the worker. For example, we can have a full-time worker with 35 working hours per week because this is the normal in the company agreement, but in a different industry we can have a worker with the same working hours, but she will be a part-timer if the normal in the company agreement is 40 hours.

- In our data, we do not have variables to distinguish dependent self-employment from proper self-employment. We will use data on self-employed workers who do not hire other employees. Therefore, this is a poor proxy for non-standard employment, but we

[7] The micro-data of this survey are freely available at the A. Krueger's web page: https://krueger.princeton.edu/pages/princeton-data-improvement-initiative-pdii

[8] The detail is: 1, not offshorable; 2, offshorable with considerable difficulty; 3, mixed or neutral; 4, offshorable with some difficulty; 5, offshorable with minor or no difficulty. In the original survey, only in 0.56 per cent of the sample (14 cases) the coders could not assign an offshorability risk to the occupation. (Blinder and Krueger, 2013).

[9] For the case of maximum risk of offshorability (equal to 1), we have 9.5 per cent, while the US survey had 9.8.

have included it for the sake of completeness. In the analyses, we will compare the results for self-employment with employers to understand if self-employed workers are more like employers or to the above groups of non-standard employment.

When possible, we will use a four categories disaggregation of wage employment. First, we consider standard employment those workers with full-time open-ended contracts. Second, those with part-time temporary contracts can be considered as 'fully' non-standard employment. Third, the other two categories correspond to a sort of 'partial' non-standard employment: full-time but temporary, and part-time but with an open-ended contract. Our hypothesis is that those in the 'intermediate' categories of non-standard employment may suffer less problems than 'fully' non-standard employment, and we will try to check it in the empirical analysis.

Unless otherwise stated, we will present in all tables the average for the period 2011-2017. In general, all the results remain along this period, which covers the end of the great recession and the beginning of an expansive period. However, we have detected a slight general pattern towards a slow increase in the proportion of workers affected by a high risk of automation, either under standard or non-standard work arrangements[10].

3. Do overlap non-standard employment with 'new' risks?

3.1 Automation risks

Total employment

Figure 1 shows the mean of the automation risk (according to Frey and Osborne (2017) transferred into the Spanish LFS) by employment status. For wage and salary workers, the mean risk is higher for temporary (almost 0.7) than for permanent workers (0.6); however, the confidence intervals are mostly overlapped. Therefore, on average there is not a significant difference between both groups, although probably the differences in the box hide markedly differences by subgroups. For self-employed workers, we have a lower mean risk (below 0.6), and much lower (almost 0.2) for employers. Now the confidence intervals are wider than before, going from slightly below 0.2 to around 0.7. The automation risk based on tasks following Torrejón (2018) shows a broad similar picture for the mean risk, but with much lower differences among all groups of employment and with a narrow rank for this risk, going from above 0.3 to slightly below 0.7. Although the confidence intervals are narrower than for Figure 1, all of them are overlapped. As we explained in the introduction section, other authors also obtained no or small differences in automation risk by contract type (Nedelkoska and Quintini, 2018; Pouliakas, 2018)

However, no differences at the mean may hide significant differences in the distribution of employment by risk level for each subgroup of workers. To analyse this distribution, we will define some thresholds for the different risks. For the automation risk based on occupations (Frey and Osborne, 2017), we will use the conventional thresholds of this literature: 0.3 as the limit between low and medium risk and 0.7 as the frontier between medium and high risk. However, as we show in Table 1, using these thresholds 40.9 per

[10] Tables by year are not included for lack of space, but they are available upon request.

cent of total employment is in the medium level. In order to have a more detailed analysis, we have divided the medium level in two groups: medium-low (until 0.5), where we have 12.9 per cent of total employment, and medium-high, where we have 28 per cent. The share of employment under high risk of automation is 33.9 per cent, which is much lower than the figure estimated by Frey and Osborne (2017) for the US (47 per cent). In addition, considering the four levels of risks we have a U-shape pattern as in the original estimation for the US. Nevertheless, in Spain the peaks are not for the lowest and highest levels of risks. The high risk has the peak of employment (33.9 per cent), but not the low risk has 25.3 per cent, which is below – although not far – the second peak in medium-high risk (28 per cent).

In the case of the task-based automation risk following Torrejón (2018), we have all observations between 0.3 and 0.7 (see Figure 4). A typical result when using a task-based estimation of automation risk is a much lower share of employment for low and high risks. In fact, using a task-based approach the distribution of employment by automation risk is similar to a sort of plateau with a smooth peak slightly below 0.2 and a slow decline toward the right and a steeper slope from 0.7 onwards, as in Arntz et al. (2016, 2017) or Pouliakas (2018). Nedelkoska and Quintini (2018) find this pattern for different countries, although the OECD countries with a highest mean risk have a sort of 'pinnacle' around 0.6 (Lithuania) or 0.8 (Slovakia).

In the case of the automation risk estimated by Torrejón (2018), conventional thresholds would not be meaningful, as we do not have any case below 0.3 or above 0.7. Therefore, we have defined two thresholds: 0.49 and 0.57, to have a distribution of employment with around one third of total employment. By construction, we have a similar share of employment affected by a high risk of automation respect to occupation-based automation risk. Other authors using a task-based approach, as Arntz et al (2016, 2017)[11], calculated a share of 9 per cent of total employment affected by a risk of automation in OECD countries above 0.7, and 12 per cent for the case of Spain, while Nedelkoska and Quintini (2018) and Pouliakas (2018) estimate a share of 14 per cent – for the OECD and the EU, respectively. Therefore, our results are not directly comparable with other authors analysing the distribution of employment by automation risk using a task-based approach. However, as we focus on non-standard employment and they do not, we consider this is an affordable cost to have a meaningful analysis of non-standard employment and automation risk.

Automation risks and types on non-standard employment

Figure 3 shows the distribution of employment by the automation risk based on occupations distinguishing the different types of standard and non-standard employment. First, the shape of total employment is a sort of U, although less clear than in Frey and Osborne (2017). In our case, this shape is created by low employment between the levels of risks 0.2 and 0.5. In fact, we have the most part of total employment above 0.5. In general, the four groups of wage employment share this pattern, either standard or non-

[11] The risk indicator calculated by Arntz et al (2017) is based on tasks using the survey of adult skills of the PIAAC (Programme for the International Assessment of Adult Competencies), launched by the OECD.

standard, but the two 'intermediate' categories of non-standard employment have around 80 per cent of their employment above the threshold of 0.5. However, employers and self-employed are mostly concentrated in low levels of automation risk (around 0.2). Therefore, considering the occupation-based automation risk, non-standard employment tends to have more risk of automation than standard employment, but not self-employment.

For the task-based automation risk shown in Figure 4, we have a mountain-shape because of the concentration of all employment between 0.3 and 0.7 level risks, as we explained above. Nevertheless, employers and self-employed are mostly below 0.5, while the groups of wage non-standard employment tend to be above this figure and standard employment (full-time and open-ended) is almost fifty-fifty around this threshold. Therefore, in relative terms, the task-based automation risk presents a similar distribution of risks for non-standard employment, which tend to have more risk of automation than standard employment, and, again, self-employment tends to have lower risk of automation than any category of wage standard or non-standard employment.

Table 2 shows a summary of the above distribution using the conventional thresholds we define in section 2. Here, we have each type of 'new' risk for the different types on standard and non-standard employment. For the risks of automation based on occupations we have the well-known U-shaped pattern presented by Frey and Osborne (2017) for three groups: the lowest and highest levels of risk concentrate the most part of employment for the standard employment relationship, for the fully non-standard employment (temporary and part-time), and the intermediate group of full-time temporary contracts. However, the other intermediate group – part-time open-ended contracts – we have a sort of 'mountain' with a peak (41.9 per cent of employment) for medium-high risk of automation.

For the other definition of automation risk based on tasks, we have increasing patterns except for standard employment relationships – full-time open-ended contracts – which presents a decreasing trend. While for part-time workers the distribution is more or less balanced, for full-timers we have a clear concentration of employment in the extremes: 47.4 per cent in high risks for those with a temporary contract and 40.6 per cent in low risk for those with an open-ended contract (i.e. standard employment relationships). The rest of groups have shares of employment in high risk below 40 per cent, but they are not very dissimilar between the two indicators of automation risk. An important difference between both indicators of automation risk corresponds to those with open-ended contracts, who have shares of employment in low risk around the double for risk based on tasks (second panel of Table 2) than for risk based on occupations (first panel of Table 2).[12]

Type of contract

[12] As we explained above, the threshold of the low risk group in the automation risk based on Frey and Osborne (2017) is 0.3, while for the risk based on tasks (Torrejón 2018) is 0.49. However, as the minimum is 0.34, all workers with a low risk according to the risk based on tasks would be in the low-medium group of the risk based on occupations.

Table 3 shows that the proportion of jobs with a high automation risk based on occupations is higher for workers with temporary contracts than with open-ended contracts, especially for male temporary workers who reach 48.8 per cent under high risk while for the corresponding women we have 37.8 per cent.[13]

The bottom panel of the same table presents the distribution considering the educational level of workers. For the compulsory level of education, the larger group is those in occupations with a thigh risk of automation: 55.7 per cent for temporary contracts and 47 per cent for open-ended contracts. For the same educational level, the lowest percentages correspond to the low automation risk: 3.2 per cent for temporary contracts and 5.4 per cent for open-ended contracts. Therefore, precariousness and automation risks overlap for workers with primary education.

At the end of the same table, workers with the university level are mostly concentrated in low risk of automation: 55.6 per cent for temporary workers and 58.5 for permanent workers. However, the lowest percentages for this educational level correspond to medium-low risk of automation (8.1 and 10.2 per cent, respectively). Therefore, only for workers with a university degree there is a sort of U-shaped distribution by automation risk, irrespective of the contract type, and with a very important concentration in low automation risk. University education shields workers against occupation-based risk of automation irrespective of their contract type, although a bit more for those an open-ended contract.

For the rest of educational levels, we have a pattern closer to the primary level of education, but with lower differences between automation risk levels, and always with higher percentages for temporary contracts in the high automation risk columns.

To sum up, only a college degree creates a major difference about having a job with a low automation risk, mostly irrespective of the contract type. For this educational level, there is a poor association between the risks of non-standard work and automation of occupations. For the rest of educational levels, the automation risk is higher for workers with temporary contracts, especially for those with only mandatory education. For this last group both risks are clearly associated.

Table 6 presents how task-based automation risk mostly affects to male workers with temporary contracts (56.2 per cent vs. 37.1 for women) with almost the same share of employment for medium and low risk. Nevertheless, for men with open-ended contracts, there is a U-shaped distribution of automation risk. For women, there is a more or less balanced distribution of this risk in the case of temporary contracts, and a decreasing pattern as risk increases for open-ended contracts. Therefore, we appreciate a marked difference respect to the occupation-based automation risk by contract type. Now, the task-based automation risk is mostly overlapped to male non-standard employment, while it was not the case for automation risk from Frey and Osborne (2017).

In the bottom panel of Table 6, the task-based automation risk by educational level does not follow the results for the occupation-based automation risk. Now, we do not have any U-shaped pattern, with a large concentration in high risk for those with compulsory

[13] Considering the evolution across time (not shown here), this gap by contract type against males was rather small in 2011 (1.5 percentage point, pp) and increased until 7.7 pp in 2017.

education especially for temporary workers (68.3 per cent) and in low risk for those with college especially for those with open-ended contracts (76.3 per cent). Nevertheless, although the general shape of the employment distribution seems different for the two definitions of automation risk, we also have that those with only compulsory education are much more affected by a high risk of automation, while those with a college degree are mostly concentrated in a low risk. The percentages are always against those with a temporary contract are different respect to the case of the occupation-based automation risk shown in Table 3, but, again, a university degree 'protects' against automation risk, irrespective of the type of contract.

Working time

Table 4 shows a U-shaped pattern by the occupation-based automation risk for full-time and part-time workers, either men or women, except for female part-timers. Anyway, part-time male workers are clearly more concentrated in occupations with high and low risk of automation (42.2 per cent and 34.4 per cent, respectively), while for part-time female workers the intermediate levels of risk have important employment shares. This is an exception to the U pattern commented above.[14]

In the bottom panel of the same table, we add the educational level. Again, we have U pattern for the university level, irrespective of working time. Therefore, for the university level the broad picture is similar to temporary and permanent workers, although we have a bit higher concentration of temporary workers with a university degree with a low risk of automation (55.6 per cent; see Table 3) respect to part-timers with the same educational level (around 53 per cent). There is a similar difference in this educational level but in the opposite direction between full-timers (around 61 per cent in low risk) and open-ended contracts (around 58 per cent in low risk; see Table 3). However, in Table 4 we also have a U pattern for part-timers with upper secondary or advanced vocational training, while for temporary workers with the same educational levels (as shown in Table 3) we had an increasing pattern with a peak in high risk of automation, especially for those with upper secondary education.

Considering part-time work for the automation risk based on tasks (Table 7), we have a U pattern apart from female full-time workers, which is not coincident with the automation risk based on Frey and Osborne (2017) in Table 4. Another difference is that full-time workers have a very different distribution by gender, while men are mostly concentrated in high automation risk (above 40 per cent), for women the greatest percentages correspond to low risk of automation (also above 40). This suggests a marked difference in tasks by gender in full-time jobs, which was not captured by the occupation-based automation risk. For male and female part-timers, the automation risk based on

[14] In the quarterly LFS, there is also information if part-time was voluntary or involuntary by gender. While voluntary part-time has a U-shape pattern for both genders, for involuntary part-time only male workers have this pattern. Female involuntary part-timers have a peak in medium-high risk of automation. In fact, for this last group of workers, medium-high and high risk add up almost three quarters of all involuntary part-time female workers. These results are not included for the sake of brevity, but they are available upon request.

tasks has an almost balanced distribution by risk levels, but with slightly lower percentages for the medium risk.

By educational level (bottom panel of Table 7), we have a very similar picture to the case of temporary and open-ended contracts (Table 6): first, there is no any U-shape pattern; second, at the compulsory level there is a huge concentration in high risk (above 55 per cent, irrespective of the working time); and, third, a very important concentration in low risk for those with a university degree, around 77 per cent for full-timers and 67 for part-timers. In general, those with temporary contracts seem to be more exposed to a high risk of automation (based on tasks) than part-timers. On the other hand, full-timers are more concentrated on a low risk of automation than workers with an open-ended contract, but these differences are very small or disappear for upper-secondary, advanced vocational training, and university.

Self-employment

Self-employed workers are part of non-standard work when they cannot control different aspects of their work or when the self-employment status is a disguise for a salaried employment relationship where the firm "transfers" the business risks to the workers and preventing them to enjoy their rights as salaried workers. These problems affect to the gig economy, where self-employment is widely used, as we explained above (see Section 1). Unfortunately, our database does not include information to distinguish bogus or dependent self-employment, but only all those classified as self-employed workers.

Table 5 reports the results for self-employed workers (those who do not hire other workers and, therefore, they are not employers) and employers. This second group is only included as a reference to analyse whether self-employed workers are a sort of 'employers without employees'. In this case, they should be rather like employers in terms of their automation risk. However, Table 5 shows that they are quite dissimilar for both genders in terms of their occupation-based automation risk. Male self-employed workers do not have a U pattern, but two peaks in low and medium-high risk of automation, while females have but they are mostly concentrated in low risk (48 per cent). About employers, males follow a U pattern with a huge concentration in low risk (54 per cent), and females are similar but with even a higher concentration in low risk of automation (58.6 per cent). Noticing that the number of female self-employed is much lower than males, self-employed workers are, on average, more exposed than employers to the risk of automation, as medium-high and high risk join around half of them, while for employers the same levels of risk affect around 34 per cent.

The bottom panel of Table 5 shows that the share of employment of self-employed and employers with low risk quickly increases from 21.9 and 41.5 per cent respectively for those with compulsory education until 72.8 y 80.8 for the university level.

For the case of automation risk based on tasks, Table 8 shows that males have a U-shaped pattern while females have a decreasing one, either self-employed or employer. As in the case of automation risk based on occupations (Table 5), female self-employed workers are concentrated in low risk of automation, now with 61.5 per cent, much higher than in Table 5 (48 per cent). In a similar way, there are higher percentages under low risk for male self-employed workers, 40.6 per cent (instead of 30.8 per cent in Table 5). For employers, we also have a similar broad picture to Table 5, with a high concentration in low risk of automation, although percentages are now larger for both genders, again female employers have a higher share for those with low risk. Therefore, we confirm that self-employed workers are more exposed to automation risk than employers, as we saw when analysing the automation risk.

About the importance of the education level (bottom panel of Table 8), we find similar results than for the first definition of automation risk, although percentages are more extreme: the shares are higher under low risk and lower for high risk, with a bit better results for employers than for self-employed workers.

Regressions on automation risk indicators

Finally, we run lineal regressions on the two indicators of automation risk to have a whole approach on the association with the old risk related to non-standard employment. Table 12 shows that part-time temporary contracts have a bit larger risk than full-time open-ended contracts: an increase of 0.47 pp for the automation risk and 0.33 for the automation risk. However, the other two cases of non-standard employment have a larger risk of automation. Therefore, we confirm what the previous crosstabs showed: the two extreme categories, the standard employment relationship – full-time and permanent contracts – and the 'full' non-standard employment relationship – part-time and temporary contracts – have weaker associations with automation risks whatever the definition of this risk – based on occupations or tasks. It is also interesting to remark that having university education is associated with the lowest levels of automation or automation risk, in line with previous results.

Focusing on self-employment, this type of employment has always a lower risk of automation than standard employment relationship. Unfortunately, because of limitations of the data we do not know whether this is typical of all self-employed workers – including dependent self-employment – or not. Finally, employers have the lowest levels of risk also in the three cases.

3.2 Offshorability risk

As we explained in Section 2, the offshorability risk correspond to the expert-based indicator presented in Blinder and Krueger (2013). We define the group of low risk of offshorability as those occupations with risk exactly equal to zero, medium for occupations with risk between 0 and 1 (excluding both extremes) and high corresponds to risk exactly equal to 1. As shown in Table 1, the most part of employment (64.9 per cent) has no risk of offshorability and 'only' 9.5 per cent of total employment has a high offshorability risk. Around one fourth of employment has a middle risk of offshorability.

Usually, routine tasks are associated with a higher risk of offshorability (Püschel, 2015), but automation and offshorability risks are not necessarily overlapped (Blinder and Krueger, 2013). For example, considering the occupation of waiter, some tasks of this occupation are routine with a high risk of automation (for example, the payment, as in many airports). We can even imagine a waiter robot, but in the same way of a police officer or a nurse robot, in other words, there are many engineering bottlenecks to disentangle before having this type of full automation of the waiter occupation. However, it is very difficult to guess how to offshore the services provided by a waiter. This would be a typical where there is a positive risk of automation but the offshorability risk is zero.

To sum up, while automation risk based upon occupations (Frey and Osborne 2017) or tasks (Torrejón 2018) share relevant information, offshorability risk lead attention toward a different type of risk. Therefore, presumably non-standard employment will have a different association pattern with these two types of jobs' risks.

First, we explore the relationship with contract type. Table 9 shows that a bit more than 70 per cent of workers with temporary contracts have no risk of offshorability – either male or female – while the share of employment with no risk of offshorability decreases to 55.4 per cent for the case of male and to 65 per cent for female permanent workers. Therefore, offshorability risks and non-standard employment risks are not overlapped. In fact, the highest offshorability risk affects to around the double of workers with open-ended contracts respect to those with temporary contracts.

Considering the educational level in the bottom panel of the same table, the group of no risk of offshorability is very high for those with compulsory education, and more for temporary than for permanent contracts (around 85 and 76 per cent, respectively). In fact, the higher the educational level, the lower the percentages for this level of risk. For those with a university degree, the no risk of offshorability group concentrates around 47 per cent of all those with temporary contracts and around 40 per cent for open-ended contracts. Therefore, we find the opposite pattern we obtained for the automation risk in terms of risk and educational level.

Table 10 shows that part-time workers also have a higher representation in no risk of offshorability for men and women (75 and 79.8 per cent, respectively). In the same way, part-timers have much lower percentages for the highest risk of offshorability – around half for both genders. By educational level, the broad picture is like the case of contract type. Here, we also have higher percentages for no risk of offshorability for the non-standard work arrangement (part-timers) and lower for full-timers. Again, the offshorability risk and non-standard employment risk do not overlap and have the opposite association with educational level found in the case of automation risk.

We present the offshorability risk by employment status in Table 11. Unlike what it looked for automation risks, we have a very similar distribution of self-employed workers and employers by the level of offshorability risk, either men or women. No offshorability risk compounds more than 70 per cent of self-employed workers and the highest risk does around 6 per cent of male self-employed and a bit lower of females. For employers, the same risk levels are around 70 per cent (more for women) and 3 per cent, respectively. The distribution of the offshorability risk for self-employed workers is close to temporary or part-time workers with secondary educational levels, and relatively far from the lowest exposure to this risk of temporary and part-time workers with the compulsory level of education. In general, we have again a decrease of shares in no risk as the educational level increases, and this trend is more intense for self-employed than for employers.

Finally, we run a regression on the offshorability risk. The bottom panel of Table 12 presents the results for the offshorability risk. Here, part-timers – either temporary or permanent – have the lowest risk respect to standard employment relationship. Anyway, full-time temporary contracts also have a lower offshorability risk than the standard employment relationship. Therefore, here there is no overlapping between old and new risks, as the previous analysis also suggested. On the educational level, having a university degree is associated with the highest risk of offshorability, which is also coherent with the previous results shown in Table 9, Table 10, and Table 11.

4. Discussion and conclusions

In this article, we have explored the possibility of an overlap of the 'old' labour market risk represented by non-standard employment and the 'new' risks as automation and offshorability. We have analysed the Spanish case using the data from the LFS from 2011 to 2017, and indicators for new risks taken from the current literature on automation and offshorability. For the case of automation, we have used two indicators: one based on occupations, taken from the seminal paper by Frey and Osborne (2017); and other task-based, following the European Jobs Monitor and taken from Torrejón (2018). Non-standard employment has been analysed following the main categories defined by ILO (2016), as deviations from the full-time open-ended employment contract.

Are workers under non-standard arrangements exposed to a higher automation risk? At first sight, the answer is no. In terms of the mean risk we do not find significant differences for the four groups considered of type of contract and working hours. The mean risk of automation of full-timers with an open-ended contract is slightly below than for the different types of non-standard employment. However, we find differences when analysing the distribution of employment by different levels of automation risk. Considering the occupation-based automation risk (taken from Frey and Osborne, 2017) we have that standard and non-standard employment are mainly on levels of risk above 0.5, but the 'intermediate' or 'mixed' groups of non-standard employment have more employment above this threshold. In fact, we find that the distribution of employment by risk levels of standard employment (full time and open-ended) is closer to 'full' non-standard employment (part time and temporary contract) than to the 'mixed' categories of non-standard employment. This was unexpected and do not support that, in general, non-standard employment is associated to a higher automation risk. However, we obtain this result only with the occupation-based automation risk and not with the task-based automation risk. For this second indicator, standard employment is clearly concentrated in low risk, the opposite to the groups of non-standard employment. Likely, the low risk of standard employment is more related to the job tasks than to the occupation.

When analysing by contract type and working time, in general we find larger shares of employment for non-standard work arrangements – either temporary or part-time – than standard – open-ended or full-time, respectively. We obtain this pattern for both indicators of the automation risk. We also find that women are less exposed to a high risk of automation than men, and the same happens for workers with a university degree. In fact, although the high risk affects to more employment for workers with temporary or part-time contracts, what really increases the shares of employment under a high risk of automation is having only compulsory education and what shields from the automation risk is a university degree.

What happens with the exposure to the offshorability risk? Previous literature remarks that there is a potential association between routinisation of tasks and offshorability, but both are different and even a higher share of routine tasks is not correlated with a higher offshorability risk (Blinder and Krueger, 2013). As routinisation of tasks is closely related to automation, because of the lack of relationship of Blinder and Krueger (2013) found between their offshorability indicator and routine tasks, we would expect different results as those obtained for the automation risk. In fact, we obtain the opposite results about the association between non-standard employment and the offshorability risk. The offshorability risk and non-standard employment – either temporary or part-time – are not overlapped: the highest offshorability risk affects more to workers with open-ended contracts than to those with temporary contracts, and more to full-timers than to part-timers. When considering the educational level, we also find the opposite relationship that we found for the automation risks: a higher educational level is associated with a lower share of employment with no offshorability risk, and this association is clearer for temporary workers and part-timers.

Therefore, the new risks are not cumulative. Although automation and offshorability are linked to the tasks they are different phenomena and while the first one overlaps to some extent to the old risk of non-standard employment this is not the case for offshorability. As the automation risk seems also closely related to a lower education level, specific training programmes for exposed workers with only compulsory education seems especially suitable to prevent further problems. Focusing these programmes on workers with non-standard work arrangements is also advisable, as they are usually much less involved in firm-provided training programmes (Albert et al., 2005). Social dialogue and public policies would be crucial to launch this type of programmes for workers in non-standard employment and low educational levels. Anyway, we must notice that also workers with permanent contracts and low educational levels are significantly exposed to automation risks. Therefore, it would necessary to incorporate the above measure for non-standard employment into a wider plan promoting the skills workers will need in the future labour market. In this line, analysing the automation risks jointly with the skill needs as Pouliakas (2018) seems a promising line of research to design this type of programme.

Finally, it is worth mention that the case of self-employment seems different than standard or non-standard employment. Our analysis show that self-employment is closer to employers in terms of general patterns of automation and offshorability risks. Probably, this is related to the difficulty to disaggregate dependent self-employment from the general category of self-employment in the LFS. Analysing what happens with dependent self-employment in terms of exposure to automation remains as a promising line of research about non-standard work arrangements. How dependent self-employment is related to the offshorability risk and to what happens with labour demand after a firm offshores part of its activities are also open issues on the understanding of non-standard employment.

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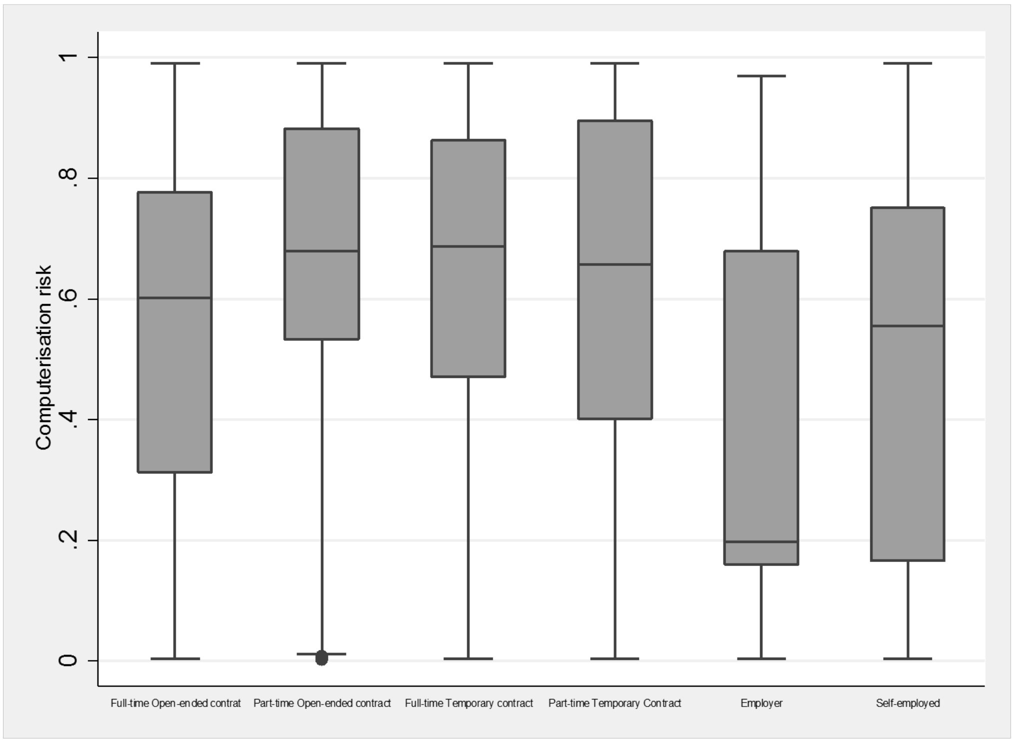
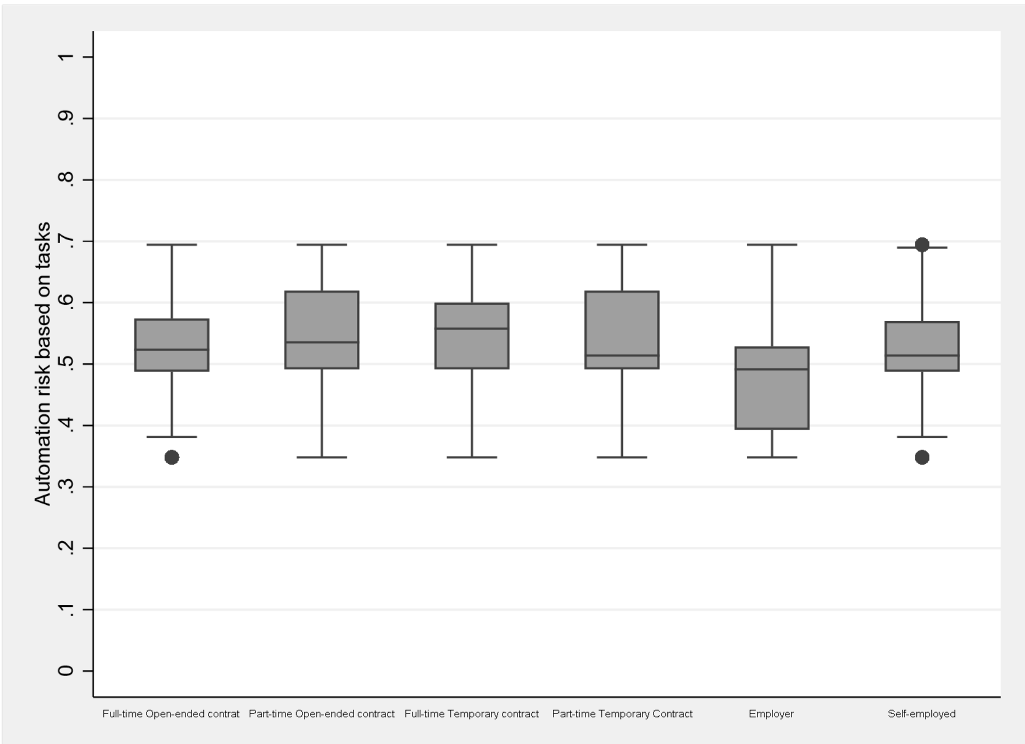
Figure 1. Means of the occupation-based automation risk for standard and non-standard employment (average 2011-2017).



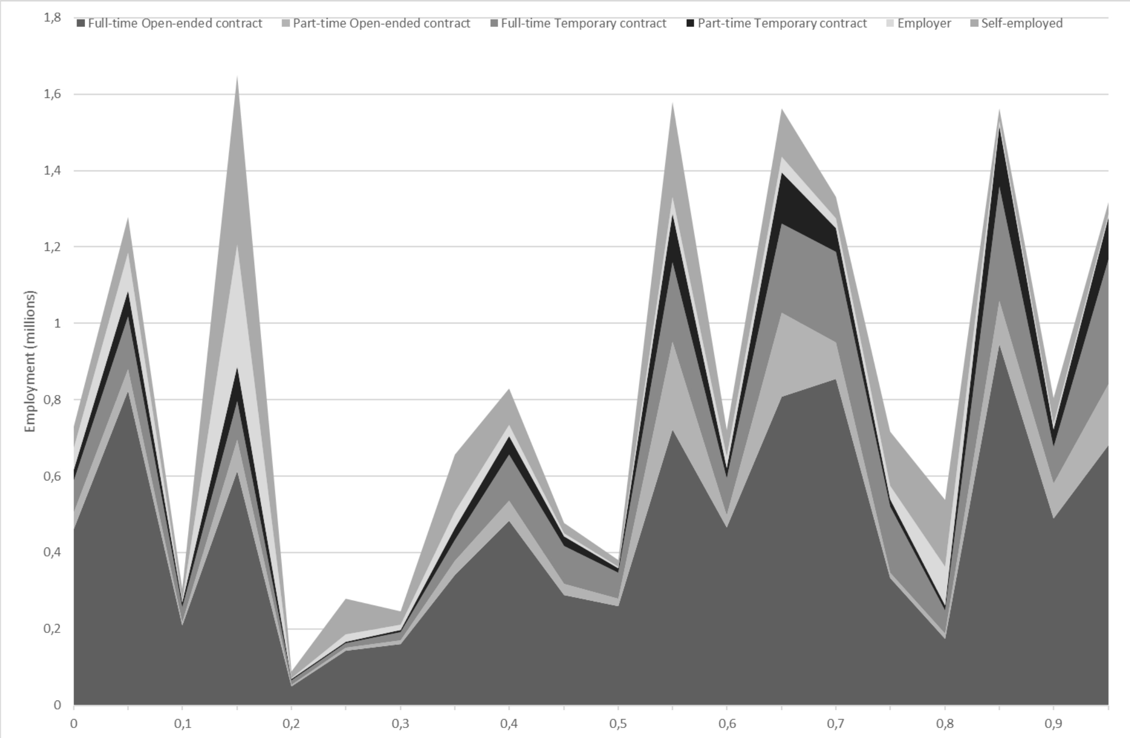
Source: LFS and own calculations.

Figure 2. Means of the task-based automation risk for standard and non-standard employment (average 2011-2017).



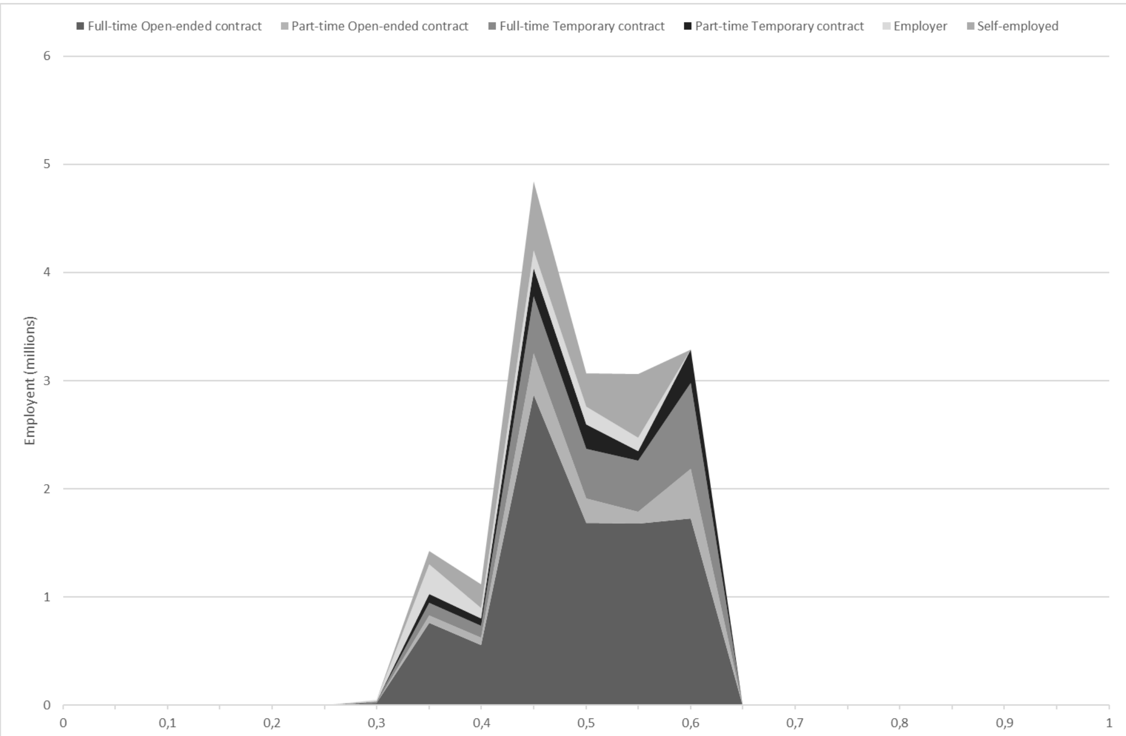
Source: LFS and own calculations.

Figure 3. Distribution of standard and non-standard employment by the occupation-based automation risk (average 2011-2017).



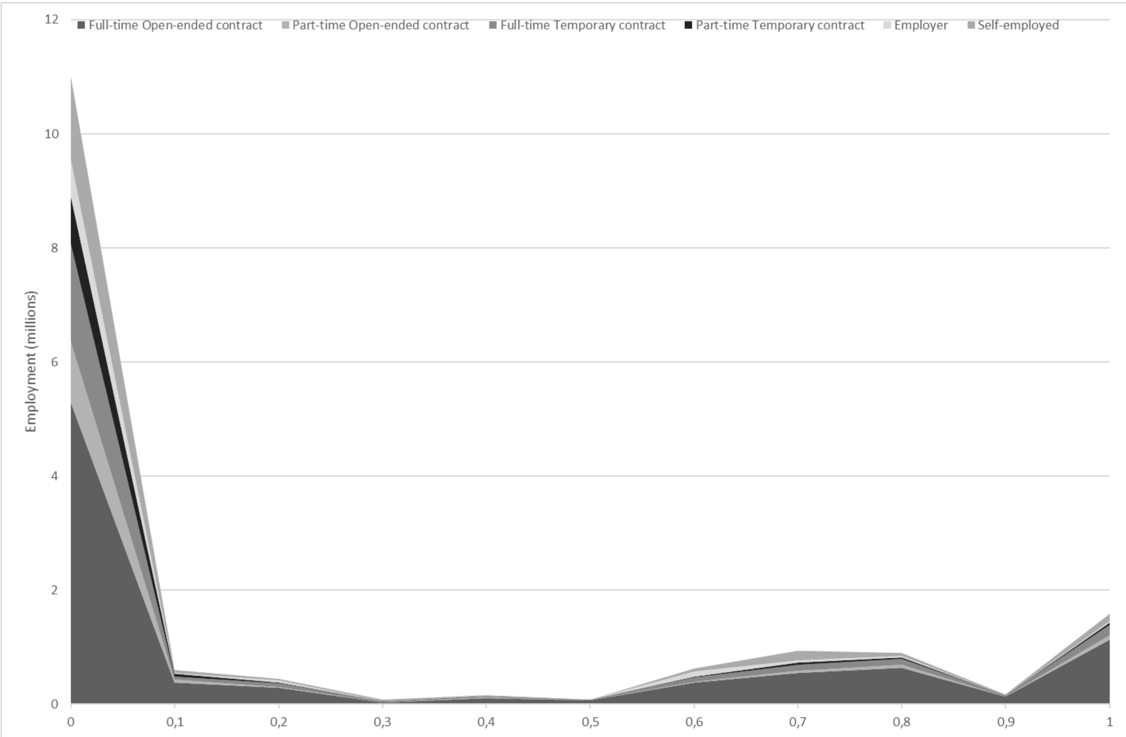
Source: LFS and own calculations.

Figure 4. Distribution of standard and non-standard employment by the task-based automation risk



Source: LFS and own calculations.

Figure 5. Distribution of standard and non-standard employment by offshorability risk (average 2011-2017).



Source: LFS and own calculations.

Table 1. Total employment for the different thresholds of the automation and offshorability risks (average 2011-2017).

	Automation risk Frey and Osborne (2017)		**Automation risk Torrejón (2018)**	**Offshorability risk Blinder and Krueger (2013)**
Low	25.3		38.7	64.9
Medium	40.9	*Med.-Low 12.9* *Med-High 28.0*	28.1	25.6
High	33.9		33.2	9.5

Source: LFS and own calculations.

Table 2 Distribution of standard and non-standard employment by each type of 'new' risks (average 2011-2017).

Automation risk (Frey and Osborne, 2017)										
	Part-time workers					Full-time workers				
	Low	Med-Low	Med-High	High	Total	Low	Med-Low	Med-High	High	Total
Temporary contract	20.0	10.7	31.2	38.0	100	15.5	11.8	27.0	45.7	100
Open-ended contract	15.2	9.8	41.9	33.1	100	24.7	13.7	28.3	33.3	100

Automation risk (Torrejón, 2018)								
	Part-time workers				Full-time workers			
	Low	Medium	High	Total	Low	Medium	High	Total
Temporary contract	29.7	34.8	35.5	100	25.0	27.6	47.4	100
Open-ended contract	30.0	31.8	38.3	100	40.6	30.1	29.3	100

Offshorability risk								
	Part-time workers				Full-time workers			
	Low	Medium	High	Total	Low	Medium	High	Total
Temporary contract	80.9	15.3	3.9	100	69.5	22.8	7.7	100
Open-ended contract	79.8	14.4	5.9	100	57.2	30.2	12.6	100

Source: LFS and own calculations.

Table 3. Distribution of employment by occupation-based automation risk considering type of contract, gender and educational level (average 2011-2017).

	Temporary contract					**Open-ended contract**				
	Low	**Medium-low**	**Medium-High**	**High**	**Total**	**Low**	**Medium-low**	**Medium-High**	**High**	**Total**
Total	16.9	11.5	28.2	43.4	100	23.5	13.2	30.0	33.3	100
Men	13.6	10.2	27.4	48.8	100	24.5	14.1	27.3	34.2	100
Women	20.2	12.9	29.1	37.8	100	22.5	12.3	33.0	32.3	100
Compulsory	3.2	8.7	32.4	55.7	100	5.4	11.9	35.7	47.0	100
Low vocational	6.3	22.7	27.6	43.4	100	8.6	21.7	31.5	38.2	100
Post-compulsory secondary	8.5	12.0	31.5	48.0	100	12.9	13.7	33.9	39.5	100
Upper vocational	13.8	16.8	31.0	38.5	100	13.4	16.7	37.5	32.5	100
University	55.6	8.1	16.7	19.6	100	58.5	10.2	17.7	13.6	100

Source: LFS and own calculations.

Table 4. Distribution of employment by occupation-based automation risk considering working time, gender and educational level (average 2011-2017).

	Full-time					**Part-time**				
	Low	**Medium-low**	**Medium-High**	**High**	**Total**	**Low**	**Medium-low**	**Medium-High**	**High**	**Total**
Total	26.4	13.3	26.6	33.7	100	19.3	10.5	35.4	34.7	100
Men	25.5	13.2	26.9	34.4	100	21.3	10.8	25.7	42.2	100
Women	27.7	13.5	26.2	32.7	100	18.6	10.4	38.9	32.1	100
Compulsory	9.7	11.3	30.0	49.0	100	6.8	9.0	47.0	37.2	100
Low vocational	11.7	22.4	28.7	37.2	100	10.1	20.0	32.1	37.7	100
Post-compulsory secondary	17.8	14.5	30.1	37.6	100	12.3	10.3	35.5	41.9	100
Upper vocational	16.8	17.9	34.9	30.4	100	17.1	13.7	30.3	38.8	100
University	61.3	10.1	16.0	12.5	100	54.0	7.4	17.7	20.9	100

Source: LFS and own calculations.

Table 5. Distribution of employment by occupation-based automation risk considering employment status, gender and educational level (average 2011-2017).

	Employer					**Own-account workers without employees**				
	Low	**Medium-low**	**Medium-High**	**High**	**Total**	**Low**	**Medium-low**	**Medium-High**	**High**	**Total**
Total	55.4	10.4	13.8	20.5	100	36.6	15.2	23.6	24.5	100
Men	54.0	9.1	16.1	20.8	100	30.8	14.8	29.3	25.1	100
Women	58.6	13.3	8.4	19.8	100	48.0	16.1	12.5	23.4	100
Compulsory	41.5	8.6	18.7	31.1	100	21.9	12.1	29.3	36.7	100
Low vocational	40.7	21.6	15.2	22.4	100	25.5	24.8	26.2	23.5	100
Post-compulsory secondary	59.0	9.5	11.8	19.7	100	32.8	20.1	24.2	22.9	100
Upper vocational	49.4	17.1	16.6	16.9	100	32.0	23.6	27.2	17.1	100
University	80.8	7.0	6.1	6.2	100	72.8	11.3	10.0	5.9	100

Source: LFS and own calculations.

Table 6. Distribution of employment by task-based automation risk considering type of contract, gender and educational level (average 2011-2017)

	Temporary contract				Open-ended contract			
	Low	**Medium**	**High**	**Total**	**Low**	**Medium**	**High**	**Total**
Total	26.4	29.7	43.9	100	39.3	30.3	30.4	100
Men	20.5	23.3	56.2	100	37.0	25.9	37.1	100
Women	32.6	36.5	31.0	100	41.9	35.3	22.9	100
Compulsory	9.9	21.8	68.3	100	17.3	24.9	57.9	100
Low vocational	15.5	42.9	41.6	100	20.6	44.6	34.7	100
Post-compulsory secondary	22.0	36.2	41.8	100	35.4	37.8	26.8	100
Upper vocational	26.2	46.2	27.6	100	29.3	47.3	23.4	100
University	66.8	25.3	7.9	100	76.3	20.2	3.4	100

Source: LFS and own calculations.

Table 7. Distribution of employment by task-based automation risk considering working time, gender and educational level (average 2011-2017).

	Full time				Part-time			
	Low	**Medium**	**High**	**Total**	**Low**	**Medium**	**High**	**Total**
Total	39.9	27.4	32.8	100	32.3	31.9	35.7	100
Men	35.8	22.5	41.7	100	34.1	29.2	36.7	100
Women	45.9	34.7	19.4	100	31.7	32.9	35.4	100
Compulsory	19.5	22.1	58.4	100	17.1	26.5	56.4	100
Low vocational	21.1	41.5	37.4	100	23.3	45.5	31.2	100
Post-compulsory secondary	37.8	33.8	28.4	100	28.7	37.1	34.1	100
Upper vocational	30.1	44.2	25.6	100	36.2	44.1	19.7	100
University	77.7	18.3	4.0	100	66.8	25.4	7.8	100

Source: LFS and own calculations.

Table 8. Distribution of employment by occupation-based automation risk considering employment status, gender and educational level (average 2011-2017).

	Employer				Own-account worker without employees			
	Low	**Medium**	**High**	**Total**	**Low**	**Medium**	**High**	**Total**
Total	60.6	19.3	20.1	100	47.7	17.1	35.3	100
Men	58.3	15.7	26.0	100	40.6	13.8	45.6	100
Women	65.9	27.6	6.5	100	61.5	23.4	15.1	100
Compulsory	44.3	22.7	33.0	100	30.7	16.6	52.7	100
Low vocational	41.5	34.0	24.4	100	31.0	30.2	38.8	100
Post-compulsory secondary	66.2	19.2	14.6	100	51.5	18.9	29.6	100
Upper vocational	54.3	25.8	19.9	100	40.7	28.0	31.4	100
University	90.0	6.7	3.4	100	87.0	7.3	5.8	100

Source: LFS and own calculations.

Table 9. Distribution of employment by offshorability risk considering type of contract, gender and educational level (average 2011-2017)

	Temporary contract				Open-ended contract			
	Risk=0	0>Risk>1	Risk=1	Total	Risk=0	0>Risk>1	Risk=1	Total
Total	72.9	20.6	6.5	100	60.0	28.2	11.7	100
Men	71.9	20.1	8.0	100	55.4	30.1	14.5	100
Women	73.9	21.0	5.1	100	65.0	26.2	8.8	100
Compulsory	85.1	9.9	5.1	100	76.0	14.2	9.9	100
Low vocational	78.3	15.1	6.6	100	71.4	18.6	10.0	100
Post-compulsory secondary	77.1	16.8	6.1	100	60.9	27.3	11.9	100
Upper vocational	63.5	27.2	9.3	100	52.5	32.3	15.2	100
University	48.3	43.5	8.2	100	40.9	46.4	12.8	100

Source: LFS and own calculations.

Table 10. Distribution of employment by offshorability risk considering working time, gender and educational level (average 2011-2017).

	Full-time				Part-time			
	Risk=0	0>Risk>1	Risk=1	Total	Risk=0	0>Risk>1	Risk=1	Total
Total	62.4	27.3	10.4	100	78.6	16.4	5.1	100
Men	61.1	27.2	11.8	100	75.0	18.6	6.3	100
Women	64.3	27.4	8.3	100	79.8	15.6	4.6	100
Compulsory	77.8	13.9	8.3	100	90.3	6.2	3.5	100
Low vocational	72.4	18.3	9.2	100	84.1	11.1	4.8	100
Post-compulsory secondary	62.6	26.4	10.9	100	80.4	14.6	5.0	100
Upper vocational	54.9	31.5	13.6	100	68.8	22.9	8.4	100
University	41.9	46.5	11.7	100	56.6	36.9	6.5	100

Source: LFS and own calculations.

Table 11. Distribution of employment by offshorability risk considering employment status, gender and educational level (average 2011-2017).

	Employer				Own-acoount worker without employees			
	Risk=0	0>Risk>1	Risk=1	Total	Risk=0	0>Risk>1	Risk=1	Total
Total	71.4	25.2	3.4	100	73.1	21.0	6.0	100
Men	68.8	27.4	3.7	100	72.8	20.5	6.7	100
Women	77.1	20.1	2.7	100	73.5	21.9	4.6	100
Compulsory	78.0	19.5	2.5	100	87.5	8.5	4.0	100
Low vocational	77.0	19.1	3.9	100	81.6	12.6	5.7	100
Post-compulsory secondary	72.1	24.3	3.6	100	69.5	21.7	8.8	100
Upper vocational	66.8	29.5	3.6	100	68.8	23.0	8.2	100
University	61.2	34.4	4.4	100	46.1	46.6	7.3	100

Source: LFS and own calculations.

Table 12. Linear regressions.

Dependent variable: Occupation-based automation risk							
		Total employment			Wage and salary workers		
		coef.	S.E.		coef.	S.E.	
	Low vocational	-3.902	0.070	***	-3.823	0.076	***
	Post-compulsory secondary	-3.716	0.061	***	-2.555	0.067	***
	Upper vocational	-6.641	0.065	***	-6.246	0.071	***
Ref: compulsory	University	-28.943	0.055	***	-29.662	0.060	***
	Part-time Open-ended contract	2.775	0.077	***	1.719	0.077	***
	Full-time Temporary contract	2.497	0.059	***	2.561	0.059	***
	Part-time Temporary Contract	0.751	0.086	***	0.471	0.086	***
	Employer	-22.552	0.090	***			
Ref: Full-time Open-ended contract	Self-employed	-14.408	0.065	***			
Dependent variable: Task-based automation risk							
	Low vocational	-1.723	0.017	***	-1.979	0.018	***
	Post-compulsory secondary	-2.861	0.014	***	-2.885	0.016	***
	Upper vocational	-3.166	0.015	***	-3.400	0.017	***
Ref: compulsory	University	-9.105	0.013	***	-9.445	0.014	***
	Part-time Open-ended contract	1.230	0.018	***	0.947	0.018	***
	Full-time Temporary contract	1.162	0.014	***	1.204	0.014	***
	Part-time Temporary Contract	0.503	0.020	***	0.333	0.020	***
	Employer	-5.503	0.021	***			
Ref: Full-time Open-ended contract	Self-employed	-2.153	0.015	***			
Dependent variable: Offshorability risk							
	Low vocational	3.027	0.092	***	3.150	0.102	***
	Post-compulsory secondary	8.819	0.080	***	9.099	0.090	***
	Upper vocational	9.840	0.086	***	10.466	0.096	***
Ref: compulsory	University	17.610	0.073	***	19.022	0.082	***
	Part-time Open-ended contract	-6.192	0.101	***	-5.772	0.104	***
	Full-time Temporary contract	-3.101	0.079	***	-2.704	0.081	***
	Part-time Temporary Contract	-6.611	0.113	***	-6.032	0.116	***
	Employer	-10.657	0.118	***			
Ref: Full-time Open-ended contract	Self-employed	-9.003	0.086	***			

Note: All regressions include the following variables: gender dummy (males=1); 4 age groups; immigrant (yes=1); public sector (yes=1); 10 sectors; year dummies; 17 regions; and a constant term.

*** significant at 1 per cent; ** 5 per cent, and * 10 per cent.

Source: LFS and own calculations.