Automation exposure and implications in advanced and developing countries across gender, age, and skills

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Automation Exposure and Implications in Advanced and Developing Countries Across Gender, Age, and Skills

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Abstract

This paper addresses three main objectives. First, the analysis estimates and compares the average share of workers at risk of automation in advanced and developing regions. Second, the study investigates the possible structural implications of automation across the Gender, Age, and Skill labour market structures at the sectoral, country, and regional levels. Third, the paper extends the analysis of the Gender structure from possible job implications to potential wage consequences; in particular, the potential effect of automation on the gender wage gap at the regional level is studied and the sources of the differentials are identified. This study uses data from the PIAAC dataset, which comprises detailed task data for individual workers including novel data for developing countries. The results indicate that, from a purely technological feasibility viewpoint, advanced countries are more vulnerable than developing countries on average. Male and middle-aged workers are also likely to be more affected by automation, whereas high-skilled workers are likely to be the least affected by automation. The results also indicate that automation could reduce gender inequality not only through jobs but also through wages.

Keywords: Unemployment, Automation risks, Inequality, Developing Countries, Gender wage gap, Decomposition

JEL: J16; J21; J31; O30; O33

1. Introduction

One of the most prominent questions facing humanity presently is the question of how new automation-based technologies will affect the future world of work. In the past decade, the growing interest in addressing this question has been evidenced by the increasing volumes of research outputs not only in academia but also across the international organization, private sector consulting, and journalism domains. Notable among the research papers is the academic work by Frey and Osborne (2013;2017) which documented that about 47 percent of US jobs face high automation risk (above 70 percent risk level). This result has contributed to reviving concerns about mass unemployment through automation.[1] International organizations such as the World Bank (2016;2019) and IMF (2019) have also been involved in investigating the impacts of automation on the labour market and so have consulting firms like McKinsey Global Institute (2017) and PwC (2017). Media outlets such as The Economist (2013;2017) have also made critical contributions.

The rising interest in understanding how automation will affect the future of work, whether welcoming or fearful, is strongly associated with the degree of recent advancements in labour-replacing technologies. The concept of Artificial Intelligence (AI) as a technology that largely replicates human cognitive abilities is contested, as some researchers have asserted that the capacity of AI is narrow, and merely as intelligent as an abacus (Floridi, 2018). However, significant advances in Big Data and AI-related technologies such as Machine Learning, Pattern Recognition, Speech Processing, as well as Mobile Robotics are well documented. Machine agents can now diagnose sicknesses accurately, spot accounting errors, drive, and conduct scientific experiments (Ivanov et al., 2020; Prettner and Bloom, 2020). Intelligent machines have also been projected to translate languages by 2024 and perform retail as well as surgeon's tasks by 2031 and 2053, respectively (Grace et al., 2018).

Following the emergence of the Covid-19 pandemic, the advanced abilities of automation technologies have been coupled with its widespread adoption and application in both advanced and developing economies. Large firms such as Amazon are deploying AI as chatbots to manage and maintain customer relations. YouTube is employing AI to monitor content (Howard & Borenstein, 2020). Chinese start-up, Neolix, has invented a driverless vending machine that can make food deliveries and is reported to have raised $22 million for mass production (Forbes, 2019; Wiggers, 2020). In the public sector, governments encouraged the use of automation technology to minimize the spread of Covid-19 and to control corruption in the

[1] The study is interested in both traditional and smart automation: that is, the replacement of tasks (both cognitive and non-cognitive), that were formerly undertaken by a human worker, by a machine entity that requires no or minimal human intervention and can learn and improve its methods over time. Automation that involves cognitive tasks has been termed as Intelligent Automation (IA) (Coombs et al., 2020).

allocation of financial support to Covid-19 victims. In Chile, for instance, the Contraloría emphasized the reception of documentation in digital format, as well as citizen consultations through virtual platforms.[2] Public service automation and virtualization (or the use of virtual platforms) also skyrocketed in Brazil; specifically, the number of users of an online portal (gov.br) provided for citizens to access several public services increased to over 80 million users, representing 40 times the number of users in January 2019.[3]

The improved capabilities of automation technologies and their increased adoption have strengthened the interest in understanding the potential implications of automation on the labour market along three broad lines. These are the quantity, structural, and wage effects (Verspagen and Nomaler, 2019). First, the quantity effect, which is an age-old issue dating back to the Luddites protests, is linked with anxieties about mass unemployment. However, a recent concern is that developing countries could be more exposed to automation than advanced countries (World Bank, 2016;2019). Second, the structural effect comprises changes to the composition of workers. Automation could favour high-skilled jobs but destroy low-skilled ones, which would exacerbate inequality. There are also fears that gender inequality could rise in sectors that are exposed to automation and comprise a large share of female workers. Bangladesh has been cited because about 80 percent of garment workers in the labour-intensive textile industry are women (Mahmud et al., 2018; Jaimovich and Siu, 2018). Changes to the age composition of workers could also have dissimilar detrimental consequences in advanced and developing economies. Specifically, while the potential hollowing out of middle-aged workers in advanced economies has been connected with the intensification of automation, the youth bulge in developing economies could threaten peace and security when coupled with automation (Urdal, 2006; Acemoglu and Restrepo, 2018). Third, the wage effect reflects the consequences for wages in terms of the overall wage share impact or compositional wage changes. Automation technologies can reduce the overall welfare of labour and increase wage inequality (Berg et al., 2018).

These anxieties are fuelled by the knowledge gap regarding the automation exposure of workers and the related implications for labour markets within sectors, countries, and regions. Furthermore, labour adaptive capacity or 'labour learning' is largely missing in the literature. However, Complex Adaptive Systems theory would contend that labour may adapt to shocks, to some degree, which could reduce the risk of replacement (Hall and Clark, 2010).

This paper leverages new task data to address three main objectives. First, the analysis estimates and compares the average proportion of workers at risk of

[2] The policy action is available on the website of the Controller General of Chile. Available at: Acciones de la Contraloría ante escenario de Covid-19 - Noticias - www.contraloria.cl.

[3] Government of Brazil's website reported the increased number of users. Available at: Mais de 80 milhões de pessoas são usuárias do gov.br — Português (Brasil) (www.gov.br).

automation in the advanced and developing regions. Second, it investigates the possible structural implications of (smart) automation across the Gender, Age, and Skill labour market employment structures at the sectoral, country, and regional levels. Third, the paper considers how automation could affect the gender wage gap at the regional level and identifies the sources of the differentials. The analysis accounts for 'learning' in the estimation of the risk estimates and provides results to contribute to the present understanding of the potential changes to the future world of work in advanced and developing economies.

The study couples the Programme for the International Assessment of Adult Competencies (PIAAC) dataset with a probabilistic approach that follows and builds on Nedelkoska and Quintini (2018) and Foster-McGregor et al. (2019), recognizing the complexity in determining how automation technologies might affect the labour market in the coming years.[4] The approach exploits the differences in tasks undertaken by workers to predict their automatability and ensures that, for instance, lawyers in the agriculture sector would face a different set of risks than lawyers in the manufacturing sector. The paper also employs the Analysis-of-covariance (ANCOVA) decomposition, as well as the Oaxaca-Blinder (OB) and Neumark decompositions to respectively identify the sources of worker automability and the gender wage differentials. The study does not include the scope and capabilities of automation technologies or the labour market-automation theoretical linkages. Nor does it predict the number of jobs that *will* be automated in the future.

The results show that, on average, a larger share of workers in advanced economies are at risk of automation than in developing economies. Also noteworthy is a bimodal structure in the distribution of automation risks in each region. The distributions further indicate that more male workers are exposed than female workers, more middle-aged workers are at risk of automation than young and aged workers, and Skill-Biased Technical Change (SBTC) is evident. Furthermore, accounting for the differences in the structure of employment also generally reveals consistent results at the country level although different sectors are likely to experience varied structural implications. Automation will likely affect the gender wage gap adversely in advanced economies. More broadly, however, discrimination or other (unobserved) factors play a more crucial role in determining the gender wage differential in both regions than the typical differences in observed characteristics between male and female workers such as education and experience.

To arrive at this set of conclusions, the study is structured as follows. Section 2 reviews the literature on the estimation of automation risks and (related) gender

[4] Multiple factors influence the choice of an automation technology including quality, cost, time, flexibility, legal and environmental sustainability considerations (Neb and Remling, 2019). The analysis acknowledges these issues but argues that technological feasibility is a necessary factor since automation cannot take place unless it is feasible to automate the task(s) in question. Consequently, the tasks that workers undertake provide a valuable way of understanding how the labour market might change because of automation technologies.

wage gap studies. Section 3 presents the data and empirical strategy. Section 4 discusses the results for advanced and developing economies separately, as well as the findings on the gender wage effects. Section 5 summarizes and concludes the study.

2. Estimation and Applications of Automation Risks

The pioneering study by Frey and Osborne (2013;2017) (henceforth F&O) introduced a new strand of literature involving the computation of automation risks based on the nature of tasks undertaken by various jobs. The empirical approach extends the theoretical task model of Autor et al. (2003) to non-routine labour inputs or tasks. The earlier task model predicted that automation would be confined to routine tasks, but F&O revisited and extended it to cover non-routine tasks that are not part of the automation bottleneck tasks. Bottleneck tasks are those that are difficult to automate, from a technological perspective, and the authors grouped them under Perception and Manipulation, Creative Intelligence, and Social intelligence (see Table 1). Jobs that embodied high levels (or frequency) of these tasks were thus less automatable than those that did not. For example, surgeons face a low risk of automation because they undertake tasks that require high finger dexterity or response to complex situations.

To employ this idea to investigate automation risks to jobs in the US, they first asked Machine Learning researchers to examine tasks and job descriptions of 70 occupations from the Occupational Information Network (O*Net) database.[5] The purpose was to assign either a 0 or 1 to an occupation depending on whether they judged its tasks to be automatable. They selected 70 occupations (out of 702 occupations) that they were highly confident about to minimize the subjectivity bias. They then chose tasks that were relevant to the three automation bottleneck categories and linked them to the occupations. The relationship between the vector of binary values of the 70 occupations and the tasks was used to develop algorithms to predict the automation risks to the 70 occupations and further extrapolated to all 702 occupations. The risks were grouped into low, medium, and high-risk categories (using threshold probabilities of 30% and 70%). The study showed that about 47% of US occupations are at high automation risk. The paper also found that wages and educational attainment were inversely related to the risk of automation.

[5] Jobs are the same as occupations in this study.

Table 1: Computerization Bottleneck Groups and Tasks in Frey and Osborne (2017)

Bottleneck Group	O*NET variable/task	Background Questionnaire for Task: O*NET description
Perception and Manipulation	Fingers dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.
	Manual dexterity	The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.
	Cramped workspace, awkward positions	How often does this job require working in cramped work spaces that requires getting into awkward positions?
Creative Intelligence	Originality	The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.
	Fine arts	Knowledge of theory and techniques required to compose, produce, and perform works of music, dance, visual arts, drama, and sculpture.
Social Intelligence	Social perceptiveness	Being aware of others' reactions and understanding why they react as they do.
	Negotiation	Bringing others together and trying to reconcile differences.
	Persuasion	Persuading others to change their minds or behaviour.
	Assisting and caring for others	Providing personal assistance, medical attention, emotional support, or other personal care to others such as co-workers, customers, or patients.

Source: Frey and Osborne (2017). The table groups and describes tasks that are difficult to automate.

Based on the same approach, subsequent studies have reported results beyond the US. In Germany, Brzeski and Burk (2015) documented that 59% of jobs are highly exposed to automation. Pajarinen et al. (2015) also recorded that about one-third of jobs in both Finland and Norway are at high risk of automation. There are significantly fewer results for developing countries such as the World Bank (2016) which concluded that, on average, about 66% of jobs in developing countries are vulnerable to automation. These risks are, therefore, typically interpreted in two main ways: either in terms of the average share of jobs at risk of automation or the share of jobs at high risk of automation.[6]

Other authors have also used different approaches to calculate the risk of automation. Nedelkoska and Quintini (2018) [henceforth N&Q (2018)] extended the scope of the risk analysis to cover the OECD area. The empirical strategy hinged on regression analysis rather than training Machine Learning algorithms. Authors first translated the subset of 70 jobs that experts adjudged to be automatable or otherwise from the Standard Occupational Classification (SOC) of O*Net to the International Standard Classification of Occupations (ISCO) of PIAAC. This was implemented by finding jobs in the latter that correspond to those in the former 70 jobs. After identifying the corresponding jobs in the PIAAC dataset, a dummy variable is created solely for workers in this subset of jobs. This means that 1 is assigned to all workers of a job that is expected to be automated and 0 is allocated to those workers in jobs that experts do not expect to be automated in the coming years. This step is followed by a logit estimation focused on the subset of workers, with the dummy as the dependent variable and the tasks in the PIAAC dataset that correspond to the

[6] This study computes the average share of jobs at risk of automation, which accounts for heterogeneity in employment structures across countries and embodies jobs that are characterized by high, medium, and low automation risks. For each region, the study additionally graphs the distribution of individual-worker risks for each risk category.

computerization bottlenecks identified in F&O as independent variables (see Table 2). The resultant regression is used to predict the risks to the selected subset of workers and subsequently extrapolated to the entire PIAAC dataset. The authors estimated the regression only for Canadian workers (rather than US jobs) because Canada had a large sample size. A crucial distinction from the previous work is the level of analysis: O*Net dataset is only available at the job level whereas PIAAC is available at the level of individual workers within jobs. Although the study documented a lower share of jobs at high risk of automation (14% of jobs) in the OECD region, the median job was estimated at 48% automation risk. The study also concluded that automation risks declined with higher education and wage levels, showing a high likelihood of Skill-Biased Biased Technical Change (SBTC).

Re-estimating automation risk for mainly EU countries, with further considerations of the role of structural change and trade, Foster-McGregor et al. (2019), showed that country-level automation risks ranged between 47% and 64%. The paper also concluded that the country-level probability of automation depends on the employment structure. The approach closely followed N&Q (2018), together with other valuable additions. One contribution was to account for the observation made by Arntz et al. (2017) which argued that incorporating differences in tasks under the same job code into their analysis reduced the share of US jobs at high risk of automation from 38% to 9%. Consequently, risk estimates that ignore these differences likely overestimate the 'true' risks. This idea was operationalized in Foster-McGregor et al. (2019), by estimating the same logit model for each sector separately. The implication is that the risks are broken down by sector such that, for instance, a different set of risks are estimated for lawyers in the agriculture sector than lawyers in the manufacturing sector. Furthermore, by weighting the country-level risk estimates using their corresponding employment structures, the authors incorporated country-level heterogeneity, which assured that, if the labour market of a country comprised a greater share of high-risk jobs, it is reflected in the overall risk estimate of the country. Another deviation from the previous work was the use of the pooled data for all countries that had the needed data (rather than a reference country such as Canada) to estimate the logit regressions.

Fewer papers have also applied the risk estimates to further investigate the possible structural implications of automation on the labour market. N&Q (2018) conducted an OLS estimation on the automation risks (as the dependent variable) and worker characteristics including gender, age, and education attainment (as independent variables) for the pooled OECD sample comprising 32 countries. The paper also plotted graphs and estimated correlations between the risk estimates and educational attainment, as well as the risks and wages. Authors found being female to be positively associated with the risk of automation (significant at 1% level) while age and education exhibited a negative and statistically significant relationship.

Gadberg et al. (2020) also studied the impact of the automation risks on the wage and employment shares of occupations in Sweden between 1996 and 2013, and considered different age and skill groups. The paper estimated that automation risks are negatively associated with both wage and employment shares, with the impact being larger for the wage shares. Therefore, it argued that wage inequality could be more significant than employment inequality.[7] The findings also indicate that it is not only the level of risks that matters in affecting wage and employment shares but also the variation in risks across jobs. Moreover, educational attainment was inversely related to automation risk in Sweden. Middle-aged workers in high-risk occupations also experienced the highest adverse impact over the study period. The authors further presented evidence of labour adaptability as workers shifted from high-risk occupations to low-risk ones within firms, but they did not incorporate labour adaptability in the computation of the risks.

Kaltenberg and Foster-McGregor (2020) takes the analysis further and covers a wider scope. The paper estimated the relative significance of automation-induced wage and employment compositional changes in determining inequality across Europe by decomposing their effects. Authors reported a different result to Gadberg et al. (2020): the composition effect was stronger than the wage effect. There is, therefore, scholastic interest in comparing how jobs and wages could be affected by automation.

Concerning gender wage inequality more specifically, a comprehensive strand of literature focuses on decomposing the gender wage gap. It involves (augmented) Mincer equations, coupled with decomposition techniques such as Oaxaca-Blinder (OB) decomposition and related extensions to identify the source of the wage differentials. The original paper by Blinder (1973) divided the source of the wage differentials into three main parts. These are the endowment effect (which captures the part of the wage gap that is attributable to differences in characteristics), the coefficient effect (or part attributable to different coefficients, except for the constant terms), and the unexplained portion (attributable to differences in the constant terms of the separate regressions of the two groups under consideration). Thus, the 'explained' aspect of the wage differential was either due to the differences in the regressors or coefficients (except the constant terms). However, because Blinder (1973) and Oaxaca (1973) further described the combined contributions of the coefficient effect and the unexplained portion as the part of the differential attributable to discrimination, some recent papers use the terms 'unexplained' and discrimination interchangeably (Jann, 2008; Castagnetti and Giorgetti, 2019). This is, nevertheless, a misnomer since the coefficient effect also explains the wage differences, as noted in the original work by Blinder. Jann, 2008 additionally considers

[7] Wages could be dampened due to competition from automation technologies for high-risk occupations (Prettner and Bloom, 2020).

the interaction effect (a residual component) since other unobserved factors or omitted variables can also affect the wage differentials.

The existence of discrimination against women, where the coefficient effect contributes significantly to the gender wage gap between male and female workers, is largely reported in the extant literature. In these contexts, female workers earn less income even if they have the same characteristics as male workers, including education and experience (Tromp, 2019). The degree of the wage gap also differs across countries and sectors, and could also vary over time. Chuang et al. (2018) concluded that the wages of female workers in Taiwan's financial sector were 3–20% below their male counterparts as compared to 15–93% in the mining sector. Additionally, the range of the inter-sector gender wage gap is larger in Taiwan than in the U.S. Seneviratne (2020) also found a steady decline in the gender wage gap between 1992 and 2014 in Sri Lanka despite a rise in the coefficient component.

The strand of literature on Intelligent Automation, particularly the automation-risk literature, has made little contribution to discussions on the gender wage gap in both advanced and developing regions. Ge and Zhou (2020) analyzed the effect of automation on the gender wage gap and estimated that computers increased the gender wage gap, but robots reduced it. Industrial robots also decreased the wages of male workers more than female workers, whereas female workers were more negatively impacted by computers than male workers. However, the study focused only on the US, and the use of physical industrial robots and computing equipment misses disembodied technical progress embedded in the advancement of algorithms and software applications. Automation risk estimates can account for disembodied technological change and contribute to the gender wage gap literature.

There is also the need to consider the ability of labour to adapt to automation shocks (within the computation of the risks), coupled with the fact that workers of a particular demographic attribute (such as male workers) in different industries may be exposed to automation differently. This study addresses these gaps.

3. Empirical Strategy

The empirical approach broadly entails two parts. The first section computes automation risks at the regional (advanced and developing regions), country, and sectoral levels. It also estimates the Analysis-of-covariance (ANCOVA) decomposition to find the tasks that strongly explain the automability of each group (such as male workers) within each region. The second part estimates an extended Mincerian regression to indicate the potential impact of automation (as proxied by automation risks) on the wages of male and female workers. The Oaxaca-Blinder (OB) and Neumark decompositions are also implemented to identify the sources of the gender wage differentials at the regional level.

3.1 Data

The study draws on the public version of the Programme for the International Assessment of Adult Competencies (PIAAC) dataset developed by the OECD. It is a survey that asks workers, among other questions, the tasks that they undertake and the frequency with which they perform them in their jobs. It also contains information on worker demographic and socio-economic characteristics including their gender, age, and educational levels, coupled with their earnings and the industries where they work. Whereas O*NET (used in Frey and Osborne's work) is limited to jobs only, PIAAC provides information at the individual-respondent level within jobs, permitting more disaggregated analyses. The survey covers 37 countries across three (3) rounds during the period 2011 – 2019. However, only countries with publicly available 4-digit-level ISCO-08 job codes are selected to ensure the operationalization of the empirical approach and to encourage replication of the results of this analysis. Like earlier automation-risk work, jobs are the same as occupations in this study.

In total, the sample of this analysis comprises 20 advanced countries and 5 developing countries.[8] It includes new data for developing countries: Ecuador, Kazakhstan, Mexico, and Peru. The study separates advanced (or high-income countries) and developing countries using the 2020-2021 World Bank Income Classification system for guidance but maintains Russia as an advanced economy.

Table 2 presents the variables that N&Q (2018) used to predict the automation risk estimates, which correspond to the bottlenecks identified by F&O. The analysis uses these variables and includes, Learning from Co-workers or Supervisors, Learning-by-Doing, and Keeping Up To Date, to account for learning in the current work (under the Social intelligence group), which could dampen the automation risks presented by

[8] The advanced countries are as follows: Belgium, Chile, Czech Republic, Denmark, France, Greece, Hungary, Israel, Italy, Japan, Republic of Korea, Lithuania, Netherlands, New Zealand, Poland, Russia, Slovakia, Slovenia, Spain, and the UK. The developing countries are Ecuador, Kazakhstan, Mexico, Peru, and Turkey.

earlier work. Each variable represents a question, and the numeric codes of the responses are used as the values of the variables to estimate the regressions. Similar to the previous work, this study also utilizes the responses coded as follows: 1 (Never); 2 (Less than once a month); 3 (Less than once a week but at least once a month); 4 (At least once a week but not every day); and 5 (Every day).[9] The dependent variable is a binary variable that equals 1 for workers involved in jobs that are expected to be automated and 0 otherwise. These jobs in the PIAAC dataset closely correspond to Frey and Osborne's 70 jobs assessed by Machine Learning experts. This study is also based on ISIC rev 4 1-digit-level industries.

Table 2: PIAAC Variables Corresponding to Bottlenecks in Frey and Osborne (2017)

Bottleneck Group	PIAAC variable/task	Variable Code	Background Questionnaire for Task
Perception Manipulation	Fingers (dexterity)	f_q06c	How often does your job involve using skill or accuracy with your hands or fingers?
Creative Intelligence	Problem-solving, Simple	f_q05a	How often are you usually faced with relatively simple problems that take no more than 5 minutes to find a good solution?
	Problem-solving, Complex	f_q05b	How often are you usually confronted with more complex problems that take at least 30 minutes to find or think of a good solution?
Social Intelligence	Teaching	f_q02b	How often does your job involve instructing, training, or teaching people, individually or in groups?
	Advice	f_q02e	How often does your job involve advising people?
	Plan for others	f_q03b	How often does your job involve planning the activities of others?
	Communication	f_q02a	How often does your job involve sharing work-relation information with co-workers?
	Negotiate	f_q04b	How often does your job involve negotiating with people either inside or outside your firm or organization?
	Influence	f_q04a	How often does your job involve persuading or influencing people?
	Sell	f_q02d	How often does your job involve selling a product or selling a service?
	Learn from co-workers and supervisors	d_q13a	How often do you learn new work-related things from co-workers or supervisors?
	Learn by doing	d_q13b	How often does your job involve learning-by-doing from the tasks you perform?
	Keeping up to date	d_q13c	How often does your job involve keeping up to date with new products or services?

Source: Nedelkoska and Quintini (2018) and PIAAC Background Questionnaire. Variables in **bold** have been added for this study.

In the subsequent analysis regarding the potential effect of automation on the gender wage differential, the log of wages (monthly earnings excluding bonuses for wage and salary earners, Purchasing Power Parity corrected $US) is regressed on the estimated gender-relevant automation risks (as an automation proxy), together with other Mincer-type covariates, as well as entity fixed effects. These variables include the following: Age (in years, with a range of 16-65), Experience (or years of paid work

[9] It is worth noting that the independent variables or tasks are ordinal in nature but are treated as continuous variables in the logit estimations.

during the worker’s lifetime, with a range of 0-55), and Education (in terms of the highest qualification attained, ranging from no formal education to a Ph.D. level based on the 1997 International Standard Classification of Education). Foreign qualification and International Standard Classification of Education (ISCED) 5A covering bachelor’s degree, 5A master’s degree, and 6 (without distinction) were not included in the analysis to permit categorization of the skill dimension into three groups of workers. Low-skilled workers are those with no formal education or below ISCED 1 to workers with ISCED 3C level education which is shorter than 2 years. Middle-skilled workers have attained education between ISCED 3C level which is more than 2 years to an undergraduate degree. High-skilled workers have a master's or a Ph.D. Regarding the age structure, young workers are between the ages of 16-24 years, middle-aged workers are 25-55 years and aged workers are between 56 and 65 years.

Consistent with existing work, the other variables in the wage regression include the Marital Status [or whether the worker is living with a spouse or partner, [Yes (1) / No (0)], Employment Contract types (covering, an indefinite contract, a fixed-term contract, a temporary employment agency contract, an apprenticeship or other training scheme, no contract, and other contracts) and Firm size (or the number of people working for an employer from 1 to 10 workers, 11 to 50 workers, 51 to 250 workers, 251 to 1000 workers, and more than 1000 workers). The analysis also includes entity fixed effects: dummies for ISCO08 1-digit-level occupations and ISIC rev 4 1-digit-level sectors, as well as country dummies. The summary statistics are presented in Table A.1 in Appendix A.

3.2 Estimation Approach

The study estimates the risk of automation using the proposed approach by Foster-McGregor et al. (2019), which is in the spirit of Nedelkoska and Quintini (2018) but breaks down the risk estimates into different sectors such that workers of the same job but in different sectors face different sets of risks. The approach exploits the variation in selected tasks that reflect automation bottlenecks to predict the likelihood of automation. The guiding intuition is that certain tasks are more difficult to automate and, therefore, workers that perform these tasks frequently are at a lower risk of automation.

Operationalizing this approach first involves translating a subset of 70 jobs that experts adjudged to be automatable or otherwise (based on job descriptions) in F&O from the Standard Occupational Classification (SOC) system to the International Standard Classification of Occupations (ISCO) system. This means that jobs in the ISCO system that correspond to the 70 jobs (based on the SOC system) are selected. For example, Physicians and Surgeons in the SOC system correspond to Generalist medical practitioners and Specialist medical practitioners in the ISCO system at the 4-digit level. This ‘matching’ is necessary because the O*Net dataset used in Frey and

Osborne's work is based on SOC whereas the PIAAC dataset used in this study employs the ISCO system.

After identifying the corresponding jobs in the PIAAC dataset, a dummy variable is created solely for the selected subset of jobs. The dummy is equal to 1 for all workers in a job (in both the developing and advanced regions) that the Frey-and-Osborne experts expect to be automated and 0 for those workers in jobs that the experts do not expect to be automated in the coming years.[10]

The next step estimates pooled logistic models with robust standard errors for the subset of workers based on the dummy as the dependent variable and the tasks that are posited to pose challenges to automation as independent variables. The regressions are conditioned on the pooled data for both advanced and developing-country workers by sector and not separate data for the two regions since "…there is no specific reason to believe that the way bottlenecks relate to the risk of automation differs across countries…", notes N&Q(2018), although accounting for the diverse employment structures is critical. Therefore, the estimation of the risks hinges on exploiting the individual-level task variation in the two regions, under the same risk-task structure, and focuses only on workers with valid answers for all the bottleneck variables. The estimated coefficients are expected to be negative since the automation bottlenecks are inversely related to the probability of automation. It is not unusual, however, to find unexpected signs for some tasks in this literature. Furthermore, all regressions are (probability) weighted by the full final sampling weights in the PIAAC dataset to improve representativeness. The paper also includes three additional tasks to the previous work, namely: Learning from Co-workers and Supervisors, Learning by doing, and Keeping up to date with current products and services (see Table 2). This is motivated by the Complex Adaptive System theory which argues that labour can adapt to threats (of displacement) in the labour market, meaning that excluding tasks relevant to adaptive capacity would likely overestimate the actual automation risk. Therefore, the study includes these tasks under the Social Intelligence bottleneck group and in all regressions.

The ensuing regression coefficients are used to (probability) predict automation risks to the subset of jobs and to make out-of-sample predictions for other workers in the PIAAC dataset. In estimating the regressions, the analysis is broken down into different groups within the Gender, Age, and Skill dimensions of the labour market in advanced and developing countries based on ISCO 4-digit level jobs and ISIC rev 4 1-digit-level industries. This is achieved by estimating separate logistic regression models for the selected subsample of jobs by the sector in question and the attribute

[10] The study assumes that if doctors (one job in the subset of the 70 Frey and Osborne jobs), for instance, are not expected to be automated in the advanced region, then they are also not expected to be automated in the developing region. While this study focuses on technological feasibility, it is worth stating that under economic feasibility or cost considerations, some automation technologies could be expensive and thus reduce automated jobs in developing region. The technology needed to automate some tasks by doctors could be costly for developing countries to adopt.

of the workers (such as male workers in the agriculture sector). In doing so, this study extends Foster-McGregor et al. (2019) by disaggregating the risks not only by sector but also by worker groups within each dimension.

Regarding the Gender dimension, this analysis estimates the regressions separately for male workers by sector and repeats this for female workers. The study also runs separate regressions for young workers (16-24 years), middle-aged workers (25-55 years), and aged workers (56-65 years) by sector. The approach is further replicated for low-skilled, middle-skilled, and high-skilled workers. The classification of workers in the Age and Skill dimensions was guided by the OECD classification and the 2019 PIAAC Technical Report (p. 31), respectively.[11]

For each region, kernel density graphs are presented to describe the distribution of the individual-respondent-level automation risks for the relevant groups within each dimension. Like F&O, risks above 70% as high whereas the medium-risk category is located between 30% and 70%. The low-risk group is found below 30%.

This study also computes the overall weighted average of automation risks at the country and sector levels, as well as the related weighted averages for the different attributes within each dimension. The full final sampling weights in the PIAAC dataset are used to calculate the weighted averages instead of the EU Labour Force Survey data (as was the case in Foster-McGregor et al., 2019). By weighting the sector and country-level averages by the sampling weights, the study accounts for differences in the labour market structures in both regions despite the prior estimation of the risks based on data pooled from both advanced and developing countries.

The average risks for all individuals at the sectoral and country levels are computed using formulas (1) and (2). The overall risk estimate is used to infer potential quantity changes while the point estimates of the attributes within each dimension are compared to conjecture the potential structural consequences of automation through the lenses of technological feasibility. For instance, if the weighted average risk estimate for female workers is higher than that of male workers in a sector or country, the results are interpreted to indicate that smart automation will likely widen the gender employment gap in the sector or country.

$$(1): \qquad \rho_{ri} = \frac{\sum_k \rho_{rik} S_{rik}}{\sum_k S_{rik}}$$

The paper denotes ρ_{ri} as the weighted average automation risk estimate for sector *i* in country *r*. This is summed over all *k* individuals in sector *i*; ρ_{rik} represents the automation risk of worker k in sector *i* and country *r*, and S_{rik} is the sampling weight of worker k, representing the number of workers of type k in sector *i* and country *r*.

[11] The OECD classification of employment by age is available at: https://data.oecd.org/emp/employment-rate-by-age-group.htm#indicator-chart

Equation (2) further takes the summation over all sectors in country *r* to calculate the country-level weighted average risk denoted as ρ_r. S_{ri} signifies the total number of workers in sector *i* and country *r*.

(2): $$\rho_r = \frac{\sum_i \rho_{ri} S_{ri}}{\sum_i S_{ri}}$$

Women and high-skilled workers are expected to be less exposed to automation. Women dominate care work, an activity that N&Q (2018) found to be correlated with the bottleneck tasks Advising and Teaching Others. Women constitute three-quarters of workers in health and social care in the OECD and invest about 4 times the time spent by men in unpaid care work in Asia and the Pacific, according to OECD and ILO respectively.[12] [13] Also, high-skilled workers are likely to be less vulnerable to automation because they tend to perform tasks that entail solving complex problems and planning for others. How the composition of workers could change in the Age dimension is more difficult to hypothesize from the standpoint of technological feasibility. The ANCOVA decomposition can, however, be employed to identify the tasks that are most predictive of automability. The paper estimates the partial sum of squares ANCOVA models weighted by the PIAAC sampling weights and based on a fractional factorial design (i.e. without interaction terms) to trace the tasks that largely explain the variation in automation risks of each group in both regions.[14] The partial sum of squares of a particular task is the difference between the explained sum of squares (ESS) of the full model and the ESS of the model with all but the task in question as independent variables.

The analysis proceeds to the second aspect of the empirical strategy in which the estimated automation risks for male and female workers are used to investigate the impact of automation on the gender wage gap for each region. The log of monthly wages & salaries in Purchasing Power Parity (PPP) terms is regressed on the gender-relevant automation risks (as a proxy for automation), together with other Mincer-type covariates and entity fixed effects to minimize the risk of omitted variable bias. These variables include the following: Age, Age-squared, Experience, Experience-squared, and dummies for Education, Marital Status, Contract Type, Firm Size, Occupations (1-digit-level), Sectors (1-digit-level), and Countries in line with the

[12] The share of women in care work within the OECD is reported at: http://www.oecd.org/gender/data/women-are-well-represented-in-health-and-long-term-care-professions-but-often-in-jobs-with-poor-working-conditions.htm

[13] The ILO report on the share of women involved in unpaid care work in Asia and the Pacific can be found at: http://www.oecd.org/gender/data/women-are-well-represented-in-health-and-long-term-care-professions-but-often-in-jobs-with-poor-working-conditions.htm

[14] The fractional factorial design is chosen over the full factorial design because of the many interaction terms to account for across the thirteen tasks in the latter case, which are not of interest in this analysis. The partial sum of squares approach is also selected instead of the sequential approach since the order of the contribution of tasks does not matter.

literature (Strawinski and Majchrowska 2018; Castagnetti and Giorgetti, 2019; Ge and Zhou, 2020). The estimation procedure for all the Mincerian regressions including those in the Oaxaca-Blinder (OB) and Neumark decompositions is based on bootstrap standard errors (with 200 replications) to account for the fact that the automation-risks variable is a constructed regressor and does not fully capture the uncertainty that exists in the unknown automation regressor which is being represented.

The model is estimated separately for either gender in the advanced and developing regions. Automation is expected to be adversely associated with wages for both male and female workers since the surplus labour created due to labour displacement places downward pressure on wages, especially in the short-to-medium term. Competition from automation technologies for high-risk occupations is also likely to negatively affect wages (Prettner and Bloom, 2020). Additionally, a larger negative impact on male wages in both advanced and developing regions is expected, following the hypothesis that more women (as compared to men) may be involved in jobs that constitute tasks that are difficult to automate.

The Oaxaca-Blinder (OB) decompositions are also implemented for both advanced and developing regions. The standard approach decomposes the difference between male and female wages, denoted as $\boldsymbol{W_g}$, (and evaluated at the sample means) into three main components under OLS assumptions including $\boldsymbol{E}(\mathcal{E}_g|\boldsymbol{X_g}) = \mathbf{0}$. Equation (4) presents the components.

$$(\mathbf{3}):\quad \boldsymbol{W_g} = \boldsymbol{X_g\beta_g} + \mathcal{E}_g \qquad \boldsymbol{for} \qquad \boldsymbol{group\ (g) = male(m), female(f)\ workers}$$

$$(\mathbf{4}):\quad \boldsymbol{E(W_m) - E(W_f) = [E(X_m) - E(X_f)]b_f + E(X_f)(b_m - b_f) + [E(X_m) - E(X_f)](b_m - b_f)}$$

$$(\mathbf{5}):\quad \boldsymbol{E(W_m) - E(W_f) = [E(X_m) - E(X_f)]b_m + E(X_m)(b_m - b_f) + [E(X_f) - E(X_m)](b_m - b_f)}$$

$$(\mathbf{6}):\quad \boldsymbol{E(W_m) - E(W_f) = [E(X_m) - E(X_f)]b_c + [E(X_m)(b_m - b_c) + E(X_f)(b_c - b_f)]}$$

On the right-hand side of equation (4), the first component (the endowment effect) explains the gender wage differential due to the average differences in the *observed* characteristics of male and female workers given the same female coefficients or wage structure. The second component (the coefficient effect) explains the proportion of the wage-gap difference attributable to differences in the coefficients of male and female workers, given the same observed characteristics of female workers.[15] The final term or the residual component (the interaction effect) accounts for differences from both characteristics and coefficients simultaneously

[15] The endowment effect captures the part of the wage gap stemming from the differences in the typical and directly observable characteristics between male and female workers, whereas the coefficient effect measures the proportion of the wage gap due to differences in the estimated relationships between the overall characteristics of each group and their wages. In the absence of the coefficient effect or discrimination (where $\boldsymbol{b_m}$ - $\boldsymbol{b_f}$ = 0**)**, gender wage differences will only arise from differences in characteristics such as education and experience.

(Jann, 2008; Fortin, et al., 2010). In other words, it captures the differences unaccounted for by the estimation method. The interaction effect is the residual component of the index and is generally regarded as negligible. Consequently, the study only reports aggregate results for the male and female reference structures but not the detailed decomposition results which include the contribution of each variable to the interaction effect.

A major drawback of the standard decomposition is the index problem: the choice of the reference structure is arbitrary, leading to identification issues. As equation (5) indicates, male reference coefficients can also be selected to construct the decomposition. This implies that the decomposition results are not invariant to the choice of the reference structure (Oaxaca and Ransom, 1999). A suggested approach to addressing the issue requires 'averaging' the male and female coefficients or estimating the coefficients of a pooled regression involving the two groups, which is denoted as $\boldsymbol{\beta_c}$ in equation (6), and subsequently using the result to compute the decomposition. This is the Neumark decomposition (Neumark, 1988; Yun, 2005). The last two terms on the right-hand side of (6) represent the coefficient effects from the perspectives of the male and female workers, respectively.[16]

The average-based approach also has an issue worth stating, however. It can result in a spillover of portions of the discrimination component into the endowment component. To tackle this challenge, Jann (2008) recommends including the group variable (in the case of the present study, the gender variable) in the pooled model, and this study employs the approach. Like Chuang et al. (2018), this analysis considers results for the male and female reference structures (or the traditional OB approach) in addition to the Neumark approach.[17]

The OB-based decompositions are also used instead of related extensions such as the Machado-Mata decomposition or RIF techniques because the interest of this study is only in the mean wage differences between male and female workers. Furthermore, as Figures 7 and 8 show in Appendix B, there is substantial information at the means of the wage distributions in advanced and developing countries, making its use worthwhile for this analysis. The wage structure is expected to prevail in both advanced and developing regions as the results of some country cases in section 2 have indicated.

[16] The coefficient effect based on the pooled model can either be split into the separate contributions of the two groups or reported as their 'pooled' contribution.

[17] Some researchers acknowledge that the male reference structure may not reflect the 'true' non-discriminatory labour market wage structure but use it, nonetheless. They assert that legal cases in gender discrimination often use men as the comparison group, and that the choice may be worthwhile in cases where male workers constitute a larger share of the workforce (Tromp, 2019; Castagnetti and Giorgetti, 2019; Seneviratne, 2020). Since the subsamples of advanced and developing countries contain more male workers (51% > 49% and 56% > 44%, respectively), this study also reports results using the male reference structure.

4. Results

Overall, the pooled logistic regression based on the full sample of advanced and developing countries showed unexpected positive and statistically significant signs for the bottleneck variables Negotiate, Sell, and Communicate like in N&Q (2018). The major differences noted are that the tasks Simple problems and Complex problems are positive but not significant while Dexterity is negative and significant. The adaptive-capacity variables Learning from Supervisors/Co-workers and Learning by doing are both negative but only the latter is significant. The task, Keeping up to date, is, however, positive but not significant (as Table 3 demonstrates).

Despite the weak outcomes for two of the new variables overall, they are maintained in the analysis since the study estimates automation risks by the sectoral subsamples rather than the full sample. Crucially, the sectoral breakdown of the risks indicated their relevance in some sectors. The coefficients of the regression conditional on female workers (in both advanced and developing countries) working in the Finance and Insurance industry, for instance, revealed that the variables Learning by doing and Keeping up to date were negative and statistically significant. Learning from Supervisors/Co-workers was also significant, albeit unexpectedly positive. These results indicate that the learning variables generally reduced automation risks as hypothesized. Table A.2 in Appendix A presents weighted averages of the sector-specific regression coefficients and standard errors. The weight of the coefficients and standard errors of a regression is the share of the observations of the regression in the total number of observations for the worker group. For the overall sector-level estimates (which represent the sectoral breakdown without consideration of individual attributes within the sector), the average number of observations per sector was 901 workers across 20 sectors and regressions. Less than 20 regressions were estimated for the worker groups within sectors, however, because each worker group was not adequately represented in all 20 sectors. For instance, there is no estimate for female workers in Agriculture in Table 6 because the number of female workers in the sector that provided valid responses for all the selected task-variables was inadequate to estimate the regression.

Table 3: Logistic Regression Results

Bottleneck Variable	N&Q (2018)	Pooled Regression	Female workers in Finance & Insurance
Fingers (Dexterity)	0.105***	-0.031*	-0.284
	[0.022]	[0.017]	[0.183]
Simple Problems	0.0573*	0.012	0.119
	[0.031]	[0.027]	[0.252]
Complex Problems	-0.0691**	0.031	-0.329
	[0.030]	[0.030]	[0.292]
Teach	-0.069***	-0.153***	0.426*
	[0.026]	[0.023]	[0.248]
Plan work of others	-0.308***	-0.117***	-0.623***
	[0.023]	[0.024]	[0.187]
Influence others	-0.235***	-0.211***	0.222
	[0.027]	[0.024]	[0.192]
Negotiate	0.046*	0.061***	0.181
	[0.026]	[0.024]	[0.221]
Sell	0.160***	0.085***	0.060
	[0.021]	[0.020]	[0.254]
Advise	-0.199***	-0.152***	0.093
	[0.027]	[0.023]	[0.214]
Communicate	0.214***	0.191***	-2.716***
	[0.026]	[0.025]	[0.758]
Learning from other		-0.003	0.644*
		[0.027]	[0.378]
Learning by doing		-0.114***	-0.728**
		[0.026]	[0.322]
Keeping up to date		0.0234	-0.466**
		[0.026]	[0.222]
Constant	0.363**	0.876***	18.090***
	[0.152]	[0.131]	[3.912]
Number of Observations	4656	18226	335
Pseudo R-squared	0.137	0.073	0.273

Standard errors in brackets

* p<0.1, ** p<.05, *** p<.01

Notes: The second column presents coefficients from Nedelkoska and Quintini (2018) which were estimated using a sample of Canadian workers only. The third column captures the coefficients of the pooled logit regression conditional on all workers in the sample and includes additional learning-related tasks. The final column presents the coefficients of a sector-specific logistic regression for female workers in the Finance sector only.

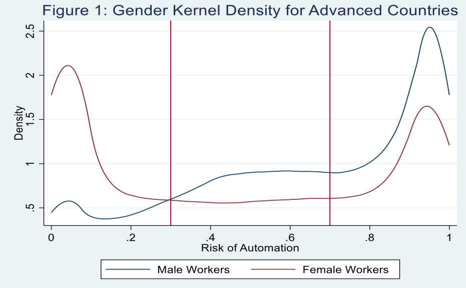
4.1 Automation Risks to Advanced-Country Workers

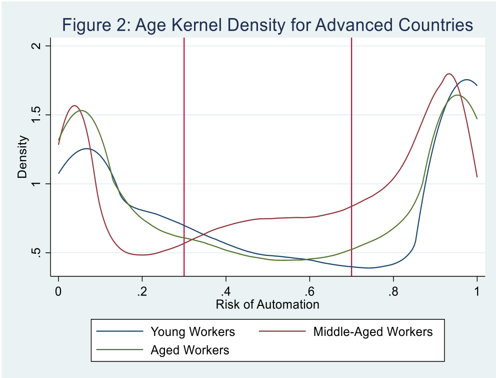
Figures 1 to 3 illustrate the overall distribution of the predicted automation risks respectively across the Gender, Age, and Skill structures of all workers in the advanced economies under study. The distributions are at the PIAAC respondent level. They are estimated using the public version of the PIAAC database and the sector-specific model at the ISIC rev 4 1-digit sector level. Broadly, the graphs indicate that fewer workers are exposed to medium-level automation risks (between 30% and 70%) across dimensions. This can be explained by the bimodal structure of bottleneck variables such as Dexterity, Advise, Negotiate, and Sell. Concerning Dexterity, for instance, about 23% of male workers report “1” or never performing related tasks while 61% report “5” or performing related tasks every day (leaving a total of only 16% of male workers reporting the remaining responses 2, 3 and 4). For the same variable, the corresponding percentages are 25% and 62% for female workers in advanced countries. Other variables such as Plan and Communicate do not exhibit bimodality but are highly skewed respectively to the right and left, indicating that fewer individuals are involved in planning the activities of others whereas more workers are involved in some manner of communication regularly.

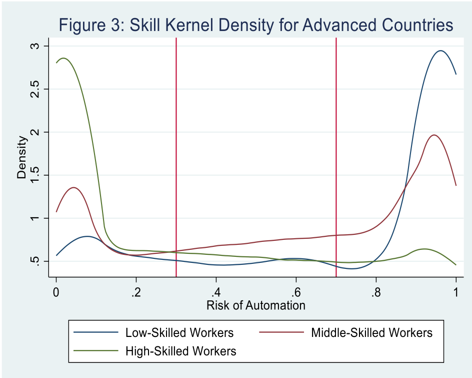
Furthermore, Figure 1 shows that automation could close the gender job gap in advanced economies. This result deviates from N&Q (2018) which found being female to be positively correlated with the risk of automation. The kernel density graph (which is plotted without the PIAAC sampling weights) demonstrates that more female workers than male workers face a low risk of automation (< 30%) while more male workers record high-risk estimates (> 0.70) than female workers.

It is worth mentioning that more women are working as “Shop Sales Assistants” (74% > 26%) than men. Moreover, a greater share of these female workers, as compared to their male counterparts, stated performing Selling-related tasks (75% > 25%) every day. This is also confirmed by the ANCOVA decomposition results which reveal that Selling is the strongest driver of female automability but plays a minimal role in explaining the risk of automation to male workers in advanced economies (see Table 4). It is, thus, likely to contribute significantly to the automation job gap between male and female workers.

Figure 1: Gender Kernel Density for Advanced Countries







Notes: Figure 1 illustrates the distribution of automation risks to male and female workers in the advanced region and separates the distribution into high risk, medium risk, and low-risk categories using the Frey and Osborne thresholds of 0.3 and 0.7. Figures 2 and 3 also demonstrate the distribution of the risks from the perspective of the Age and Skill dimensions.

Table 4: Worker Automability Vs Bottlenecks: ANCOVA, Pooled Sample for Advanced Region

Source	Male: Partial SS	Female: Partial SS	Young: Partial SS	Mid-Aged: Partial SS	Aged: Partial SS	Low-Skill: Partial SS	Mid-Skill: Partial SS	High-Skill: Partial SS
Dexterity	2.011***	5.654***	9.661***	0.175	6.692***	1.229***	6.710***	5.938***
Simple Problems	4.218***	16.366***	4.795***	9.434***	0.101	0.163	5.938***	2.721***
Complex Problems	0.317**	3.684***	8.734***	1.486***	1.939***	0.000	7.408***	6.551***
Teach	38.864***	71.429***	0.000	**115.548*****	17.757***	0.001	**85.796*****	**27.767*****
Advise	10.439***	9.356***	**12.182*****	13.627***	1.565***	0.239	14.252***	3.481***
Plan	**45.480*****	**77.544*****	1.047***	75.939***	**26.641*****	7.814***	64.695***	16.389***
Communicate	20.512***	44.081***	1.049***	73.687***	15.105***	**21.589*****	18.233***	**56.730*****
Negotiate	3.668***	1.153***	0.003	0.512**	0.545**	0.000	2.099***	3.515***
Influence	**41.618*****	66.880***	**12.345*****	**102.359*****	**28.268*****	1.585***	**109.877*****	8.353***
Sell	0.913***	**226.113*****	5.350***	50.251***	22.458***	5.151***	38.466***	1.491***
Learn from others	0.039	0.421**	0.140	1.622***	0.149	1.534***	7.432***	0.858***
Learning by doing	3.192***	52.740***	2.991***	10.672***	0.305*	**14.937*****	30.436***	1.510***
Keeping up to date	11.577***	60.612***	0.798**	0.007	0.388*	0.306*	2.324***	0.050
Observations	29,412	28,091	4,448	40,448	7,564	6,964	37,952	5,822
R-squared	0.269	0.240	0.133	0.207	0.228	0.063	0.201	0.247
Root MSE	0.249	0.321	0.370	0.301	0.335	0.335	0.299	0.297

* F(Prob) <0.1, ** F(Prob)<.05, *** F(Prob)<.01

Notes: Table 4 summarizes the ANCOVA decomposition results for the advanced region. The partial sum of squares (SS) of a particular task is the difference between the explained sum of squares (ESS) of the full model entailing all tasks and the ESS of a partial model with all but the task in question as independent variables. Comparing the partial sum of squares (SS) of the tasks illustrates the tasks that are most predictive of worker automability. For instance, the automability of male workers is mostly explained by the tasks Plan (followed by Influence) in **bold**.

Figure 2 illustrates automation risks relating to the age structure of labour markets in advanced countries. More middle-aged workers could be hollowed out since they comprise the highest density of workers at both medium and high-risk levels. The Teaching and Influencing tasks play leading roles in explaining the risks to middle-aged workers (see Table 4). This finding is consistent with Gadberg et al. (2020) for the case of Sweden: the paper concluded that middle-aged workers in high-automation-risk jobs have experienced the greatest job loss. One implication relates to more intensive use of automation technologies which can be linked to greater levels of unemployment. The reason is that a scarcity of middle-aged workers through automation could increase their wages, making further use of automation technologies more attractive (Acemoglu and Restrepo, 2018).

Within the Skill dimension, Figure 3 reveals a greater likelihood of Skill-Biased Technical Change (SBTC) across the advanced-country labour markets under study. The distribution of high-skilled workers is densest in the low-risk section whereas low-skilled workers dominate the high-risk category of the kernel density graph. This result concurs with previous work on the OECD area by N&Q (2018). Automation would likely worsen job inequality in advanced economies by displacing more low-skilled workers. The study finds that the automability of low-skilled workers is largely driven by Communication and Learning by doing (see Table 4).

Table 5: Weighted Average of Automation Risks in Advanced Countries, By Gender, Age & Skills

Advanced Country	Overall	Male	Female	Young	Middle-Aged	Aged	Low-Skilled	Middle-Skilled	High-Skilled
Belgium	0.498	**0.580**	0.388	0.306	**0.486**	0.444	**0.594**	0.502	0.277
Chile	0.445	**0.490**	0.346	0.221	**0.435**	0.289	0.341	**0.447**	0.099
Czech Republic	0.536	**0.549**	0.467	0.477	**0.517**	0.477	**0.559**	0.548	0.256
Denmark	0.474	**0.544**	0.383	0.226	**0.452**	0.361	**0.545**	0.446	0.209
France	0.479	**0.561**	0.367	0.282	**0.481**	0.395	0.455	**0.483**	0.262
Greece	0.443	**0.474**	0.362	0.286	**0.447**	0.259	0.315	**0.446**	0.171
Hungary	0.583	**0.644**	0.492	-	-	-	-	-	-
Israel	0.449	**0.531**	0.365	0.254	**0.433**	0.378	**0.475**	0.458	0.188
Italy	0.509	**0.566**	0.393	0.410	**0.514**	0.373	**0.502**	0.474	0.171
Japan	0.572	**0.624**	0.481	0.286	**0.574**	0.492	0.553	**0.558**	0.379
Republic of Korea	0.502	**0.557**	0.418	0.336	**0.499**	0.339	0.428	**0.506**	0.204
Lithuania	**0.621**	**0.673**	0.537	0.389	**0.606**	0.477	0.523	**0.650**	0.232
Netherlands	0.470	-	-	0.236	**0.452**	0.368	**0.576**	0.439	0.188
New Zealand	0.444	**0.509**	0.353	-	-	-	**0.481**	0.432	0.168
Poland	0.524	**0.556**	0.433	0.341	**0.503**	0.365	0.417	**0.572**	0.222
Russia	0.505	-	-	0.260	**0.486**	0.392	0.293	**0.562**	0.223
Slovakia	0.546	**0.577**	0.467	0.428	**0.531**	0.442	**0.623**	0.556	0.236
Slovenia	0.548	**0.598**	0.485	0.480	**0.538**	0.401	-	-	-
Spain	0.481	**0.549**	0.386	0.199	**0.485**	0.365	0.465	**0.484**	0.218
UK	0.430	**0.499**	0.342	0.208	**0.404**	0.395	-	-	-

Notes: Table 5 presents the average share of workers at risk of automation in the sample of advanced countries. The second column comprises the overall weighted average risk estimate for each country while the remaining columns show the risks to specific worker groups within each dimension: Gender, Age, and Skill. The estimates in **bold** indicate the highest risk estimate overall or within the relevant dimension. All empty cells did not have adequate data to estimate the associated risks.

At the country level within the advanced region, automation risks average 50% and range between 43% (for the UK) and 62% (for Lithuania), as reported in Table 5. The range is similar to Foster-McGregor et al. (2019), which documented a range of 47% (for Norway) to 64% (for Romania) across EU countries although the country-level risk estimates differ since this study considers additional tasks and uses a larger dataset. Note that Table 5 presents the results for automation risks aggregated to the country level from the respondent level using the PIAAC sampling weights. Hence, the procedure accounts for differences in employment structures across countries.

The country-level weighted average estimates show the potential quantity and structural implications of automation disruption and reinforce the kernel density graphs for the Gender and Age dimensions. In particular, the results reveal that, in the sample of advanced countries, more male workers are susceptible to automation than female workers. More male workers are also more likely to be vulnerable to automation in some countries like Lithuania (67%) than in others such as Greece (47%). The results further suggest that, within the age structure, the largest share of workers exposed to automation is from the middle-aged group. While there is heterogeneity across countries within the Skill dimension, high-skilled workers are generally the least exposed to automation as compared to low- and middle-skilled workers.

Table 6 further reports the sector-level estimates. It indicates that a greater share of workers in the Finance sector is susceptible to automation while the risk estimate is the lowest for the activities of households as employers, followed by Health care. The possible structural consequences are more varied across sectors than is the case at the country level. For instance, a greater proportion of women (rather than men) are exposed in the Finance, and the Information and Communication sectors. Additionally, a larger share of young workers (as compared to middle-aged workers) is exposed to automation in multiple sectors, including Manufacturing and Transport. Some sectors may also not experience significant structural changes in a particular dimension. An example is the Gender dimension in the Manufacturing sector which registers risk estimates of approximately 76% and 74% for male and female workers, respectively. Overall, these results indicate that some sectors would experience structural implications that vary from the country-level situation.

Additionally, the sector-level risk estimates for the Skill structure of the advanced region generally show that SBTC is looming across sectors since high-skilled workers are recorded as the least exposed. Conversely, most sectors (except for Construction, for instance) indicated that low-skilled workers are the most vulnerable to the adoption of automation technologies. Construction registered the highest risk estimate for middle-skilled workers. The job category, "Bricklayers and Related Workers", constitutes the highest number of (middle-skilled) workers in Construction. About 77% responded that they never sell as part of their tasks. This is followed by corresponding percentages of 59% and 58% for the variables Teaching others and

Planning the activities of others, respectively. The low execution frequency of these tasks contributes to their high exposure to automation.

Table 6: Sector-Level Weighted Average Risks in Advanced Countries, By Gender, Age, and Skills

Sectors	Overall	Male	Female	Young	Middle-Aged	Aged	Low-Skilled	Middle-Skilled	High-Skilled
Agriculture	0.643	0.609	-	-	0.606	-	-	0.580	-
Mining	0.578	-	-	-	-	-	-	0.710	-
Manufacturing	0.732	**0.759**	0.738	**0.860**	0.713	0.666	**0.871**	0.709	0.477
Energy sector	0.620	0.604	-	-	0.632	-	-	0.670	-
Water	0.739	0.729	-	-	0.772	-	-	0.832	-
Construction	0.344	0.321	**0.553**	**0.431**	0.336	0.419	0.323	**0.387**	0.262
Trade	0.701	0.663	**0.767**	-	0.652	0.628	**0.763**	0.684	0.420
Transportation	0.768	**0.786**	0.566	**0.848**	0.768	0.711	**0.820**	0.759	0.326
Hotels, restaurants	0.426	**0.458**	0.417	0.332	0.436	**0.549**	0.433	0.394	-
Information & communication	0.649	0.578	**0.753**	-	0.681	-	-	0.690	-
Finance	**0.784**	0.795	**0.821**	0.737	**0.777**	0.752	-	0.792	0.654
Real estate	0.533	-	-	-	0.624	-	-	-	-
Professional activities	0.448	0.442	**0.482**	**0.633**	0.432	0.486	**0.523**	0.518	0.308
Administrative service	0.534	**0.620**	0.440	-	0.547	0.315	0.441	0.599	-
Public administration	0.601	**0.616**	0.503	0.456	**0.595**	0.561	**0.626**	0.594	0.483
Education	0.104	**0.184**	0.114	-	0.100	0.113	-	0.122	0.039
Health	0.102	**0.203**	0.082	0.063	0.088	**0.174**	**0.230**	0.101	0.021
Entertainment	0.252	0.201	**0.368**	0.207	0.301	-	-	0.223	-
Other services	0.104	**0.197**	0.093	0.092	0.094	**0.145**	0.157	0.084	-
Household employers	0.036	-	0.024	-	0.032	-	-	0.031	-

Notes: Table 6 documents the average share of workers at risk of automation in the sample of sectors in advanced economies. The second column comprises the overall weighted average risk estimate for each sector whereas the remaining columns show the risks to specific worker groups within each dimension: Gender, Age, and Skill. The estimates in **bold** indicate the highest risk estimate overall or within the relevant dimension. All blank cells did not have adequate data to estimate the related risks.

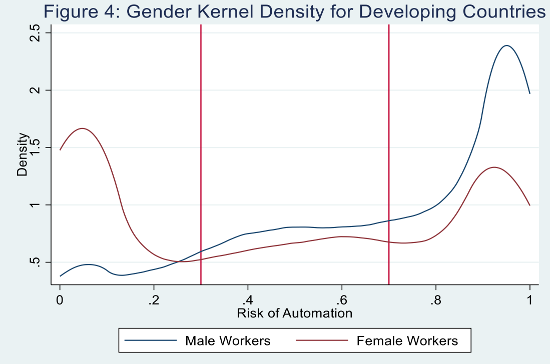
4.2 Automation Risks to Developing-Country Workers

In the sample of developing countries, Figures 4, 5, and 6 demonstrate that, at the PIAAC respondent level, automation-induced structural changes in employment would likely follow similar patterns in advanced economies across Gender, Age, and Skill.[18] Bimodality is also observed in the developing world.

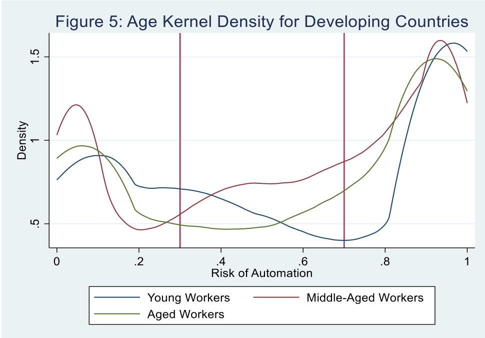
Within the Gender dimension more particularly, it is noted in Figure 4 that more male workers are exposed to automation than female workers. Like the advanced region, the largest difference between male and female workers stems from the Shop Sales Assistant category (after accounting for the PIAAC sampling weights). In both samples of advanced and developing regions, workers under this job code (mostly operating within the Wholesale and retail trade sector) recorded the highest frequency.

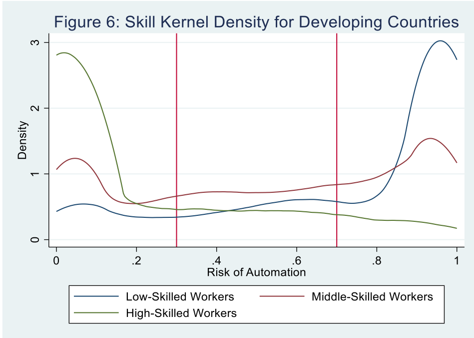
Concerning the drivers of gender automability, the task Plan (followed by Teach) is the strongest predictor of male automability whereas female automability is mostly explained by Sell (followed by Plan), according to the ANCOVA decomposition results (see Table 7). The contribution of the tasks to automability closely mirrors the situation in advanced countries where Plan (followed by Influence) is the bottleneck task that mostly explains the variation in the risk of automation of male workers while Sell (followed by Plan) corresponds to female workers. Thus, planning-related tasks strongly predict the risk of automation for both male and female workers. Selling, however, seems to drive female automability more and would, therefore, likely impact the automation gap between male and female workers in both regions.

Figure 4: Gender Kernel Density for Developing Countries



[18] It is worth mentioning that the developing countries in the dataset for this study are high middle-income countries and do not include lower-income countries. Therefore, interpretations apply mainly to countries in the high middle-income group. Additionally, as shown by the Gender structure distributions of Figures 9 and 10 in Appendix B, the use of the sector-specific pooled model is not the cause of the similar patterns documented because similar patterns are observed even under separate risk-task structures (coefficients) for both regions.





Notes: Figure 4 presents the distribution of automation risks to male and female workers in the developing region. The Frey and Osborne thresholds of 0.3 and 0.7 are used to separate the distributions into high-risk, medium-risk, and low-risk categories. Figures 5 and 6 also demonstrate the distribution of the risks for the developing region's Age and Skill dimensions.

Table 7: Worker Automability Vs Bottlenecks: ANCOVA, Pooled Sample for Developing Region

Source	Male: Partial SS	Female: Partial SS	Young: Partial SS	Mid-Aged: Partial SS	Aged: Partial SS	Low-Skill: Partial SS	Mid-Skill: Partial SS	High-Skill: Partial SS
Dexterity	3.541***	1.533***	2.627***	4.716***	1.590***	0.040	2.444***	0.005
Simple Problems	1.551***	1.171***	0.024	8.143***	0.189	0.073	0.000	0.002
Complex Problems	0.239*	0.745***	0.499**	1.990***	0.052	0.037	2.069***	0.224**
Teach	**9.388*****	16.360***	0.877***	20.638***	**3.317*****	0.161	**25.873*****	**1.575*****
Advise	6.946***	0.448**	**4.008*****	5.877***	3.305***	1.246***	5.747***	0.306**
Plan	**12.367*****	**17.000*****	0.116	**21.238*****	2.562***	1.523***	18.389***	0.001
Communicate	3.133***	11.892***	0.017	**23.267*****	1.583***	1.128***	8.768***	0.478***
Negotiate	1.265***	0.079	0.005	0.568***	1.189***	0.012	0.004	0.449***
Influence	8.318***	2.877***	**3.528*****	9.435***	2.360***	0.007	**22.711*****	0.221**
Sell	5.221***	**37.059*****	3.449***	11.411***	**4.010*****	**2.633*****	19.040***	**0.893*****
Learn from others	1.067***	3.440***	2.293***	6.819***	0.899***	1.883***	5.744***	0.209*
Learning by doing	1.867***	6.218***	0.031	5.427***	0.302*	**3.548*****	7.107***	0.264**
Keeping up to date	5.677***	4.706***	0.383*	4.101***	1.176***	0.002	5.821***	0.173*
Observations	7,365	5,377	1,131	9,713	1,034	3,126	8,631	304
R-squared	0.274	0.171	0.188	0.207	0.268	0.033	0.226	0.292
Root MSE	0.251	0.327	0.345	0.295	0.317	0.307	0.294	0.238

* F(Prob) <0.1, ** F(Prob)<.05, *** F(Prob)<.01

Notes: Table 7 summarizes the ANCOVA decomposition results for the developing region. Comparing the partial sum of squares (SS) of the tasks illustrates the tasks that are most predictive of worker automability. For instance, the risk of automation to male workers is strongly predicted by the tasks Plan (followed by Teach) in **bold**.

Furthermore, Figure 5 illustrates that more middle-aged workers are exposed to automation than young and aged workers, similar to the advanced region. Unlike, the advanced region, however, the tasks Communicate (followed by Plan) rather than Teach (followed by Influence) were the most predictive of the automation risk to developing-country middle-aged workers. Tasks involving influencing and advising others are the strongest predictors of the automability of young workers in both regions. This resonates with the recent rise in social media influencers who are largely younger workers although this study does not focus on these workers. The corresponding tasks for aged workers relate to influencing and planning for others in advanced countries as compared with selling and teaching in the developing region (see Tables 4 and 7). These findings imply that leadership-oriented tasks could be more instrumental in determining the automation of aged workers in advanced economies whereas entrepreneurial ability (comprising selling products in difficult business terrains) could matter more in developing countries.

Regarding the developing-country Skill dimension, Figure 6 demonstrates that more low-skilled workers are exposed to automation than medium and high-skilled workers. The findings indicate that Learning by doing (followed by Sell) largely explains the automation probabilities of low-skilled workers in developing countries as compared with Communication (followed by Learning by doing) in the case of the advanced countries under study (see Tables 4 and 7). Accordingly, the partial sum of squares estimates for low-skilled workers in both regions showed that (digital skills) programs targeted at enhancing the frequency or level of learning (at work) can increase the adaptive capacity of workers, limit the automation of low-skilled workers, and combat inequality.

It was also noted that the developing-country-level risk averaged 46% (< 50% in advanced countries), with a narrower range of approximately 14% (< 19% in the advanced region). Consequently, the results do not support the World Bank (2016) which suggested that, on average, the share of jobs that would likely experience automation is higher in developing economies than in advanced countries. The previous result stemmed from the use of STEP surveys and was mostly based on occupations at the 3-digit level (ISCO08) and not the preferred 4-digit level of jobs.

In the developing-country sample, Turkey recorded the highest share of workers exposed to automation while the lowest risk estimate is documented for Peru. The potential structural changes within the Gender and Age dimensions broadly mimic those in advanced countries: specifically, male and middle-aged workers are the most exposed to automation. The results for the Skill dimension in the developing countries also indicate that high-skilled workers will likely be the least affected. As compared to advanced countries, however, a larger share of middle-skilled workers is at risk of automation than low-skilled workers across developing countries, except for Turkey (see Table 8). Hollowing-out of middle-skilled workers could, therefore, be more prevalent in the developing world.

Table 8: Weighted Average of Automation Risks in Developing Countries, By Gender, Age & Skills

Developing Country	Overall	Male	Female	Young	Middle-Aged	Aged	Low-Skilled	Middle-Skilled	High-Skilled
Ecuador	0.403	**0.470**	0.261	0.202	**0.383**	0.227	0.265	**0.378**	0.213
Kazakhstan	0.491	**0.541**	0.374	0.248	**0.452**	0.351	0.412	**0.492**	0.135
Mexico	0.482	**0.536**	0.381	0.315	**0.457**	0.319	0.434	**0.455**	0.131
Peru	0.395	**0.426**	0.282	0.231	**0.366**	0.213	0.187	**0.417**	0.156
Turkey	**0.531**	**0.554**	0.452	0.380	**0.504**	0.331	**0.541**	0.487	0.198

Notes: Table 8 documents the developing country-level average share of workers at risk of automation. The second column presents the overall weighted average risk estimate for each country while the remaining columns indicate the risks to worker groups within each dimension: Gender, Age, and Skill. The estimates in **bold** indicate the highest risk estimate overall or within the relevant dimension. All empty cells did not have adequate data to estimate the associated risks.

Table 9: Sector-Level Weighted Average Risks in Developing Countries, By Gender, Age & Skills

Sector	Overall	Male	Female	Young	Middle-Aged	Aged	Low-Skilled	Middle-Skilled	High-Skilled
Agriculture	0.601	0.588	-	-	0.608	-	-	0.637	-
Mining	0.596	-	-	-	-	-	-	0.668	-
Manufacturing	0.614	**0.677**	0.552	**0.807**	0.582	0.411	**0.718**	0.599	0.161
Energy sector	0.533	0.572	-	-	0.547	-	-	0.598	-
Water	0.534	0.507	-	-	0.649	-	-	0.702	-
Construction	0.349	0.315	**0.513**	**0.452**	0.348	0.388	0.331	**0.388**	0.085
Trade	0.547	**0.613**	0.496	-	0.480	0.375	0.526	**0.551**	0.359
Transportation	0.507	0.489	**0.581**	**0.590**	0.505	0.363	**0.542**	0.493	0.427
Hotels, restaurants	0.370	**0.417**	0.362	0.323	0.382	**0.477**	0.375	0.361	-
Information & communication	0.605	0.505	**0.842**	-	0.623	-	-	0.608	-
Finance	**0.812**	0.822	**0.858**	0.801	**0.822**	0.622	-	0.832	0.637
Real estate	0.431	-	-	-	0.579	-	-	-	-
Professional activities	0.441	0.427	**0.469**	**0.626**	0.413	0.450	**0.585**	0.476	0.321
Administrative service	0.524	**0.641**	0.431	-	0.537	0.284	0.416	0.601	-
Public administration	0.571	**0.574**	0.487	0.411	0.578	**0.628**	**0.584**	0.582	0.440
Education	0.117	**0.205**	0.134	-	0.125	0.118	-	0.117	0.028
Health	0.096	**0.223**	0.074	0.048	0.078	**0.207**	**0.185**	0.092	0.026
Entertainment	0.212	0.191	**0.289**	0.229	0.217	-	-	0.203	-
Other services	0.055	**0.126**	0.027	0.014	0.044	**0.181**	0.063	0.057	-
Household employers	0.031	-	0.010	-	0.033	-	-	0.047	-

Notes: Table 9 presents the sector-level average share of workers at risk of automation in the sample of developing economies. The second column comprises the overall weighted average risk estimate for each sector whereas the remaining columns show the risks to each worker group. The estimates in **bold** indicate the highest risk estimate overall or within the relevant dimension.

Furthermore, Table 9 presents the sector-level aggregated risks for developing countries and indicates that, similar to the case of the advanced countries, a greater percentage of workers would likely be automated in the Finance industry than in other sectors. Workers involved in activities of households for domestic consumption as well as those in the Health, Education, and Entertainment industries are less vulnerable to automation.

Like the advanced world, varied structural changes could be experienced at the sectoral level. An example is the Gender structure in the Information and Communication sector where the risk-estimate difference between male and female workers is larger than the Gender dimension in Finance. Excluding Finance, Manufacturing records the highest risk estimates for male workers whereas a greater share of female workers is exposed to automation in the Information and Communication sector than in other sectors. The results suggest that a greater proportion of young workers, as well as low-skilled workers, could be automated in the manufacturing sector in the developing region. Additionally, aged workers are vulnerable to automation in the developing-region Public Administration sector.

4.3 The Potential Effects of Automation on the Gender Wage Gap

In this subsection, the paper studies the potential impact of smart automation on the gender wage gap (beyond the gender job gap). Table 10 illustrates the partial output of the empirical model and its constituent variables, which were presented in section 3. Additional results are reported in Table A.3 in Appendix A. Note that the variable, Automation, was constructed by collapsing the separate vectors of risks to male and female workers into a single vector for this analysis. Only the risk estimates relevant to the Gender dimension are employed in this section.

In both advanced and developing regions, Table 10 reports that automation registers a negative association with the monthly wages and salaries of workers. The association is also stronger for male than female workers, as expected. However, automation did not significantly affect the wages and salaries of developing-country male and female workers. In both regions, experience and education remain instrumental wage determinants although the returns to education are limited below the ISCED 3C (>= 2 years) education level. The returns to education from ISCED 4 A-B to master's degree holders appear to increase with the education level for both male and female workers. However, master's holders tend to enjoy greater returns to education than Ph.D. holders in developing countries while Ph.D. holders typically receive greater returns in advanced-country labour markets.

Table 10: Effect of Automation on Log of Wages (Monthly earnings, PPP corrected $US)

	Advanced Region: Males	Advanced Region: Females	Developing Region: Males	Developing Region: Females
Automation	-0.255***	-0.089*	-0.077	-0.060
	[0.040]	[0.050]	[0.069]	[0.065]
Age	0.046***	0.0259***	0.00893	0.0072
	[0.007]	[0.008]	[0.009]	[0.011]
Age-squared	-0.001***	-0.000***	-0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Experience	0.023***	0.027***	0.026***	0.027***
	[0.003]	[0.004]	[0.005]	[0.005]
Experience-squared	-0.000***	-0.000**	-0.001***	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]
ISCED 1	0.0503	-0.00401	0.111*	0.108
	[0.094]	[0.146]	[0.067]	[0.069]
ISCED 2	0.0494	0.0167	0.0917	0.082
	[0.099]	[0.139]	[0.059]	[0.058]
ISCED 3C (<2years)	0.162	0.174	-	-
	[0.141]	[0.144]	-	-
ISCED 3C (>=2years)	0.118	0.129	0.206***	0.201***
	[0.098]	[0.139]	[0.072]	[0.069]
ISCED 3 A-B	0.109	0.0815	0.265***	0.270***
	[0.100]	[0.140]	[0.076]	[0.084]
ISCED 3 (no distinction A-B-C, 2+)	0.169	0.128	0.294***	0.291***
	[0.108]	[0.142]	[0.070]	[0.074]
ISCED 4C	0.0738	0.204	-	-
	[0.114]	[0.149]	-	-
ISCED 4 A-B	0.109	0.0752	0.239***	0.235***
	[0.106]	[0.159]	[0.075]	[0.081]
ISCED 4 (without distinction A-B-C)	0.145	0.179	0.289**	0.442***
	[0.108]	[0.163]	[0.119]	[0.136]
ISCED 5B	0.214**	0.223	0.369***	0.365***
	[0.099]	[0.139]	[0.123]	[0.118]
ISCED 5A, bachelor degree	0.299***	0.314**	0.455***	0.452***
	[0.101]	[0.140]	[0.080]	[0.078]
ISCED 5A, master degree	0.411***	0.429***	0.890***	0.877***
	[0.103]	[0.141]	[0.165]	[0.148]
ISCED 6, PhD	0.599***	0.678***	0.847***	0.842***
	[0.111]	[0.151]	[0.242]	[0.240]
Other Worker characteristics, Firm, ISIC 1-				

digit industry & Country dummies				
Constant	6.986***	7.404***	6.638***	6.496***
	[0.188]	[0.181]	[0.189]	[0.219]
Observations	16785	16619	5211	4928
adjusted R-squared	0.413	0.357	0.262	0.269

Bootstrap Standard errors in brackets

* p<0.1, ** p<.05, *** p<.01

Notes: Table 10 presents the partial output of the Mincerian regressions estimated separately for male and female workers in both regions. Automation is likely to adversely affect the wages of male and female workers in advanced economies but not the developing countries analyzed. Table A.3 in Appendix A contains the remaining coefficients except for the sector and country dummies.

Table 11: Sources of Gender-Wage Differential (Oaxaca-Blinder and Neumark Decompositions)

REFERENCE STRUCTURE	**POOLED WAGE STRUCTURE**		**MALE WAGE STRUCTURE**		**FEMALE WAGE STRUCTURE**	
Region	**Advanced Country Wages**	**Developing Country Wages**	**Advanced Country Wages**	**Developing Country Wages**	**Advanced Country Wages**	**Developing Country Wages**
Aggregate						
Mean of Male Wage	7.773***	6.738***	7.773***	6.738***	7.773***	6.738***
	[0.010]	[0.019]	[0.009]	[0.020]	[0.010]	[0.019]
Mean of Female Wage	7.274***	6.556***	7.274***	6.556***	7.274***	6.556***
	[0.009]	[0.023]	[0.009]	[0.022]	[0.009]	[0.023]
Difference	0.498***	0.182***	0.498***	0.182***	0.498***	0.182***
	[0.013]	[0.029]	[0.013]	[0.030]	[0.013]	[0.032]
Endowment	0.157***	-0.003	0.131***	-0.021	0.136***	-0.040
	[0.011]	[0.023]	[0.012]	[0.028]	[0.015]	[0.055]
Coefficients	0.341***	0.185***	0.362***	0.222***	0.367***	0.203***
	[0.012]	[0.030]	[0.016]	[0.060]	[0.014]	[0.034]
Interaction			0.005	-0.019	-0.005	0.019
			[0.019]	[0.060]	[0.017]	[0.053]
Detailed: Endowment						
Automation	-0.029***	-0.018	-0.046***	-0.035**	-0.016*	0.010
	[0.006]	[0.013]	[0.007]	[0.017]	[0.009]	[0.020]
Detailed: Coefficient						
Automation	-0.099**	-0.134*	-0.111**	-0.162	-0.081***	-0.118*
	[0.039]	[0.072]	[0.044]	[0.103]	[0.029]	[0.067]
Observations	33404	5797	33404	5797	33404	5797

Bootstrap Standard errors in brackets

* p<0.1, ** p<.05, *** p<.01

Notes: Table 11 documents the partial output of the Oaxaca-Blinder decomposition (estimated using the separate male and female coefficients) and the Neumark decomposition (estimated using the coefficients of the pooled model comprising both male and female workers). They reflect equations (4) to (6). Except for the pooled reference structure, the mean difference between the male and female wages is decomposed into the endowment, coefficient, and interaction effects. The detailed decomposition results (entailing the contribution of each variable to the aggregate decompositions parts) are also provided for automation only with a focus on the endowment and coefficient effects (see Table A.4 in Appendix A for other variables).

Table 11 depicts the results of the Oaxaca-Blinder and Neumark wage decompositions for the mean wage difference between male and female workers in the two regions of interest. The male and female coefficients (due to Oaxaca-Blinder), as well as the pooled coefficients (due to Neumark), are used as the reference wage structures. On average, advanced-country workers earned more than workers in developing countries as expected. Male workers also earned more than female workers in both regions. However, the gender wage gap is wider in advanced countries. From the pooled wage structure viewpoint, for instance, they are respectively 0.498 and 0.182 in advanced and developing economies in terms of the mean of the log wages (which are respectively 7.773 and 7.274 for male and female workers in advanced economies as compared to 6.738 and 6.556 in developing countries).

Furthermore, a larger part of the gender wage differential in both regions is explained by the coefficient effect rather than the differences in male and female characteristics (including automation exposure), on average. This is indicative of wage discrimination against women in both regions. The endowment effect is significant in advanced economies but not in the sample of developing countries. The implication is that differences in group characteristics tend to matter in advanced countries but not so much in developing countries. The interaction effects for the decompositions are also not statistically significant indicating that the model significantly explains the wage gap differences in both regions.

Despite the limited contribution of differences in characteristics to the developing-country gender wage gap overall, automation recorded a negative and significant effect on the gender wage gap from the perspective of the male reference structure. The results show that the difference in the automation (probabilities) of developing-country male and female workers resulted in a reduction of the gender wage gap by about 16%. The study found a negative and significant effect of automation (through the endowment effect) on the gender wage gap across all reference structures for the sample of advanced economies. In percentage terms, the typical differences in automation exposure between advanced-country male and female workers could adversely affect the gender wage gap by 5%, 9%, and 3% based on the pooled, male, and female reference structures, respectively. Additionally, the contribution of automation through the coefficient effect is broadly negative and significant across regions and reference structures. This result implies either discrimination against male workers regarding their automation-wage relationship or the role of other (automation-related) factors beyond the mean differences between the observed automation exposure of male and female workers through the tasks that they undertake at work. Stated differently, even if male and female workers are equally exposed to automation (from the standpoint of technological feasibility), male workers will likely suffer a larger wage loss than their female counterparts. Other factors such as automation costs could matter.

5. Summary and Conclusions

This paper focuses on three main objectives. First, the research estimates and compares the average share of workers at risk of automation in advanced and developing regions. Second, the study investigates the possible structural implications of automation across the Gender, Age, and Skill labour market structures at the sectoral, country, and regional levels. Third, the paper extends the analysis of the Gender structure beyond employment to wages to estimate the potential effect of automation on the gender wage gaps at the regional level while identifying the sources of the differentials.

The first two objectives are addressed using detailed task data from PIAAC and the suggested approaches by Nedelkoska and Quintini (2018) and Foster-McGregor et al. (2019). Broadly, these methods involve the use of logit regressions to determine worker-automability by exploiting the task variation of workers (operating in separate sectors). This study incorporates labour adaptive capacity in the estimation of the risk estimates and breaks down the risk estimates into eight groups, namely: male, female, young, middle-aged, aged, low-skilled, middle-skilled, and high-skilled workers. Doing so enabled the study to investigate potential compositional changes to the Gender, Age, and Skill labour market structures in advanced and developing regions, countries, and sectors. Furthermore, ANCOVA decompositions are employed at the regional level to identify the most influential bottleneck tasks that explain the risk of automation of each group. The paper addressed the third objective by implementing Oaxaca-Blinder and Neumark decompositions based on an extended Mincer-based empirical model that incorporates gender-relevant automation risks as a proxy for automation, together with entity fixed effects to reduce bias.

The main results indicate that, on average, more workers in advanced countries are exposed to automation than in developing countries; the average share of developing-country workers at risk of automation was found to be 46% (< 50% in advanced countries). The results further reveal a bimodal structure in each dimension, as well as similar patterns in both regions. Specifically, male and middle-aged workers are the most vulnerable groups in both regions whereas low-skilled workers are the least exposed. The results were also broadly consistent at the country level when differences in employment structures were considered. In both regions, however, different sectors could experience structural implications that do not reflect the country-level results. For instance, in developing countries, a greater percentage of elderly workers is susceptible to automation in the Public Administration sector than middle-aged and young workers. This is also the situation for young workers in the manufacturing sector. Furthermore, the task, Learning by doing, strongly drives the automability of low-skilled workers in the advanced and developing countries considered in this analysis, emphasizing the relevance of digital skills programs and strategies in mitigating the risk of automation to low-skilled workers and combatting inequality.

Finally, the paper finds that differences in the automation (probabilities) of male and female workers could reduce gender inequality in advanced countries not only through jobs but also through wages. A possible reduction in the gender wage gap could range between 3-9% in advanced economies. Developing countries could also experience a reduction in the gender wage gap but through discrimination against male workers or other automation-relevant factors beyond technological feasibility such as automation costs since male workers typically earn higher wages. Future work can extend the analysis beyond technological feasibility to consider automation costs, for instance. Given data availability, future research can also apply this empirical approach to study the implications of (intelligent) automation on (the structure of) employment and wages in lower-income countries.

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APPENDIX A

Table A.1 Summary Statistics of Male and Female Workers, By Region

Variable	Advanced Countries: Male		Advanced Countries: Female		Developing Countries: Male		Developing Countries: Female	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Log of Monthly earnings excluding bonuses, PPP corrected $US	7.65	0.79	7.30	0.81	6.68	0.68	6.65	0.68
Automation	0.65	0.30	0.47	0.37	0.59	0.34	0.57	0.34
Age (in years, 16-65)	40.49	12.49	40.56	12.21	38.48	12.19	38.51	12.05
Experience (in years, 0-55)	19.21	12.81	17.07	11.95	13.77	11.20	13.43	11.10
No formal Education	0.01	0.09	0.01	0.08	0.06	0.24	0.06	0.23
ISCED 1	0.04	0.18	0.03	0.16	0.14	0.35	0.13	0.34
ISCED 2	0.12	0.32	0.10	0.29	0.16	0.36	0.16	0.36
ISCED 3C (<2years)	0.02	0.12	0.02	0.14	-	-	-	-
ISCED 3C (>=2years)	0.18	0.39	0.12	0.33	0.05	0.22	0.05	0.23
ISCED 3 A-B	0.25	0.43	0.24	0.43	0.20	0.40	0.19	0.40
ISCED 3 (no distinction A-B-C, 2+)	0.02	0.13	0.02	0.14	0.08	0.26	0.08	0.27
ISCED 4C	0.01	0.12	0.01	0.11	-	-	-	-
ISCED 4 A-B	0.01	0.12	0.02	0.15	0.03	0.16	0.03	0.16
ISCED 4 (without distinction A-B-C)	0.01	0.09	0.01	0.11	0.00	0.07	0.00	0.07
ISCED 5B	0.10	0.30	0.15	0.35	0.08	0.27	0.08	0.27
ISCED 5A, bachelor degree	0.13	0.33	0.15	0.35	0.19	0.39	0.19	0.39
ISCED 5A, master degree	0.10	0.30	0.12	0.33	0.02	0.13	0.02	0.14
ISCED 6, PhD	0.01	0.11	0.01	0.09	0.00	0.05	0.00	0.05
Living with spouse or partner	0.73	0.45	0.69	0.46	0.62	0.49	0.61	0.49
Contract type: Indefinite contract	0.75	0.43	0.72	0.45	0.43	0.50	0.43	0.50
A fixed term contract	0.14	0.34	0.15	0.36	0.19	0.39	0.19	0.39
Temporary employment agency contract	0.02	0.14	0.02	0.14	0.04	0.20	0.04	0.20
An apprenticeship	0.01	0.10	0.01	0.09	0.02	0.16	0.03	0.16
No contract	0.07	0.25	0.07	0.25	0.30	0.46	0.30	0.46
Other	0.02	0.14	0.03	0.17	0.01	0.12	0.02	0.12
Firm size: 1 to 10 people	0.27	0.44	0.31	0.46	0.42	0.49	0.42	0.49
11 to 50 people	0.30	0.46	0.31	0.46	0.28	0.45	0.28	0.45
51 to 250 people	0.24	0.42	0.22	0.41	0.18	0.39	0.18	0.39
251 to 1000 people	0.12	0.32	0.10	0.30	0.07	0.25	0.07	0.25
More than 1000 people	0.08	0.27	0.06	0.24	0.05	0.22	0.05	0.21

Notes: Table A.1 presents a partial output of the summary statistics of the Mincerian regressions for male and female workers in the advanced and developing regions corresponding to Table 10. It excludes the dummies for ISCO08 1-digit-level jobs, ISIC rev 4 1-digit-level sectors, and country dummies that were used in the regressions to address fixed effects.

Table A.2 Weighted Averages of Sector-Specific Regression Coefficients and Standard Errors

	Overall	Male	Female	Young	Mid-aged	Aged	Low Skill	Middle-Skill	High-Skill
Dexterity	0.075	0.111	0.009	0.060	0.065	0.119	0.116	0.090	-0.078
	0.024	0.033	0.039	0.079	0.029	0.093	0.077	0.033	0.116
Simple Problems	-0.056	-0.090	-0.076	0.041	-0.119	0.115	-0.082	-0.039	0.017
	0.035	0.050	0.049	0.154	0.044	0.108	0.102	0.048	0.148
Complex Problems	-0.105	-0.054	-0.112	-0.155	-0.080	0.207	-0.026	-0.039	0.124
	0.047	0.053	0.091	0.209	0.058	0.132	0.118	0.048	0.148
Teach	-0.126	-0.092	-0.148	0.022	-0.145	-0.419	0.046	-0.161	-0.564
	0.031	0.043	0.049	0.119	0.040	0.126	0.095	0.038	0.155
Advise	-0.112	-0.102	-0.013	-0.340	-0.127	0.086	-0.050	-0.088	-0.223
	0.032	0.045	0.043	0.160	0.035	0.099	0.090	0.041	0.150
Plan	-0.113	-0.240	-0.129	-0.038	-0.113	-0.410	-0.239	-0.118	-0.267
	0.029	0.039	0.053	0.104	0.033	0.146	0.083	0.035	0.135
Communicate	0.176	0.073	0.121	-0.116	0.264	0.020	0.183	0.066	1.367
	0.033	0.050	0.058	0.133	0.040	0.151	0.088	0.044	0.363
Negotiate	-0.026	-0.107	0.051	-0.163	-0.046	-0.090	0.046	0.004	0.198
	0.031	0.042	0.060	0.095	0.037	0.109	0.083	0.036	0.128
Influence	-0.209	-0.198	-0.253	-0.017	-0.227	-0.474	-0.059	-0.262	-0.129
	0.031	0.044	0.064	0.107	0.037	0.134	0.083	0.038	0.134
Sell	-0.080	-0.100	0.011	-0.080	-0.073	0.023	-0.035	-0.072	0.373
	0.035	0.041	0.049	0.105	0.044	0.094	0.081	0.045	0.188
Learn from others	-0.041	-0.058	-0.056	-0.079	-0.027	-0.049	-0.082	0.002	-0.266
	0.038	0.051	0.054	0.143	0.043	0.120	0.112	0.049	0.165
Learning by doing	-0.029	0.001	-0.077	0.022	-0.037	0.040	-0.044	-0.082	0.003
	0.034	0.049	0.051	0.174	0.038	0.139	0.099	0.042	0.156
Keeping up to date	-0.058	-0.075	0.025	0.056	-0.008	-0.234	-0.036	-0.127	0.373
	0.036	0.049	0.053	0.122	0.042	0.125	0.102	0.044	0.146
Constant	1.468	3.444	0.600	1.906	1.259	2.927	1.757	2.084	-5.177
	0.172	0.260	0.289	0.567	0.219	0.716	0.431	0.236	1.951
Observations	901	430	616	169	620	173	195	575	189
Number of Regressions	20	17	15	10	19	12	11	19	9

Notes: Table A.2 presents weighted averages of the regression coefficients and standard errors (below them) that were used to predict the automation risks to workers in the advanced and developing economies under study. The weight for the coefficients (and standard errors below them) of a regression is calculated as the share of the number of observations of the regression in the total number of observations of the group in question. Regarding the overall sector-level estimates, the average number of observations per sector was 901 workers across 20 sectors and regressions. Less than 20 regressions were estimated for the worker-groups within sectors, however, since there were inadequate respondents of the given attribute within those sectors that provided valid responses for all the task variables. For example, there is no estimate for female workers in Agriculture in Table 6 because the number of female workers that provided valid responses for all the task variables in the sector was inadequate.

Table A.3: Potential Automation Impact on Log of Wages (Monthly earnings, PPP corrected $US)

Independent Variables	Males in Advanced Countries	Females in Advanced Countries	Males in Developing Countries	Females in Developing Countries
Automation	-0.255***	-0.089*	-0.077	-0.060
	[0.040]	[0.050]	[0.069]	[0.065]
Age	0.046***	0.0259***	0.00893	0.0072
	[0.007]	[0.008]	[0.009]	[0.011]
Age-squared	-0.001***	-0.000***	-0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Experience	0.023***	0.027***	0.026***	0.027***
	[0.003]	[0.004]	[0.005]	[0.005]
Experience-squared	-0.000***	-0.000**	-0.001***	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]
ISCED 1	0.0503	-0.00401	0.111*	0.108
	[0.094]	[0.146]	[0.067]	[0.069]
ISCED 2	0.0494	0.0167	0.0917	0.082
	[0.099]	[0.139]	[0.059]	[0.058]
ISCED 3C (<2years)	0.162	0.174	-	-
	[0.141]	[0.144]	-	-
ISCED 3C (>=2years)	0.118	0.129	0.206***	0.201***
	[0.098]	[0.139]	[0.072]	[0.069]
ISCED 3 A-B	0.109	0.0815	0.265***	0.270***
	[0.100]	[0.140]	[0.076]	[0.084]
ISCED 3 (no distinction A-B-C, 2+)	0.169	0.128	0.294***	0.291***
	[0.108]	[0.142]	[0.070]	[0.074]
ISCED 4C	0.0738	0.204	-	-
	[0.114]	[0.149]	-	-
ISCED 4 A-B	0.109	0.0752	0.239***	0.235***
	[0.106]	[0.159]	[0.075]	[0.081]
ISCED 4 (without distinction A-B-C)	0.145	0.179	0.289**	0.442***
	[0.108]	[0.163]	[0.119]	[0.136]
ISCED 5B	0.214**	0.223	0.369***	0.365***
	[0.099]	[0.139]	[0.123]	[0.118]
ISCED 5A, bachelor degree	0.299***	0.314**	0.455***	0.452***
	[0.101]	[0.140]	[0.080]	[0.078]
ISCED 5A, master degree	0.411***	0.429***	0.890***	0.877***
	[0.103]	[0.141]	[0.165]	[0.148]
ISCED 6, PhD	0.599***	0.678***	0.847***	0.842***
	[0.111]	[0.151]	[0.242]	[0.240]
With Spouse or Partner	0.141***	-0.0643***	0.0713***	0.0699**

	[0.018]	[0.018]	[0.027]	[0.029]
Contract size: A fixed term contract	-0.139***	-0.181***	-0.033	-0.034
	[0.020]	[0.022]	[0.042]	[0.045]
Temporary employment agency contract	-0.140***	-0.252***	-0.135	-0.139*
	[0.052]	[0.075]	[0.083]	[0.083]
An apprenticeship	-0.421***	-0.381***	-0.027	-0.025
	[0.104]	[0.083]	[0.105]	[0.102]
No contract	-0.155***	-0.310***	-0.207***	-0.216***
	[0.030]	[0.036]	[0.041]	[0.044]
Other	-0.132	-0.230***	-0.223	-0.293**
	[0.106]	[0.062]	[0.142]	[0.122]
Firm size: 11 to 50 people	0.054**	0.119***	0.091**	0.090**
	[0.023]	[0.020]	[0.041]	[0.042]
51 to 250 people	0.157***	0.175***	0.089**	0.089**
	[0.024]	[0.023]	[0.040]	[0.043]
251 to 1000 people	0.193***	0.261***	0.113**	0.115**
	[0.026]	[0.025]	[0.054]	[0.057]
More than 1000 people	0.269***	0.344***	0.247***	0.244***
	[0.038]	[0.028]	[0.078]	[0.086]
Professionals	-0.196***	-0.277***	-0.090	-0.093
	[0.040]	[0.033]	[0.085]	[0.092]
Technicians & associate professionals	-0.307***	-0.390***	-0.269***	-0.281***
	[0.046]	[0.033]	[0.080]	[0.079]
Clerks	-0.422***	-0.550***	-0.455***	-0.482***
	[0.052]	[0.040]	[0.083]	[0.081]
Service, shop and market sales workers	-0.515***	-0.628***	-0.361***	-0.375***
	[0.054]	[0.034]	[0.076]	[0.078]
Skilled agricultural and fishery workers	-0.526***	-0.456***	-0.532***	-0.539***
	[0.103]	[0.108]	[0.115]	[0.117]
Craft and related trades workers	-0.461***	-0.589***	-0.212***	-0.219***
	[0.058]	[0.052]	[0.080]	[0.083]
Plant/machine operators & assemblers	-0.445***	-0.640***	-0.223***	-0.234***
	[0.059]	[0.052]	[0.081]	[0.085]
Elementary Occupations	-0.544***	-0.710***	-0.421***	-0.430***
	[0.054]	[0.041]	[0.077]	[0.078]
ISIC 1-digit industry dummies & Country dummies				
Constant	6.986***	7.404***	6.638***	6.496***

	[0.188]	[0.181]	[0.189]	[0.219]
Observations	16785	16619	5211	4928
R-sq	0.415	0.36	0.27	0.277
adjusted R-squared	0.413	0.357	0.262	0.269

Bootstrap Standard errors in brackets

* p<0.1, ** p<.05, *** p<.01

Notes: Table A.3 records the estimation results of the Mincer-based regressions for male and female workers in advanced and developing regions. It corresponds to the partial output documented in Table 10.

Table A.4: Oaxaca-Blinder and Neumark Decomposition Results

REFERENCE	**POOLED WAGE STRUCTURE**		**MALE WAGE STRUCTURE**		**FEMALE WAGE STRUCTURE**	
Region	**Advanced Country Wages**	**Developing Country Wages**	**Advanced Country Wages**	**Developing Country Wages**	**Advanced Country Wages**	**Developing Country Wages**
Aggregate						
Mean of Male Wages	7.773***	6.738***	7.773***	6.738***	7.773***	6.738***
	[0.010]	[0.019]	[0.009]	[0.020]	[0.010]	[0.019]
Mean of Female Wages	7.274***	6.556***	7.274***	6.556***	7.274***	6.556***
	[0.009]	[0.023]	[0.009]	[0.022]	[0.009]	[0.023]
Difference	0.498***	0.182***	0.498***	0.182***	0.498***	0.182***
	[0.013]	[0.029]	[0.013]	[0.030]	[0.013]	[0.032]
Endowment	0.157***	-0.003	0.131***	-0.021	0.136***	-0.040
	[0.011]	[0.023]	[0.012]	[0.028]	[0.015]	[0.055]
Coefficients	0.341***	0.185***	0.362***	0.222***	0.367***	0.203***
	[0.012]	[0.030]	[0.016]	[0.060]	[0.014]	[0.034]
Interaction			0.005	-0.019	-0.005	0.019
			[0.019]	[0.060]	[0.017]	[0.053]
Detailed: Endowment						
Automation	-0.029***	-0.018	-0.046***	-0.035**	-0.016*	0.010
	[0.006]	[0.013]	[0.007]	[0.017]	[0.009]	[0.020]
Age	0.008	-0.013	0.011	-0.008	0.006	-0.027
	[0.007]	[0.011]	[0.010]	[0.012]	[0.007]	[0.017]
Age-squared	-0.012	0.006	-0.014	0.002	-0.010	0.017
	[0.009]	[0.008]	[0.011]	[0.008]	[0.008]	[0.016]
Experience	0.102***	0.064***	0.082***	0.054***	0.097***	0.071***
	[0.011]	[0.016]	[0.014]	[0.017]	[0.015]	[0.020]
Experience-squared	-0.038***	-0.050***	-0.043***	-0.049***	-0.035**	-0.043**
	[0.010]	[0.014]	[0.012]	[0.014]	[0.016]	[0.021]
ISCED 1	0.000	0.006	0.001	0.016***	-0.000	-0.016*
	[0.001]	[0.005]	[0.001]	[0.006]	[0.001]	[0.008]

ISCED 2	0.001	0.003	0.001	0.007	0.000	-0.006
	[0.002]	[0.003]	[0.003]	[0.005]	[0.004]	[0.005]
ISCED 3C (<2years)	0.000	0.000	0.000	0.000	0.000	0.000
	[0.001]	[0.000]	[0.001]	[0.000]	[0.001]	[0.000]
ISCED 3C (>=2years)	0.004	0.003	0.004	0.005	0.005	-0.001
	[0.003]	[0.003]	[0.004]	[0.005]	[0.005]	[0.003]
ISCED 3 A-B	-0.002	-0.001	-0.002	-0.002	-0.002	0.000
	[0.002]	[0.002]	[0.003]	[0.003]	[0.003]	[0.001]
ISCED 3 (no distinction A-B-C, 2+)	-0.001*	-0.000	-0.001	-0.000	-0.001	0.000
	[0.001]	[0.003]	[0.001]	[0.003]	[0.001]	[0.001]
ISCED 4C	-0.000	0.000	-0.000	0.000	-0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ISCED 4 A-B	-0.00011	-0.00134**	-0.00012	-0.002**	-0.000	0.000
	[0.000]	[0.001]	[0.000]	[0.001]	[0.000]	[0.000]
ISCED 4 (without distinction A-B-C)	-0.001	0.000	-0.001	0.000	-0.001	0.000
	[0.001]	[0.000]	[0.001]	[0.000]	[0.001]	[0.000]
ISCED 5B	-0.013**	-0.008***	-0.014*	-0.013***	-0.014	0.001
	[0.005]	[0.003]	[0.007]	[0.005]	[0.009]	[0.004]
ISCED 5A, bachelor	0.010***	-0.045***	0.009**	-0.057***	0.010**	-0.014
	[0.003]	[0.010]	[0.004]	[0.015]	[0.005]	[0.011]
ISCED 5A, masters	-0.004*	-0.008*	-0.003	-0.010*	-0.004*	-0.004
	[0.002]	[0.005]	[0.002]	[0.006]	[0.002]	[0.003]
ISCED 6, PhD	0.001*	0.001	0.001	0.001	0.001	0.001
	[0.001]	[0.003]	[0.001]	[0.003]	[0.001]	[0.004]
With Spouse or Partner	0.002**	0.007	0.007***	0.009	-0.003***	0.006
	[0.001]	[0.005]	[0.001]	[0.006]	[0.001]	[0.006]
Detailed: Coefficient						
Automation	-0.099**	-0.134*	-0.111**	-0.162	-0.081***	-0.118*
	[0.039]	[0.072]	[0.044]	[0.103]	[0.029]	[0.067]
Age	0.795**	-0.836	0.797*	-0.822	0.793*	-0.841
	[0.402]	[0.566]	[0.441]	[0.598]	[0.474]	[0.569]
Age-squared	-0.309	0.524*	-0.312	0.513*	-0.308	0.528*
	[0.213]	[0.294]	[0.231]	[0.303]	[0.251]	[0.302]
Experience	-0.082	-0.077	-0.077	-0.085	-0.062	-0.068
	[0.093]	[0.104]	[0.091]	[0.120]	[0.078]	[0.088]
Experience-squared	-0.023	-0.010	-0.026	-0.017	-0.018	-0.011
	[0.056]	[0.060]	[0.057]	[0.071]	[0.042]	[0.053]

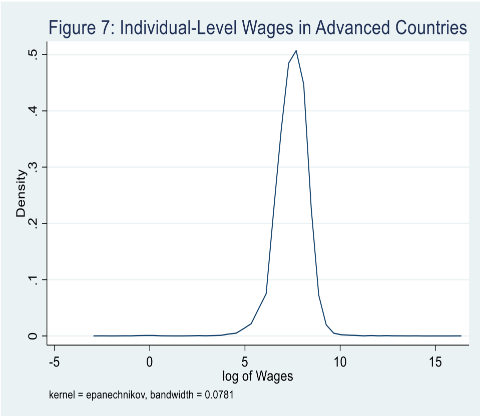
ISCED 1	0.002	0.056***	0.002	0.077***	0.001	0.046***
	[0.004]	[0.015]	[0.006]	[0.021]	[0.004]	[0.012]
ISCED 2	0.004	0.109***	0.005	0.118***	0.004	0.105***
	[0.019]	[0.036]	[0.026]	[0.040]	[0.017]	[0.032]
ISCED 3C (<2years)	-0.000	0.000	-0.000	0.000	-0.000	0.000
	[0.003]	[0.000]	[0.004]	[0.000]	[0.003]	[0.000]
ISCED 3C (>=2years)	-0.001	0.050**	-0.002	0.055**	-0.001	0.049**
	[0.023]	[0.020]	[0.031]	[0.022]	[0.020]	[0.019]
ISCED 3 A-B	0.007	0.029**	0.007	0.027**	0.007	0.029***
	[0.041]	[0.011]	[0.044]	[0.011]	[0.041]	[0.010]
ISCED 3 (no distinction A-B-C, 2+)	0.001	0.025**	0.001	0.025**	0.001	0.025***
	[0.003]	[0.010]	[0.003]	[0.010]	[0.004]	[0.009]
ISCED 4C	-0.000	0.000	-0.000	0.000	-0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ISCED 4 A-B	0.000	0.005**	0.000	0.004**	0.000	0.005**
	[0.001]	[0.002]	[0.001]	[0.002]	[0.001]	[0.002]
ISCED 4 (without distinction A-B-C)	-0.000	0.001	-0.000	0.001	-0.001	0.001*
	[0.003]	[0.001]	[0.002]	[0.001]	[0.003]	[0.001]
ISCED 5B	-0.00244	0.0173***	-0.001	0.00879**	-0.00161	0.022**
	[0.024]	[0.006]	[0.020]	[0.004]	[0.026]	[0.010]
ISCED 5A, bachelor	-0.003	0.090***	-0.003	0.060***	-0.002	0.103***
	[0.026]	[0.032]	[0.035]	[0.022]	[0.024]	[0.030]
ISCED 5A, masters	-0.001	0.011**	-0.001	0.007*	-0.001	0.013**
	[0.013]	[0.005]	[0.014]	[0.004]	[0.013]	[0.006]
ISCED 6, PhD	-0.001	-0.002	-0.001	-0.002	-0.000	-0.002
	[0.001]	[0.003]	[0.001]	[0.003]	[0.001]	[0.003]
With Spouse or Partner	0.144***	0.0103	0.149***	0.011	0.139***	0.008
	[0.018]	[0.027]	[0.018]	[0.036]	[0.017]	[0.024]
Firm, Job, industry & Country dummies						
Observations	33404	5797	33404	5797	33404	5797

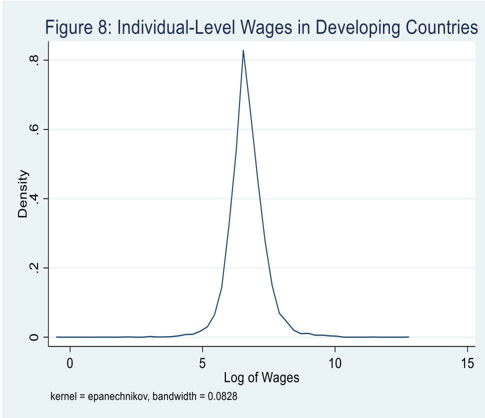
Bootstrap Standard errors in brackets

* p<0.1, ** p<.05, *** p<.01

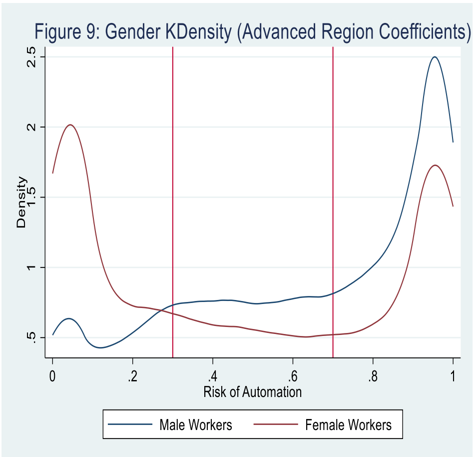
Notes: Table A.4 provides the results for the Oaxaca-Blinder decomposition estimated using the pooled, male, and female coefficients. Except for the pooled reference structure, the mean difference between the male and female wages is decomposed into the endowment, coefficient, and interaction effects. The detailed decomposition results are provided for only the endowment and coefficient effects. The table corresponds to the partial output presented in Table 11.

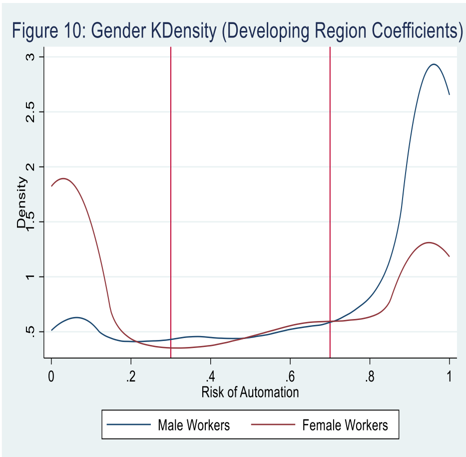
APPENDIX B





Notes: Given the shapes of the distributions illustrated by Figures 7 and 8, it is reasonable to assume that the Oaxaca-Blinder Decomposition (which is evaluated at the sample means) captured substantial information at the means to construct the index for both advanced and developing regions.





Notes: Figure 9 graphs the distribution of automation risks for the Gender dimension of the advanced region based on coefficients from the advanced region only and likewise Figure 10 is based on the developing region coefficients only. As illustrated by Figures 9 and 10, the use of the sector-specific pooled model is not the source of the similar patterns documented for both regions.

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