Don’t Fear the Robots: Automatability and Job Satisfaction

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Abstract

We analyse the correlation between job satisfaction and automatability – the degree to which an occupation can be or is at risk of being replaced by computerised equipment. Using multiple survey datasets matched with various measures of automatability from the literature, we find that there is a negative and statistically significant correlation that is robust to controlling for worker and job characteristics. Depending on the dataset, a one standard deviation increase in automatability leads to a drop in job satisfaction of about 0.64% to 2.61% for the average worker. Unlike other studies, we provide evidence that it is not the fear of losing the job that mainly drives this result, but the fact that monotonicity and low perceived meaning of the job drive both automatability as well as low job satisfaction.

Keywords: Job Satisfaction, Automation, Monotonous Tasks
JEL Classifications: J01, J28, J81, O33

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1 Introduction

Technical innovation, aimed at increasing labour efficiency, often comes with a fear of jobs being at risk and whole industries shifting away from human capital. Past industrial revolutions, like those associated with the invention of the steam engine, the introduction of assembly lines in manufacturing work, and robotics, typically reduced the physical stress of jobs. However, they were also associated with psychological stress originating from the risk of the job being made redundant (Curtis, 1983), previously even prompting workers to destroy machinery as a drastic form of protest against having their jobs made redundant (also known as *Luddism*, see e.g. Costinot and Werning, 2018).

In today's technical revolution, technologies such as Artificial Intelligence (from hereon: AI) and advanced robotics have progressed to the point where they are capable of replacing much of the manual labour in any productive sector, and more recently, large parts of the most common work type in western societies: office and administrative occupations.[1] The extent to which this capability for replacement will be turned into actual job losses is a matter of costs and regulations[2] and is currently an active field of research (e.g. Frey and Osborne, 2017; Arntz et al., 2017; Acemoglu and Restrepo, 2018, 2020).

Definition 1 (Automatability)**.** *Potential or risk for a job to be completed by means of computer-controlled equipment.*

Acemoglu and Restrepo (2020) investigate the effects of automatability (in particular, robotics adoption) on the US labour market in terms of employment and wages. They exploit regional variation to estimate the total employment effect to be an absolute job loss of 400,000 jobs and an overall wage reduction of 0.42%. The authors indicate that given the rapid increase in the abilities of robotics, these effects are likely to be lower bounds in the mid- to long-run.

One of the main driving forces of innovation and investment in new technologies is how likely they are to improve well-being. Politicians and economists alike agree that income, either in aggregate as GDP per capita or individual earnings after taxes, cannot serve as a sole indicator to test whether they do. The focus has thus shifted to subjective measures of life quality more generally, such as health and overall happiness, and to job-satisfaction in specific (Stiglitz et al., 2010). While the discussion of the effects of automation on the economy and the labour market is currently largely centred around potential GDP growth and unemployment risks (see Dauth et al., 2017; Calvino and Virgillito, 2018), there might be more immediate ways in which it affects employees' subjective quality of (work) life.

[1] This sentence was indeed created with the help of talktotransformer.com (King, 2020), which uses a neural network to generate text from a sample – the first paragraph in our case.

[2] For example, with respect to autonomous driving and safety standards concerning so-called cobots that interact with humans in the workplace.

Thus, our main research question asks whether jobs associated with lower job satisfaction are the ones with higher automatability, i.e. whether the employees in these jobs have a higher potential or risk to be replaced by AI and robotics. Further, we explore the prevalence of these effects across countries and across industries. Finally, we argue that these effects are largely due to the nature of the respective jobs, rather than the workers' fear of losing their jobs to automation.
Thus far and to our knowledge, the only study that works in this direction is Schwabe et al. (2020), who study a micro-dataset of Norwegian workers.[3] Their focus is on identifying the specific effects of workers' job-related fears of automation, rather than the general correlation between automatability and job satisfaction. While they try to identify the causal effects of the fear of losing a job through automation, we argue that it is partially in the nature of jobs with high automatability to be associated with lower job satisfaction, even before this fear arises.[4] Monotonicity of a job thus allows for easier automation – as less contingencies need to be considered by the computer – but it also causes the job to be less interesting and meaningful, affecting job satisfaction (Melamed et al., 1995).

We use survey data from multiple sources (the General Social Survey, GSS; the European Social Survey, ESS; the Work Orientations IV dataset of the International Social Survey Programme, ISSP) and combine them with estimated automatability measures from the literature (Frey and Osborne, 2017; Arntz et al., 2017; Manyika et al., 2017) to investigate their correlation while controlling for available confounding variables within each dataset. We find that there is a negative, statistically significant and robust relationship between automatability on job satisfaction. Depending on the job satisfaction scale and automatability measure used, a one standard deviation increase in the automatability measure results in a 0.64% to 2.61% reduction in job satisfaction for the average worker. We show that controlling for the fear of losing their job or their subjective feeling of job security does not significantly affect this result. However, when we control for the subjective assessment of how interesting and/or meaningful the occupation is to the worker the effect completely vanishes. Also, we repeat our regressions with data from the 1970s where automation was less present and less salient, arriving at the same results, which demonstrates that the fear of losing their job is not the main, or at least not the sole, channel that determines the correlation of automatability and job satisfaction.

Our results have normative implications for the effects of skill-biased technical change on worker utility and related issues like taxation and welfare (Blankenau and Ingram, 2002; Ales et al., 2015; Costinot and Werning, 2018). Within this line of research, non-monetary components to worker welfare are important for the design of optimal labour taxation and social benefit schemes, particularly, if these components change systematically with the technical advances. The

[3] Hinks (2020) is similar in spirit but focusing on overall life satisfaction.
[4] See Mokyr et al. (2015) for a discussion of technological anxiety and economic growth.

usual debate is often centred around new forms of capital taxation when capital changes from tangible machines to intangible algorithms (e.g. Abbott and Bogenschneider, 2018; Thuemmel, 2018; Rebelo et al., 2019), but our findings suggest that a debate on new forms of labour taxation could be due.

Further, we add to the discussion on the consequences of automation beyond employment and wage depression. Given the well-documented evidence on job-anxiety-related and stress-related illnesses (see e.g. Nieuwenhuijsen et al., 2010) and the associated health costs (see e.g. Van der Klink et al., 2001), it is important to shed light on how job satisfaction is expected to change with the increased use of AI and robotics in the workplace, whenever they are replacing parts of the workforce rather than merely augmenting its productivity.

We also complement research on productivity effects of robotics, by providing an additional channel from automation to worker productivity. While robotics and AI can aid workers and fulfil tedious tasks wherever they assist humans, they also seem to mainly replace jobs that are associated with lower job satisfaction. This is likely affecting intrinsic work motivation in the long run and thus suggests another important channel to worker productivity beyond task complementarities with machines.

However, this paper should not be misunderstood as a blind advocacy of automation and for the reduction of the workforce overall or in any specific industry. If we were to compare the satisfaction of workers in high-risk jobs with that of unemployed respondents, it would likely be hard to argue in favour of automation at the cost of structural unemployment. Instead we argue that the current phase can become another transitional period from manual labour to largely automated production, where technologies allow it. Our results indicate that once such a transition is complete, and the corresponding labour market frictions are overcome, the resulting set of jobs would contribute towards a more satisfied workforce. It is thus paramount to politically lay out adequate plans to reduce those frictions and train future workers, thus enabling them to fulfil the emerging jobs and those jobs that remain.

The remainder of the paper is structured as follows. In Section 2.1 we review the literature on job satisfaction. In Section 2.2 we consider contributions to the estimation of automation risks. Section 3 describes the datasets utilised and how they were merged. In Section 4 we state our empirical models and results, which are in turn discussed in Section 5. Section 6 concludes.

2 Literature Review

As we are combining data on subjective job satisfaction with estimated measures of automatability, our study roughly falls between two streams of literature.

2.1 Job Satisfaction

Working adults spend roughly a third of their day at work. Thus work is a major factor contributing to happiness (Clark et al., 2017) beyond the income that it generates (Layard, 2011; De Neve and Ward, 2017). How people feel about their work and the degree to which people like their jobs can be captured by an attitudinal variable, known as job satisfaction, which is typically elicited through survey questions (Spector, 1997). These can either be single survey questions which assesses how people feel about their work on a global level or a series of survey questions assessing how people feel about the various domains or facets of their work.[5] From the perspective of employers, high job satisfaction is desirable as they are correlated with low levels of employee turnover rates (Lambert et al., 2001), low levels of absenteeism (Hacket, 1989) and ultimately increased levels of organisational productivity (Inuwa, 2016).

Typical studies on job satisfaction investigate its correlation with income, gender, ethnicity, work-life balance, industry/sector, the terms of employment contract and prior experience of unemployment, as well as its variation across countries (Judge et al., 2001; Westover and Taylor, 2010). Being self-employed (Lange, 2012), having a higher income (Rayo and Becker, 2007), previously experiencing phases of unemployment (Clark et al., 2001), as well as higher age (Kalleberg and Loscocco, 1983) are typically associated with higher levels of current job satisfaction.
Being non-white (Antecol and Cobb-Clark, 2009) (the typical explanation being race discrimination), male (Clark, 1997; Bender et al., 2005) and working in a blue collar job (Hu et al., 2010) are typically associated with lower subjective job satisfaction. In our regression analysis, we show that the correlation between automatability and job satisfaction is robust to controlling for these factors known to the literature, whenever appropriate measures are available.

We consider job satisfaction scores measured on 4,7 and 11 point Likert scales, depending on the dataset used. There are limitations to using these measures. As the measures are self-reported, workers could have systematic biases that drive or weaken our results. The use of indices created from several facets of satisfaction in the workplace (e.g., with respect to career paths, salary, excitement about the daily tasks) does not mitigate this concern, since these measures themselves are typically elicited through surveys as well, and thus do not result in objective measures either. Thus, we use the global measure of job satisfaction – the answer to a question like "All things considered, how satisfied are you with your present job?" on one of the above-mentioned scales – as this is widely done across the literature for seminal research in social psychology (e.g. Scarpello and Campbell, 1983), sociology (e.g. Ross and Reskin, 1992) and economics (e.g. Freeman, 1977). By demonstrating the robustness of our results across the different scales, we avoid advocating one of them over the others.

[5]These domains include, but are not limited to, wage and rewards, job design, job autonomy, job security, organisational environment and culture, job variety and social capital (Spector, 1997).

2.2 Automatability Measures

To our knowledge, the first article that provides concrete estimates of automatability by job code is Frey and Osborne (2017). They use the O*Net dataset to match engineers' ability to automate tasks which are necessary in 702 jobs. They identify a list of bottlenecks – intelligence features that are currently hard or impossible to computerise: 'perception and manipulation', 'creative intelligence' and 'social intelligence' – which are assigned to skills listed in the O*Net dataset. These skills are in turn matched to the jobs in which they are needed. Frey and Osborne (2017) regress a dummy of expert assessments of automatability in 70 jobs on whether each of these bottlenecks apply to skills relevant in the respective job. Once the training results of the machine learning algorithm were validated, they ran it on the entire set of 702 jobs to provide their estimates. Studies trying to estimate automatability largely build on theoretical frameworks in which workers need a specific set of skills to perform tasks needed for the job they are assigned to. The allocation of tasks and skills to jobs is then taken to the data. Autor and Dorn (2013) is a seminal example of this stream of literature and Frey and Osborne (2017), both theoretically and conceptually, build largely on it. Other foundational papers include Aghion and Howitt (1994) and Brynjolfsson and McAfee (2014).

Frey and Osborne (2017) triggered a body of follow-up research that either critically assessed their approach (see e.g. Brandes and Wattenhofer, 2016; Bonin et al., 2015), applied it to other labour markets (see e.g. Bonin et al., 2015; Dengler and Matthes, 2015; Arntz et al., 2016; Manyika et al., 2017) and specific industries (see e.g. Decker et al., 2017), or built on it by investigating further questions that result from many jobs being prone to automation (see e.g. Acemoglu and Restrepo, 2018; Autor and Salomons, 2018; Bessen et al., 2019; Acemoglu and Restrepo, 2020). We largely see our contribution to the latter type of research, as we take the various sources of data on job satisfaction and automatability as given, and investigate the correlation between these variables.

Other articles within the broader literature investigate the empirical contributions to production from the side of robotics (see e.g. Graetz and Michaels, 2018).

3 Data Description

As we are combining numerous data sources for our empirical analysis in Section 4, this section provides a broad description of the data. We utilise three survey datasets: the General Social Survey or GSS (Smith et al., 2020), the European Social Survey or ESS (Anonymous, 2012) and the Work Orientations IV dataset of the International Social Survey Programme or ISSP (Carton et al., 2017). These surveys provide data on job satisfaction; as well as other individual and household characteristics, which provide a range of relevant control variables. They also include job codes which we use to match them to measures of automatability. We consider four such measures which we summarise in Section 3.2.

Our empirical analysis, firstly, considers the US case in Section 4.1, which combines the GSS dataset with the estimates from Frey and Osborne (2017) for the bulk of the analysis. Then, secondly, it considers the European case in Section 4.2, which combines the ESS dataset with the estimates from Dengler and Matthes (2015). Lastly, it considers the general world-wide case in Section 4.3, which combines the ISSP dataset with the two aforementioned automatability measures, as well as a measure provided by Manyika et al. (2017). However, also for the first two survey datasets, we consider the other measures as robustness checks. Some of the control variables relate to demographics and appear in all three survey datasets. These are used in a baseline specification for purposes of comparison. We then exploit the unique aspects of each survey dataset to gain additional insights.

3.1 Survey Data on Job Satisfaction

This subsection briefly describes the three survey datasets used in the empirical analysis to give the reader a feel for the size and scope of each.

3.1.1 The General Social Survey

The General Social Survey (GSS) has been conducted in the United States of America since 1972. It began as an annual survey but since 1994 it has been conducted biennially in even numbered years. The survey is conducted by the University of Chicago's National Opinion Research Center (NORC).[6] While it contains some topical questions which can vary between waves of the survey, it contains a core of demographic, behavioural and attitudinal questions. The main survey provides cross-sectional data, from which we consider the period from 2006 to the most recent available year, 2018. This is a time frame in which we believe automation became both relevant and salient. This cross-sectional survey design was augmented with a rotating panel design. It includes three panels starting in 2006, 2008 and 2010, respectively, each consisting of three biennial waves. They therefore finished in 2010, 2012 and 2014 respectively. After 2014, the rotating panel design was discontinued.

We combine the cross-sectional data with the panel data. Overall this dataset therefore spans from 2006 to 2018 and contains 12,121 observations (for which both job satisfaction and job codes

[6]The General Social Survey (GSS) is a project of the independent research organization NORC at the University of Chicago, with principal funding from the National Science Foundation (Smith et al., 2020).

are available). Due to the overlap between the panel data and the cross-sectional data, there are more observations in the earlier years, up to 2014. Due to the additional overlap between the panel-waves, there are more observations in 2010 than in the other years. Table 1 shows the breakdown of observations by year and data type.

Table 1: GSS Observations (by Year and Data-type)

Year	Cross-Section Obs	Panel Obs	Total Obs
2006	1126	747	1873
2008	786	1382	2168
2010	802	1925	2727
2012	814	1152	1966
2014	964	513	1477
2016	960	0	960
2018	950	0	950
Total	6402	5719	12121

Job Satisfaction is elicited through a single question which asks the respondent how satisfied they are with the work they do on the whole[7]. The respondent chooses from four responses: very satisfied, moderately satisfied, a little dissatisfied, or very dissatisfied. The data also contains Census 2010 Occupation Codes (OCC2010) which are matched to the relevant automatability measures.

The main demographic variables available, which make up our baseline specification of controls, are income, work hours, employment type, age, gender, ethnicity, level of education, marital status, number of children, and a self-reported measure of health. In addition, we consider variables relating to subjective job security, socio-economic class/financial position, religion and other worker opinions.

3.1.2 The European Social Survey

The European Social Survey (ESS) is a cross-national survey conducted across Europe. Established in 2001, with the first round of data collection in 2002, this is also a biennial survey which aims to measure attitudes, beliefs and behavioural patterns in over thirty European nations. Job satisfaction is only available for 2012, which restricts the dataset to a cross-section from this single year. Still, we obtain 23,852 observations across 29 countries that provide sufficient cross-country variation to exploit. The frequency of observations for each country is given in Table 27 in Appendix B.

Just as in the GSS, job satisfaction is elicited through a single question asking how satisfied the

[7]Exact phrasing: "On the whole, how satisfied are you with the work you do–would you say you are very satisfied, moderately satisfied, a little dissatisfied, or very dissatisfied?"

respondent is with their present job[8]. However, in the ESS dataset, job satisfaction is measured on a scale from 0 'extremely dissatisfied' to 10 'extremely satisfied'. This larger range of potential responses offers more nuance than the GSS dataset. The data contains the 2008 International Standard Classification of Occupations (ISCO-08) codes which are used to match the relevant measures of automatability.

The same main demographic variables (as for the GSS dataset) are considered to establish a baseline specification of controls. There are some differences in how these variables are measured between the datasets, which are discussed further in Section 4 when exploring descriptive statistics. Despite this, there are sufficient similarities to allow a comparison between the results of the datasets. Then, in addition, we exploit the cross-country variation within the ESS dataset, as well as items relating to the workers' attitudes on current and future aspects of their job and life, and other worker and job characteristics that are absent from the other datasets.

3.1.3 The International Social Survey Programme

The International Social Survey Programme (ISSP) carries out annual surveys since 1984 across a growing number of member states. Initially the survey covered the four member states - Australia, Germany, Great Britain, and the United States – while the current dataset we are using provides data on 37 states. In total, the dataset provides 23,055 observations collected over the years 2015 (13,987 obs.), 2016 (8,137 obs.) and 2017 (931 obs.). The frequencies for each country are given in Table 28 in Appendix B.

In this dataset job satisfaction is again elicited through a single question asking how satisfied the respondent is with their present job[9]. Here, job satisfaction is measured on a scale from 1 'extremely dissatisfied' to 7 'extremely satisfied'. This completes the list of usually employed scales for measuring job satisfactions with direct questions in surveys and provides a middle ground between the GSS' 4-point and the ESS' 11-point Likert scale. The data as well contains the 2008 International Standard Classification of Occupations (ISCO-08) codes which are again used to match all available measures of automatability.

On top of questions considered in the GSS and ESS sections, the ISSP provides items that are more specific to the respondents' occupations, as opposed to their life in general. We use these to test the fear-based explanation versus our suggested explanation that job satisfaction and automatability are both correlated with the degree of task-monotonicity and low perceived meaning of the job.

[8]Exact phrasing: "All things considered, how satisfied are you with your present job?"
[9]Exact phrasing: "How satisfied are you in your (main) job?"

3.2 Estimates of Automation Risk

The automatability measures stem from research articles starting with the seminal contribution by Frey and Osborne (2017).

Table 2: Sources for Automation Risk and Potential from Various Sources

Name	# of Jobs	Regional Scope	Concept	Approach	Acronym	Job Code
Frey and Osborne (2017)	700	US	Risk	Jobs	FO	SOC10
Dengler and Matthes (2015)	133	Germany	Potential	Tasks	GER	ISCO08
Arntz et al. (2016)	**	OECD Countries	Potential	Tasks	OECD	ISCO08
Manyika et al. (2017)	***	US	Potential	Tasks	MK	SOC2018

**: Arntz et al. (2016) provide overall automation potential for entire countries, rather than professions.

***: In Manyika et al. (2017) Exhibit E4, measures for 19 selected sectors were considered. We manually assigned these to the SOC2018 codes.

Table 2 lists the different sources used, how many jobs they consider and for which regions they were estimated. We use the acronyms in the last column for the respective measures from hereon. The MK measure is slightly problematic, since it only varies across 19 values. We include it here to show that even with this fairly coarse measure we reach a good degree of robustness of our main result. The table also includes whether the estimates should be interpreted as *automation risk* or *automation potential*, according to the respective authors. Since we are aiming to discuss differences between and disentangle effects of fear of automation on the one hand and automation correlating with the monotonicity of the job on the other hand, this distinction is conceptually crucial. While these potentials and risks should clearly be positively correlated, they might differ substantially for some jobs and might evolve differently over time. *Automation risk* refers to the actual probability that a given job will be automated in the next couple of years. While a more concrete definition of the time frame is usually not given, these estimates do typically incorporate the cost of the automation technology, both acquisition and maintenance, the labour costs of workers in that industry, home and abroad, as well as political regulations on the type of technology that had to be used. When we refer to *automation potential*, we merely refer to the share of tasks of a job that could technically already be fully automated. The automation risk for cab drivers in Germany, for example, is thus considerably lower than the automation potential for this job, as the regulatory frameworks for driving assistants are very strict, passengers might prefer human drivers, and the technology is still fairly expensive. Yet, from a purely technical vantage point, autonomous driving is already being piloted in many locations across the globe.[10] Conceptually, automation risk does not necessarily have to be lower than potential though. If health and safety considerations demand

[10]For example, Daimler in San Jose (Daimler Mobility AG, 2020) or Waymo in numerous states in the US (Waymo LLC, 2020).

the deployment of immature technology or investment opportunities encourage higher current investment in technologies that increase the future automation potential of certain jobs, we can also think of opposite cases. While this certainly does not apply to the majority of occupations, those that come to mind are bomb disposal workers and industry divers.

In order to combine the automatability measures with the survey data, we create crosswalks containing and matching the available job codes in the survey datasets on the one hand and those used for the estimation of the automatability measures on the other hand. For some occupations one classification system might be more coarse or finer than another. This means that some job codes have less distinct subcategories within occupations, leading to multiple jobs being assigned the same automatability figure or the same job being assigned multiple, different automatability figures. The former case is only a problem of reduced variability and there is not much we can do about it, other than estimating our own figures, which is beyond the scope of the paper. The latter problem, with one job having different automatability figures is potentially more problematic. We use the mean of these figures for each job throughout our analysis, unless mentioned otherwise. Generally, we can say that results are robust to the use of the median, maximum or minimum of these values.

4 Empirical Analysis

Our analysis is divided into three parts that mainly differ by their regional scope. Section 4.1 considers data from the US, followed by Section 4.2 which utilises data from 29 countries across Europe. Lastly, Section 4.3 uses data from 37 countries across the world. In each case we begin by displaying various simple specifications to show the negative correlation between automatability and job satisfaction, and then provide robustness checks for the sign and significance of the relationship. We then exploit aspects of each dataset to provide supporting evidence for our main hypothesis, that job satisfaction is mainly affected through the nature of the job, rather than the fear of automation.

4.1 General Social Survey - The US Case

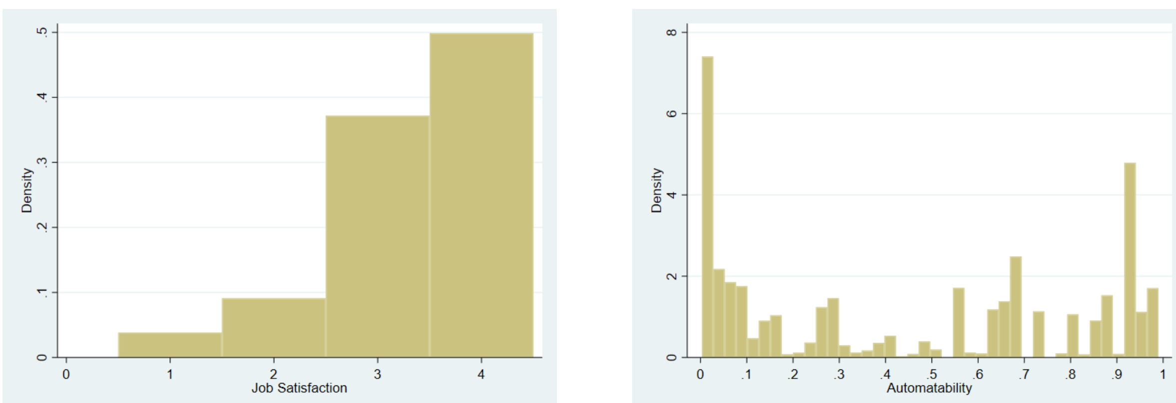
The data used in this subsection is from the General Social Survey or GSS (Smith et al., 2020). It offers both cross-sectional and panel-data. We combine these datasets to an unbalanced panel of 12,121 observations covering the period from 2006 to 2018. To this data, we match the *FO* automatability estimates discussed in Section 2.2 by the Census 2010 Occupation Codes (OCC2010) given in the data.

As the panel-data lacks survey weights and the cross-sections lack a panel-data structure, our initial analysis is estimated using an ordered Probit model (o-Prob) on the pooled data. We conduct our main empirical analysis on this entire dataset, before splitting the data into panel-data and cross-sections again for our robustness checks. Splitting the data in this way allows us to apply survey weights to the cross-sections and use panel-data techniques on the panels to exploit time variations in job satisfaction and some of the covariates. Our findings are robust to using the pooled or separated datasets. In additional robustness checks, we also consider the other measures of automatability as the main explanatory variable of interest, in place of the *FO* estimates.

4.1.1 Descriptive Statistics and Correlations

As our dependent variable, the dataset contains the respondents' job satisfaction scores on a scale from 1 'Very Dissatisfied' to 4 'Very Satisfied'.[11] We call this variable *JobSat4*.

Figure 1: Histograms



(a) *JobSat4* (b) *Autom-FO*

Figure 1 Panel (a) shows that the distribution of job satisfaction is fairly skewed towards the more positive evaluations. While this negative skew (of -1.12) in the data is not a large concern in itself, as our sample size is large and we are mainly considering ordered Probit regressions, the main issue is the limited variation in responses. 49.88% of respondents reported to be "very satisfied", while 87.06% report to be at least "moderately satisfied" (i.e. categories 3 and 4). This leaves only 12.94% expressing dissatisfaction. We have some concerns that the phrasing of categories (with "moderately satisfied" as category 3) may have anchored the responses to the upper end of the distribution, with a low threshold of giving a high score and therefore some potential variation grouped together in the top categories. This is addressed to some extent in the ESS and ISSP which both offer more potential responses and a more symmetric wording along the

[11]The original scale ranges from 4 'Very Dissatisfied' to 1 'Very Satisfied'. For a more intuitive uptake of the results we opted to invert it.

more detailed scales.
Figure 1 panel (b) shows the distribution of the *FO* automatability measure. Their distribution is strongly bi-modal with jobs close to 1 being fully automatable by computerised equipment, while those close to 0 are not automatable at all.

Additional to these main variables of interest to our research question, we use an extensive list of additional information on the respondents covering their key demographics (age, ethnicity, sex, marital status, number of children, etc.), their financial status, job characteristic and responses that are typically found to be important covariates in studying life or job satisfaction as outlined in Section 2.1. Table 3 provides descriptive statistics for job satisfaction, the *FO* measures and the most important demographics. The exact questions to the variables we use can be found in Smith et al. (2019).

Table 3: Descriptive Statistics of Sample Demographics

	N	Mean	Std. Dev.	Min.	Max.
JobSat4	12,121	3.331	0.796	1	4
Autom-FO	12,121	0.449	0.368	0	1
Income	9,186	10.392	2.835	1	12
WkHrs	9,759	41.850	14.827	1	89
WkSlf	12,115	0.133	0.340	0	1
Age	12,044	44.093	13.772	18	89
Male	12,121	0.442	0.497	0	1
White	12,121	0.745	0.436	0	1
Educ	12,100	13.765	3.047	0	20
Marital	12,121	0.535	0.499	0	1
Childs	12,115	1.764	1.572	0	8
Health	7,939	3.012	0.774	1	4

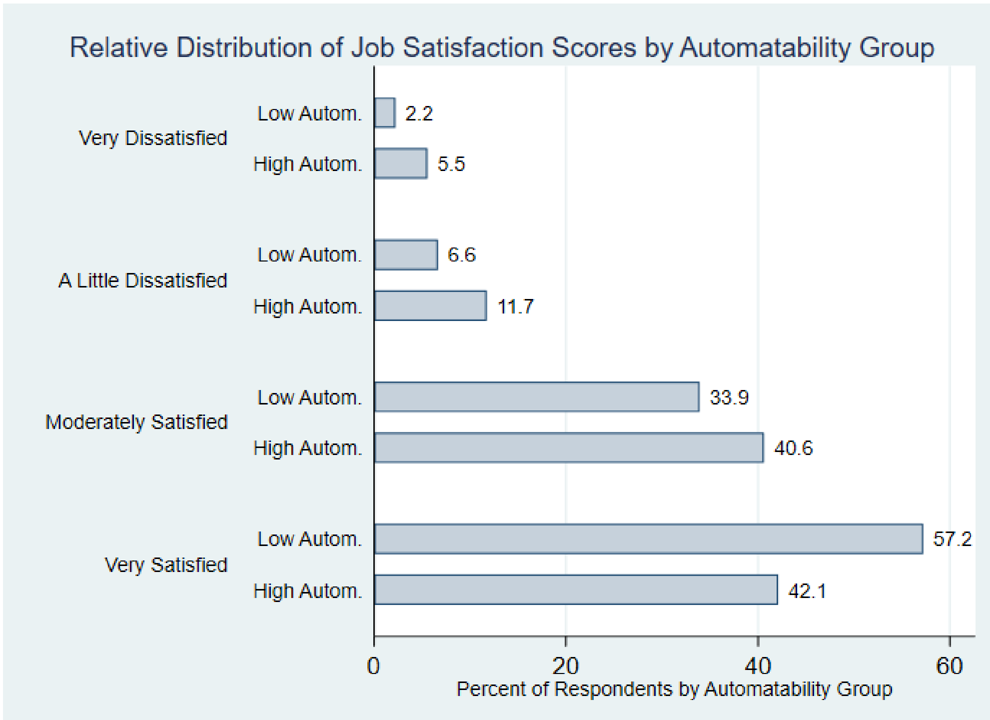
Inspection of these summary statistics does not reveal anything peculiar beyond the high values of Job Satisfaction mentioned earlier.[12] The only thing worth noting is that due to the nature of eliciting the data, income is measured in twelve income categories, ranging from 1 (less than \$1,000 per year) to 12 (more than \$25,000 per year), where fairly many respondents fall into the highest class, particularly for more recent years.[13] From an empirical vantage point, this is of course not ideal. We would prefer more precise income data and data that would allow to report effects on logarithmic scales to interpret coefficients in percentage terms. However, the increasing size of category widths produces steps that approximate the logarithmic scale, at least to an extent. From previous results on the relationship between job satisfaction and income (Bakan and Buyukbese, 2013), we might expect that, at higher incomes, larger increases in income are

[12]While *Income*, *WkHrs* and particularly *Health* are not available for all respondents, they are important covariates, so we choose to keep them nonetheless.

[13]The question was added to the GSS in 1972. The scale is reasonable for households at that time and the item has since stayed unchanged.

required to have the same effect on job satisfaction as smaller increases have job satisfaction for lower incomes. As we conduct a robustness check with data from the 1970s, we demonstrate that even in a time where these income categories more accurately reflected the actual distribution in the working population, our results remain robust.

Figure 2: Relative Distribution of Job Satisfaction Scores by Automatability Group



Note: An *FO* measure greater than 0.5 is classified as 'High Autom.', *FO* measures up to and including 0.5 are classified as 'Low Autom.'. The figure does not change qualitatively when using the mean or median as threshold.

Figure 2 gives an early indication of the expected negative relationship between job satisfaction and automatability. While the variables have a relatively low, but highly significant, pairwise correlation of -0.164 (significant at the 0.1% level), the figure adds further nuance. For simplicity here, we consider a threshold of 0.5 to classify automatability as low or high. While, as previously discussed, a high proportion of respondents report to be satisfied with their job, there are more respondents with high automatability than low automatability in every category except for the top one. Of those in this top category who report to be "very satisfied" with their job, there are more respondents with low automatability than those with high automatability.

Table 29 (presented in Appendix B) shows the pairwise correlations among our variable of interest, *Autom-FO*, and the main control variables which make up our baseline specification. There are highly statistically significant (at the 0.1% level) correlations among our independent variables. All are highly correlated with *Autom-FO* and expected to also be related to *JobSat4* making them relevant covariates to control for.

4.1.2 Regression Analysis

As our dependent variable, *JobSat4*, is measured on a 4-point likert scale, we use an ordered probit model for our main analysis. Table 4 displays a negative and highly statistically significant relationship between *Autom-FO* and *JobSat4*, which persists as we add a number of demographic control variables to establish our baseline model.

Table 4: Controlling for Demographics (Baseline)

Dep. Var.: JobSat4	(1)	(2)	(3)	(4)	(5)	(6)
Autom-FO	-0.523***	-0.502***	-0.465***	-0.419***	-0.402***	-0.382***
	(0.0283)	(0.0335)	(0.0355)	(0.0380)	(0.0382)	(0.0470)
Income		0.0245***	0.0197***	0.0118*	0.00976	0.00293
		(0.00425)	(0.00516)	(0.00535)	(0.00537)	(0.00667)
WkHrs			0.00486***	0.00643***	0.00657***	0.00844***
			(0.000943)	(0.000973)	(0.000975)	(0.00120)
WkSlf			0.412***	0.344***	0.343***	0.332***
			(0.0396)	(0.0406)	(0.0406)	(0.0494)
Age				0.0109***	0.00964***	0.00924***
				(0.00101)	(0.00109)	(0.00134)
Male				-0.0927***	-0.0973***	-0.0904**
				(0.0265)	(0.0266)	(0.0328)
White				0.0860**	0.0731*	0.0684
				(0.0298)	(0.0301)	(0.0372)
Educ				0.00547	0.00658	0.00276
				(0.00468)	(0.00484)	(0.00609)
Marital					0.129***	0.123***
					(0.0276)	(0.0341)
Childs					0.00256	0.00777
					(0.00971)	(0.0120)
Health						0.176***
						(0.0222)
Pseudo R^2	0.0133	0.0165	0.0249	0.0332	0.0345	0.0414
N	12,121	9,186	8,270	8,221	8,219	5,416

Standard errors in parentheses
Ordered Probit Model
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Column (1) of Table 4 presents the results of a simple ordered probit regression. It shows a negative relationship between *Autom-FO* and *JobSat4*, which is statistically significant at the 0.1% level. In Column (2), we control for *Income*. As expected, it has a positive effect on *JobSat4*. The coefficient on *Autom-FO* becomes only marginally smaller in magnitude and remains statistically significant at the 0.1% level. This suggests that, while jobs with lower automatability are also associated with higher pay (a negative correlation established in Table 29), there are additional reasons driving the negative relationship between *Autom-FO* and *JobSat4*.

Column (3) additionally controls for *WkHrs* and *WkSlf*, both of which have positive associations with *JobSat4*, holding *Income* constant. We suggest these are both selection effects as, with *Autom-FO* as well as *Income* held constant, those who work longer hours are more likely to enjoy their job (Leontaridi et al., 2001; Vieira, 2005). Similarly, those who choose to be self-employed are more likely to enjoy their work (Bradley and Roberts, 2004; Lange, 2012). In Column (4), we add further demographics and find that older and more educated respondents report higher job satisfaction (significant at the 0.1% and 1% level, respectively), while males report lower job satisfaction (significant at the 0.1% level). The effect of education is not statistically significant though when controlling for all covariates.

Column (5) suggests that married respondents are more satisfied in their jobs (statistically significant at the 0.1% level), as are those with more children, though this effect is statistically insignificant. Finally, Column (6) of Table 4 suggests that respondents who report better health are also more satisfied in their jobs.

In terms of our research question, although the magnitude of the coefficient on *Autom-FO* attenuates as more control variables are added, it remains highly statistically significant (at the 0.1% level) throughout all specifications presented in Table 4. This is also despite the reduction in sample size (of about 55%) as more variables are considered. We therefore have very strong evidence of a negative relationship between automatability and job satisfaction, even after accounting for the most relevant job characteristics and demographic information available in the GSS data.

Thus far, our analysis has focused on the sign and statistical significance of coefficients, rather than a practical interpretation of their magnitude. This is due to the subjective nature of self-reported job satisfaction (dependent variable) and elements of the estimation procedures for automatability (main variable of interest). However, some useful practical interpretations can be made by considering standard deviation and percentage changes.

Table 5: Marginal Effects for Standardised Autom-FO Measures

	JobSat4=			
	1	2	3	4
FO-Std	0.00711***	0.0178***	0.0313***	-0.0561***
	(.000997)	(.00228)	(0.00397)	(0.00691)
Observations	5,416			

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5 shows the predicted marginal probabilities of reporting each job satisfaction score with respect to a one standard deviation increase in *AutomFO*, with all covariates evaluated at their respective mean. These are based the full baseline specification, given in Column (6) of Table 4, where the variable *Autom-FO* was standardised. We see that a one standard deviation increase in *Autom-FO* of 0.368 (Table 3) is predicted to approximately increase the probabilities of reporting a job satisfaction of 1, 2 and 3, by 0.83%, 1.73% and 2.74% respectively. However, it is predicted to *decrease* the probability of reporting a maximum job satisfaction of 4 by 5.31%. To give a single headline figure, when considering the distribution of respondents over *JobSat4*, a one standard deviation increase in automatability for the average respondent is predicted to decrease job satisfaction by 2.61%.[14] Not that this overall effect is mainly driven by the large number of respondents in the maximum job satisfaction categories 3 and 4, the latter of which is associated with a decrease.

One may question whether the relationship between automatability and job satisfaction may be explained by co-correlations with other job and personal characteristics, additional to the ones considered in our baseline model. This is explored in Table 6. Each specification here includes the baseline controls, though for brevity these coefficients are not reported.
A particularly salient issue is job security. When automatability is high, a worker may fear that their job may be automated. This fear and anxiety may negatively affect reported job satisfaction. However, we argue that the nature of the jobs is more important, in which case we would expect the negative relationship between *Autom-FO* and *JobSat4* to persist, even when controlling for job security.

In Panel (a) of Table 6, we consider different measures of job security. *JobSec* measures the respondents' agreement with the statement "the job security is good" on a scale from 1 "Not true at all" to 4 "Very true". Column (1) of Panel (a) shows that respondents who feel more secure in their jobs report a higher job satisfaction. Similarly, *JobLose* measures the respondents' assessments of how likely they are to lose their job in the next 12 months from 1 "Not likely" to 4 "Very likely", while *JobFind* measures the perceived difficulty of finding a similar job (in terms of income and fringe benefits) from 1 "Not easy" to 3 "Very easy". These are considered in Columns (2) and (3) of Panel (a). Again as expected, those more likely to lose their jobs report decreased job satisfaction, while those that are confident of finding a similar job report higher job satisfaction. These results suggest that job security does indeed impact job satisfaction. However, in each of these specifications, while controlling for measures of job security, *Autom-FO* remains negative and highly statistically significant. The magnitude of the coefficient again attenuates, but not to a large extent. This suggests that the relationship between workers' *Autom-FO* and *JobSat4* cannot mainly or solely be attributed to the fear of losing their job.
Lastly, Column (4) of Table 6 Panel (a) considers *CompRepl* which asks whether the respondent has heard of jobs being replaced by computers in their firm. It is a dummy variable with 0 "No"

[14]See Appendix A for a detailed description of how this figure is computed.

Table 6: Controlling for Attitudes related to the Respondents' Job and Socio-Economic Status

Dep. Var.: JobSat4	(1)	(2)	(3)	(4)
AutomFO	-0.371***	-0.313***	-0.326***	-0.155
	(0.0686)	(0.0680)	(0.0681)	(0.154)
JobSec	0.286***			
	(0.0279)			
JobLose		-0.156***		
		(0.0295)		
JobFind			0.130***	
			(0.0307)	
CompRepl				-0.293*
				(0.146)
Controls	✓	✓	✓	✓
Pseudo R^2	0.0622	0.0437	0.0424	0.0592
N	2,614	2,603	2,600	528

(a): Job Security

Dep. Var.: JobSat4	(1)	(2)	(3)	(4)
Autom-FO	-0.332***	-0.359***	-0.356***	-0.385***
	(0.0474)	(0.0473)	(0.0475)	(0.0473)
FinSat	0.343***			
	(0.0236)			
RelFmIn		0.136***		
		(0.0211)		
SEClass			0.137***	
			(0.0290)	
RichWrk				0.366***
				(0.0346)
Controls	✓	✓	✓	✓
Pseudo R^2	0.0607	0.0452	0.0431	0.0516
N	5,413	5,391	5,399	5,389

(b): Financial Situation

Dep. Var.: JobSat4	(1)	(2)	(3)	(4)	(5)
Autom-FO	-0.338***	-0.362***	-0.380***	-0.440***	-0.382***
	(0.0476)	(0.0474)	(0.0472)	(0.0661)	(0.0471)
Happy	0.498***				
	(0.0278)				
Excite		0.341***			
		(0.0299)			
GetAHead			0.133***		
			(0.0233)		
EducCon				0.143***	
				(0.0355)	
Religion					✓
Controls	✓	✓	✓	✓	✓
Pseudo R^2	0.0709	0.0530	0.0443	0.0492	0.0443
N	5,412	5,378	5,394	2,790	5,416

(c): Other Opinions

Standard errors in parentheses
Ordered Probit Model
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

and 1 "Yes". This was only asked in 2008 and vastly reduces the sample size, but is included for completeness. As expected, hearing of jobs being replaced in the respondent's firm decreases *JobSat4*, significant at the 5% level, while *Autom-FO* remains negative but becomes much smaller in magnitude and insignificant at the 5% level. On top of the reduction in sample size, *CompRepl* is not necessarily capturing the respondents' fear of having their job automated themselves (*JobLose* and *CompRepl* have a correlation coefficient of 0.0877 that is insignificant at the 10%-level). When investigating the occupations of the 77 respondents, who replied knowing of someone in their firm having their job replaced by computerised equipment, a vast number of these are managers, supervisors and chief executives. It is the nature of their jobs to know about the reasons for layoffs (or even make such layoff decisions) in their firms, while at the same time their own jobs tend to be less automatable. This results in a negative (though insignificant) correlation between *CompRepl* and *Autom-FO* (of -0.02).

Panel (b) of Table 6 considers the respondents' wider financial situations. In particular we control for whether they are financially satisfied, *FinSat*; their relative family wealth, *RelFmIn*; their self-reported socio-economic groups, *SEClass*; and a dummy variable indicating whether they would still work if they were rich enough not to, *RichWrk*. Columns (1) and (2) suggest that a more comfortable subjective financial situation is associated with higher job satisfaction. Columns (3) and (4) suggest those who consider themselves to be in a higher socio-economic group also report higher job satisfaction, as do those who would continue to work regardless of their financial situation. All of these effects reported in Panel (b) are statistically significant at the 0.1% level. Yet, importantly for our research question, the negative coefficient on *Autom-FO* still persists at the same significance level.

Lastly, Panel (c) controls for other personal opinions of the respondents which we deem relevant. These include responses to subjective happiness measured on 3-point likert scale (*Happy*); whether life is exciting (*Excite*); whether respondents feel that people, in general, 'get ahead' through hard work, luck or help, or both equally (*GetAHead*); whether they have confidence in the country's education system (*EducCon*); and finally, *Religion*. Again, all additional coefficients presented in Table 6 Panel (c), other than the categorical variable *Religion*, are positive and statistically significant at the 0.1% level. The negative coefficient on *Autom-FO* persists at the same significance level throughout.

4.1.3 Robustness Checks

Having established a negative relationship between job satisfaction and automatability, which is robust to the inclusion of numerous relevant covariates, this section conducts additional robustness checks relating to the econometric techniques used, splitting the sample, using different estimates of automatability, and the time frame considered.

Schwabe et al. (2020) consider two additional issues which we explore here to show the robustness of our result. Firstly, they investigate whether differences exist in the relationship between automatability and job satisfaction depending on the respondents' education levels. Column (1) of Table 7 repeats our previous result, considering the entire sample. In Columns (2) and (3), we consider those classified as having low ($<$ 14 years) and high ($\geq$ 14 years) education, respectively.[15]

[15]This is the mean of the variable *Educ*.

While Schwabe et al. (2020) find a smaller negative coefficient for the highly educated, we find a larger negative coefficient. However the difference between the coefficients on *Autom-FO* reported in Columns (2) and (3) is small and they are not significantly different. Therefore, the evidence here suggests that the relationship between automatability and job satisfaction does not depend on whether the respondent is highly educated.[16] In both cases, though, the coefficients are negative and statistically significant at the 0.1% level.

Table 7: Manual Occupation Dummy and Educational Differences

Dep. Var.: JobSat4	(1)	(2)	(3)	(4)	(5)	(6)
Autom-FO	-0.382***	-0.362***	-0.384***	-0.372***	-0.357***	-0.367***
	(0.0470)	(0.0717)	(0.0633)	(0.0479)	(0.0738)	(0.0641)
ManOcc				-0.0500	-0.0165	-0.141
				(0.0462)	(0.0581)	(0.0826)
Controls	✓	✓	✓	✓	✓	✓
Pseudo R^2	0.0414	0.0455	0.0382	0.0415	0.0455	0.0387
N	5,416	2,407	3,009	5,416	2,407	3,009
Educ	All	Low	High	All	Low	High

Standard errors in parentheses
Ordered probit model
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Secondly, Schwabe et al. (2020) include a dummy variable indicating whether the respondent works in an industry job, as they argue that industry jobs are more monotonous which negatively affects job satisfaction. In Columns (4) to (6), we repeat the first three columns, but with the inclusion of the dummy variable, *ManOcc*, which takes value 1 for manual occupations[17] and 0 otherwise. We elect not to include this variable in our baseline specification as its relationship with the OCC2010 codes results in collinearity with the automatability measures, which also match with the OCC2010 codes. This collinearity will then only cause a (further) underestimation of the true effect. We argue that the monotonicity of a job is linked to its automatability, more than whether it is an industry job. The results in Table 7 give evidence in favour of argument, with only a small decrease in the coefficient of *Autom-FO*, while the coefficient on *ManOcc* is negative but statistically insignificant[18].

Table 8 reports the results from applying different econometric techniques after splitting the sample into panel and cross-sectional data. Panels (a) and (b) consider the panel data only, which allows random effects (RE), fixed effects (FE) and multilevel/mixed effects (ME) models to be utilised. Panel (c) considers only the cross-sectional data, allowing survey weights to be applied.

[16] We ran alternative specifications with interaction terms on the full sample. While coefficients differ slightly in magnitude, the overall conclusion is the same.

[17] OCC2010 code≥6005

[18] The coefficient on *ManOCC* is only statistically significant at the 10% level for the High Education sub-sample.

Table 8: Different Econometric Models

Dep. Var.: JobSat4	(1)	(2)	(3)	(4)	(5)
Autom-FO	-0.404***	-0.687***	-0.253***	-0.209***	-0.0826
	(0.0677)	(0.114)	(0.0420)	(0.0445)	(0.0883)
Controls	✓	✓	✓	✓	✓
LogL ratio	-2554.347	-2552.161	-2828.579		
(Pseudo) R^2	0.0415	0.0423	0.0777	0.0757	0.0206
N	2,619	2,619	2,619	2,619	2,619
Model	O-Probit	O-Logit	OLS	RE	FE

(a): Panel Models

Dep. Var.: JobSat4	(6)	(7)	(8)	(9)
Autom-FO	-0.212***	-0.212***	-0.460***	-0.826***
	(0.0442)	(0.0443)	(0.0978)	(0.173)
Controls	✓	✓	✓	✓
LogL ratio	-2748.3	-2748.3	-2473.9	-2470.0
(Pseudo) R^2				
N	2,619	2,619	2,620	2,620
Model	ME	MEGLM	MEoProb	MEoLog

(b): Mixed Effects Models

Dep. Var.: JobSat4	(1)	(2)	(3)	(4)	(5)
Autom-FO	-0.295***	-0.488***	-0.186***	-0.324***	-0.524***
	(0.0741)	(0.125)	(0.0474)	(0.0822)	(0.133)
Controls	✓	✓	✓	✓	✓
N	2,797	2,797	2,797	2,797	2,797
Model	O-Probit	O-Logit	OLS	Probit	Logit
Survey Weights	✓	✓	✓	✓	✓

(c): Using Survey Weights

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Column (1) of Panel (a) repeats our baseline specification using an ordered probit model. Column (2) shows a qualitatively identical result when using an ordered logit model.[19] The result also persists at the 0.1% significance level when using OLS, as shown in Column (3). In Columns (4) and (5) of Panel (a), the panel data uses *Year* as the time identifier and respondents' *ID* as the individual identifier. Column (4) shows that the coefficient on *Autom-FO* remains negative and statistically significant at the 0.1% level, when considering random effects (RE). When considering fixed effects (FE) in column (5), the coefficient remains negative but becomes statistically insignificant at the 5% level. However, this is not altogether surprising. While the sample size remains at 2,616, the same as previous models in Panel (a), including individual fixed effects for each of the 1,590 individual respondents in our unbalanced panel reduces the degrees of freedom to 1,014. Furthermore, only 346 of the 1,590 respondents changed their job between waves. With few changes in our main variable of interest it is of little surprise that the coefficient is found to be statistically insignificant. The FE results are reported here for completeness.

Panel (b) of Table 8 considers four ME models. Columns (6) and (7) show almost no difference between the standard and generalised least squares approach. The main result is also shown to be

[19]Indeed these results are quantitatively similar once probit/logit scaling is considered (rule of thumb: logit=1.61*Pobit).

robust to using ME ordered probit and ordered logit models in Columns (8) and (9) respectively.

Lastly for Table 8, Panel (c) considers only the cross-sectional data for which survey weights are available. Columns (1)-(3) repeat the ordered probit, ordered logit and OLS models for the cross-sectional data but with the survey weights applied. The magnitudes of the coefficients are smaller and standard errors are larger compared to the comparable models in Panel (a) Columns (1)-(3). Though different datasets are considered in this comparison, it is the use of survey weights which accounts for the majority of the difference.[20] Despite this, the coefficients on *Autom-FO* remain statistically significant at the 0.1% level.
In Columns (4) and (5), the dependent variable is adjusted to allow for probit and logit models to be estimated. Rather than considering *JobSat4* on a 4-point Likert scale, we consider a dummy variable which takes the value 1 if the respondent reports maximum job satisfaction of 4, and 0 otherwise.[21] The magnitude of the coefficients becomes slightly larger than their ordered counterparts and the coefficients remain statistically significant at the 0.1% level.[22]

Overall, we conclude that the negative relationship between automatability and job satisfaction is generally robust to splitting the sample and the use of various econometric techniques. While the relationship did not remain highly statistically significant when considering FE, this stems from reduced degrees of freedom and a lack of *within* variation. Survey weights also appear to attenuate the strength of the relationship both in terms of magnitude and statistical significance, though the significance level is still high in these models, especially considering the high thresholds chosen (Benjamin et al., 2018).

We also consider the robustness of our result to the use of different estimates of automatability.

Table 9: Different Measures of Automatability

Dep. Var.: JobSat4	(1) FO	(2) GER	(3) MK
Autom-	-0.338***	-0.641***	-0.939***
	(0.0476)	(0.127)	(0.196)
Controls	✓	✓	✓
Pseudo R^2	0.0709	0.0678	0.0674
N	5,412	3,477	3,491

Standard errors in parentheses
Ordered Probit Model
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Thus far, this section has only considered the automatability estimates of Frey and Osborne (2017): *Autom-FO*. Table 9 also considers the other two estimates discussed in Section 2.2: *Autom-GER*

[20]Running models (1)-(3) from Panel (c) without survey weights results in coefficients more similar to those of Columns (1)-(3) in Panel (a).

[21]We opt for this definition of the dummy as it splits the data at the median/mean.

[22]This is also true for applying the binary dependent variables models without survey weights.

and *Autom-MK*. All three models of Table 9 use an ordered probit model and include the baseline demographic controls. The sample size decreases in Columns (2) and (3), compared to Column (1), as the *FO* estimates are a better match to the OCC2010 job codes available in the GSS dataset, while there is some attrition when matching the other automatability estimates using our crosswalk. However, despite this, the coefficients remain negative and statistically significant at the 0.1% level across all three automatability estimates. Though all three measures range between 0 and 1, the magnitude of the coefficients do vary due to differences in their standard deviations. The Pseudo R^2 are similar for each measure. Particularly the MK measure is problematic as, with the data publicly available from Manyika et al. (2017), we can only match the GSS to 12 distinct different levels of *Autom-MK*, making the variables relatively coarse.

Table 10: Robustness Check – 1970s Data

Dep. Var.: JobSat4	(1)	(2)	(3)	(4)	(5)	(6)
Autom-FO	-0.334***	-0.315***	-0.291***	-0.256***	-0.256***	-0.302***
	(0.0372)	(0.0515)	(0.0520)	(0.0558)	(0.0559)	(0.0622)
Income		0.0283***	0.0275***	0.0302***	0.0291***	0.0227**
		(0.00543)	(0.00544)	(0.00645)	(0.00648)	(0.00725)
WkSlf			0.235***	0.161**	0.161**	0.153*
			(0.0601)	(0.0614)	(0.0615)	(0.0689)
Age				0.0145***	0.0131***	0.0163***
				(0.00142)	(0.00155)	(0.00175)
Male				-0.188***	-0.190***	-0.186***
				(0.0411)	(0.0412)	(0.0457)
White				0.283***	0.271***	0.197**
				(0.0566)	(0.0573)	(0.0651)
Educ				0.00560	0.00713	-0.00161
				(0.00692)	(0.00700)	(0.00792)
Marital					0.131**	0.0897
					(0.0422)	(0.0474)
Childs					0.00676	0.00982
					(0.0116)	(0.0127)
Health						0.195***
						(0.0268)
Pseudo R^2	0.00505	0.00985	0.0115	0.0299	0.0313	0.0395
N	7,547	4,264	4,258	4,238	4,220	3,410

Standard errors in parentheses
Ordered Probit Model
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For the final robustness check of this section, we consider whether our main result is sensitive to the time frame of our sample. The fear-based explanation for automatability affecting job satisfaction requires workers to be aware that their job has a certain likelihood of being automated. While machines and the first incidences of automation have been present in various labor markets for a long time, the capabilities to fully replace workers by robotics is more recent. We can thus plausibly assume that workers in the 1970s were relatively less afraid of their jobs being automated by robotics and certainly AI.

Table 10 shows that this consideration has no effect on the relationship between automatability and job satisfaction. We still obtain a negative and statistically significant coefficient that is robust to the inclusion of covariates.[23]

4.2 European Social Survey - The European Case

This section considers data from the European Social Survey (Anonymous, 2012). Although data is available from this survey biennially from 2002 to 2018, unfortunately for our purposes, only the 2012 wave elicits job satisfaction from the participants. We can therefore only utilise this single cross-section. Despite the lack of time variation, we obtain 23,852 observations across 29 countries which allows cross-country variation to be exploited adding a new, alternative dimension.
The data contains 2008 International Standard Classification of Occupations (ISCO-08) codes which are matched to the estimates of automatability of Dengler and Matthes (2015) (*AutomGER*) for the bulk of the analysis. These measures were calculated on the basis of German labour market and occupation data. While there are clear differences between the German labour market and those of other European countries, we consider it more suitable than the FO or MK measures, as these are calculated from US data, though we do consider these other measures in robustness checks. Similarly, our main analysis considers ordered probit estimation, while other econometric methodology is considered in further robustness checks.

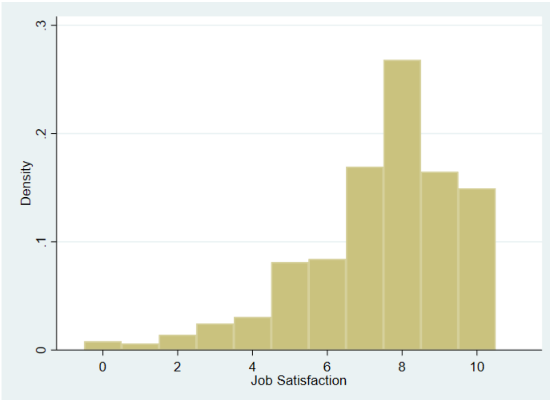
4.2.1 Descriptive Statistics and Correlations

Our dependent variable is again job satisfaction, but in the ESS dataset, this is measured on an 11-point Likert scale. We therefore call this variable *JobSat11*. Figure 3 Panel (a) shows the distribution of *JobSat11*. As in the GSS data, it is also negatively skewed, though marginally less so (-1.06 compared to -1.12). The larger scale allows for more detail and the highest category is no longer the mode, which instead lies at 8. This somewhat alleviates the concerns of clustering at the maximum in the GSS data. It allows for more precise responses and has a more symmetric wording.[24]

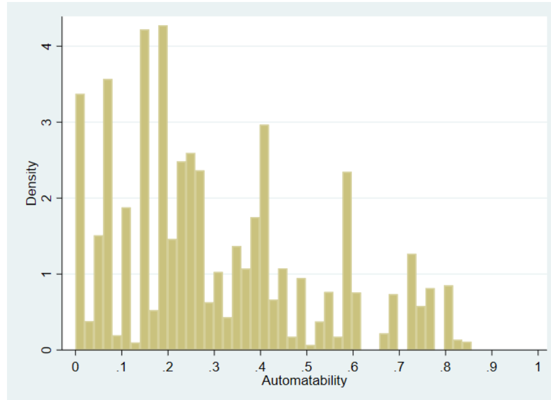
[23]The variable *WkHrs* for this time period has only been elicited in the last years, thus only containing 255 observations. Including it attenuates the sample to less than 200 observations due to missing values in the other variables, deeming its inclusion uninformative.

[24]*JobSat11* is labeled from 0 ”Extremely dissatisfied” to 10 ”Extremely satisfied” with numbers 1-9 in-between.

Figure 3: Histograms



(a) *JobSat11*



(b) *Autom-GER*

Figure 3 Panel (b) shows the distribution of the GER measure. Compared to the FO estimates, it is noticeable that the distribution is less bi-modal/polarised and more skewed towards lower values. This could be due to aim of Dengler and Matthes (2015) to estimate actual automation risks, rather than mere automation potential.

Table 11: Descriptive Statistics of Independent Variables

	N	Mean	Std. Dev.	Min.	Max.
JobSat11	23,852	7.447	2.027	0	10
Autom-GER	23,852	0.303	0.224	0	1
Income	20,105	6.219	2.614	1	10
WkHrs	23,852	40.340	12.728	0	130
WkSlf	23,852	0.138	0.345	0	1
Age	23,806	42.964	12.362	15	91
Male	23,852	0.503	0.500	0	1
White	23,852	0.928	0.258	0	1
Educ	23,743	13.890	3.561	6	24
Marital	23,852	0.046	0.209	0	1
Childs	23,851	0.512	0.500	0	1
Health	23,824	4.005	0.783	1	5

To enable comparison of the results from each dataset, we consider the same baseline specification. Descriptive statistics of the variables used are presented in Table 11. Most variables are directly comparable to those in the GSS, but some small differences should be noted.[25] Firstly, *Income* is reported in income deciles within each country. It thus ranges from 1 to 10, rather than to 12 as in the GSS data, where the income categories were chosen more arbitrarily. The approach

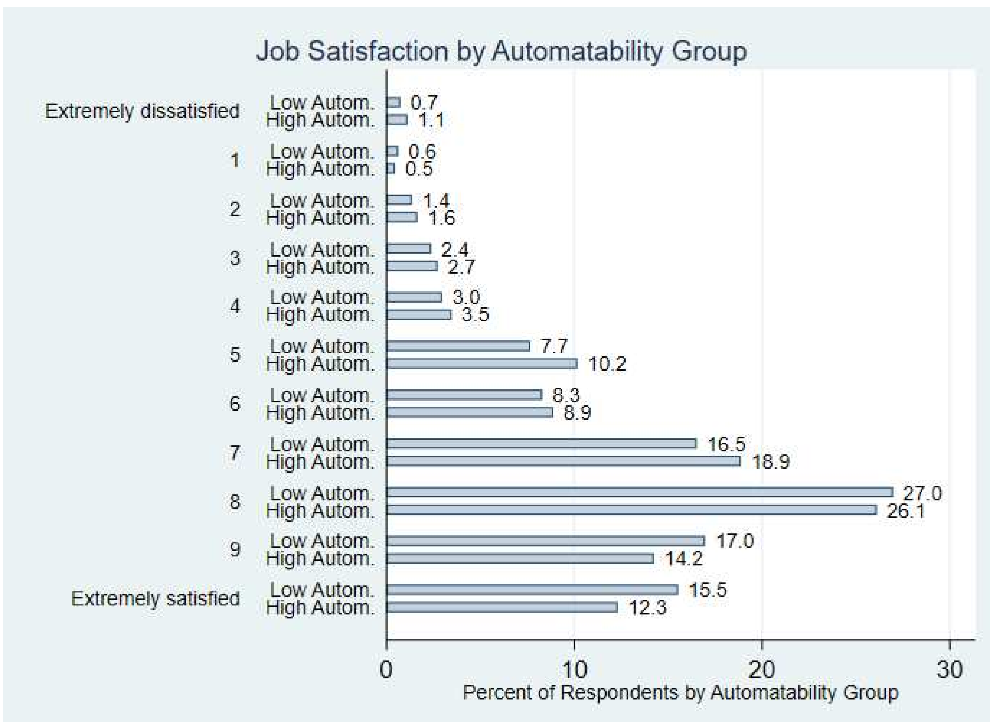
[25]We exclude observations that stated to have more than 130 contracted weekly working hours. There are 8 observations claiming this to be 168, which is literally 7 days of 24 hours. Our results are all robust to including these observations.

negates the need for purchasing power or exchange rate conversions between countries. Also, as in the GSS data, widening income ranges at higher deciles have a similar effect to considering a logarithmic transformation.

Educ is converted from a categorical variables in the ESS data, that reports each respondent's highest educational qualification, to the average number of years taken to achieve each qualification, allowing a more direct comparison to the GSS data.

Childs is a dummy variable taking a value of 1 if the respondent lives with children and 0 otherwise, rather than reporting the number of children. *Health* is measured on a 5-point Likert scale, rather than 4-point as in GSS.[26]

Figure 4: Relative Distribution of Job Satisfaction Scores by Automation Risk Group



Note: A GER measure greater than 0.5 is classified as 'High Autom.', GER measures up to 0.5 are classified as 'Low Autom.'. The figure does not change qualitatively when using the mean or median as cutoff value.

Figure 4 gives an initial insight into the relationship between job satisfaction and the GER automatability measure for this dataset. As in the GSS data, for job satisfaction categories below the average (Mean=7.430, Median & Mode=8) there are generally more high risk than low risk respondents, in terms of job automatability (except for *JobSat*=1, where low autom. is slightly larger than high autom., but with few respondents). Again, the opposite is true in the higher

[26]Pairwise correlations between the variables included in the baseline specification are presented in Table 30 of Appendix B. As in the GSS data, we note highly statistically significant correlations (at the 0.1% level) between many of our control variables, *Autom-GER* and *JobSat11* indicating the relevance of the controls chosen.

categories, which indicates a negative relationship between the variables in the ESS data.

4.2.2 Regression Analysis

We begin our regression analysis by building up to the same baseline specification of demographic controls as considered for the GSS data. Again, we use ordered probit models to allow for comparability. The results are presented in Table 12.

Table 12: Controlling for Demographics (Baseline)

Dep. Var.: JobSat11	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Autom-GER	-0.475***	-0.413***	-0.390***	-0.405***	-0.405***	-0.366***	-0.311***
	(0.0321)	(0.0349)	(0.0350)	(0.0367)	(0.0367)	(0.0367)	(0.0372)
Income		0.0479***	0.0496***	0.0501***	0.0509***	0.0464***	0.0497***
		(0.00279)	(0.00281)	(0.00298)	(0.00302)	(0.00303)	(0.00321)
WkHrs			-0.00282***	-0.00270***	-0.00268***	-0.00244***	-0.00135*
			(0.000589)	(0.000606)	(0.000606)	(0.000608)	(0.000623)
WkSlf			0.322***	0.300***	0.301***	0.289***	0.279***
			(0.0222)	(0.0225)	(0.0225)	(0.0226)	(0.0228)
Age				0.00471***	0.00463***	0.00801***	0.00724***
				(0.000603)	(0.000611)	(0.000630)	(0.000637)
Male				0.00644	0.00543	-0.0174	-0.0410**
				(0.0152)	(0.0153)	(0.0154)	(0.0155)
White				0.158***	0.157***	0.140***	0.123***
				(0.0280)	(0.0280)	(0.0281)	(0.0287)
Educ				-0.00437	-0.00445*	-0.00685**	-0.00638**
				(0.00226)	(0.00226)	(0.00227)	(0.00232)
Marital					0.0288	0.0473	0.102**
					(0.0354)	(0.0354)	(0.0357)
Childs					-0.0236	-0.0286	-0.0340*
					(0.0147)	(0.0147)	(0.0149)
Health						0.219***	0.180***
						(0.00973)	(0.0104)
Country	✗	✗	✗	✗	✗	✗	✓
Pseudo R^2	0.00232	0.00582	0.00855	0.00989	0.00993	0.0164	0.0221
N	23,852	20,105	20,105	19,995	19,995	19,978	19,978

Standard errors in parentheses
Ordered probit model
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Column (1) shows the negative relationship between *JobSat11* and *Autom-GER*, which is statistically significant at the 0.1% level. This relationship is robust to the incremental inclusion of demographic control variables through to Column (6) which presents the full baseline specification. Although the family demographics *Marital* and *Childs* in Column (5) reduce the regression sample to less than half of that in Column (4) and even though the coefficient on *Autom-GER* attenuates in magnitude as more controls are added, the relationship remains negative and statistically significant at the 0.1% level throughout our specifications. Lastly, Column (7) additionally includes country dummies to the baseline specification. This causes some interesting general changes, such as the coefficient on *Marital* becoming statistically significant at the 1% level. The coefficient of *Autom-GER* again attenuates in magnitude, but the relationship still remains negative and statistically significant at the 0.1% level.

Table 13 shows the marginal effects of a one standard deviation increase in *Autom* on *JobSat11* for the average respondent. As with the GSS, the increase in automatability is predicted to increase the probability of lower job satisfaction responses, while decreasing the probability of high responses. The turning point lies between *JobSat11*=7 and *JobSat11*=8 (as also indicated in Figure 4).

Table 13: Marginal Effects for Standardised Autom-GER Measure

JobSat11	GER-Std	Std Errors
0	0.00107***	(0.000150)
1	0.000784***	(0.000115)
2	0.00159***	(0.000210)
3	0.00255***	(0.000323)
4	0.00277***	(0.000348)
5	0.00610***	(0.000741)
6	0.00477***	(0.000582)
7	0.00537***	(0.000655)
8	-0.00259***	(0.000343)
9	-0.00856***	(0.00104)
10	-0.0139***	(0.00166)
Obs	19,978	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To give a headline figure comparable to the one presented in the GSS section, a one standard deviation increase in automatability is predicted to decrease job satisfaction by 1.56%, compared to 2.61% predicted by the GSS results.[27]

Table 14 considers other relevant covariates that can be found in the ESS dataset. In Column (1) of Panel (a), we control for the respondents' general happiness.[28] Despite a lower magnitude, the coefficient on *Autom-GER* remains negative and highly statistically significant (at the 0.1%

[27] The ESS headline figure is larger (1.86%) when not considering country dummies.

[28] In the literature, job satisfaction is considered a major domain-specific element of general happiness (see e.g. Fisher, 2010, for a survey of contributing concepts).

Table 14: Controlling for Job Attitudes

Dep. Var.: JobSat11	(1)	(2)	(3)	(4)
Autom-GER	-0.283***	-0.334***	-0.333***	-0.253***
	(0.0373)	(0.0375)	(0.0390)	(0.0373)
Happy	0.188***			
	(0.00464)			
WkLfBal		0.283***		
		(0.00381)		
CntLgth			0.113***	
			(0.0148)	
Interest				0.211***
				(0.00458)
Controls	✓	✓	✓	✓
Country	✓	✓	✓	✓
Pseudo R^2	0.0432	0.0943	0.0197	0.0494
N	19,890	19,916	17,625	19,916

(a): General Characteristics

Dep. Var.: JobSat11	(1)	(2)	(3)	(4)
Autom-GER	-0.268***	-0.228***	-0.286***	-0.251***
	(0.0373)	(0.0374)	(0.0374)	(0.0374)
Accomp	0.358***			
	(0.00986)			
ValWrth		0.354***		
		(0.0108)		
Absorb			0.181***	
			(0.00438)	
Enthus				0.204***
				(0.00424)
Controls	✓	✓	✓	✓
Country	✓	✓	✓	✓
Pseudo R^2	0.0390	0.0356	0.0442	0.0517
N	19,908	19,915	19,895	19,870

(b): Opinion of Own Activities

Dep. Var.: JobSat11	(1)	(2)	(3)	(4)	(5)
Autom-GER	-0.269***	-0.289***	-0.293***	-0.299***	-0.307***
	(0.0375)	(0.0373)	(0.0373)	(0.0372)	(0.0374)
NewSkll	0.144***				
	(0.0168)				
LrnNew		0.165***			
		(0.00624)			
Capable			0.181***		
			(0.00752)		
Optimist				0.230***	
				(0.00857)	
Hopeful					0.108***
					(0.00750)
Controls	✓	✓	✓	✓	✓
Country	✓	✓	✓	✓	✓
Pseudo R^2	0.0230	0.0311	0.0295	0.0315	0.0247
N	19,861	19,911	19,894	19,938	19,785

(c): Capabilities and Future Prospects

Standard errors in parentheses
Ordered probit model
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

level). Column (2) controls for whether the respondents are satisfied with their work/life balance (on a 10-point scale), while Column (3) considers employment contract length (on a 3-point scale: 1 “No Contract”, 2 “Limited”, 3 “Unlimited”). In both specifications, the coefficient on *Autom-*

GER again remains negative and highly statistically significant (at the 0.1% level) but marginally increases in magnitude. The two items have the expected positive sign and are also significant at the 0.1% level. Lastly for Panel (a), in Column (4) we control for whether the respondent often finds what they do interesting on a 10-point scale (in general, as opposed to asking for whether they find their job interesting in specific). A high score in this item is associated with significantly higher job satisfaction, but the coefficient on *Autom-GER* still remains negative and highly statistically significant (at the 0.1% level). Again, it decreases in magnitude, almost to the same extent as in the first column.

In Panel (b), we consider four more variables which are similar in nature, in that they relate to the respondents' opinions on what they currently do. Specifically, whether what they do makes them feel accomplished (*Accomp*), whether it is valuable/worthwhile (*ValWrth*) and how absorbed (*Absorb*) and enthusiastic (*Enthus*) they are about what they do. Finally, Panel (c) considers variables which are generally more related to future prospects. Firstly, *NewSkll* measures whether the respondent has received training to learn a new skill in the last year, and *LrnNew* whether they think it is important to do so. *Capable* asks whether they feel they get a chance to showcase their capabilities, and *Optimist* and *Hopeful* whether they feel optimistic and hopeful for the future, respectively. All coefficients are positive and statistically significant at the 0.1% level, and attenuate the coefficient on *Autom-GER* to differing degrees.[29]

The strongest attenuations are found in Panels (a) and (b) which consider opinions on the current situation of respondents, specifically when including the variables *ValWrth*, *Interest* and *Enthus*. The variables of Panel (c) that relate to a respondent's potential fear of their future, particularly *Optimist* and *Hopeful*, do not seem to change the effect of automatability on job satisfaction much. While the changes in coefficients are generally not too large, even for the former set of covariates, it is important to note here that the questions are not particularly framed towards the respondent's occupation but rather to 'what they do in their life'. As the same questionnaire is also eliciting items on voluntary and charitable work as well as social and physical activities, these questions are not necessarily interpreted as mainly concerning job-specific activities.

4.2.3 Robustness Checks

Beyond the inclusion of further job and worker-specific characteristics and the workers' opinions, we also exploit information on the countries in the sample and vary the underlying econometric techniques applied to the data to check for robustness of the negative correlation between automatability and job satisfaction.

The additional factors of Schwabe et al. (2020) are again considered in Table 15. As in the

[29] A number of other such variables from the dataset were trialled with similar results. The most relevant variables are presented here as an overview.

GSS dataset, but contradictory to Schwabe et al. (2020), we find a larger negative coefficient when considering the highly educated subsample in Column (3), compared to those with less than 14 years of education in Column (2). Though the difference between the coefficients is larger here, it is not statistically significant (even though only marginally so).

Table 15: Manual Occupation Dummy and Educational Differences

Dep. Var.: JobSat11	(1)	(2)	(3)	(4)	(5)	(6)
Autom-GER	-0.311***	-0.215***	-0.429***	-0.284***	-0.194***	-0.395***
	(0.0372)	(0.0493)	(0.0581)	(0.0395)	(0.0535)	(0.0603)
ManOcc				-0.0427*	-0.0264	-0.0701*
				(0.0208)	(0.0269)	(0.0336)
Controls	✓	✓	✓	✓	✓	✓
Country	✓	✓	✓	✓	✓	✓
Pseudo R^2	0.0221	0.0249	0.0245	0.0222	0.0250	0.0246
N	19,978	10,289	9,689	19,978	10,289	9,689
Educ	All	Low	High	All	Low	High

Standard errors in parentheses
Ordered probit model
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The variable *ManOcc*, which takes value 1 for manual occupations[30], is added in Columns (4) through (6). As in the GSS data, the inclusion of this additional covariate attenuates the size of the coefficients on *Autom-GER*, but the attenuation is small and their statistical significance at the 0.1% level persists.

In Table 16 we report results from replacing the pure country dummy with aggregate labour market statistics for the respective nation[31]. A higher share of manufacturing employment as a proportion of total employment within the country (*Manu*) is associated with a lower job satisfaction score. A higher *GDP* is associated with higher job satisfaction. The unemployment rate (*Unemp*) has a negative effect, which is partly expected as it negatively correlates (with a coefficient of -0.259) with *GDP*. In line with the literature, the degree of unionisation (*Union*) is positively associated with job satisfaction (Bryson et al., 2010) and also leads to a stronger effect of automatability on job satisfaction.

For each aggregate labour market statistic, through Columns (2)-(5), the coefficients on *Autom-GER* are larger than in Column (1) which considers country dummies. This indicates that each statistic individually does not account for all the relevant country differences, though it is interesting to see which individual statistics have the largest effects. In Column (6), we consider the four

[30] Classified by NACE Rev. 2 codes (leq 32).

[31] *Manu*, *Unemp* and *Union* statistics are collected from ILO Data Explorer (International Labour Organization, 2020), while *GDP* is taken from the World Bank Open Data (The World Bank, 2020).

Table 16: Country Characteristics

Dep. Var.: JobSat11	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Autom-GER	-0.311***	-0.331***	-0.333***	-0.373***	-0.354***	-0.326***	-0.378***
	(0.0372)	(0.0370)	(0.0368)	(0.0368)	(0.0368)	(0.0370)	(0.0472)
Manu		-1.355***				-0.461*	
		(0.159)				(0.186)	
GDP			0.0406***			0.0310***	
			(0.00322)			(0.00366)	
Unemp				-0.977***		-0.351*	
				(0.149)		(0.161)	
Union					0.293***	0.129***	
					(0.0334)	(0.0388)	
Autom-OECD							-1.297***
							(0.325)
Pseudo R^2	0.0221	0.0173	0.0184	0.0170	0.0174	0.0189	0.0160
N	19,978	19,978	19,978	19,978	19,978	19,978	12,851
Controls	✓	✓	✓	✓	✓	✓	✓
Country	✓	✗	✗	✗	✗	✗	✗

Standard errors in parentheses
Ordered probit model
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

statistics together which suggests that *GDP* and *Union* are the most important statistics to control for.[32]
Column (7) considers estimates of country-wide automatability within OECD countries (estimated by Arntz et al., 2016), *Autom-OECD*, alongside our occupation-specific automatability measure, *Autom-GER*. Both coefficients are negative and statistically significant at the 0.1% level. This suggests there may be some negative spillover effects of high country-wide automatability, even when holding the automatability of a respondent's job constant. The negative coefficient on *Autom-GER* also increases in magnitude when including *Autom-OECD*. Overall, our main conclusions are robust to the inclusion of country characteristics.

Table 17 reports the results from varying the econometric model used. We have mainly considered models without applying survey weights to allow for easier computation of marginal effects and for comparison to other results where we applied techniques that are incompatible with weights (e.g. ME-Model in the previous section). Alternatives to ordered probit estimation are considered in Panel (a), while we repeat the same models with survey weights in Panel (b). Table 17 shows that their inclusion, while attenuating the effect of automatability, does not affect our results qual-

[32]We also considered interactions terms between these statistics and automatability, but did not feel these results were noteworthy enough to present here. They are available from the authors upon request.

Table 17: Different Regression Models

Dep. Var.: JobSat11	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Autom-GER	-0.311***	-0.539***	-0.516***	-0.365***	-0.596***	-0.283***	-0.485***	-0.470***	-0.316***	-0.517***
	(0.0372)	(0.0642)	(0.0697)	(0.0467)	(0.0759)	(0.0435)	(0.0745)	(0.0833)	(0.0532)	(0.0866)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
(Pseudo) R^2	0.0221	0.0236	0.0886	0.0624	0.0624					
N	19,978	19,978	19,978	19,978	19,978	19,978	19,978	19,978	19,978	19,978
Model	O-Probit	O-Logit	OLS	Probit	Logit	O-Probit	O-Logit	OLS	Probit	Logit
Svy. Weights	✗	✗	✗	✗	✗	✓	✓	✓	✓	✓

(a) Without survey weights (b) With survey weights

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

itatively.
We see that our main result is robust to considering an ordered logit model in Columns (2) and (7), and OLS in Columns (3) and (8). Using OLS specifications we can use the direct interpretation that an individual with a GER measure of 1 is predicted to report an almost half a point lower job satisfaction score than a respondent with GER measure of 0, all other things held constant. Columns (4)-(5) and (9)-(10) use logit and probit models for a dummy which considers above versus below average job satisfaction. Again, our result is robust. The effect remains negative and highly statistically significant at the 0.1% level across all econometric models.

Table 18: Different Measures of Automation Risk

Dep. Var.: JobSat11	(1) FO	(2) GER	(3) MK
Autom-	-0.311***	-0.276***	-0.801***
	(0.0372)	(0.0305)	(0.107)
Controls	✓	✓	✓
Country	✓	✓	✓
Pseudo R^2	0.0221	0.0219	0.0254
N	19,978	12,780	10,254

Standard errors in parentheses
Ordered probit model
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Lastly, Table 18 shows the robustness of our main result to the use of different estimates of automatability. While this section has, thus far, considered the GER measures, as they are estimated from German as opposed to US labour market data, this is reported in Column (2) for consistency and comparability with the GSS results in Table 9. Column (2) has the largest number of observations, with some lost in Columns (1) and (3) when using the crosswalk. Our main result is robust across the different measures and also comparable in magnitude to the GSS estimates. As mentioned before, the MK estimates are fairly coarse measures of automatability. Though all possible values for the MK measure are present in the ESS dataset, this still means that there are only 19 different values.

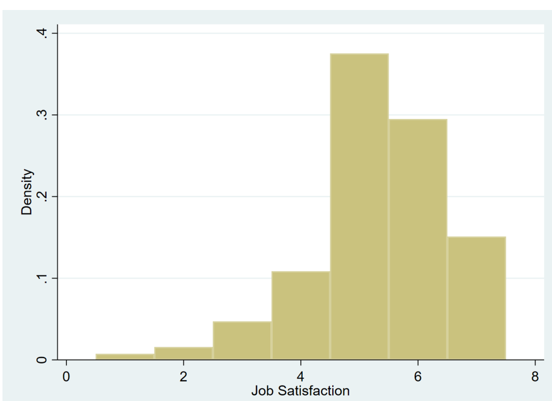
4.3 ISSP

In this section we consider data from the ISSP Worker Orientations Survey. Since this dataset spans 37 countries across the globe on all continents and thus does not have a regional focus, like the GSS and the ESS, we therefore match it to all three automatability measures available.

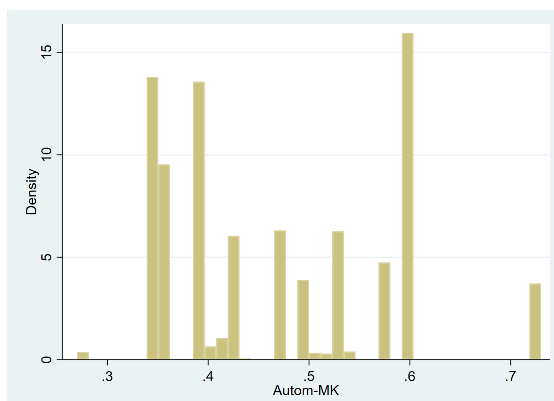
4.3.1 Descriptive Statistics and Correlations

Similar to the previous datasets, we see that job satisfaction is skewed (-0.762) towards the higher values. This can also be seen in Figure 5 Panel (a). As the distributions of the FO and GER measures of automation risk have been presented in previous sections, we display the MK automatability measures estimated by Manyika et al. (2017) in panel (b) of Figure 5. We see that they are much more compressed than the other two measures, but qualitatively also exhibit the bi-modal structure we have seen with the measures of Frey and Osborne (2017) and Dengler and Matthes (2015). Table 19 shows the summary statistics. This dataset does not provide a homogeneous measure of ethnicity[33], so we use an item that asks for the source of discrimination for those who replied having been discriminated against in the workplace. Those who replied that they believe this happened on racial grounds are coded with a one while those who did not experience discrimination or were discriminated for other reasons are coded with a zero. We believe this is

Figure 5: Histograms



(a)



(b)

[33]There are country-specific ethnicities, the matching and merging of which is impossible without numerous arbitrary decisions of grouping or separating classifications.

capturing the essence of typically including race in studies on job satisfaction and that it serves as a reasonable proxy for the variables used in the previous sections. Income is provided as percentiles among the respondents from the same country to allow for comparison with the previous sections.[34]

Table 19: Descriptive Statistics of Independent Variables

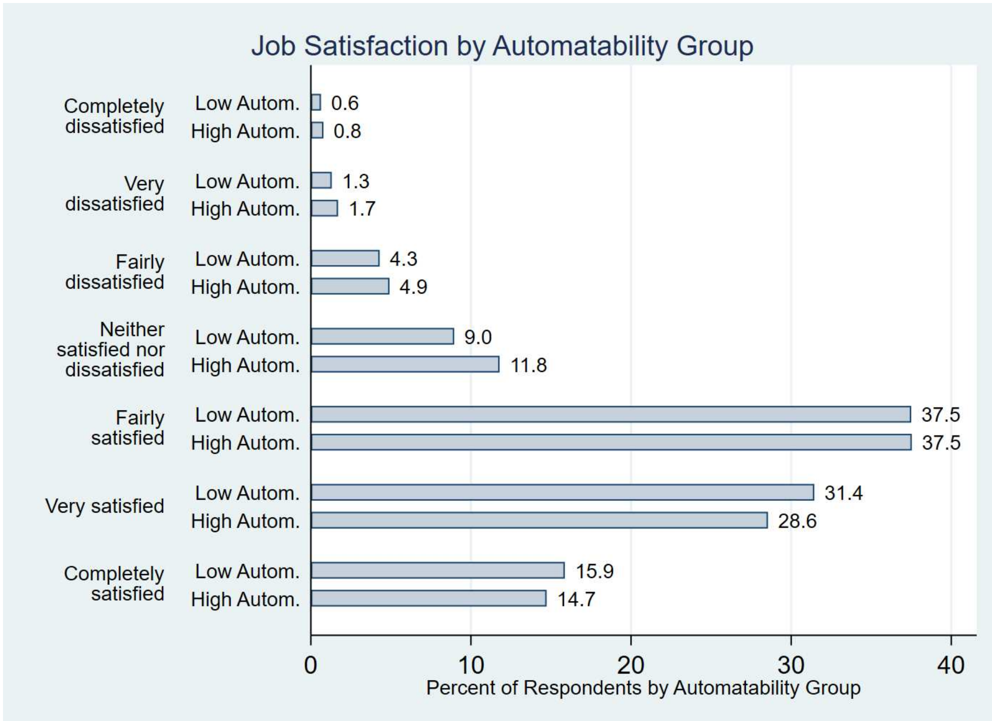
	Mean	Std. Dev.	Min.	Max.
JobSat7	5.315	1.168	1	7
Autom-FO (Mean)	0.367	0.338	0	1
Autom-GER (Mean)	0.306	0.208	0	1
Autom-MK (Mean)	0.468	0.109	0	1
Income	0.439	0.253	0.001	1
WkHrs	42.927	17.025	1	99
WkSlf	0.063	0.243	0	1
Age	43.329	12.892	16	95
Male	0.505	0.500	0	1
Race Disc	0.013	0.112	0	1
Educ	13.461	3.898	0	58
Marital	0.540	0.498	0	1
Childs	0.819	1.119	0	11
Subjective health	3.255	1.021	1	5
Observations		23,055		

Note: For multiple assignments of automatability measures, due to matching datasets based on different occupation codes, we use the mean of these. All results are qualitatively robust to using the median, minimum or maximum respectively.

Educ is provided as years of schooling[35] and *Childs* is the sum of both the number of children up to the country specific school age and those between school age and being of legal age. The variables do not seem to exhibit characteristics worth noting. Again, our main result, that job satisfaction and automatability are negatively correlated is visible when grouping them into respondents with high and low automatibility measures, as can be seen in the familiar Figure 6. The tipping point for the share of low autom. respondents exceeding the share of high autom. respondents is the response ‘Fairly Satisfied’. Again, although the wording is more symmetric than in the GSS, we suppose that this category could be focal among the possible replies.

[34]Our results are robust to using income corrected for purchasing power parity.
[35]Denmark only elicited this in categories which have been converted into years of schooling.

Figure 6: Relative Distribution of Job Satisfaction Scores by Automation Risk Group



Note: An MK measure greater than 0.5 is classified as 'High Automatability', MK measures up to and including 0.5 are classified as 'Low Automatability'. The figure does not change qualitatively when using the mean or median as threshold.

4.3.2 Regression Analysis

Tables 20 through 22 again consider our baseline specification of covariates for each of the automatability measures in turn to provide models comparable to the ones in the previous sections. The significantly negative relationship between automatability appears in all models and across the three measures used. Again, the inclusion of additional covariates affects the magnitude, and in some cases the statistical significance, of the the coefficients. This seems to be most pronounced for the MK measure, less so for the GER measure and least for the FO measure. Most covariates have the expected signs and thus are in line with our previous results and those known in the literature. Self-employed respondents, older respondents and those with a better self-reported general health condition have a significantly higher job satisfaction, while race discrimination on the job is associated with lower job satisfaction. The only coefficient that runs counter to results in the literature and previous results from the other datasets, is the one on *Male* showing no effect on job satisfaction across models and measures.

For automatability, we see that the effects are again negative and statistically significant (at the 0.1%, 1% and 5% level for the FO, GER and MK measures, respectively). Table 23 shows the

Table 20: Controlling for Demographics using FO Measures (Baseline)

Dep. Var.: JobSat7	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Autom-FO	-0.368***	-0.278***	-0.272***	-0.280***	-0.277***	-0.220***	-0.184***
	(0.030)	(0.034)	(0.034)	(0.034)	(0.036)	(0.047)	(0.048)
Income		0.467***	0.464***	0.485***	0.489***	0.341***	0.412***
		(0.044)	(0.045)	(0.049)	(0.052)	(0.069)	(0.073)
WkHrs			-0.002***	-0.002***	-0.003***	-0.002*	-0.002*
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
WkSlf			0.354***	0.342***	0.336***	0.317***	0.301***
			(0.045)	(0.045)	(0.048)	(0.061)	(0.062)
Age				0.003**	0.002*	0.007***	0.007***
				(0.001)	(0.001)	(0.001)	(0.001)
Male				0.001	-0.014	-0.030	-0.035
				(0.024)	(0.025)	(0.033)	(0.033)
RaceDisc				-0.326***	-0.345***	-0.185	-0.214
				(0.099)	(0.104)	(0.158)	(0.159)
Educ				-0.008**	-0.011**	-0.012*	-0.014**
				(0.003)	(0.003)	(0.005)	(0.005)
Marital					-0.014	0.017	0.080*
					(0.025)	(0.034)	(0.034)
Childs					0.013	0.017	-0.009
					(0.011)	(0.015)	(0.015)
Health						0.259***	0.266***
						(0.016)	(0.017)
Country dummies	✗	✗	✗	✗	✗	✗	✓
Pseudo R^2	0.005	0.009	0.012	0.013	0.012	0.029	0.049
N	10,839	9,294	9,294	9,150	8,313	4,899	4,899

Standard errors in parentheses; Ordered Probit Model; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

marginal effects of a one standard deviation increase in the respective measure on the likelihood of responding with each respective job satisfaction score. We see a familiar pattern, where the two highest scores are affected negatively, while the lower and middle range scores have positive marginal probabilities associated with a one standard deviation increase in the respective automatability measure. If the GER measure increases by one standard deviation, for example, a respondent on average becomes 0.68% less likely to respond with a job satisfaction score of 6, all other things being equal. On average, such an increase would lead to a drop in the likelihood of responding with one of the highest two ratings of somewhere between (0.0063+0.0066=) 1.29% (GER) and (0.0112+0.0124=) 2.36% (FO). In general, we see that an increase in automatability increases the likelihood to respond with a job satisfaction score between (and including) 1 and 5, while it reduces the likelihood to respond with a job satisfaction score of 6 or 7. As the responses to job satisfac-

Table 21: Controlling for Demographics using GER Measures (Baseline)

Dep. Var.: JobSat7	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Autom-GER	-0.342***	-0.291***	-0.291***	-0.302***	-0.294***	-0.234***	-0.161**
	(0.033)	(0.036)	(0.036)	(0.038)	(0.039)	(0.050)	(0.050)
Income		0.525***	0.529***	0.536***	0.541***	0.371***	0.443***
		(0.030)	(0.030)	(0.033)	(0.035)	(0.046)	(0.049)
WkHrs			-0.002***	-0.002***	-0.003***	-0.002***	-0.002*
			(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
WkSlf			0.339***	0.322***	0.313***	0.280***	0.298***
			(0.032)	(0.032)	(0.034)	(0.042)	(0.042)
Age				0.004***	0.003***	0.010***	0.009***
				(0.001)	(0.001)	(0.001)	(0.001)
Male				0.003	-0.007	-0.006	-0.036
				(0.016)	(0.017)	(0.022)	(0.022)
RaceDisc				-0.321***	-0.326***	-0.362**	-0.417***
				(0.068)	(0.072)	(0.111)	(0.112)
Educ				-0.005**	-0.007**	-0.006	-0.005
				(0.002)	(0.002)	(0.003)	(0.003)
Marital					0.001	0.002	0.066**
					(0.017)	(0.023)	(0.023)
Childs					0.017*	0.034***	-0.001
					(0.007)	(0.010)	(0.010)
Health						0.226***	0.237***
						(0.010)	(0.012)
Country dummies	✗	✗	✗	✗	✗	✗	✓
Pseudo R^2	0.002	0.007	0.009	0.010	0.010	0.024	0.046
N	22,841	19,650	19,650	19,371	17,788	10,849	10,849

Standard errors in parentheses; Ordered Probit Model; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

tion are fairly centred around the higher values of the scale, the negative marginal probabilities on these values contribute more towards the overall effect of automatability on job satisfaction. This is particularly visible as only 7.02% of workers responded with a score of 3 or lower.

Calculating the single headline figures as described in previous sections, we see that a one standard deviation increase of automatability for a mean worker results in a 1.18% (FO), 0.64% (GER) and a 0.70% (MK) decrease in predicted job satisfaction, respectively. The result that job satisfaction is negatively correlated with automatability – may it be interpreted as automation risk or potential – is thus robust across all our datasets and the inclusion of covariates. Still, the magnitude is relatively low, even when accounting for the relatively low variability of both job satisfaction and automatability. Beyond demonstrating the robustness of the effects and discussing their relatively small magnitude, our aim is to provide evidence that is suggestive of the origin of the correlation.

Table 22: Controlling for Demographics using MK Measures (Baseline)

Dep. Var.: JobSat7	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Autom-MK	-1.051***	-0.648***	-0.608***	-0.751***	-0.773***	-0.503***	-0.332*
	(0.088)	(0.100)	(0.100)	(0.108)	(0.112)	(0.141)	(0.146)
Income		0.468***	0.465***	0.452***	0.443***	0.302***	0.372***
		(0.043)	(0.044)	(0.047)	(0.050)	(0.064)	(0.067)
WkHrs			-0.001*	-0.002*	-0.002**	-0.002	-0.001
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
WkSlf			0.342***	0.310***	0.291***	0.295***	0.302***
			(0.041)	(0.042)	(0.044)	(0.053)	(0.054)
Age				0.004***	0.004***	0.011***	0.011***
				(0.001)	(0.001)	(0.001)	(0.001)
Male				0.042	0.037	0.021	0.005
				(0.022)	(0.023)	(0.030)	(0.030)
RaceDisc				-0.390***	-0.394***	-0.317*	-0.361*
				(0.097)	(0.102)	(0.159)	(0.160)
Educ				-0.009**	-0.012***	-0.009*	-0.004
				(0.003)	(0.003)	(0.004)	(0.005)
Marital					-0.020	-0.016	0.043
					(0.024)	(0.031)	(0.032)
Childs					0.018	0.033*	0.000
					(0.010)	(0.013)	(0.014)
Health						0.239***	0.247***
						(0.014)	(0.016)
Country dummies	✗	✗	✗	✗	✗	✗	✓
Pseudo R^2	0.004	0.007	0.010	0.012	0.011	0.026	0.049
N	11,931	10,240	10,240	10,093	9,246	5,838	5,838

Standard errors in parentheses; Ordered Probit Model; $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Table 23: Marginal Effects for Standardised Autom Measures

JobSat7=	1	2	3	4	5	6	7
FO-Std	0.0008***	0.0014***	0.0050***	0.0086***	0.0084***	-0.0117***	-0.0125***
	(0.0003)	(0.0004)	(0.0013)	(0.0022)	(0.0022)	(0.0030)	(0.0032)
GER-Std	0.0005**	0.0008**	0.0026**	0.0046**	0.0043**	-0.0063**	-0.0066**
	(0.0002)	(0.0003)	(0.0008)	(0.0015)	(0.0014)	(0.0020)	(0.0021)
MK-Std	0.0006*	0.0010*	0.0028*	0.0052*	0.0042*	-0.0068*	-0.0069*
	(0.0003)	(0.0004)	(0.0012)	(0.0023)	(0.0019)	(0.0030)	(0.0030)

Obs. (FO): 5,838 Obs. (GER): 4,899 Obs. (MK): 10,849

Standard errors in parentheses; $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Table 24: Controlling for Job Attitudes

Dep. Var.: JobSat7	(1)	(2)	(3)	(4)
Autom-FO	-0.146**	-0.161**	-0.098*	0.042
	(0.048)	(0.048)	(0.048)	(0.049)
JobSec	0.223***			
	(0.015)			
JobWorry		-0.146***		
		(0.017)		
JobUse			0.259***	
			(0.018)	
JobInt				0.589***
				(0.019)
Controls	✓	✓	✓	✓
Country	✓	✓	✓	✓
Pseudo R^2	0.065	0.055	0.065	0.116
N	4,850	4,873	4,838	4,866

(a): FO Measures

Dep. Var.: JobSat7	(1)	(2)	(3)	(4)
Autom-GER	-0.150**	-0.141**	0.039	0.061
	(0.051)	(0.051)	(0.052)	(0.051)
JobSec	0.229***			
	(0.010)			
JobWorry		-0.126***		
		(0.011)		
JobUse			0.271***	
			(0.012)	
JobInt				0.546***
				(0.012)
Pseudo R^2	0.064	0.050	0.063	0.115
N	10,740	10,796	10,708	10,777
Controls	✓	✓	✓	✓
Country	✓	✓	✓	✓

(b): GER Measures

Dep. Var.: JobSat7	(1)	(2)	(3)	(4)
Autom-MK	-0.313*	-0.307*	-0.245	-0.015
	(0.147)	(0.147)	(0.148)	(0.149)
JobSec	0.219***			
	(0.013)			
JobWorry		-0.130***		
		(0.015)		
JobUse			0.261***	
			(0.015)	
JobInt				0.527***
				(0.016)
Pseudo R^2	0.065	0.054	0.066	0.115
N	5,774	5,808	5,752	5,795
Controls	✓	✓	✓	✓
Country	✓	✓	✓	✓

(c): MK Measures

Standard errors in parentheses
Ordered Probit Model
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panels (a) - (c) in Table 24 demonstrate our second main result, applying the GER, FO and MK measures in that order. We see that including subjective job security does attenuate the effect of Autom on *JobSat7* in all three cases, relative to the corresponding full baseline specifications (column (6) in Tables 20 to 22). Still, the effect is still negative and significant at the 1%-level (and at the 0.1% level for FO). This is different for the variables *JobUse* and *JobInt* – asking how 'useful to society' and 'interesting' are attributes which apply to the worker's job.[36] These variables not only reduce the effect of Autom more drastically, but for the GER measure, when considering *JobUse*, and for all measures, when considering *JobInt*, they reduce the statistical significance far beyond conventionally applied levels. We thus have weak evidence for the fear of losing their job driving the effects of looming automation on job satisfaction, but the evidence for our alternative explanation seems to be stronger in the data at hand. Note that, in contrast to the ESS items, these are specific to the job and do not indiscriminately apply to the respondents' general activities.

4.3.3 Robustness Checks

We conduct similar robustness checks to the ones presented in Section 4.2.3 with respect to country specific information. They are presented in Tables 32 through 34 in Appendix B. They do not reveal fundamentally new insights, other than that the inclusion of country specific information does not further attenuate coefficients, be it in magnitude or in terms of their statistical significance. As the ISSP also elicits the regions within countries, we also used dummies on combined country-region indicators. As the results are almost exactly the same as the ones in Columns (5) of Tables 32 through 34, we refrain from showing it here, as the low number of observations in some country-regions leads to them being dropped.
Survey weights are applied in Table 25. We see that the MK measures cease to significantly correlate with the *HighJobSat* Dummy (which is 0 whenever *JobSat7* is up to and including 5 and 1 otherwise), when considering logit and probit estimation while controlling for all individual characteristics and country differences (Columns (4) and (5)). This does not come as a surprise though, as the measure contains only 19 distinct values for the entire dataset and there is hardly any variation left within countries, when additionally splitting the the sample according to *HighJobSat*.[37] As a general bottom line we can say that the usage of survey weights does not change previous results. Schwabe et al. (2020) also control for whether the respondent works in an industry job. They argue, in line with , that this is due to these jobs being more monotonous than other occupations. Due to our approach of using an occupation-specific automatability measure instead of respondent-specific answers to whether think their job could be automated, this is econometrically problematic. Including a comparable dummy for our setting though, picks up almost the same effect as the inclusion of *JobInt*, which is in line with our alternative explanation. This can be seen in Table 26. While the variable *ManOcc*[38] reduces the magnitude and statistical significance of all three measures, it does not add much to the attenuation caused by *JobInt*. This is in line with our explanation that it is the nature of the job driving both automatability and job satisfac-

[36] Both are elicited on a 5-point Likert-scale.
[37] An almost identical result obtains when running the models in Columns (4) and (5) without survey weights.
[38] A dummy for all occupations with ISCO08-Code no less than 7000.

Table 25: Survey Model Regressions for ISSP and FO Measures

	(1) JobSat	(2) JobSat	(3) JobSat	(4) HighJobSat	(5) HighJobSat
Autom-FO	-0.199***	-0.380***	-0.195***	-0.207**	-0.332**
	(0.0524)	(0.0920)	(0.0531)	(0.0648)	(0.108)
N	4,899	4,899	4,899	4,899	4,899
Autom-GER	-0.134*	-0.237*	-0.128*	-0.149*	-0.241*
	(0.0545)	(0.0947)	(0.0559)	(0.0687)	(0.113)
N	10,849	10,849	10,849	10,849	10,849
Autom-MK	-0.398*	-0.750**	-0.407*	-0.360	-0.599
	(0.165)	(0.282)	(0.170)	(0.202)	(0.336)
N	5,838	5,838	5,838	5,838	5,838
Controls	✓	✓	✓	✓	✓
Model	O-Probit	O-Logit	OLS	Probit	Logit

Standard errors in parentheses
All models incoroporate survey weights
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

tion. *ManOcc* apparently proxies for *JobInt* and the automatability measures. Running separate regressions for respondents with high and low education reveals no difference across these groups. Furthermore, looking at the automatability measures across different countries, more automatable

Table 26: Controlling for Manual and Interesting Occupations

Dep. Var.: JobSat7	(1) FO	(2) FO	(3) FO	(4) GER	(5) GER	(6) GER	(7) MK	(8) MK	(9) MK
Autom-	-0.173***	0.042	0.042	-0.081	0.061	0.089	-0.109	-0.015	0.035
	(0.048)	(0.049)	(0.049)	(0.053)	(0.051)	(0.054)	(0.160)	(0.149)	(0.163)
ManOcc	-0.144***		-0.007	-0.128***		-0.046	-0.127***		-0.029
	(0.040)		(0.041)	(0.027)		(0.028)	(0.037)		(0.038)
JobInt		0.550***	0.550***		0.546***	0.545***		0.527***	0.527***
		(0.018)	(0.018)		(0.012)	(0.012)		(0.016)	(0.016)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo R^2	0.050	0.116	0.116	0.047	0.115	0.115	0.050	0.115	0.115
N	4,899	4,866	4,866	10,849	10,777	10,777	5,838	5,795	5,795

Standard errors in parentheses; Ordered Probit Model; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

jobs seem to be located in poorer countries. In the ISSP data, there is a negative correlation between *Autom-OECD* and *GDP* of -0.423 (statistically significant at the 0.1% level). If any similar such correlation is present in their data and if our alternative explanation is (at least partially) correct, using regional variation in robot adoption is not an exogenous instrument to job satisfaction.

More results on country-specific variables akin to those presented in Section 4.2.3 can be found in Tables 32 through 34 in Appendix B.

5 Discussion

Our results provide two main insights. Firstly, job satisfaction is negatively correlated with automatability. This remains true, even when controlling for covariates concerning the worker's characteristics and the overall characteristics of, and opinions on, their job. Furthermore, this result is also robust across different survey datasets and measures for automatability, as well as when controlling for country differences.

Secondly, we provide evidence that suggests that the fear of losing a job due to automation is not the main, or at least not the only driver of this negative correlation. When controlling for different survey items relating to workers' job security, automatability still has a significantly negative effect on job satisfaction and only drops slightly in magnitude. However, when controlling for survey items that ask for whether a job (specifically) is perceived as interesting or useful to society, the effect of automatability on job satisfaction drops in magnitude and loses its statistical significance. As stated earlier, we do not try to establish causality, precisely because we do not think that the relationship between automatability and job satisfaction is indeed causal. Rather we believe that jobs with low job satisfaction and those with high automatability share a common characteristic. Automatable jobs have less contingencies that have to be considered when programming computerised equipment, making them more monotonous and resulting in a lack variety of tasks. This also affects how interesting and meaningful the worker perceives the job to be. Thus, this job characteristic is a common cause for both the measures of automatability and how interesting and meaningful an occupation is to a worker.

While our headline figures are based on robust coefficients, suggesting a drop in job satisfaction between 0.64% and 2.61% after a one standard deviation increase in the respective automatability measure, their values appear relatively small. Yet, with subjective measures on ordinal scales, it is not apparent why such an increase should not be associated with a large increase in perceived well-being. Establishing statistical significance and the sign of the coefficient is thus an important step.

Nonetheless, it would be important to understand whether we are more prone to over or understate the true magnitude, particularly when anticipating future technological changes. While it is hard to predict the course of automation and the new technologies developed in the near future, there are two paths that seem plausible and to some extent consistent with the present data. In the top categories of the item relating to whether a job is interesting, automatability measures are strongly concentrated at the lower end. For the lower categories, the measures are much more spread out. It

seems plausible to assume that technologies that allow jobs to be largely automated from a current automatability of 50% are more likely to be developed in the near future, rather than the technology needed to increase the automatability for a job with a current automatability of 5%. Should this conjecture be true our estimates would serve as a lower bound in the long run.
Another, yet more speculative, path could be through considerations of well-being and work-life balance that are typically more pronounced in high-skilled and high-income jobs (Stoilova et al., 2020). In that case, workers could grow more sceptical and demanding towards job quality, thus reducing (subjective) job satisfaction score at the upper end of the automatability scale. Since automation in the labour market is currently an active field of research, future studies are likely to provide new, improved and potentially dynamic measures. This would allow further robustness checks of our results and an investigation into the variation of the coefficients' magnitude over time.

We are the first to use automatability measures (estimated on the basis of expert judgements on the automatability of specific tasks) alongside multiple datasets on job satisfaction. Even though these measures are not unproblematic (see e.g. Arntz et al., 2017), we show that it is not the specific methodology used that drives our results, as we employ different types of these measures. Other papers (e.g. Hinks, 2020; Schwabe et al., 2020) have used questions relating to workers' own opinions on the automatability of their jobs for their main analysis, rather than the worker-objective measures used here. Furthermore, they have focused on the fear of automation as their main explanation, while using either non work-related items or items that do not address fear directly. In our data, we see that whether a survey item relates to the job specifically, or life more generally, makes a difference. When considering non-work related measures of how interesting a job is to a worker in the ESS, the statistical significance of the negative effect of automatability persists. However, when considering job-specific items in the ISSP, the statistical significance of automatability vanishes.
Schwabe et al. (2020) loosely proxy our explanation through a dummy, which captures whether the respondent works in an industry job. The negative effect relating to this variable, and their explanation of why it is included, support our main hypothesis, though our measure of automatability is more specific and adds more nuance. While we hint at problems with using regional variation of robot-adoption as an instrument, we cannot fully explain why their result is robust to the inclusion of this industry dummy, which loosely proxies occupations and thus differences in automatability. An ultimate test would be to elicit appropriate measures that specifically ask whether a worker fears being replaced by computerised equipment.

Our result is not a prediction as to how satisfied workers are when they work alongside robotics and/or computerised equipment. Interestingly, Gihleb et al. (2020) find that this correlation is indeed positive and workers' job satisfaction is indeed positively affected by the exposure to robotics.

The results of this study are indicative for a labour market transition, where emerging jobs are less likely to be automatable and existing automatable jobs disappearing. Once this transition is complete, our findings suggest that the overall workforce will be more satisfied with their work-life, assuming that automation does not spur unemployment in the long run. This latter qualification is important as we do not claim that potential unemployment resulting from job automation will lead to a higher degree of overall well-being. While the contrary should be intuitive, we can even back this with evidence showing that former spells of unemployment significantly increase job satisfaction, suggesting that having a job is an improvement in terms of well-being. The frictions in this transition, as well as the severity of their consequences, depend on economic and political decision-making. Our analysis abstracts from issues such as long-term unemployment and any resulting hysteresis, as well as radical increases in inequality, shifting rents from labour to capital or from low-skilled to high-skilled workers, with the associated impact on overall well-being (see e.g. Acemoglu, 2002b). This is only valid in the long run when adequate policies in terms of (re-)education and taxation of the changing production factors are implemented. Relating to the latter, our results are informative to studies on labour taxation. They suggest that (skill biased) technical change not only implies a change in marginal labour and machine productivity (see e.g. Acemoglu, 1998, 2002a), but also in the workers' utilities. For all the aforementioned issues of long-term developments, it is important to note that, while we discussed the difference between automation potential (technological feasibility of automation) and risk (adding pragmatic regulatory and ethical considerations) earlier, the choice to use the term 'automatability' is precisely because, with the current measures available, it is not possible to disentangle them in a clean way. Intuitively, automation risk is lending itself more to the fear-based explanation, while the potential rather fits with explaining the negative correlation between automatability and job satisfaction by their common cause of uniform and monotonous tasks. For a final judgement on the role of fear and monotonicity in the relation between job satisfaction and automatability, one would need specific measures for both risk and potential to be determined on the same basic methodology, preferably with variation over time.

6 Conclusion

We demonstrate that automatability, the degree to which a worker's occupation can or is likely to be automated, has a significantly negative relationship with subjective job satisfaction. Using data from three different surveys (the GSS, ESS and the Worker Orientation Data from the ISSP), we show that this result is robust to the inclusion of variables typically relevant to job satisfaction and to different econometric specifications. The fear of losing their job or their feeling of job security respectively, do not attenuate our coefficients. In contrast, when controlling for whether a job is perceived as meaningful and/or interesting, the negative effect of automatability vanishes. We conclude, that this is likely because monotonous jobs tend to be both more likely to be perceived as unsatisfying and are more easily described in algorithmic terms, making it easier to automate them. This runs counter to other studies in the literature that focus mainly on the distress caused to workers by the fear of losing their job.

The datasets we used are happenstance to our question and have not been elicited for the specific purpose of testing our hypotheses. This is apparent, particularly whenever key covariates are unavailable or can only be proxied through the use of similar items. There is other survey data available, that contain similar variables (e.g. the German SOEP or the British Annual Population and Labour Force Surveys). Nonetheless, they have the identical issues with the same or perhaps other variables, or both. A survey or survey item specifically tailored to the questions raised here could thus contribute to our results.

The job satisfaction scores in the data are typically fairly centred around a focal answer and do not vary much. Coefficients could be underestimated due to the low level of variation in the dependent variable. Using biometric measures of job-related stress and fatigue could address this and investigate whether our results, using subjective job satisfaction, serve as a lower bound of the relationship between a job's automatability and a more objective equivalent.

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Appendix

A Calculation of Headline Figures

We repeatedly report single percentage changes in job satisfaction due to a one standard deviation increase in the respective automatability measure. We assume the reader is generally familiar with limited dependent variables and the formulation of these in terms of latent variables. Throughout this section all vectors are column vectors.

For our figures, we first run an ordered probit model of the probability of a respondent to state a job satisfaction of $k \in \boldsymbol{\kappa} = \{1, ..., K\}$ conditional on the included variables and observations in matrix $\boldsymbol{x}$. For a normally distributed error of the latent variable $y^* = \boldsymbol{x}\boldsymbol{b} + \epsilon$, the model takes the form

$$Pr(y = k|\boldsymbol{x}) = \Phi(\mu_k - \boldsymbol{x}\boldsymbol{b}) - \Phi(\mu_{k-1} - \boldsymbol{x}\boldsymbol{b}).$$

Using maximum likelihood, one obtains estimates $\hat{\mu}_k$ for $k \in \boldsymbol{\kappa}$ and $\hat{\boldsymbol{b}}$ and the estimated probabilities at the mean of all variables $\overline{\boldsymbol{x}}$

$$\hat{\boldsymbol{p}} = \{\widehat{Pr(y = k)}|\forall k\} = \{\Phi(\hat{\mu}_k - \overline{\boldsymbol{x}}\hat{\boldsymbol{b}}) - \Phi(\hat{\mu}_{k-1} - \overline{\boldsymbol{x}}\hat{\boldsymbol{b}})|\forall k\}.$$

Using the corresponding marginal probabilities at the mean with respect to automatability

$$\widehat{\boldsymbol{mp}} = \left\{ \frac{\partial \widehat{Pr(y = k)}}{\partial Auto\_Std} \middle| \forall k \right\} = \{-\boldsymbol{b}'(\phi(\hat{\mu}_k - \overline{\boldsymbol{x}}\hat{\boldsymbol{b}}) - \phi(\hat{\mu}_{k-1} - \overline{\boldsymbol{x}}\hat{\boldsymbol{b}}))|\forall k\},$$

our headline figures obtain as

$$HF = 100 \cdot \frac{((\hat{\boldsymbol{p}} + \widehat{\boldsymbol{mp}})'\boldsymbol{\kappa} - \hat{\boldsymbol{p}}'\boldsymbol{\kappa})}{\hat{\boldsymbol{p}}'\boldsymbol{\kappa}}.$$

B Tables

Table 27: ESS Observations (by Country)

Country	ISO-3166 Prefix	Freq.	Percent
Albania	AL	297	1.25
Belgium	BE	942	3.95
Bulgaria	BG	878	3.68
Cyprus	CY	494	2.07
Czech Republic	CZ	973	4.08
Denmark	DK	880	3.69
Estonia	EE	1,151	4.83
Finland	FI	1,086	4.55
France	FR	910	3.82
Germany	DE	1,373	5.76
Great Britain	GB	959	4.02
Hungary	HU	780	3.27
Iceland	IS	444	1.86
Ireland	IE	907	3.80
Israel	IL	1,238	5.19
Italy	IT	281	1.18
Kosovo	XK	290	1.22
Lithuania	LT	859	3.60
Netherlands	NL	955	4.00
Norway	NO	976	4.09
Poland	PL	874	3.66
Portugal	PT	620	2.60
Russia	RU	1,046	4.39
Slovakia	SK	844	3.54
Slovenia	SI	486	2.04
Spain	ES	791	3.32
Sweden	SE	1,014	4.25
Switzerland	CH	768	3.22
Ukraine	UA	736	3.09
Total		23,852	100.00

Table 28: ISSP Observations (by Country)

Country	ISO-3166 Prefix	Freq.	Percent
Australia	AU	656	2.85
Austria	AT	88	0.38
Belgium	BE	1,136	4.93
Chile	CL	616	2.67
China	CN	564	2.45
Taiwan	TW	1,289	5.59
Croatia	HR	180	0.78
Czech Republic	CZ	769	3.34
Denmark	DK	634	2.75
Estonia	EE	652	2.83
Finland	FI	624	2.71
France	FR	505	2.19
Georgia	GE	417	1.81
Germany	DE	844	3.66
Great Britain	GB	626	2.72
Hungary	HU	553	2.40
Iceland	IS	683	2.96
India	IN	350	1.52
Israel	IL	780	3.38
Japan	JP	745	3.23
Latvia	LV	573	2.49
Lithuania	LT	523	2.27
Mexico	MX	565	2.45
New Zealand	NZ	368	1.60
Norway	NO	843	3.66
Philippines	PH	548	2.38
Poland	PL	867	3.76
Russia	RU	635	2.75
Slovakia	SK	520	2.26
Slovenia	SI	475	2.06
South Africa	ZA	692	3.00
Spain	ES	863	3.74
Suriname	SR	378	1.64
Sweden	SE	633	2.75
Switzerland	CH	651	2.82
United States	US	851	3.69
Venezuela	VE	359	1.56
Total		23,055	100.00

Table 29: Correlations between Independent Variables (GSS)

	Autom-FO	Income	WkHrs	WkSlf	Age	Male	White	Educ	Marital	Childs	Health
Autom-FO	1.000										
Income	-0.234***	1.000									
WkHrs	-0.135***	0.346***	1.000								
WkSlf	-0.086***	-0.048***	0.015	1.000							
Age	-0.079***	0.131***	-0.031**	0.158***	1.000						
Male	0.005	0.155***	0.231***	0.096***	-0.010	1.000					
White	-0.104***	0.116***	0.030**	0.060***	0.122***	0.014	1.000				
Educ	-0.368***	0.249***	0.083***	0.009	0.033***	0.022*	0.142***	1.000			
Marital	-0.119***	0.126***	0.012	0.063***	0.263***	-0.007	0.155***	0.056***	1.000		
Childs	0.041***	-0.027**	-0.003	0.070***	0.333***	-0.076***	-0.071***	-0.242***	0.280***	1.000	
Health	-0.123***	0.125***	0.067***	0.026*	-0.080***	0.023*	0.056***	0.219***	0.079***	-0.084***	1.000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 30: Correlations between Independent Variables (ESS)

	Autom-GER	Income	WkHrs	WkSlf	Age	Male	White	Educ	Marital	Childs	Health
Autom-GER	1.000										
Income	-0.065***	1.000									
WkHrs	0.052***	0.111***	1.000								
WkSlf	-0.033***	0.007	0.173***	1.000							
Age	-0.039***	0.017**	0.002	0.121***	1.000						
Male	0.133***	0.061***	0.240***	0.117***	-0.016**	1.000					
White	-0.007	0.050***	-0.013**	0.015**	0.031***	-0.008	1.000				
Educ	-0.266***	0.324***	0.047***	-0.022***	-0.036***	-0.079***	0.011*	1.000			
Marital	-0.022***	-0.096***	-0.026***	-0.003	0.162***	-0.086***	-0.026***	-0.030***	1.000		
Childs	-0.016**	0.126***	0.021***	0.019***	0.030***	-0.071***	-0.019***	0.029***	-0.026***	1.000	
Health	-0.056***	0.107***	0.010	0.019***	-0.239***	0.064***	0.033***	0.091***	-0.071***	0.010	1.000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 31: Correlations between Independent Variables

	Autom-FO	Autom-GER	Autom-MK	Inc. (kPPP)	WRKHRS	WkSlf	AGE	Male	racedisc	Educ	Married	Children	Health
Autom-FO	1.000												
Autom-GER	0.207***	1.000											
Autom-MK	0.459***	0.315***	1.000										
INC (kPPP)	-0.129***	-0.057***	-0.191***	1.000									
WRKHRS	-0.085***	0.030***	0.016	0.046***	1.000								
WkSlf	-0.074***	0.015*	-0.055***	0.036***	0.081***	1.000							
AGE	-0.049***	-0.044***	-0.027**	0.115***	-0.032***	0.066***	1.000						
Male	-0.159***	0.151***	0.075***	0.077***	0.181***	0.088***	0.005	1.000					
racedisc	0.003	-0.010	-0.009	-0.004	0.033***	0.005	-0.031***	0.028***	1.000				
Educ	-0.190***	-0.226***	-0.368***	0.163***	-0.054***	-0.037***	-0.076***	-0.098***	-0.009	1.000			
marital	-0.074***	-0.013	-0.036***	0.061***	0.026***	0.081***	0.277***	0.055***	-0.009	-0.019**	1.000		
HHCHILDS	-0.026*	-0.033***	-0.013	-0.002	0.015*	0.047***	-0.187***	-0.003	0.036***	-0.033***	0.209***	1.000	
Health	-0.095***	-0.062***	-0.128***	-0.083***	0.007	-0.010	-0.238***	0.013	0.028***	0.147***	-0.029***	0.063***	1.000

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 32: Country Characteristics using the FO Measures

Dep. Var.:JobSat7	(1)	(2)	(3)	(4)	(5)	(6)
Autom-FO	-0.229***	-0.228***	-0.242***	-0.220***	-0.204**	-0.184***
	(0.049)	(0.049)	(0.049)	(0.053)	(0.071)	(0.048)
MANU	-2.692***					
	(0.335)					
GDP		0.031***				
		(0.008)				
UNEMP			-0.885			
			(0.653)			
UNION				0.055		
				(0.077)		
Autom-OECD					1.405	
					(0.844)	
Controls	✓	✓	✓	✓	✓	✓
Country	✗	✗	✗	✗	✗	✓
Pseudo R^2	0.034	0.030	0.029	0.033	0.050	0.049
N	4,412	4,412	4,412	3,864	2,165	4,899

Standard errors in parentheses; Ordered Probit Model; $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

Note: For *MANU* we use manufacturing as percentage of value added to GDP from the World Development Indicators (The World Bank, n.d.) to reduce the loss of observations. Results are robust to using other measures.

Table 33: Country Characteristics using the GER Measures

Dep. Var.: JobSat7	(1)	(2)	(3)	(4)	(6)	(7)
Autom-GER	-0.219***	-0.246***	-0.248***	-0.194***	-0.290***	-0.161**
	(0.053)	(0.053)	(0.053)	(0.057)	(0.078)	(0.050)
MANU	-2.625***					
	(0.219)					
GDP		0.033***				
		(0.005)				
UNEMP			-1.235**			
			(0.435)			
UNION_DENS				-0.017		
				(0.053)		
Autom-OECD					2.851***	
					(0.588)	
Controls	✓	✓	✓	✓	✓	✓
Country	✗	✗	✗	✗	✗	✓
Pseudo R^2	0.027	0.024	0.023	0.026	0.045	0.046
N	9,597	9,597	9,597	8,303	4,488	10,849

Standard errors in parentheses; Ordered Probit Model; $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

Note: For *MANU* see note in Table 32.

Table 34: Country Characteristics using the MK Measures

Dep. Var.: JobSat7	(1)	(2)	(3)	(4)	(5)	(6)
Autom-MK	-0.486**	-0.469**	-0.537***	-0.514**	-0.632**	-0.332*
	(0.151)	(0.152)	(0.151)	(0.166)	(0.220)	(0.146)
MANU	-2.700***					
	(0.312)					
GDP		0.041***				
		(0.008)				
UNEMP			-1.722**			
			(0.597)			
UNION				0.087		
				(0.074)		
Autom-OECD					2.036*	
					(0.802)	
Controls	✓	✓	✓	✓	✓	✓
Country	✗	✗	✗	✗	✗	✓
Pseudo R^2	0.030	0.027	0.026	0.030	0.046	0.049
N	5,161	5,161	5,161	4,402	2,568	5,838

Standard errors in parentheses
Ordered Probit Model
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: For *MANU* see note in Table 32.