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Fear of robots at work: the role of economic self-interest

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Abstract

There is a lively ongoing debate about the effects of the widespread introduction of robots in work environments. Many people in the labor market worry about inequality and possible job loss that robot technology may create. However, large-scale studies on the determinants of these perceptions are thus far lacking. This article assesses which members of the labor force are most fearful of the introduction of robots at work by using the 2012 Eurobarometer *Public Attitudes towards Robots* dataset, covering 11 206 respondents in 20 European countries. Our study shows that those (a) in economic positions that are more likely to be negatively affected by robotics are more likely to be fearful of robots at work, along with, to some extent, those living in countries (b) with adverse economic conditions and (c) where employees are less protected from market forces. The theoretical and practical implications of these findings are discussed.

Key words: technological change, robots, labor market institutions, trade unions, fear of robots

JEL classification: O33, O39

1. Introduction

Technological progress has been a central driving force behind the rise in living standards since the Industrial Revolution. The current wave of technological innovation, known as the Digital Revolution, has engendered digital technologies encompassing desktop computing, the Internet and other information and communication technologies, bio- and nano-technologies and robotics.

There is a lively public debate about the introduction of these digital technologies in the workplace and its consequences for jobs.[1] Such technologies are sometimes argued to be detrimental for future employment opportunities (Frey and Osborne, 2013; Ford, 2015), and these concerns are reflected in newspaper headlines such as ‘Coming to an office near you’ (*The Economist*, 2014), ‘Third of Britons fear the rise of robots’ (*The Guardian*, 2014) and

'What happens to society when robots replace workers?' (*Harvard Business Review*, 2014). This fits into a long-standing public debate on the perceived threat of technological innovation to job opportunities that started with the Luddite protests during the Industrial Revolution, and has ever since periodically come to the fore again (Forester, 1980; Autor, 2015; Mokyr *et al.*, 2015).

The current public debate is, to a large extent, centered on robotics. The word 'robot' was first introduced in 1921: robots are machines that can navigate through and interact with the physical world of factories, warehouses, battlefields and offices (Brynjolfsson and McAfee, 2014, p. 27). The adoption of robots in the workplace has been rapid: in developed countries, the stock of robots per million hours worked has increased by over 150% in the past decade and a half (Graetz and Michaels, 2015). Furthermore, robotic technologies are continuing to advance, for example, with the application of machine-learning algorithms that do not require tasks to follow a well-defined protocol; and the development of 'cobots',[2] which are robots designed to interact with humans (e.g. Colgate *et al.*, 1996).

In addition to the public debate, there has also been an academic debate on the labor market impacts of digital technologies. Along with other factors such as globalization, the introduction of new technologies has been found to change the jobs that are available, the skills those jobs require, and the wages they pay. This is argued to be the case because technological change is a biased shock: it does not affect all work in the same way [see Acemoglu and Autor (2011) for an overview]. In particular, rule-based digital technologies are argued to replace human labor in so-called routine tasks (Autor *et al.*, 2003). Jobs intense in such routine tasks are typically medium skilled (including white-collar jobs such as office clerks and blue-collar jobs like machine operators), whereas jobs intense in nonroutine tasks are both high- (such as managers and professionals) and low skilled (such as hairdressers and cleaners). Empirical studies do indeed demonstrate that digital technology has led to a decline in the relative demand for routine jobs in advanced economies (e.g. Goos and Manning, 2007; Goldin and Katz, 2009; Autor and Dorn, 2013; Goos *et al.*, 2014). To the extent that robots still mostly use rule-based technologies, we would expect that the findings from the literature on the declining relative demand for routine jobs apply. Indeed, Graetz and Michaels (2015) show that the introduction of industrial robotics has led to a decline in hours worked for both low- and middle-skilled workers. This does not rule out that the (future) impact may be different insofar as machine-learning technologies and cobots allow automating different types of tasks[3] and could intrinsically more strongly complement (rather than replace) human labor.

While many studies have been published on the impact of technology on employment, much less is known about how people subjectively experience technological change. Therefore, in this era of digitization, we will focus on a better understanding of fears of robots in work settings. This is important because fear may impact rates of public acceptance of the development and introduction of new (robotic) technologies and, therefore, influence innovation and investment in them, ultimately affecting the economic growth potential[4] of economies worldwide.[5] This study also contributes to discussions on the societal implications of unemployment and the fear of job loss. Previous studies have revealed a positive link between adverse labor market conditions and crime (e.g. Lin, 2008), as well as between a fear of job loss and status anxiety on the one hand and racism and support for right-wing extremism on the other (e.g. Stynen and De Witte, 2011). A fear of robots in the workplace may also fuel these anxieties (Chijindu and Inyiama, 2012). It is against this background that this study aims to provide a better understanding of the ways in which people interpret the introduction of new technologies in their working lives.

Worries about the use of robots in various societal domains have already been the subject of scientific study. Existing work has focused on human–robot interactions (e.g. Nomura *et al.*, 2006; Bethel and Murphy, 2010; Kim and Mutlu, 2014), and documents people's attitudes toward specific types of robots. Bartneck et al. (2007), for example, study differences in people's attitudes toward commercial robots; Shibata *et al.* (2004) examine perceptions of the therapeutic robot *Paro*; and Broadbent *et al.* (2009) investigate human responses to healthcare robots. Several authors have considered country-specific attitudes: Han *et al.* (2009) examine differences in attitudes toward tutoring robots between Korean, Japanese and Spanish parents; Choi *et al.* (2008) study preferences for educational robots among European and Korean parents; while MacDorman *et al.* (2009) report no clear differences in robot-related perceptions between Japanese and US survey participants. These studies provide various valuable insights, but mostly use small-scale surveys and/or do not focus on the fear of robots at work specifically. Two exceptions are Fink *et al.* (1992), who demonstrate that American production workers perceive industrial robots as a threat, and Taipale *et al.* (2015), who analyze people's overall attitudes to the use of robots in different domains of life, demonstrating that approximately 50% of Europeans support the use of robots in manufacturing. Despite these empirically informed accounts of the fear of robots at work, it is thus far not entirely clear who is most fearful and why. Until recently, it was not possible to investigate this topic systematically, due to a lack of data.

This article aims to fill this gap by assessing the determinants of the fear of robots at work across a broad set of European countries using a large and representative survey dataset from the Eurobarometer *Public Attitudes towards Robots* survey of 2012. This dataset covers 27 European countries and includes several questions on the perceived consequences of robots at work.

Our research will be guided theoretically by the implicit notions in the public concerns outlined above. As robots are increasingly being used in the workplace (e.g. see International Federation of Robotics, 2016), some groups of workers may feel threatened by them, making them feel less secure. We will assess whether the fear of robots at work is strongest among those who are most likely to be adversely affected. To do this, we draw on the scholarly literature on the antecedents of self-reported job insecurity at both the micro and macro level (e.g. Anderson and Pontusson, 2007; Emmenegger, 2009; Chung and Van Oorschot, 2011; Mau *et al.*, 2012; Dixon *et al.*, 2013; Chung and Mau, 2014). This literature indicates that such fears are largely driven by economic self-interest. At the individual level, it can, therefore, be expected that those in weak economic positions are more likely to be fearful of robots at work. Meanwhile, at the macro level, those living in countries with adverse economic conditions or low decommodification are also more likely to be fearful. We will, therefore, address the following research question: *Can fear of robots at work be explained by economic self-interest?*

This article is structured as follows. First, we develop the theoretical background for our analyses. Next, we introduce the dataset and methods, followed by the results obtained from testing our hypotheses across a range of different models. Finally, we discuss the theoretical and practical implications of our findings.

2. Fear of robots at work: theorizing the role of self-interest

This study considers whether a fear of robots in the workplace can be understood as resulting from one's individual economic position (Section 2.1); and is related to country-level economic (Section 2.2) and institutional (Section 2.3) conditions that have been shown to determine perceptions of job insecurity more generally (e.g. Emmenegger, 2009; Chung and Van Oorschot, 2011; Mau *et al.*, 2012; Chung and Mau, 2014). All these factors may be associated with people's fear of robots, based on different levels of self-interest: we expect that people with stronger labor market positions respond more positively to robots, and that higher levels of macroeconomic prosperity, lower levels of unemployment and more regulated labor markets are accompanied by positive attitudes to robots in the workplace as well. In other words, a fear of robots is fueled by people being exposed to greater risks in the labor market, without having the means to gain security. Finally, to examine the impact of these conditions more precisely, we include several control variables that may influence a fear of robots as well (Section 2.4).

2.1 Individual-level explanations: economic position

Research on the individual-level determinants of perceived job insecurity has concluded that socioeconomic determinants are an important part of the explanation. Specifically, those in stronger labor market positions report lower levels of subjective job insecurity for two reasons. First, their labor contracts are more secure and they are, therefore, better able to retain their jobs. Second, when those in a strong labor market position become unemployed, they find a new job relatively easily. This is why the higher educated, managers, workers in full-time employment and men report lower levels of subjective job insecurity than their lower educated, nonmanager, part-time employee and female counterparts (e.g. Green, 2009; Mau *et al.*, 2012).

A similar argument may apply to the fear of robots at work. In particular, those in economic positions that are not negatively, or even positively, affected by automation may be less fearful of robots being used in the workplace. As such, those (a) in a strong labor market position, (b) participating in activities at work that are hard to automate via robotics and (c) who directly reap the benefits of automation, can be expected to be less fearful of robots at work than their counterparts in a weak economic position, whose work is easy to automate, and who do not directly benefit from automation. Consequently, we expect that *the higher educated and the employed are less fearful of robots at work than, respectively, the less educated* (H1a) *and the unemployed* (H1b). The former are in a stronger labor market position, and their labor market opportunities (in terms of the odds of job loss, and the chances of finding a new job after being laid off) are, therefore, not (or are less) negatively affected by the introduction of robotics. Furthermore, the employed are not only in a stronger overall labor market position as compared to the unemployed, but may also have more opportunities to keep their skills up to date by working with the latest technologies.[6] In addition, among the employed, *managers and professionals are less fearful of robots at work than manual and white-collar workers* (H1c), as the former's main activities in the workplace are more difficult to automate than those of the latter. Finally, *employers are less fearful of robots than employees* (H1d), as employers are expected to benefit directly from automation-driven productivity gains, whereas the latter might see their job opportunities decline due as technology replaces labor in routine tasks.[7]

2.2 Macro-level explanations: economic conditions

It has been established that economic conditions may affect perceptions of job insecurity. In particular, existing work has shown that perceived job insecurity is higher in insecure macroeconomic environments. Gross domestic product (GDP) growth, for example, is found to be negatively related to the perception of job insecurity (e.g. Lübke and Erlinghagen, 2014). The explanation given for this is that workers view their future economic fortunes more optimistically, as high economic growth rates are associated with better employment opportunities. Furthermore, the literature suggests that workers are more insecure in countries with higher unemployment rates (e.g. Green, 2006; Erlinghagen, 2008; Chung and Van Oorschot, 2011), to which the same argument applies: in periods of high unemployment, the likelihood of holding on to or getting a job decreases.

Along a similar line of argument, we expect robotic technology to be perceived as a greater threat in contexts of low economic growth and high unemployment levels. In those contexts, the labor market adjustments resulting from the introduction of new technologies are more likely to be painful, for example, because changes in the structure of employment occur through job destruction rather than slower job growth (Jaimovich and Siu, 2012). Accordingly, we expect that the *fear of robots at work is higher as GDP growth is lower* (H2a) and *unemployment rates are higher* (H2b).

2.3 Macro-level explanations: institutional conditions

In addition to the economic position of individuals and macroeconomic conditions, institutional conditions may be linked to the fear of robots at work as well. It seems plausible that people may adapt more easily to new situations in the labor market under conditions of institutional security. Various institutional arrangements are directed at shielding employees from market forces. Three important sources of such protection are (a) the generosity of unemployment benefits, (b) the level of employment protection legislation (EPL) and (c) trade union density. If unemployment benefits are more generous, the consequences of becoming unemployed are less dire, and one is less dependent on the labor market for providing the means of existence. This is probably why people report less-subjective job insecurity in contexts with higher levels of public social expenditure (Mau *et al.*, 2012). In addition, a higher level of EPL and more powerful trade unions make it more difficult to lay off workers. In other words, EPL and trade unions may serve to protect workers against actions by management that would harm the employee (Sverke *et al.*, 2006, p. 11). This, in turn, affects an individual's perception of insecurity. Indeed, it has been demonstrated that workers feel less job-insecure in countries with higher levels of EPL (Anderson and Pontusson, 2007) and a greater trade union density (Sverke *et al.*, 2006; Esser and Olson, 2012; Dixon *et al.*, 2013). In a broader sense, most scholars relate this finding to differences in the institutional design of welfare states (e.g. Esping-Andersen, 2000) and labor markets (e.g. Gallie, 2007).

In a similar vein, the fear of robots at work is likely to be related to institutional conditions aimed at protecting employees from market forces. It can be expected that institutional conditions aimed at abating the consequences of unemployment and unemployment risks will reduce the fear of robots at work. The generosity of unemployment benefits makes being replaced by robots less problematic in terms of providing a livelihood. In addition, EPL and powerful unions may make it less likely that robots can be used to replace employees as a strategy for increasing productivity. Accordingly, we expect that the *fear of robots is lower when unemployment benefits are more generous* (H3a), *employment protection is higher* (H3b) and *trade union density is higher* (H3c).

2.4 Confounding factors

Finally, the fear of robots at work may be influenced by other factors, both at the macroeconomic and the individual level, and these factors may be correlated to our independent variables of interest. For one, cultural conditions may have a strong impact on such fears. While the notion of culture can be defined in several ways, we associate this concept with the set of shared values, norms and beliefs among individuals in a country (DiMaggio, 1994). Cultural beliefs can affect individual actions and perceptions, which is why cultural differences are argued to explain variation in attitudes toward technological change across countries (e.g. Shibata *et al.*, 2004; Bartneck *et al.*, 2007; Choi *et al.*, 2008; Han *et al.*, 2009; MacDorman *et al.*, 2009; Shaw-Garlock, 2009). Although most relevant research does not focus on the world of work and/or relies on a small number of observations, it does indicate that attitudes toward robots can covary with people's cultural backgrounds (Bartneck *et al.*, 2007, p. 225). For example, despite the fact that there are many subcultures within countries, people in Western economies are usually less positive toward robots than their counterparts in Eastern economies (e.g. Shaw-Garlock, 2009). Moreover, it is likely that such cultural factors correlate with countries' institutional conditions: institutional protections may arise in part as a result of cultural preferences. We will attempt to capture these cultural factors by controlling for countries' 'uncertainty avoidance'. Uncertainty avoidance is one of the central indicators developed by Hofstede (1991) to capture cultural differences across countries. In nations characterized by lower uncertainty avoidance, people are expected to adapt more easily to change. In these settings, risks such as changing jobs and entering unknown situations are more accepted (Hofstede, 2001). As the introduction of robots in the workplace is a concrete example of this, it can be expected that people in low uncertainty avoidance countries will perceive the appearance of robots at work more optimistically.

Similarly, it is necessary to control for previous individual experience with robots, since previous exposure to robots decreases fear of robots in the workplace (e.g. Nomura *et al.*, 2006; Bartneck *et al.*, 2007; Stafford *et al.*, 2010). A possible explanation is fear of the unknown: people who are not used to new technology have more negative attitudes toward it. Such experience with robotics at work may be related to labor market position as well, such as education level, since not all workers are equally likely to have opportunities to interact with robots at work. Finally, we control for two sociodemographic variables, gender and age, which also influence the way individuals perceive robots (e.g. Nomura *et al.*, 2006; Enz *et al.*, 2011; Heerink, 2011), and are likely correlated with education levels and with labor market position. For example, men and women work in different types of jobs; and younger workers are more likely to be highly educated.

3. Data and methodology

This article uses data from the Eurobarometer survey *Public Attitudes towards Robots* (2012), which interviewed 26 751 people aged 15 years and over in 27 European countries[8] (European Commission, 2014). In this survey, respondents were first provided with the following broad definition of robots, including both industrial robots and cobots: 'A robot is defined here as an autonomous machine which can assist humans in everyday tasks e.g. as a kind of co-worker helping on the factory floor or as a robot cleaner, or in activities which may be dangerous for humans, like search and rescue in disasters. Robots can come in many shapes or sizes, including human-like. Traditional kitchen appliances, such as a blender or a

Table 1. Items and factor scores of *Fear of robots at work*

Questions and answer categories	Factor loadings
Please tell me to what extent you agree or disagree with each of the following statements about robots	
• Robots steal people's jobs [(1) 'Totally disagree', (2) 'Tend to disagree', (3) 'Tend to agree', (4) 'Totally agree']	0.65
• Robots are necessary as they can do jobs that are too hard or too dangerous for people [(1) 'Totally agree', (2) 'Tend to agree', (3) 'Tend to disagree', (4) 'Totally disagree']	0.65
• Widespread use of robots can boost job opportunities in the EU [(1) 'Totally agree', (2) 'Tend to agree', (3) 'Tend to disagree', (4) 'Totally disagree']	0.68
Generally speaking, do you have a very positive, fairly positive, fairly negative or very negative view of robots? [(1) 'Very positive', (2) 'Fairly positive', (3) 'Fairly negative', (4) 'Very negative']	0.76
Here is a list of things that could be done by robots. For each of them, please tell me, using a scale from 1 to 10, how you would personally feel about it.	
• Having a robot assist you at work (e.g. in manufacturing) [from (1) 'totally comfortable' to (10) 'totally uncomfortable']	0.71
Eigenvalue	2.38
Number of items with valid scores needed for calculating factor scores	3
R^2 (%)	47.59
Cronbach's α	0.72

Source: Eurobarometer *Public Attitudes towards Robots* (2012).
Notes: A total of 11 206 observations. The variable *Fear of robots at work* is constructed as the mean of these five items at the individual level whenever at least three items were available, and where the score for 'Having a robot assist you at work' was first rescaled to match the 1–4 scale of the other items. Finally, this summed score was rescaled to lie between 1 and 5. Item scales reversed from the original Eurobarometer questionnaire to reflect fear of robots.

coffee maker, are not robots.' As our focus is on fear of robots in the workplace, we only include the labor force, consisting of those respondents who are self-employed, employed or unemployed, and between 15 and 65 years old. Furthermore, our dataset is restricted by the availability of country-level data needed to test our hypotheses.[9]

3.1 Individual-level variables

The dependent variable —*fear of robots at work*— is measured as the mean of scores for five survey items listed in Table 1[10]: this is inspired by a factor analysis,[11] which reveals that these five items have similar factor loadings. The resulting variable lies between 1 and 5, where a higher number indicates a greater fear of robots at work, as for instance indicated by higher agreement with the statement 'Robots steal people's jobs' or higher disagreement with the statement 'Widespread use of robots can boost job opportunities in the EU'.

Two individual-level independent variables are used as indicators for economic position to test our individual-level hypotheses: *level of education* and *labor market position*. *Level of education* consists of three categories: (a) studied until the age of 15 years (including those with no full-time education), (b) studied until the age of 16, 17, 18 or 19 years and (c) studied after the age of 20 years: we code these as three dummy variables and use respondents who studied until after the age of 20 years as the reference category throughout. A higher number of years of education indicates a higher skill level and, thus, a stronger labor market position. Comparing levels of education, therefore, allows us to test Hypothesis 1a, which predicts that workers with lower levels of education will be more fearful of robots at work.

Labor market position is a variable consisting of six categories. The first two are respondents who categorize themselves as self-employed: (1) *large business owners* ('Business proprietors, owner (full or partner) of a company'), and (2) *small business owners* ('Farmer', 'Fisherman', 'Professional (lawyer, medical practitioner, accountant, architect, etc.)', 'Owner of a shop, craftsmen, other self-employed person'). Although the number of employees needed for the respondents to self-categorize as business proprietors versus the other self-employed categories is not explicitly mentioned in the questionnaire, we assume that, on average, business proprietors will tend have more employees. Categories 3–5 are different types of employees from an aggregate occupational indicator available in the data: (3) *managers and professionals* ('Employed professional (employed doctor, lawyer, accountant, architect)', 'General management, director or top management (managing directors, director general, other director)', 'Middle management, other management (department head, junior manager, teacher, technician)'), (4) *white-collar workers* ('Employed position, working mainly at a desk', 'Employed position, not at a desk but travelling (salesmen, driver, etc.)' and (5) *manual workers* ('Employed position, not at a desk, but in a service job (hospital, restaurant, police, fireman, etc.)', 'Supervisor', 'Skilled manual worker', 'Other (unskilled) manual worker, servant'). The sixth and final category is (6) *the unemployed*.

These six categories allow us to compare the employed with the unemployed, where the former are obviously in a stronger labor market position than the latter. Comparing the fear of robots at work between these two categories informs on Hypothesis 1b. Furthermore, a comparison of the fear of robots at work between those in occupations to some extent threatened (manual workers and white-collar workers) with the fear of those in occupations not threatened by robotics (managers and professionals) allows us to test Hypothesis 1c. Lastly, as business owners may reap the benefits of increased productivity by means of robotics more than employees, we test Hypothesis 1d by comparing the fear of robots of large and small business owners on the one hand with that of managers and professionals, white-collar workers and manual workers on the other.

In addition to the *level of education* and *labor market position*, the three individual-level control variables outlined in Section 2.4 are added. *Age* is measured in the number of years and *female* is a dummy for female gender. Previous experience with robots at work is captured by *used robots at work*, a dummy variable for having this experience.

Table 2 reports descriptive statistics for the dependent variable as well as all individual-level regressors, calculated while applying the appropriate post-stratification weight factor provided in the Eurobarometer dataset (*W1*). This shows that within the European labor force, fear of robots at work is 2.66 on average (on a scale ranging between 1 and 5), with an overall standard deviation of 0.77 (and, at the country level, a standard deviation of 0.27).[12] Some 40% of all respondents have studied at least until the age of 20 years, whereas

Table 2. Descriptives for individual-level variables

	Mean	Standard deviation	Minimum	Maximum
Fear of robots at work	2.66	0.77	1	5
Studied after age 20	0.39	0.49	0	1
Studied until 16–19	0.50	0.50	0	1
Studied until 15	0.10	0.30	0	1
Large business owners	0.04	0.19	0	1
Small business owners	0.09	0.28	0	1
Managers and professionals	0.17	0.38	0	1
White-collar workers	0.20	0.40	0	1
Manual workers	0.36	0.48	0	1
Unemployed	0.14	0.35	0	1
Used robots at work	0.09	0.29	0	1
Age	40.74	11.45	16	65
Female	0.46	0.50	0	1

Source: Eurobarometer *Public Attitudes towards Robots* (2012).
Notes: A total of 11 206 observations; Eurobarometer post-stratification weight factor (*W1*) is applied. At the country level, the mean of fear of robots at work is 2.75 with a standard deviation of 0.27.

10% studied until the age of 15 years only. Manual and white-collar workers make up, respectively, 36 and 20% of the employed; 17% are managers and professionals; and the remainder are small and large business owners. Furthermore, 14% of the labor force is unemployed. Finally, only 9% of the labor force has experience with using robots at work.

3.2 Country-level variables

Seven country-level independent variables are used: two for measuring economic conditions, four for measuring institutional conditions, and one as a control variable for measuring cultural conditions. The two indicators for economic conditions are *GDP growth rate*, defined as real GDP growth in the previous year (source: Eurostat), and *unemployment rate*, measured as the share of the unemployed within the labor force (source: Eurostat). Similar indicators for economic conditions have previously been used by other authors with an interest in the impact of these conditions on perceived economic insecurity (e.g. Mau *et al.*, 2012), which is similar to the type of fear considered here.

The first two institutional indicators measure the level of social protection regarding unemployment risks (e.g. Van Vliet, 2011): *unemployment replacement rate* (the proportion of income from work replaced by unemployment benefits) and *unemployment benefits duration* (the number of weeks of unemployment benefit entitlement). Data on both are provided by the Welfare State Entitlements Data Set (Scruggs *et al.*, 2014). The third institutional indicator is *strictness of employment protection*, and measures how difficult it is to dismiss employees (source: The Organisation for Economic Co-operation and Development; OECD). The final institutional indicator is *trade union density*, which measures the share of wage and salary earners who are trade union members (source: OECD).

The cultural condition assumed to be relevant for understanding the fear of robots at work is *uncertainty avoidance*. This is measured by the degree to which the members of a society feel uncomfortable with uncertainty and ambiguity, and consists of an index based on aggregated scores with respect to three survey items (provided by Hofstede *et al.*, 2010). These ask whether employees (a) feel 'company rules should not be broken even when the employee thinks it is in the company's best interests', and probe employees' (b) self-perceived job stability and (c) nervousness and strain at work. The index is scaled from 0 to 100, with higher scores indicating higher levels of uncertainty avoidance (Hofstede, 1991): this index is widely used, and generally considered valid and reliable (Minkov and Hofstede, 2014).

Table 3 reports the country-level indicators used in our analyses. The variables measuring economic conditions (*GDP growth rate* and *unemployment rate*) clearly reflect the aftermath of the 2008 financial crisis: many countries have negative growth rates and high unemployment rates. These two economic indicators are negatively correlated.

Next to be considered are the institutional characteristics of countries, starting with the two indicators covering decommodification by means of unemployment benefits. Here, the UK and Poland can be seen to have the lowest unemployment replacement rates as well as the lowest unemployment duration; whereas Portugal and Spain have the highest values for these indicators. However, there are also countries that offer high unemployment replacement rates but relatively low benefit durations, such as Slovakia and Slovenia. It also should be noted that the extremely high score of Belgium for *unemployment benefits duration* (999) reflects this country's unlimited duration of benefit entitlement (Van Vliet, 2011; Scruggs *et al.*, 2014). For this reason, we will check the robustness of our results by removing Belgium from the data when testing country-level hypotheses in our upcoming analyses. *Strictness of employment protection*, the third institutional variable, is highest in Italy, Germany and Belgium, but low for countries like the UK, Ireland and Finland. This measure is positively correlated to both measures of the generosity of unemployment benefits, although these correlations are not excessively high, indicating the multidimensional nature of decommodification. The same conclusion can be drawn from the moderate to low relationships between the fourth decommodification indicator, *trade union density*, and the first three. In addition, the low to moderate relationship between the decommodification indicators on the one hand and the economic condition indicators on the other underscore the fact that economic and institutional conditions can largely operate independently from one another. This may also be the case when it comes to understanding country-level differences in terms of the fear of robots at work.

Turning to the last column in Table 3, *uncertainty avoidance*—our indicator for cultural conditions—is lowest for Denmark, Sweden and the UK, whereas it is highest in Greece, Portugal and Belgium. Furthermore, it is moderately related to both the economic indicators and to the unemployment benefit duration and replacement rate. Its relationship with *strictness of employment protection* and *trade union density*, on the other hand, is more substantial, and in the direction that one would expect: populations characterized by high (low) levels of uncertainty avoidance have high (low) trade union densities and the strictest (least strict) employment protection.

3.3 Methodology

Given that our hypotheses are formulated at two levels of analysis (the individual and the country), we apply a linear multilevel regression analysis to test them (DiPrete and Forristal, 1994; Hox, 2002). Multilevel models are a class of model recognizing that macro processes may have an impact on the individual actor over and above the effects of any individual-

Table 3. Scores country-level variables

	GDP growth rate	Unemployment rate	Unemployment replacement rate	Unemployment duration	Strictness employment protection	Trade union density	Uncertainty avoidance
Country scores†							
Austria	0.90	**4.90**	0.55	39.00	2.44	27.40	70.00
Belgium	0.10	7.60	0.67	**999.00**	2.94	55.00	94.00
Czech Republic	−0.80	7.00	0.38	**21.66**	2.60	13.40	74.00
Denmark	−0.70	7.50	0.56	104.00	2.32	67.20	**23.00**
Estonia	**4.70**	10.00	0.50	52.00	2.06	**6.40**	60.00
Finland	−1.40	7.70	0.56	100.00	2.16	**68.60**	59.00
France	0.30	9.80	0.71	104.00	2.82	7.70	86.00
Greece	**−6.60**	24.50	0.51	52.00	2.44	21.30	**100.00**
Germany	0.40	5.40	0.60	52.00	2.97	17.90	65.00
Hungary	−1.50	11.00	0.51	39.00	2.26	10.60	82.00
Ireland	−0.30	14.70	0.37	52.00	2.06	31.20	35.00
Italy	−2.80	10.70	0.55	34.00	**3.03**	36.30	75.00
The Netherlands	−1.60	5.80	0.80	90.00	2.88	17.70	53.00
Poland	1.80	10.10	0.26	52.00	2.39	12.50	93.00
Portugal	−4.00	15.80	0.77	121.00	2.90	20.50	99.00
Slovakia	1.60	14.00	0.63	26.00	2.16	16.80	51.00
Slovenia	−2.60	8.90	0.70	39.00	2.66	23.10	88.00
Spain	−2.10	**24.80**	**0.80**	104.00	2.55	17.50	86.00
Sweden	−0.30	8.00	0.60	60.00	2.51	67.50	29.00
UK	0.70	7.90	**0.18**	26.00	**1.71**	25.80	35.00

Sources: Eurostat, Hofstede et al. (2010), OECD, Welfare State Entitlements Data Set.
†Lowest and highest value for each country-level variable printed in bold.

Table 4. Multilevel regression analysis

Sample:	Model 1 Full	Model 2 Full	Model 3A Full	Model 3B Excl. Belgium
Individual-level regressors				
Constant	2.66***	2.31***	2.30***	2.29***
	(0.06)	(0.08)	(0.07)	(0.07)
Studied after age 20		Ref.	Ref.	Ref.
Studied until 16–19		0.18***	0.18***	0.17***
		(0.02)	(0.02)	(0.02)
Studied until 15		0.36***	0.36***	0.36***
		(0.03)	(0.03)	(0.03)
Large business owners		Ref.	Ref.	Ref.
Small business owners		0.06	0.06	0.06
		(0.05)	(0.05)	(0.05)
Managers and professionals		−0.07~	−0.07~	−0.07
		(0.04)	(0.04)	(0.04)
White-collar workers		0.11**	0.11*	0.11*
		(0.04)	(0.04)	(0.04)
Manual workers		0.19***	0.19***	0.18***
		(0.05)	(0.05)	(0.05)
Unemployed		0.21***	0.21***	0.20***
		(0.04)	(0.04)	(0.04)
Used robots at work		−0.32***	−0.32***	−0.32***
		(0.03)	(0.03)	(0.03)
Age		0.00~	0.00~	0.00*
		(0.00)	(0.00)	(0.00)
Female		0.18***	0.18***	0.19***
		(0.03)	(0.03)	(0.03)
Country-level regressors (standardized)				
GDP growth rate			−0.06	−0.06
			(0.04)	(0.05)
Unemployment rate			0.06*	0.05
			(0.03)	(0.03)
Unemployment replacement rate			−0.03	−0.05
			(0.05)	(0.06)
Unemployment benefits duration			0.04~	0.05
			(0.02)	(0.04)
Strictness employment protection			−0.00	0.00
			(0.04)	(0.04)
Trade union density			−0.07~	−0.08*
			(0.04)	(0.04)
Uncertainty avoidance			0.07~	0.07
			(0.04)	(0.04)
Variance individual level	0.536	0.490	0.490	0.494
Variance country level	0.064	0.043	0.013	0.013

Source: Eurobarometer *Public Attitudes towards Robots* (2012), Eurostat, Hofstede et al. (2010), OECD, Welfare State Entitlements Data Set.

Notes: Dependent variable is fear of robots at work. All models are linear multilevel models with random intercepts and fixed slopes. A total of 11 206 respondents within 20 countries for models 1, 2 and 3A; 10 650 respondents within 19 countries for model 3B; country-level regressors standardized to have a zero mean and unit standard deviation; standard errors reported in parentheses. Ref., reference category.

***$P < 0.001$, **$P < 0.01$, *$P < 0.05$, ~$P < 0.10$.

level variables. In particular, this type of regression analysis is sensitive to the nested structure of the data—in this case, individuals nested within countries—recognizing that individual-level outcomes are correlated within macro-level units.[13] These models are also known as contextual models (since they recognize that individuals operate within a macro context), hierarchical models or random coefficients models. Importantly, they disentangle the variance of the dependent variable into its individual- and country-level components, allowing us to test both individual- and country-level hypotheses.

Various types of linear multilevel models exist, depending on to what extent the individual-level coefficients are assumed to depend on the macro-level context. Our baseline specification allows random intercepts across countries, meaning that different countries may have different baseline levels of fear of robots. In this model, slopes for the individual-level variables are assumed fixed across countries, and, therefore, do not depend on context. As a robustness test, we also estimate random slopes models, which represent a more flexible specification in the sense that the effects of the individual-level variables may also vary by country. Futhermore, we will consider results when alternatively using the ordinary least squares (OLS) estimator, with and without country fixed effects.

4. Results

4.1 Main findings

Table 4 shows estimates from multilevel models that include a random intercept at the country level. In the first column, we estimate the null model to gauge the variance in the *fear of robots at work* at the two levels of analysis. This indicates that some 10% [(0.064/(0.536 + 0.064))*100] of the total variation in individuals' fear of robots is due to cross-country differences in fear of robots, and highlights the need for a multilevel model. Furthermore, variance at both levels is a necessary condition for testing our hypotheses, since we formulated them at both the individual (H1a–H1d) and country level (H2–H3). Model 2 then adds all individual-level variables to the model, and model 3A additionally includes all country-level variables. Finally, model 3B reestimates model 3A while excluding Belgium from the analysis.

The first two individual-level hypotheses—H1a and H1b—are corroborated. First, fear of robots falls in the number of years in education as predicted by H1a. Second, the unemployed are generally more fearful of robots at work than employed workers, consistent with H1b. Indeed, this higher fear among the unemployed is statistically significant relative to all employed groups except manual workers.[14] The third individual-level hypothesis—H1c—is also corroborated,[15] although the level of fear among white-collar workers is significantly lower than among manual workers.[16] The fact that white-collar workers demonstrate higher levels of fear of robots at work than managers and professionals suggests that, in line with previous findings of falling relative demand for middle (routine) rungs of the occupational ladder due to technological change (e.g. Goos and Manning, 2007; Autor and Dorn, 2013), white-collar employees (such as office clerks), also feel threatened by the introduction of digital technologies such as robotics.

Finally, the findings reported in Table 4 with respect to the last individual-level hypothesis, H1d, are mixed. On the one hand, manual workers fear robots at work more than both large and small business owners, while white-collar workers fear robots at work more than large business owners.[17] On the other hand, the level of fear of robots among small business owners does not differ significantly from that of white-collar workers, nor do managers and professionals fear robots significantly more than either large or small business owners. Indeed, managers and professionals are significantly *less* fearful than the two types of business owners.

Our results at the individual level are robust across models 2, 3A and 3B. With regard to the control factors, previous experience with robots has a significantly negative impact on fear of robots as expected. Furthermore, women are more likely than men to fear robots. Overall, at the individual level, most of the hypotheses derived from the notion of self-interest are supported.

We now turn to testing the country-level hypotheses, using model 3A in Table 4: in this model, the indicators for economic, institutional and cultural conditions (each standardized to have a zero mean and unit standard deviation across countries) are all included simultaneously. Although several country-level indicators are individually statistically insignificant, we keep them in our specification to avoid omitted variable bias. Model 3A shows that *unemployment rate* and *trade union density* yield significant coefficients in the hypothesized direction: respondents in countries with high unemployment rates (H2b) or lower trade union densities (H3c) have a higher fear of robots at work. Other indicators such as *GDP growth rate*, *unemployment replacement rate* and *uncertainty avoidance* have the expected sign, but are not individually statistically significant. Finally, *strictness of employment legislation* does not correlate with the fear of robots at work, and *unemployment benefits duration* has an unexpected positive relationship with the fear of robots. Comparing model 3A with 3B, where Belgium has been excluded, coefficients for all country-level indicators retain the same sign and similar magnitudes, but significance levels are lower (with the exception of *trade union density*), reflecting the reduced variation at the country level.

However, one may suspect that the zero average effect of EPL on the fear of robots is the result of different effects across worker groups. Indeed, for the employed, such legislation may lower fear of robots, whereas it could be neutral or even raise fear among business owners and those out of a job. We tested this by including a set of interactions of all labor market position categories with EPL in the specification of model 3A (results available on request). From this, we find that the effect of EPL on the fear of robots is almost zero (and statistically insignificant) for all worker groups except large business owners, where the effect is indeed positive but only significant at the 13% level. This provides only modest support for the idea that the impact of EPL in Table 4 goes undetected because of effect heterogeneity across worker groups. Similarly, the effect of trade union density may be argued to differ across worker groups: to the extent that trade unions protect the interests of employees only, we would expect its fear-reducing effect to be driven by employees rather than business owners or the unemployed. Here, when we add interactions between these three groups and trade union density we do find that the effect is statistically significant for employees only, and insignificant for business owners and the unemployed (results available on request).[18]

Summing up, one out of two indicators for a country's economic conditions (the unemployment rate) and one out of four indicators for a country's institutional conditions (trade union density) yield associations that are both statistically significant and in the expected direction: the effect sizes are nonnegligible, such that one standard deviation increase in trade union density or decrease in the unemployment rate reduces fear of robots at work by around a quarter (= 0.07/0.27*100) of a standard deviation. As such, country-level Hypotheses 2b and 3c are corroborated, whereas no statistically significant evidence is found in favor of country-level hypotheses 2a, 3a and 3b. Tentatively, this implies that economic and institutional conditions matter to some extent for understanding country-level differences in the fear of robots at work. However, these results should be interpreted with caution given the high number of insignificant estimates: this is likely the result of a relatively low amount of variation at the country level combined with high correlations among several country-level indicators. Especially, the control variable for cultural conditions (*uncertainty avoidance*) is problematic in this respect, since it has a statistically significant effect on fear of robots at work and is relatively strongly correlated with both economic and institutional conditions. However, one might argue that this shared variation can nonetheless be meaningful for identifying the effect of economic and institutional conditions. Indeed, when we do not control for uncertainty avoidance, we find similarly sized but statistically significant effects for four out of six macro-level indicators (all except the unemployment replacement rate and EPL).

4.2 Robustness checks

Table 5 presents further robustness checks on our results by modifying our multilevel model specification. By using the multi-item scale *fear of robots*, we have so far included a broad set of questions related to robots in the workplace. To consider the item arguably most narrowly in line with our research question, we also test our hypotheses on an alternative dependent variable: the single item '*robots steal people's jobs*', which has four answer categories [(1) totally disagree, (2) tend to disagree, (3) tend to agree and (4) totally agree].[19] Model 1 in Table 5, therefore, uses this alternative dependent variable, while including the full set of regressors at both the individual and country levels, as before.

The results for our individual-level hypotheses are robust to using this alternative dependent variable: they are qualitatively identical to the results reported in Table 4. The only difference is that we find slightly more support for H1b, since manual workers are found to have a lower fear than the unemployed. For the country-level hypotheses, we again confirm the role of the unemployment rate in increasing fear of robots, but the effect of trade union density is no longer present when considering this more narrowly defined dependent variable.

As a further robustness check on our model specification, model 2 in Table 5 estimates a multilevel model with *fear of robots* as the dependent variable (as in Table 4), but using random slopes for the individual-level regressors. This is a more flexible model specification as compared to our models from Table 4, since they allow coefficients of individual-level regressors to vary across countries. A comparison with the random-intercept specifications in model 3A from Table 4 reveals that the findings about our individual-level hypotheses are not affected by allowing random slopes. The estimated variances of the slopes (results available on request) show that the coefficients of individual-level regressors do vary somewhat across countries: in terms of our variables of interest, most variation is found for the coefficient for manual workers and the coefficient for small business owners (which have a variance of 0.007 and 0.005, respectively). Furthermore, the effects of country-level regressors do change as compared to the random-intercept model: in particular, the effect of the unemployment rate (H2b) disappears. On the other hand, the previously found effect of trade union density (H3c) does remain present.

Finally, Table 6 presents robustness checks using the OLS estimator, while clustering standard errors at the country level. Model 1 is consistent with results from Table 4 in terms

Table 5. Robustness checks, multilevel regression

	Model 1	Model 2
Dependent variable:	Robots steal jobs	Fear of robots at work
Model:	Random intercept	Random slopes
Individual-level regressors		
Studied after age 20	Ref.	Ref.
Studied until 16–19	0.21***	0.17***
	(0.03)	(0.02)
Studied until 15	0.30***	0.36***
	(0.03)	(0.03)
Large business owners	Ref.	Ref.
Small business owners	0.05	0.06
	(0.06)	(0.05)
Managers and professionals	−0.07~	−0.06
	(0.04)	(0.04)
White-collar workers	0.10*	0.12**
	(0.04)	(0.04)
Manual workers	0.19***	0.20***
	(0.05)	(0.05)
Unemployed	0.25***	0.23***
	(0.04)	(0.04)
Used robots at work	−0.18***	−0.31***
	(0.04)	(0.03)
Age	0.00	0.00~
	(0.00)	(0.00)
Female	0.14***	0.18***
	(0.02)	(0.02)
Country-level regressors (standardized)		
GDP growth rate	0.03	−0.06
	(0.05)	(0.04)
Unemployment rate	0.13*	0.03
	(0.05)	(0.03)
Unemployment replacement rate	0.01	−0.01
	(0.05)	(0.05)
Unemployment benefits duration	−0.00	0.04
	(0.03)	(0.03)
Strictness employment protection	0.02	0.01
	(0.07)	(0.05)
Trade union density	−0.01	−0.08~
	(0.05)	(0.04)
Uncertainty avoidance	0.07	0.08
	(0.05)	(0.05)
Variance individual level	0.751	0.484
Variance country level	0.023	0.007

Source: Eurobarometer *Public Attitudes towards Robots* (2012), Eurobarometer *Public Attitudes towards Robots* (2012), Eurostat, Hofstede et al. (2010), OECD, Welfare State Entitlements Data Set.
Notes: A total of 11 139 respondents within 20 countries for model 1; 11 206 respondents within 20 countries for model 2. Country-level regressors standardized to have a zero mean and unit standard deviation; standard errors reported in parentheses. Ref., reference category.
$^{***}P < 0.001$, $^{**}P < 0.01$, $^{*}P < 0.05$, $\sim P < 0.10$.

of both individual- and country-level hypotheses. Model 2 shows a fixed effect OLS model: this does not have either random intercepts or slopes, but captures all macro-level variation by means of a separate, fixed, intercept for each country. Since such fixed intercepts absorb all variation in our macro-level regressors, this model does not allow testing our country-level hypotheses. Our conclusions with respect to our individual-level hypotheses, however, are again unaffected by using this estimator. Finally, model 3 reestimates the fixed effect model but on the extended sample of all 27 European countries, including those for whom we do not have data on the macro-level variables. None of the individual-level coefficients are statistically significantly different across models 2 and 3, indicating that results for our individual-level hypotheses do not depend on this sample restriction.

To sum up, the conclusions about our individual-level hypotheses described in Section 4.1 seem to be quite robust to model specification. However, specific results for the country-level hypotheses are less stable: this sensitivity to modeling choices likely reflects the lower amount of variation at this level as well as the high correlations among some country-level regressors. However, we do still find some support for the overall hypothesis that country-level economic and institutional conditions matter for the fear of robots at work.

5. Conclusion and discussion

By focusing on the question *Can fear of robots at work be explained by economic self-interest?*, this article contributes to the public and academic debate on the perceived impact of robotics on work-related issues. This debate has intensified during the ongoing Digital Revolution as developments in robotics have sped up and adoption rates have increased. Notwithstanding the many benefits that can be gained in various domains by applying robotics, for some workers such changes may be disruptive. As a consequence, the introduction of robots may result in fear among those whose economic standing is likely to be adversely affected.

We find that a fear of robots at work can partly be understood along the lines of self-interest. Managers, professionals and the highly educated—who hold positions in the labor market that are unlikely to be affected negatively by the introduction of robotics—fear robots at work less than manual and white-collar workers and the less well educated. Results for macro-level factors are more mixed, but do suggest that those living in countries where economic conditions indicate better labor market prospects (through abundant job opportunities or higher GDP growth rates) and insulating institutional conditions (particularly a high trade union density) tend to be less fearful of robots in the workplace. Yet, as this study is a first step to examine how individuals perceive robots in the workplace, some of these conclusions may also result from limitations in our study design (cross-sectional data for a limited number of countries).

Our findings of course do not imply that notions other than self-interest are irrelevant for understanding the fear of robots at work, and some of our results may already point to this. Indeed, we cannot rule out that cultural differences also provide a partial explanation for differences in the fear of robots at work. One indication is that the level of education is among the strongest predictors of the fear of robots. This is suggestive, as one's education level has various cultural corollaries in addition to the labor market position and cognitive abilities it indicates. These cultural aspects are referred to as 'cosmopolitanism' (Hainmueller and Hiscox, 2006) or 'cultural capital' (Van der Waal and De Koster, 2015). Irrespective of the label used, it has been demonstrated that these cultural aspects of

Table 6. Robustness checks, OLS regression

Model:	Model 1 OLS	Model 2 OLS with country fixed effects	Model 3 OLS with country fixed effects
Sample:	Full	Full	Extended
Individual-level regressors			
Studied after age 20	Ref.	Ref.	Ref.
Studied until 16–19	0.17***	0.18***	0.18***
	(0.03)	(0.02)	(0.01)
Studied until 15	0.39***	0.36***	0.36***
	(0.04)	(0.03)	(0.02)
Large business owners	Ref.	Ref.	Ref.
Small business owners	0.05	0.06	0.07~
	(0.05)	(0.04)	(0.04)
Managers and professionals	−0.06	−0.07~	−0.06~
	(0.05)	(0.04)	(0.04)
White-collar workers	0.08~	0.11**	0.10**
	(0.04)	(0.04)	(0.03)
Manual workers	0.18**	0.18***	0.18***
	(0.05)	(0.04)	(0.03)
Unemployed	0.19***	0.21***	0.19***
	(0.04)	(0.04)	(0.04)
Used robots at work	−0.33***	−0.32***	−0.33***
	(0.03)	(0.02)	(0.02)
Age	0.00	0.00*	0.00**
	(0.00)	(0.00)	(0.00)
Female	0.19***	0.18***	0.17***
	(0.03)	(0.01)	(0.01)
Country-level regressors (standardized)			
GDP growth rate	−0.06		
	(0.04)		
Unemployment rate	0.06~		
	(0.03)		
Unemployment replacement rate	−0.03		
	(0.05)		
Unemployment benefits duration	0.04~		
	(0.02)		
Strictness employment protection	0.00		
	(0.04)		
Trade union density	−0.07~		
	(0.04)		
Uncertainty avoidance	0.07		
	(0.04)		

Source: Eurobarometer *Public Attitudes towards Robots* (2012), Eurobarometer *Public Attitudes towards Robots* (2012), Eurostat, Hofstede et al. (2010), OECD, Welfare State Entitlements Data Set.

Notes: Dependent variable is fear of robots at work. A total of 11 206 respondents within 20 countries for models 1 and 2; 14 386 respondents within 27 countries for model 3. Country-level regressors standardized to have a zero mean and unit standard deviation; standard errors clustered by country reported in parentheses. Ref., reference category.

***$P < 0.001$, **$P < 0.01$, *$P < 0.05$, ~$P < 0.10$.

education account for the high levels of cultural discontent—also referred to as 'anomie' (Srole, 1956) or 'cultural insecurity' (Van der Waal *et al.*, 2010)—among the less educated in Western societies in recent decades (Margalit, 2012; Van der Waal and De Koster, 2015). This discontent entails feeling threatened by the complexities of modern life, which is considered to be fickle and disorderly. The introduction of robots may add to that complexity, and the high levels of fear of robots at work among the less educated might, therefore, not exclusively reflect economic self-interest but also be part of their cultural discontent. In our analyses, we strive to control for such cultural differences by including Hofstede's (1991) and Hofstede's *et al*. (2010) country-level indicator for uncertainty avoidance. The estimated coefficient for this regressor is always positive and economically sizable—although not always statistically significant— suggesting that countries with higher uncertainty avoidance are indeed more likely to be fearful of robots. This does not rule out, of course, that there are other cultural dimensions of fear of robots which our model does not include, and which are correlated with workers' education level.

Turning from the academic to the societal relevance of what we identified, our findings indicate that, for those interested in tempering the fear of robots at work, investment in education and training could be one way forward. Here, training in nonroutine skills such as creativity, problem-solving, and analytical thinking could be particularly relevant, since these are not easy to automate (Smit, 2013). On the other hand, our results indicate that those who have used robots at work fear them less, which tentatively suggests that a more widespread use of robotics may lower such fears.

Finally, we must address some of the limitations of our study and make suggestions for future research. First, the associations shown here are purely descriptive: they should be interpreted as partial correlations rather than causal effects. For example, we cannot claim that experience with robots causes workers to be less afraid, since workers who are less afraid of robots may have self-selected into labor market positions exposing them to this technology. Second, our analyses and conclusions at the country level are limited by the relatively low amount of variation at this level. Third, due to data limitations, we were unable to study industry-level differences, but it is to be expected that the fear of robots at work is higher in industries where robots are most likely to replace human labor. Work in the automobile industry, for instance, is easier to automate than that in personal service industries where most tasks involve human interaction.

An interesting avenue for future studies could be to try and investigate fears of various types of robots: our analyses do not make this distinction. Although survey respondents were provided with a broad definition of robotics (Section 3), it may be that today's fears of robots mostly refer to industrial and factory robots, since these are currently most predominant in the workplace. However, it is possible that service robots and cobots are less likely to fully replace human workers. In particular, assistive technologies (such as cobots in healthcare) are designed to complement labor, and still require human oversight and input. A similar point can be made about robots embodying machine-learning technologies which are likely to be more widely implemented in the future: since such technologies do not provide rule-based solutions but rather 'best guesses' based on statistical models, human judgment is likely to remain both valuable and necessary. However, working with cobots or other new robotic technologies does not rule out the possibility that people still perceive insecurity concerning the continuity of several aspects of their jobs (e.g. Hartley *et al.*, 1991), such as the level of autonomy and self-actualization (Carr, 2015). Furthermore, working side to side with such robots may require different skills than the ones needed prior to their implementation, and as such still prove a disruptive force from the perspective of workers.

Finally, more research on the cultural conditions that affect the fear of robots at work is needed, as we were only able to consider the role of country-wide uncertainty avoidance. For example, exposure to robots through cultural products such as movies may also play a role in understanding the acceptability of robots in the workplace (cf. Katz *et al*., 2015). Related to this, individual personality traits such as extraversion could also be included in future studies directed at understanding the fear of robots at work, since these have been found to affect the way humans interact with devices (cf. Luzack *et al*., 2003).

Notes

1. These labor market impacts are not the sole focus of the public debate about robotics: other aspects, such as concerns about quality (e.g. the quality of care in the health sector), safety and privacy also play a role.
2. An example of cobots are care-giving robots (e.g. Hirsch *et al*., 2000; Sparrow and Sparrow, 2006), designed to improve the quality of life of the elderly (e.g. Enz *et al*., 2011; Dahl and Boulos, 2014).
3. New robotic technologies are being applied across a wide range of sectors, such as in health care, cleaning and entertainment (Frey and Osborne, 2015). Also see Remus and Levy (2015) for a careful consideration of the future automation potential of job tasks for one particular occupation, lawyers.
4. Although some would argue that economic growth is not a primary goal of economic policy *per se*.
5. Graetz and Michaels (2015) estimate that the increased use of robots raised advanced countries' average growth rates by about 0.37 percentage points over 1993–2007.
6. For an overview of the literature on the effects of unemployment and the introduction of new technologies on skill depreciation and obsolescence, see De Grip and Van Loo (2002).
7. We are aware that robotic technology may be introduced for other reasons than productivity gains: for example, robots can be used to improve the quality of work (i.e. improving adverse and unsafe working conditions). Nevertheless, we assume that, on average, employers introduce robotic technology to increase productivity, and, therefore, expect that their profits will rise as routine labor is replaced by robots.
8. For survey details, see http://ec.europa.eu/digital-agenda/en/news/dataset-eurobarometer-survey-public-attitudes-towards-robots.
9. The included countries are: Austria, Belgium, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, the Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden and the UK. The macro-level data are missing for Bulgaria, Cyprus, Latvia, Lithuania, Luxembourg, Malta and Romania. As a robustness check, we will test our individual-level hypotheses on the extended sample of all 27 countries, also.
10. For the exact procedure of calculation, see the footnote of Table 1.
11. Factor analysis is a method of data reduction that considers to what extent variables exhibit similar patterns of responses.
12. This fear furthermore differs across countries, with the highest level of fear being observed in Greece, Portugal and Spain, whereas workers in Denmark, Sweden and Slovakia are the least fearful.

13. Multilevel models also have more power and produce less-biased standard errors (Hox, 2002) than OLS models even when clustering standard errors to address the Moulton (1986) aggregation problem (Cheah, 2009).
14. The null hypothesis of equality of the coefficients is rejected for white-collar workers ($P = 0.00$), managers and professionals ($P = 0.00$) and small business owners ($P = 0.00$); but not for manual workers ($P = 0.40$).
15. The null hypothesis of equality of the coefficients is rejected with $P = 0.00$ for both white-collar workers and for manual workers.
16. The null hypothesis of equality of the coefficients is rejected, with $P = 0.00$.
17. The null hypothesis of equality of the coefficients between white-collar workers and small business owners is not rejected, with $P = 0.16$.
18. The results for these interactions hold irrespective of whether the interactions with EPL are also included.
19. Although we continue using a linear multilevel regression model for ease of interpretation and comparability with Table 4, our results are robust to alternatively using an ordered logit regression analysis in recognition of the ordered response nature of the outcome variable.

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