Oxford Review of Economic Policy, Volume 36, Number 4, 2020, pp. 903–924

Do technological advances reduce the gender wage gap?

Guido Matias Cortes,* Ana Oliveira,** and
Anna Salomons***

Abstract: Gender wage gaps in developed economies have narrowed substantially in past decades: these changes are driven by institutional, cultural, and economic factors. A key economic driver shaping modern labour markets is technological change, yet there is a paucity of evidence on its direct impact on gender wage disparities. We study this question by considering how men and women are differentially exposed to the structural employment and wage changes across occupations associated with advancing technology, and how this has impacted gender wage gaps since the mid-1980s for two countries, Portugal and the United States. Our findings suggest that while women have generally been less exposed to the automation of work, this has not always led to declining gender wage gaps: at times, women have transitioned to jobs where wage levels or wage growth were lower. Non-technological changes appear at least as important in understanding the evolution of the gender wage gap.

Keywords: gender wage gap, task-biased technological change, occupational tasks

JEL classification: J16, J21, J24, J31

I. Introduction

Gender wage gaps are a persistent characteristic of modern economies, though much progress has been made over the past decades. A large literature studies the underlying causes of these declining disparities, which can be divided into three broad strands. The first focuses on societal and institutional changes which have removed barriers to women's careers. This includes antidiscrimination legislation and affirmative action policies

* York University; e-mail: gmcortes@yorku.ca
** University of Porto; e-mail: anaoliveira.phd@fep.up.pt
*** Utrecht University; e-mail: a.m.salomons@uu.nl

We are grateful to Abi Adams-Prassl, Almudena Sevilla, and an anonymous reviewer for very helpful comments on an earlier draft. Cortes thanks the Social Sciences and Humanities Research Council of Canada for support, under grant numbers 430-2018-00686 and 435-2018-0280. Oliveira acknowledges financial support from Fundação para a Ciência e Tecnologia, I.P., under the grant SFRH/BD/146095/2019 and from Centro de Economia e Finanças da Universidade do Porto, under the project UIDB/04105/2020. Salomons thanks Stichting Instituut Gak for support.
doi:10.1093/oxrep/graa051

(Bertrand, 2011); lower maternal burdens through the expansion of family policies such as childcare provision and spending on early education (Olivetti and Petrongolo, 2017), as well as health care innovations such as infant formula (Albanesi and Olivetti, 2016) and the dissemination of the birth control pill (Bailey *et al.*, 2012); and the abolition of the marriage bar and other institutional arrangements which constrained labour market access for married women (Goldin, 1988). Some important barriers remain, such as the wage premium for working long hours (Goldin, 2014; Cortes and Pan, 2019*a*). The second strand considers changes in social norms related to gender, for example about women's careers and educational investments, and changes in labour market discrimination more broadly. Also here, there is evidence of progress as well as ongoing challenges. While women have increasingly entered occupations traditionally dominated by men (Goldin, 2006; Bertrand, 2011), women's career ambitions continue to hurt their marriage market prospects, while men face no such trade-off (Bursztyn *et al.*, 2017). The third and last strand of literature analyses the gender wage gap effects of structural economic change, through the types of jobs that are available, the skills they require, and the wages they pay. These structural changes are not necessarily gender-biased in nature, but may result in gender-biased impacts if men and women have different labour supply patterns across these jobs, for example because they have different skill sets. In particular, the structural transformation of the economy from goods to services has been found to have favoured women by creating jobs that are less physically demanding and more intense in interpersonal skills (Ngai and Petrongolo, 2017; Petrongolo and Ronchi, 2020), in which women have an (acquired or innate) comparative advantage (Borghans *et al.*, 2006).

A key driver of structural change is technological change: technological advances have been shown to reduce the demand for labour in certain jobs through automation, while also increasing labour demand in jobs where workers are complemented and where entirely new activities are created (Autor *et al.*, 2015, Autor and Salomons, 2018). In doing so, the job and wage structures of our economies are being transformed (Acemoglu and Autor, 2011). In a recent review paper, Blau and Kahn (2017) show that gender differences in occupations and industries now constitute the largest measured factors accounting for the gender pay gap. This suggests technological change may be important in understanding wage gap dynamics.

Evidence directly linking technological change to the evolution of the gender wage gap is scarce. First, while it has been widely documented that the gender wage gap has decreased as women have moved up the occupational ladder (Blau and Kahn, 2017; Cortes *et al.*, 2018), this has not yet been directly related to changes in the job structure associated with technological change. Second, current papers on gender and technological change have only considered the employment structure side by documenting to what extent women's jobs are more or less subject to automation, without analysing the contribution from related changes in the structure of wages. Specifically, Black and Spitz-Oener (2010) and Cortes and Pan (2019*b*) find that women's jobs are less exposed to automation in West Germany and the United States, respectively. Further, Cortes *et al.* (2017) show that being employed in jobs prone to automation has had more adverse effects on employment probabilities for men than for women. While suggestive of a gender dimension in the effects of technological change, these studies do not take into account how technological change impacts occupational wages: as a result, they do not directly inform on the consequences of technological change for the gender wage gap.

This paper studies the gender wage gap impacts of technological change through both its employment and wage structure changes. We separately quantify the effects operating through these two channels, and also compare their importance to non-technological, i.e. 'residual', factors in accounting for gender wage gap dynamics. We further add a cross-country comparison by using data from the mid-1980s onwards for both Portugal and the United States. We choose these countries because labour force participation margins are quite comparable across the two. Female employment to population rates increase in both countries by around 10 percentage points between the mid-1980s and the mid-1990s, and remain relatively stable at around 50–55 per cent thereafter (Ortiz-Ospina and Tzvetkova, 2017). Both countries also have low rates of part-time employment among women—unlike other European countries where working hours for women are substantially lower than for men (OECD, 2017). However, while the private-sector gender wage gap has narrowed in both countries, its dynamics over time are quite different, as we document in the next section. Since structural change driven by the Digital Revolution was occurring for both countries throughout this period, we use these different settings and time periods as a way of considering whether recent technological change has always had the same type of impact on the gender wage gap, or not.

Our key finding is that, while women have generally been less exposed to the automation of work in both countries, this has not always led to declining gender wage gaps: at times, women have transitioned to jobs where wage levels or wage growth were lower. That is, while technology-driven changes in the employment structure have mostly benefited women, this has not always been the case with regards to the wage impacts of technological change. Further, non-technological changes appear to be at least as important as technological factors in understanding the evolution of the gender wage gap.

The remainder of the paper is organized as follows. We first provide a brief overview of the data we use, and document the evolution of the private-sector gender wage gap for Portugal and the United States over more than three decades based on these sources. In section III, we outline how technological change has impacted employment and wage structures, and why this could have an effect on gender wage gaps. Section IV shows empirical results where we quantify these impacts and compare them across countries and time periods. Section V concludes and provides policy recommendations based on our findings.

II. Data

Our analysis is based on detailed micro-data for both Portugal and the United States. For Portugal, we use *Quadros de Pessoal*, the country's official matched employer–employee dataset, which is based on a mandatory survey collected once a year by the Portuguese Labor and Social Security Ministry since 1985 (in March until 1993 and in October in subsequent years). It covers all private-sector firms and establishments with at least one employee between 1985 and 2017 (except 1990 and 2001, for which data on employees are not available). Unique identifiers are provided for each establishment, firm, and worker. Civil servants, self-employed workers, and household employees are excluded from the database.

For the United States, we use national labour force survey data from the Current Population Survey (CPS), the primary source for the country's labour force statistics. The CPS is conducted at a monthly frequency and is sponsored jointly by the US Census Bureau and the US Bureau of Labor Statistics (BLS). We use the microdata made publicly available by IPUMS (Flood *et al.*, 2018). For consistency with the Portuguese data, we exclude the self-employed, as well as public-sector and unpaid family workers in the US data.

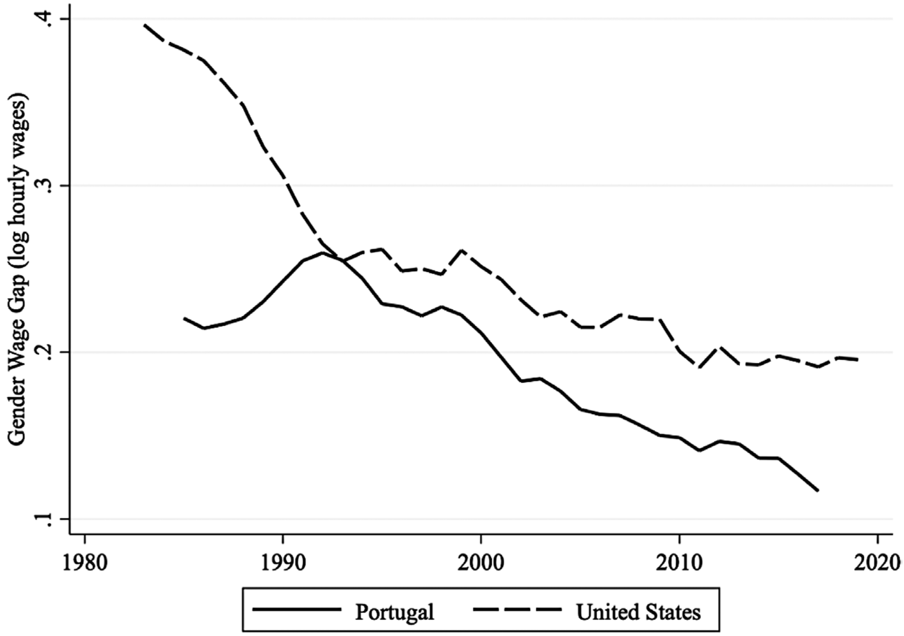
We use all available years of data for Portugal, covering 1985–2017. For the US we use the years 1983–2019. We focus on workers aged 18 to 68. In the Portuguese data, we drop a small number of observations for which gender, schooling, base remuneration, or total remuneration are missing. Given our focus on the impacts of technology that operate through changes in the occupational task composition of the economy, we exclude observations with missing or imprecise occupational information.[1] We also exclude workers in farming, fishing, or forestry occupations in both countries. Our final dataset includes 64.7m worker-year observations for Portugal, and 20.0m worker-month observations for the US.

We construct hourly wages from the Portuguese data by dividing individuals' total monthly remuneration (which includes base pay as well as additional payments such as meal allowances, shift work allowances, and any bonuses or severance payments paid in the corresponding month) by their usual monthly hours, and deflate these using the Consumer Price Index (2012 = 100). In order to exclude outliers, we drop observations below the 1st and above the 99th percentile in terms of either base or total remuneration. Wages in the US are based on hourly wages, when available, or weekly earnings divided by usual (or actual) hours worked per week. As in Lemieux (2006), top-coded earnings are adjusted by a factor of 1.4. We convert nominal values to 2009 dollars based on the monthly Consumer Price Index (CPI, All Urban Consumers) from the BLS.

Figure 1 plots the evolution of the gender wage gap, i.e. the gap in log real hourly wages between men and women in each year. The gender wage gap starts off much higher in the mid-1980s in the US compared to Portugal, at nearly 40 per cent. The US gender wage gap then decreases rapidly over subsequent years, falling to around 26 per cent in 1993, and then continues to decline, but at a much slower rate (as also established by, for example, Blau and Kahn (2017)). In Portugal, the gender wage gap increases from the mid-1980s until 1992, peaking at around 26 per cent. It subsequently declines quite steadily until reaching a value of approximately 12 per cent at the end of the sample period. Overall, both countries experience substantial progress towards pay equality. The main goal of the paper is to explore the role of technological change, and more specifically of task-biased shocks, in driving these changes in the gender wage gap. The following section discusses the different channels through which this may occur.

[1] This is never an issue in the US data. However, over the early years of the Portuguese data (1985–94), an important fraction of workers is assigned to a set of general categories which do not provide clear information on the occupation performed (e.g. 'Residual Intern', 'Residual Helper', 'Residual Apprentice'). Individuals with these non-descriptive designations cannot be readily classified into an occupation group and hence must be dropped from the analysis. They represent 21.3 per cent of the annual samples over the 1985–94 sub-period. From 1995 onwards, the proportion of workers that must be dropped for this reason is much smaller (and negligible for the most recent years).

Figure 1: The evolution of the gender wage gap



Note: The figure shows the difference between average log hourly wages for men and average log hourly wages for women based on *Quadros de Pessoal* and CPS data for private-sector non-agricultural workers.

III. Impacts of technological advances on the gender wage gap: mechanisms

In this section, we explain why technological advances could impact the gender wage gap. Specifically, we outline that technological change is a task-biased shock (section III(i)), that tasks matter for workers' wages (section III(ii)), and that men's and women's jobs have different task content (section III(iii)). Combining these insights, we put forward two specific channels through which technological change impacts the gender wage gap (section III(iv)).

(i) Technological change as a task-biased shock

Technological advances such as automation may affect the gender wage gap through different channels. In this paper, we focus on the impacts of technology on the job and wage structure of the economy. An influential literature has shown that digital technologies have, since the 1980s, led to a decline in the demand for labour in so-called routine tasks (Acemoglu and Autor, 2011). Routine tasks are rules-based, and can therefore be codified and embodied in digital technology. Occupations that are intensive in routine tasks are found in production (such as assembly) but also in clerical and administrative work: these occupations tend to pay around average wages. Non-routine tasks, on the other hand, have experienced increases in labour demand:

these tasks involve problem-solving and flexibility of either the mental or physical kind, which are as yet difficult to codify. Occupations intense in non-routine tasks are predominantly found at both ends of the wage distribution: that is, in high-paying professional jobs (such as managers and engineers) which require mental adaptability, but also in low-paying in-person service occupations (such as hairdressers or babysitters) which require physical adaptability. Social interaction is also an example of a non-routine task which is disproportionately found in both high- and low-paying jobs, and the demand for interpersonal skills is rising (Deming, 2017; Cortes *et al.*, 2018).

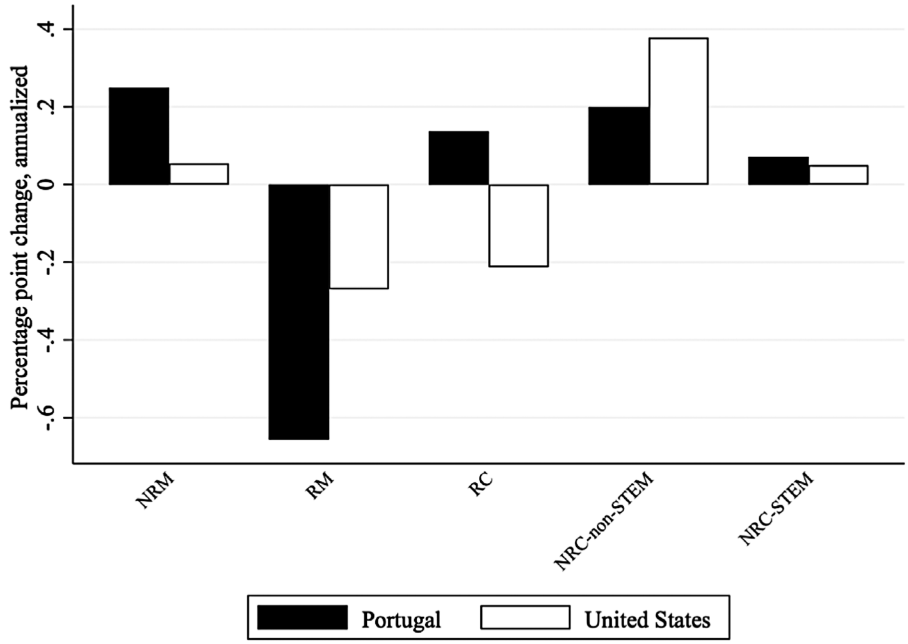
Following this literature, we group occupations into broad categories which we label according to the main task that is generally performed by workers in these occupations, namely (i) non-routine cognitive (NRC), (ii) routine cognitive (RC), (iii) routine manual (RM), and (iv) non-routine manual (NRM). The grouping is based on the job titles available from the detailed occupational codes. NRC occupations are professional, managerial, and technical occupations; RC occupations include administrative support and clerical occupations, as well as sales-related occupations; RM occupations include production and craft workers; while NRM occupations are personal service and other unskilled occupations. In order to investigate whether patterns differ between STEM and non-STEM occupations, we further sub-divide the NRC category based on whether the occupations can be classified as related to science, technology, engineering and math. We think of STEM jobs as the most directly technology-intense occupations. The detailed crosswalk for the Portuguese occupation codes is provided in Appendix A (Table A.1). The grouping for the US occupation codes follows Cortes *et al.* (2020), with the additional distinction between STEM and non-STEM occupations detailed in Appendix A (Table A.2).[2]

Figure 2 depicts the average annualized change in the employment share of each of the five broad task groups over our period of analysis. Task groups are ranked by their average wage, in ascending order (with non-routine manual being the lowest paying and non-routine cognitive STEM the highest paying). The graph illustrates the well-documented pattern of job polarization (Goos *et al.*, 2009; Acemoglu and Autor, 2011): in both countries, the employment share of middle-paying routine manual tasks has fallen, while relative employment in non-routine tasks—both in high-paying NRC STEM and non-STEM tasks, as well as in low-paying NRM tasks—has grown. RC tasks grow in Portugal, but shrink in the US. This is consistent with related empirical literature on Portugal and other European countries (Goos *et al.*, 2014). In what follows, we interpret changes along these task lines as being related to biased technological shocks.[3]

[2] Both countries experience major revisions to their occupational classification systems throughout our sample period. In Portugal, this occurs in 1995 and 2010. In the US there are minor revisions in 1991 and 2011, and a major revision in 2003. Throughout all of our analysis, we avoid computing annual changes that overlap the years when these coding system changes occur, i.e. we only compute annual changes across years with consistent coding systems, and present results for average annualized changes.

[3] In this paper, we do not directly rule out the possibility that changes in the employment shares of these broad task groups may be driven by other shocks such as offshoring. However, the literature has so far concluded that technological change is by far the more important driving force behind task-biased changes (e.g. see Goos *et al.*, 2014; Autor *et al.*, 2015; Cortes and Morris, 2019).

Figure 2: Annualized change in task group employment shares



Note: Task groups are ranked by their average wage, in ascending order. NRM = non-routine manual; RM = routine manual; RC = routine cognitive; NRC-non-STEM = non-routine cognitive non-STEM; NRC-STEM = non-routine cognitive STEM.

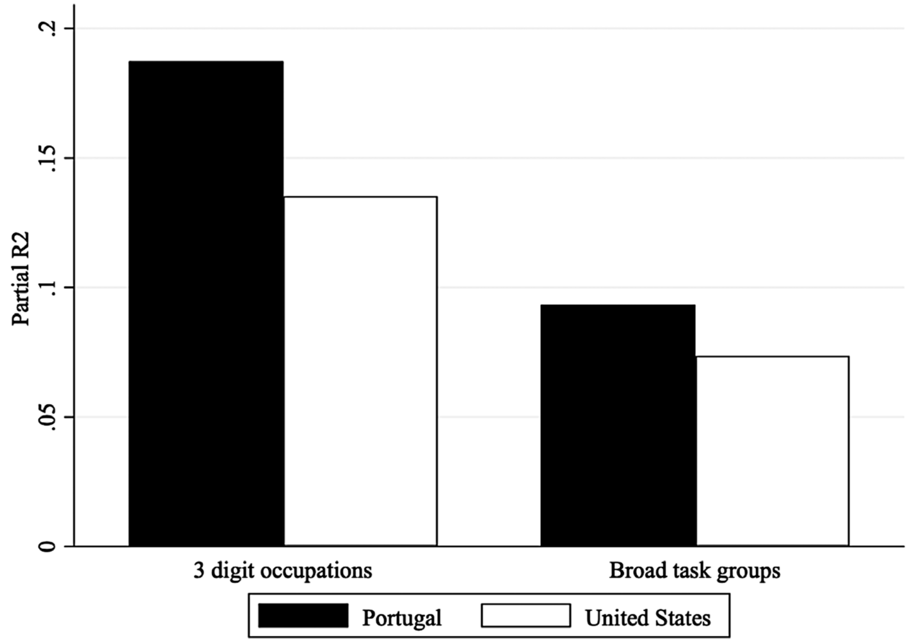
(ii) Importance of occupational tasks for wage determination

Next, we confirm the importance of occupations in accounting for variation in individual wages. In a similar way to Acemoglu and Autor (2011), Figure 3 depicts the additional explanatory power (measured as the partial R^2) that can be attributed to occupational affiliation in a wage regression, in addition to what can be accounted for by individual characteristics, namely age, age squared, education (a college dummy), gender, and detailed (3-digit) industry fixed effects. The two bars on the left show the additional explanatory power obtained from detailed (3-digit) occupational categories; while the two bars on the right show the additional explanatory power obtained from the five broad task groups, alone. The results show that occupations account for an important fraction of wage variation, conditional on individual characteristics. Moreover, a substantial proportion of the variation attributable to the detailed (3-digit) occupations can already be accounted for by focusing simply on our five broad task groups. Hence, we can conclude that the five broad task categories are an important driver of individual wages. Changes in occupational affiliation and changes in occupational returns will therefore have significant impacts on individual wages.

(iii) Occupational segregation of men and women

Task-biased shocks will have an impact on the gender wage gap due to the well-documented heterogeneity in the occupational composition of employment for men and

Figure 3: Importance of occupations and occupational tasks for wage determination



Note: The figure plots the partial R-squared obtained from adding 3-digit occupation dummies, or dummies for the five broad task categories, to an individual-level regression of log real wages on age, age squared, education (a college dummy), gender, and 3-digit industry fixed effects. The regression is run separately for each year of data, and the figure plots the average across all available years.

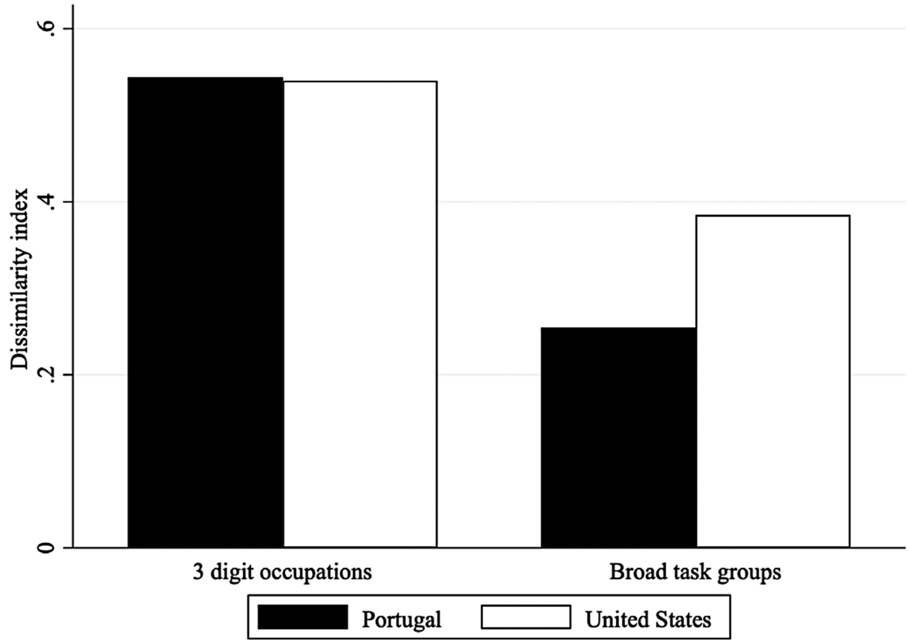
women (Blau and Kahn, 2017). Figure 4 describes occupational segregation by gender in Portugal and the US. It plots the so-called dissimilarity index, which indicates the proportion of women or men that would need to change occupations for the job structure to be the same across genders (Duncan and Duncan, 1955).[4] The bars on the left show a high degree of segregation at the detailed (3-digit) occupational level in both countries: more than 50 per cent of women or men would need to change occupations in order to equalize the job structure across genders. The bars on the right show the analogous measures based on the five broad task categories. Given their broader nature, the segregation index is lower; however, it is still substantial in both countries. In Portugal, 25 per cent of men or women would have to switch across broad task groups for the two genders to be equally distributed across the occupations that are expected to be differently affected by advancing technology. In the US, the corresponding figure is 38 per cent.

(iv) Channels through which technological advances impact the gender wage gap

We have shown above that: (i) there have been important changes in the occupational structure of employment, which are arguably technology-driven, (ii) occupations, and

[4] The index ranges between 0 and 1, where 0 indicates no segregation, and 1 indicates full segregation.

Figure 4: Gender segregation index for occupations and occupational tasks



Note: The figure plots the dissimilarity index of Duncan and Duncan (1955), which indicates the proportion of women or men that would need to change 3-digit occupations or broad task categories for the job structure to be the same across genders in the respective country. The index is computed separately for each year of data and then averaged across all available years.

in particular the broad task categories that occupations belong to, are major determinants of individual-level wages, even conditional on observable worker characteristics, and (iii) men and women differ in the occupational tasks that they perform. Taken together, these insights imply that technological change may affect the gender wage gap. In particular, we can distinguish two main channels through which biased labour demand changes from advancing technology impact the gender wage gap.

1. *Differential employment exposure*: Men and women could be differently exposed to task-biased employment changes resulting from advancing technology.
2. *Differential wage exposure*: Men and women could be differently exposed to task-biased wage changes resulting from advancing technology.

The first, *differential employment exposure*, occurs when the occupational employment distribution changes, holding occupational wages constant. In the context of technological change, this can be thought of as follows. Automation of work in routine-intense occupations has reduced employment in these types of jobs, while increasing employment in non-routine occupations. These occupations pay different average wages. Therefore, even holding (gender-specific) occupational wages constant, these occupational employment changes will change the gender wage gap, given that men and women are not distributed equally across occupations with different levels of routine task intensity. These differences in exposure may result both from differences in the initial occupational composition of employment for men and women, and from differences in the extent to which men and women are able to adapt to task-biased shocks by transitioning to different occupations. As such, automation has the potential to change the average wages of men and women differently through pure occupational employment effects, without any changes in occupational wages.

The direction of this effect for the gender wage gap is theoretically ambiguous: for example, if men are more segregated in declining routine occupations, the gender wage gap may still rise if at the same time women are overrepresented in lower-paying non-routine occupations which are expanding. However, the gender wage gap may narrow if women have experienced stronger occupational upgrading relative to men: that is, if they have experienced a stronger reallocation from declining routine jobs towards high-paying non-routine occupations compared to men. Overall, if differential employment exposure to technological change narrows the gender wage gap, we would conclude that women are better positioned than men to deal with the changing task demands in the labour market, either because they have an initial advantage in performing tasks which are not being automated and higher-paid, and/or because they are better willing or able to switch to these occupations than men are.

Differential wage exposure, on the other hand, occurs when relative occupational wages change for a given occupational employment structure. This is driven by the wage component of the biased labour demand shock from technological change. Here, men and women are differently exposed if the occupations in which they are employed differ in their wage (rather than employment) evolutions.

As with employment exposure, differential wage exposure to task-biased shocks may either help or hinder women relative to men. For example, the wage gap may narrow if interpersonal skills are increasingly valuable in the labour market, and women are over-represented in occupations requiring such skills. On the other hand, the gender wage gap may widen to the extent that high-paying non-routine jobs (for example in STEM occupations) are still predominantly male and are experiencing higher wage gains from advancing technology.

In sum, these two exposure channels imply that occupational employment and wage changes by occupational task group can be used to inform on the impact of technological advances on the gender wage gap. The empirical analysis presented in the next section quantifies these channels by means of a decomposition analysis (technical details are reported in Appendix B), grouping occupations into the task categories outlined above. This allows us to quantify the separate contributions of these two technology-related channels to changes in the gender wage gap. We compare these impacts to residual changes in the gender wage gap which are unrelated to technological advances: this tells us how important advancing technology has been relative to other factors. These residual changes may have a wide range of non-technological drivers, including changes in social norms, family structure, institutions such as child care policies, and non-discrimination legislation, but are not directly attributable to labour demand changes from technological change or any gender-specific ability to respond to these changes.[5] Note that such residual changes may still be related to changes occurring at

[5] These residual changes may also include some technological impacts not directly operating through the labour market, for example, through the increased availability of technologies substituting for home production or relevant medical technologies such as the contraceptive pill: while these changes can be interpreted as being driven by technological advances, we view their impact on the gender wage gap as a distinct topic of study.

a detailed occupational level: for example, if women are increasingly entering higher-paid management functions as a result of increasing educational attainment and labour force attachment, or from reduced negative attitudes towards against women in leadership positions. We only attribute to technology those occupational effects occurring at the level of the five broad task groups outlined above, where technological substitution and complementarity are expected to operate.

IV. Impacts of technological advances on the gender wage gap: findings

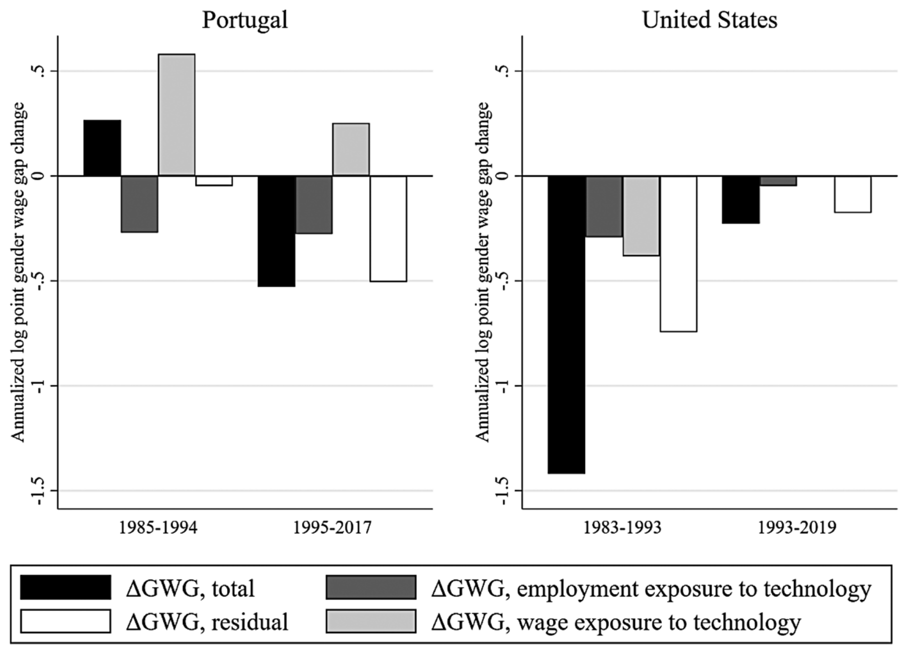
To consider how advancing technology has impacted the private-sector gender wage gap in Portugal and the United States since the (mid-)1980s, we perform a descriptive decomposition analysis highlighting men and women's differential exposure to task-biased employment and wage changes, as explained in the previous section. The equations underlying this analysis are outlined in Appendix B. We perform and report this analysis separately over two sub-periods for each country. For Portugal, we use 1985–94, and 1995–2017: the first period corresponds to a time when the gender wage gap was rising, whereas the gap narrowed during the second period.[6] For the United States, we separately analyse 1983–93 and 1993–2019. The first period saw a rapid closing of the gender wage gap, whereas progress has been much slower since the mid-1990s. Throughout, long differences are annualized to make them comparable.

Results are shown in Figure 5: for Portugal in the left-hand panel, and the US in the right-hand panel. The black bars show, for each subperiod, the annual change in the gender wage gap in log points. This shows the different evolution for the two countries: in Portugal, the gender wage gap widened over the first period, whereas rapid progress was made in the US. Conversely, since the mid-1990s, the gap closed in Portugal whereas little progress was made in the US. The remaining bars decompose this total change into technology-related factors, and other changes. Specifically, the dark and light grey bars show how men and women's differential exposure to employment and wage changes from task-biased technological change have impacted this gap, respectively. The white bars show the contributions of non-technological (i.e. 'residual') forces. Three key findings emerge.

First, the differential employment exposure channel has acted to narrow the gender wage gap in both periods for both countries, as seen from the dark grey bars. Specifically, this implies that the changing distribution of work as a result of technological advances has robustly tended to benefit women relative to men. These contributions are quantitatively important for both periods in Portugal. Importantly, this implies that women's employment structure was more favourable to task-biased shocks even in a period when the wage gap was growing: the gender wage gap would have widened even more, had women not had this advantage. The employment exposure impacts for Portugal are remarkably similar in the first period to those in the US. However, the size of this channel has been much smaller for the US since the mid-1990s.

[6] To avoid spurious changes, we do not calculate changes across the two occupational data breaks for Portugal; see footnote 2.

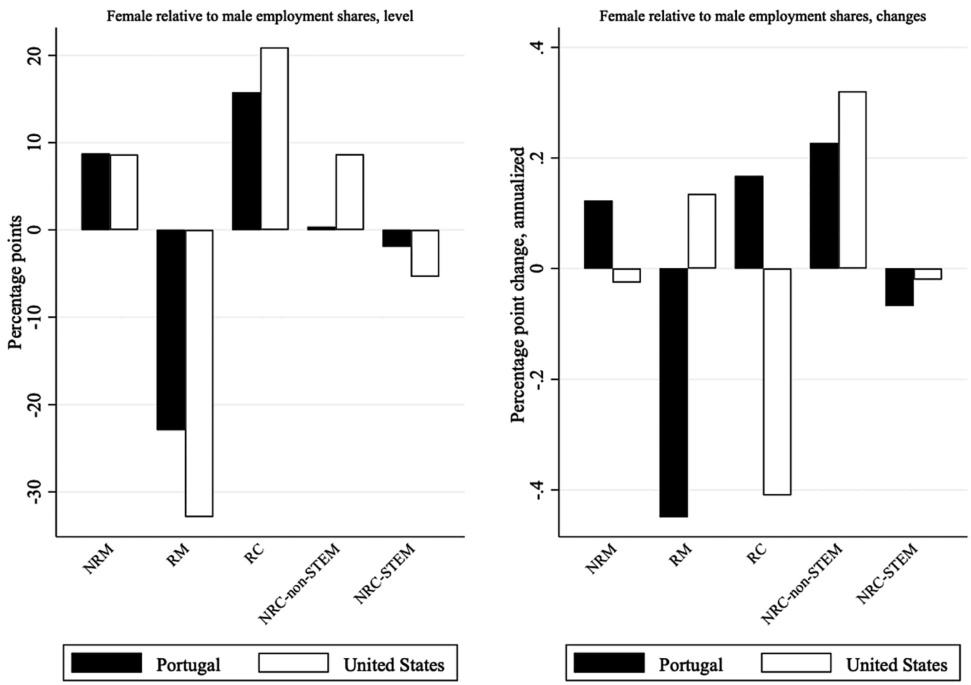
Figure 5: Decomposition results



There are two reasons why women's employment is less exposed to technological change than men's employment; these are illustrated in Figure 6. First, the left-hand panel shows the relative employment share of women relative to men in each of the five broad task groups. Positive values indicate that women are over-represented relative to men in these occupations, while negative values indicate that they are under-represented relative to men. A clear pattern emerges: women have substantially lower employment shares in declining routine manual jobs as compared to men. These jobs are the most directly negatively impacted by technology. Hence, this implies that women are less exposed to automation of their jobs, which may benefit them, all else equal. However, it should also be noted that women are overrepresented in non-routine manual jobs, the lowest-paid task category: the expansion of this task group (as shown in Figure 2) puts downward pressure on women's average wages relative to men's, dampening the extent to which the employment exposure effect has benefited women through this channel.

A second reason why women are less exposed to automation is that they have moved out of declining routine-intense occupations at a faster rate than men. This is shown in the right-hand panel of Figure 6. The figure plots the annual change in the employment share in each of the task groups for women relative to men. Positive values indicate higher entry (or lower exit) of women relative to men into a particular task group, while negative values indicate higher exit (or lower entry) of women relative to men from the task group. In both countries, women have moved out of routine-intensive occupations at a faster rate than men. However, an interesting difference emerges between the two countries: in Portugal, women have disproportionately moved out of RM occupations, whereas in the US, they have disproportionately moved out of RC occupations. As shown in Figure 2, RC jobs have been declining in the US, so this indicates that women

Figure 6: Female relative to male employment share by task group, level, and change over time



Note: The left-hand panel shows the share of female employment in each task group, minus the share of male employment in each task group. Positive values for a task group imply women are over-represented in that task group compared to men. The right-hand panel shows the annualized change in the share of female employment in each task group, minus the change in the share of male employment in each task group. Negative values for a task group imply that women are moving out of these jobs at a faster rate than men (or moving into these jobs at a slower rate than men). Task groups are ranked by their average wage, in ascending order. NRM = non-routine manual; RM = routine manual; RC = routine cognitive; NRC-non-STEM = non-routine cognitive non-STEM; NRC-STEM = non-routine cognitive STEM.

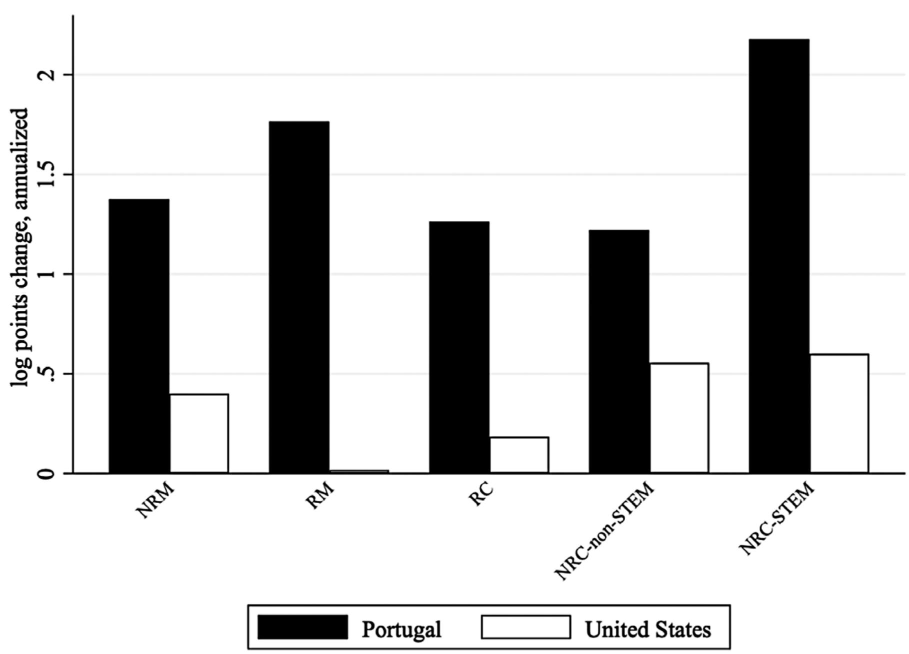
have been able to move out of declining occupations at a faster rate than men in both countries. It is also important to highlight that, in both countries, women have disproportionately transitioned towards higher-paying NRC tasks: since these occupations pay higher average wages, the gender wage gap declines. An important exception are NRC-STEM jobs: as seen in the rightmost bars of Figure 6, women moved into these high-paying jobs at a lower rate than men, an issue we return to below.

In sum, the first finding is that men's jobs have left them more exposed to routine task automation, whereas women have been better able to adjust to these changes. This is the case both because they have always been more concentrated in jobs intense in non-routine tasks, and because they have moved out of routine tasks more rapidly than men. This has narrowed the gender wage gap because of the nature of women's occupational reallocation: on average, they have disproportionately moved into higher-paying (NRC) jobs.

The second key finding from the decomposition analysis reported in Figure 5 is that, unlike differential employment exposure, differential exposure to the wage effects of technological change has *not* been unambiguously favourable for women relative to men. While this channel has acted to reduce the gender wage gap in the first period for the US, differential wage growth across task groups has *increased* the gender wage gap for Portugal in both periods, and not contributed to any closing of the gender wage gap in the US since the mid-1990s.

Negative gender wage gap impacts through wage exposure occur whenever women have been underrepresented in jobs where wage growth from task-biased shocks was strongest. Figure 7 shows annual wage growth for each task group in each country. In Portugal, wage growth was higher than in the US for all task groups over our sample period. This is primarily due to strong overall wage increases in Portugal during the early part of our sample period, which coincides with the country's accession to the European Union. For our purposes, however, we are interested in the extent to which wage growth *differs* across task groups. The figure shows that, in Portugal, wage growth was highest in NRC-STEM and RM jobs. Women are underrepresented in and/or moving away from both of these task groups. Conversely, wage growth rates were lower in RC jobs (such as administrative support work) and NRM jobs (such as personal service occupations), which are predominantly female (see left-hand panel of Figure 6). The wage exposure effect is decreasing in size over time in Portugal because real wage growth slowed considerably over time. Overall, gender wage disparities have widened as a result of differential wage exposure from technological change in Portugal. This contrasts with the patterns for the US, where wage growth across task groups has been

Figure 7: Wage growth by task group



Note: Task groups are ranked by their average wage, in ascending order. NRM = non-routine manual; RM = routine manual; RC = routine cognitive; NRC-non-STEM = non-routine cognitive non-STEM; NRC- STEM = non-routine cognitive STEM.

more favourable to women. In particular, US wages for jobs intense in non-routine tasks have grown faster than wages for jobs intense in routine tasks: this has reduced the US gender wage gap since women are (increasingly) overrepresented in non-routine task-intensive jobs.

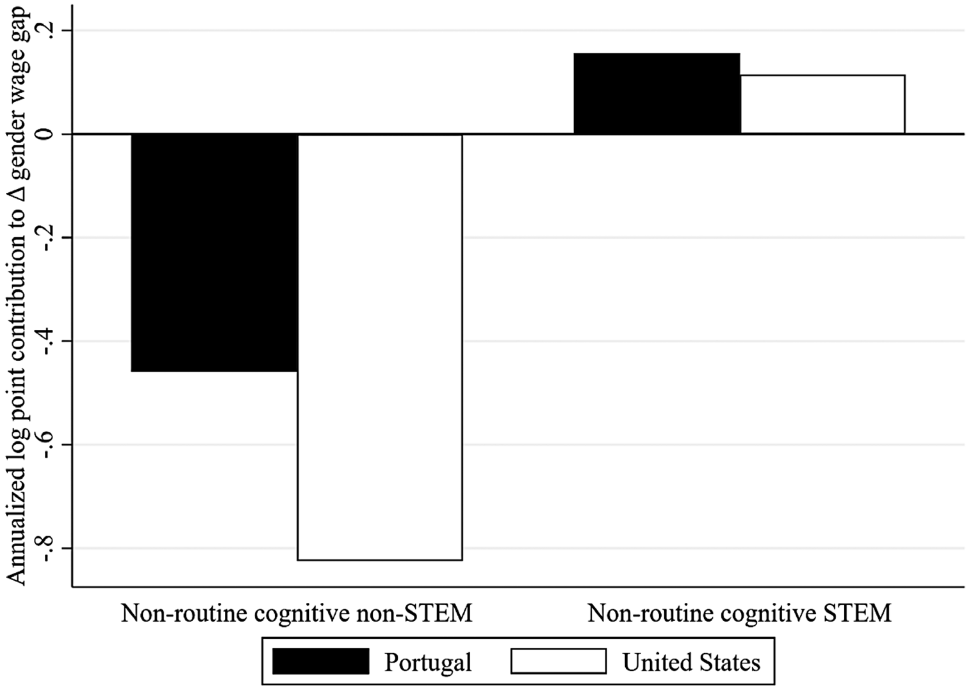
The net effect of these two technological channels (employment exposure and wage exposure) on the gender wage gap varied across periods and across countries. This can be seen by adding up the two grey bars in Figure 5. While task-biased shocks reduced the gender wage gap in the US over 1983–93, they strongly increased the gap in Portugal over a similar period (1985–93), due to the wage exposure effect. The net effect for the mid-1990s onwards is much more muted for both countries. This highlights that it is not an 'automatic' outcome that task-biased technology reduces the gender wage gap: although it has the potential to do so, this is not always the case. While women have been less exposed to routine (manual) task automation over the past 35 years for both countries, these effects can be cancelled out when women are transitioning to occupations where wage levels or wage growth have been lower. This gives a rather nuanced picture of how technological change has impacted the gender wage gap.

It is worth noting that STEM jobs play a salient role here: although women's occupational upgrading has been beneficial to the gender wage gap, as argued above, this effect is limited to NRC jobs outside of STEM fields. Figure 8 isolates the overall technology effects (i.e. the sum of the employment and wage exposure effects) attributable to STEM and non-STEM NRC jobs. Technological impacts through NRC jobs have greatly reduced the gender wage gap, but no such contribution has been made by jobs in science, engineering, technology, and maths-related fields. Rather, these jobs have contributed to widening gender labour market disparity in both Portugal and the US.

The final key result from the decomposition analysis in Figure 5 concerns the importance of technology compared to other factors in driving changes in the gender wage gap. Here, our finding is that non-technological changes have been more important since the early 1990s. These 'residual' forces, many of which are surveyed in the introduction, have acted to reduce the gender wage gap throughout the entire period for both countries, and cannot be easily attributed to task-biased shocks since they concern changes in relative wages by gender occurring *within* broad task groups. Note that these forces could also be reducing the gender wage gap through occupational upgrading for women across narrower occupations within these task groups. Such upgrading, however, is less directly attributable to technological change.

All in all, over the entire period and across both countries, technological change appears not to have robustly favoured women's wages more than men's. It can be misleading to look only at job automation exposure: while women are less exposed to the automation of routine-task-intensive work so far, we cannot draw conclusions about the gender wage gap impact without also taking into account job reallocation patterns and how wages have evolved in non-routine relative to routine work. Further, for the narrowing of the gender wage gap, non-technological forces are at least as important in most periods. Together, these findings suggest we should not expect to 'automate ourselves' into gender equality.

Figure 8: Impact of technology on the gender wage gap: STEM and non-STEM occupations



Note: The figure plots the technology-related changes in the gender wage gap (coming from employment and wage exposure effects) attributable to NRC STEM and non-STEM occupations.

V. Conclusions and policy recommendations

Do technological advances reduce the gender wage gap? To answer this question, we analyse how technology has changed the job and wage structure across broad task groups among non-agricultural private-sector workers in Portugal and the United States since the mid-1980s. Specifically, we distinguish between tasks which can be automated, and tasks which cannot be automated, or where technology strongly complements work. We find that women have on average benefited from changes in the *employment* structure for the periods and countries we consider. This is consistent with a long-standing literature which shows that women have moved up the occupational ladder in recent decades. Our results suggest that this is at least partly driven by advancing technologies which increase the demand for work in tasks in which women have an (acquired or innate) comparative advantage.

These results from an employment perspective, however, do not necessarily imply that technological change has reduced the gender wage gap. Technological change also affects relative wages across jobs, and this could exacerbate gender wage disparities even if employment structure changes are more favourable to women. We indeed find that the gender wage gap impacts of 'task-biased' technological change depend crucially on the wage levels and wage growth of the jobs women are employed in, and are transitioning towards. These patterns have generally been more favourable for the United States than for Portugal, though they also vary substantially within these countries over time. Simply put, the impact of technological change on occupation-level wages has not consistently been in women's favour.

Hence, the key conclusion from our analysis is that, while technological advances *can* reduce the gender wage gap, this is not always the case. Taking into account both the employment *and* the wage impacts of technological change, we find that the overall impact of advancing technology on the gender wage gap in Portugal and the United States has been muted, and in some cases even detrimental to women. The main exception is for the US case between the mid-1980s and the mid-1990s, when technological forces have aided in closing the gender wage gap. Overall, non-technological factors seem to have been at least as important, and often more important, in reducing gender wage inequality. These non-technological factors may include occupational upgrading *within* the broad tasks groups differently impacted by technology, but also the well-known narrowing of gender wage gaps within jobs—changes that are not clearly attributable to technological advances. All in all, our analysis suggests we should not expect technological change to eliminate gender wage disparities in and by itself.

These findings have several policy implications. First, they highlight that policies aimed at gender pay equality continue to be relevant: the effects of women's occupational upgrading on the gender wage gap can be substantially muted if women continue receiving lower wages and achieving lower wage growth both between and within occupations.

Second, we should not assume that women's current lower exposure to task automation and higher ability to adapt to changing task demands continue indefinitely into the future. For one, a new wave of technologies related to artificial intelligence is projected to impact more cognitive jobs (Webb, 2020), which is where women have been increasingly represented. Furthermore, while our analysis does not explicitly consider the participation margin, it may be the case that our finding regarding women's higher ability to adapt to technological change by transitioning across occupations is linked to rising labour force participation: additional women who enter the labour market would not have been entrenched in jobs with declining employment prospects, and this may have facilitated their transition into different career paths. This channel may inevitably be muted as participation increases plateau.

Third, our analysis suggests occupational segregation along task lines remains pervasive, which can be to the detriment of both genders. After all, the aim should be for the closing of the gender wage gap to arise from women advancing, not men's outcomes deteriorating. Structural labour market changes such as those caused by technological advances require workers to adapt, and the ongoing gender-segregation of work could be an important barrier to such adjustments. A specific example of such segregation which disadvantages women are STEM jobs: we find that the technology-related employment expansion and wage growth in these jobs have benefited men more than women. Policy aimed at improving women's entry to these jobs should target pre-labour market choices: recent work suggests these differences are to an important extent driven by subject choice at the secondary school level, and that STEM subject choice is largely unexplained by different aptitudes between genders (Delaney and Devereux, 2019). These gaps are also smaller in more affluent areas, suggesting further targeting of policy interventions. It should also be noted that the definition of STEM itself is under discussion: nursing jobs are not included, yet these jobs are arguably technology- and science-intensive. However, while nursing jobs—which are both female-dominated and not subject to automation—have seen strong employment growth, wage growth has lagged behind male-dominated traditional STEM categories: this is another example of how employment evolutions favouring female-dominated work can be countervailed by wage structure effects.

Lastly, more study is needed into the topic of technological change and gender wage gaps. Following much of the recent literature on technological change, we have used a task-based approach to help understand the broad outlines, but more insight is needed into the micro-level mechanisms and worker-level adjustments underlying these aggregate effects. For example, different job reallocation across genders could arise at labour market entry, or throughout the whole career. It could be the case that women's rising labour force participation until the mid-1990s partly underlies their better ability to adapt to the changing job structure of the economy: unlike men, these women had not yet accumulated task-specific human capital in jobs affected by automation. However, it may also be the case that women are more willing and/or better able to switch to non-routine jobs requiring high interpersonal skills, for example because these jobs are already female-dominated and there is a social norm reducing men's entry into female-dominated jobs (Pan, 2015). To study this, one needs longitudinal evidence following individual workers over time. Similarly, a recent literature has shown that differences in firm-level wages are an important driving force behind increasing inequality (Barth *et al.*, 2016): this appears to have a gender component (Card *et al.*, 2016) which may be contributing to the wage exposure effects we find. And finally, our aggregate analysis may miss some technological forces which play out at the micro level. For example, if men and women perform different tasks within the broad task clusters that we consider, it may be the case that automation leads to differential wage changes between men and women *within* these groups (something we do not attribute to technological forces in the current analysis). This could occur if men and women tend to be concentrated in different types of firms with different levels of technology investments, such that their day-to-day tasks (and hence their exposure to automation) may differ, even though their jobs may fall within the same broad task category at a macro level. Importantly, such micro-level studies would also help better inform and target policy to further reduce gender wage disparities.

Appendix A: Occupational classifications

Table A.1: Mapping of detailed occupation codes to broad task groups—Portugal

Broad occupation	Occupation classification coding		
	1985–94	1995–2009	2010–17
Non-routine cognitive STEM	011–031, 051–054, 082–084	211–221, 312, 313, 321	133, 142, 211–216, 251, 252, 311, 314, 331, 351
Non-routine cognitive non- STEM	032–043, 061–081, 090–300, 400–422, 500, 510	112–131, 222–311, 314, 315, 322–515	111–132, 134, 141, 143, 221–243, 261–265, 312, 313, 315–332, 333, 335–343
Routine cognitive	310–399, 431–490, 591	521–523	334, 352, 411–441, 511, 521–524
Routine manual	711–799, 801–899, 901–999	711–745, 811–834, 916–933	711–754, 811–835, 911–933, 961
Non-routine manual	520–589, 592, 599, 700	516, 911–915	512–516, 941–952, 962

Table A.2: Mapping of detailed occupation codes to broad task groups—United States

Broad occupation	Census coding system			
	1983–91	**1992–2002**	**2003–10**	**2011–19**
Non-routine cognitive STEM	043–083, 213–225, 229	044–083, 213–225, 229	036, 100–176, 190–194	0030, 0360, 1000–1760, 1900–1940
Non-routine cognitive non- STEM	003–037, 084–208, 228, 234–235	003–037, 084–208, 234–235	001–035, 040–095, 180–186, 194–195, 200–354	0010–0230, 0310–0350, 0400–0950, 1800–1860, 1950–3540
Routine cognitive	243–389	243–389	470–465	4700–5940
Routine manual	229–227, 233, 503–769, 774–799, 803–869, 873–889	229–227, 233, 503–769, 774–799, 803–869, 873–889	620–975	6200–9750
Non-routine manual	403–469, 486–487, 773	403–469, 486–487, 773	360–465	3600–4650

Appendix B: Decomposition framework

Here we formally outline the descriptive decomposition framework we use in the paper. First, we write average female log wages at time t, w_{ft}, as the employment-weighted average of female task group wages w_{fjt} (and analogously for men):

$$w_{ft} = \sum_j w_{fjt} \frac{E_{fjt}}{E_{ft}}$$

where j indexes the five task groups, t indexes years, and E denotes employment. The change over time in average log female wages can then be decomposed into two additive components as follows:

$$\Delta w_{ft} = \underbrace{\sum_j \overline{w}_{fj} \Delta \left(\frac{E_{fjt}}{E_{ft}} \right)}_{A:\ between\ task\ groups} + \underbrace{\sum_j \Delta w_{fjt} \left(\frac{\overline{E_{fj}}}{E_f} \right)}_{B:\ within\ task\ groups}$$

where upper bars indicate time averages. This shows that female wage changes arise from two sources: The first component (A) is a 'between task group' effect, driven by changes in the proportion of women in different occupational groups (e.g. if women increasingly sort into high-paying non-routine tasks, female average wages will rise, even if wages by task group remain constant). The second component (B) is a 'within task group' effect, driven by changes in female wages within occupational groups (e.g. even if women did not change their sorting patterns across task groups, their wages will rise if the wages of task groups they are employed in rise).

The same decomposition can also be done for male wage changes. Comparing these two sources of wage changes across genders, we can then study how these two channels have impacted the gender wage gap. In particular, we can use this shift-share framework to analyse the extent to which a changing task group distribution among women relative to men has closed or widened the gender wage gap (the between-effect); and the extent to which changing within task group gender wage gaps play a role (the within-effect).

Formally, changes in the gender wage gap ($\Delta\ GWG \equiv\ \Delta\ w_{mt} -\ \ \Delta\ w_{ft}$) can be decomposed into the following two components:

$$\Delta\ \mathrm{GWG}_{\mathrm{between}} = \sum_j \overline{w}_{mj} \Delta \left(\frac{E_{mjt}}{E_{mt}} \right) - \sum_j \overline{w}_{fj} \Delta \left(\frac{E_{fjt}}{E_{ft}} \right)$$

$$\Delta\ \mathrm{GWG}_{\mathrm{within}} = \sum_j \Delta w_{mjt} \left(\frac{\overline{E_{mj}}}{E_m} \right) - \sum_j \Delta w_{fjt} \left(\frac{\overline{E_{fj}}}{E_f} \right)$$

In the literature, advancing technology is typically understood to be related to task-biased demand shocks that are shared across worker types, including gender. To consider the role of technology, we therefore want to distinguish channels that are plausibly related to task group demand and supply changes common across genders from other labour market changes that impact the gender wage gap.

In terms of the two components outlined above, the between effect is entirely in this category: it reflects task-biased shocks which may result in gendered impacts if men and women are differently distributed across these occupations, or if men and women are differently changing their distribution across jobs as a result of such shocks. In the paper, we refer to this as the *employment exposure channel*.

Meanwhile, the within-occupational component captures differential changes in occupational-level wages across men and women. Here, we want to distinguish between common wage trends at the task level (to which men and women are differently exposed due to their different occupational employment patterns) from changes in the gender wage gap that are seen within task groups. Whereas the former reflects impacts of task-biased shocks such as technological change, the latter captures a potentially wide range of directly gender-biased changes.

To achieve this, we further decompose within task group wage growth (labelled B in the equation above), by using the fact that $w_{fjt} = \frac{w_{fjt}}{w_{jt}} w_{jt}$, as follows:

$$\underbrace{\sum_j \Delta w_{fjt} \left(\frac{\overline{E_{fj}}}{E_f} \right)}_{B} = \underbrace{\sum_j \left(\frac{\overline{E_{fj}}}{E_f} \right) \left(\frac{\overline{w_{fj}}}{w_f} \right) \Delta w_{jt}}_{B1:\ \Delta\ overall\ task\ group\ wage} + \underbrace{\sum_j \left(\frac{\overline{E_{fj}}}{E_f} \right) \overline{w}_j \Delta \left(\frac{w_{fjt}}{w_{jt}} \right)}_{B2:\ \Delta\ female\ task\ group\ wage}$$

This separates average within-task-group wage growth for women into a component driven by overall task group wage changes, given women's distribution across task groups (B1), and a component driven by changes in female relative wages within task groups (B2). We can write analogous equations for average male within-task-group wage growth and then take the difference to arrive at these two additional channels through which gender wage gaps may change:

$$\Delta\ \mathrm{GWG}_{\mathrm{within,\quad tech}} = B1_m - B1_f = \sum_j \left(\frac{\overline{E_{mj}}}{E_m} \right) \left(\frac{\overline{w_{mj}}}{w_j} \right) \Delta w_{jt} - \sum_j \left(\frac{\overline{E_{fj}}}{E_f} \right) \left(\frac{\overline{w_{fj}}}{w_j} \right) \Delta w_{jt}$$

This reflects how overall task group wage changes impact men and women differently because of their different distributions across task groups: we interpret these common wage shocks as related to task-biased technological progress, which changes demand for different tasks and therefore has an impact on overall task-level wages. In the paper, we refer to this as the *wage exposure channel*.

The final component is given by:

$$\Delta\ \mathrm{GWG}_{\text{within,}\quad \text{residual}} = B2_m - B2_f = \sum_j \left(\frac{\overline{E_{mj}}}{E_m}\right) \overline{w}_j \Delta\left(\frac{w_{mjt}}{w_{jt}}\right) - \sum_j \left(\frac{\overline{E_{fj}}}{E_f}\right) \overline{w}_j \Delta\left(\frac{w_{fjt}}{w_{jt}}\right)$$

This component reflects changes in the wages that men and women are paid in the same occupational task group, given their respective task group employment distributions and overall average task group wages. We interpret this as a residual change, as it reflects any labour market factors which serve to narrow or widen gender wage gaps *within* task groups, and are therefore not directly attributable to technology. This component could be related to factors such as changing labour force discrimination, or changes in women's up- or down-skilling relative to men within task groups.

Summarizing, this simple decomposition framework provides a way to think about how task-biased technology shocks can produce changes in the gender wage gap through employment and wage exposure effects, and how these can be empirically distinguished from other gender-biased shocks which can have a multitude of sources.

References

Acemoglu, D., and Autor, D. (2011), 'Skills, Tasks and Technologies: Implications for Employment and Earnings', *Handbook of Labor Economics*, **4**, Amsterdam, Elsevier, 1043–171.

Albanesi, S., and Olivetti, C. (2016), 'Gender Roles and Medical Progress', *Journal of Political Economy*, **124**(3), 650–95.

Autor, D. H., and Salomons, A. (2018), 'Is Automation Labor-displacing? Productivity Growth, Employment and the Labor Share', *Brookings Papers on Economic Activity*, **49**(1), 1–87.

— Dorn, D., and Hanson, G. H. (2015), 'Untangling Trade and Technology: Evidence from Local Labour Markets', *The Economic Journal*, **125**(584), 621–46.

Bailey, M. J., Hershbein, B., and Miller, A. (2012), 'The Opt-in Revolution? Contraception and the Gender Gap in Wages', *American Economic Journal: Applied Economics*, **4**(3), 225–54.

Barth, E., Bryson, A., Davis, J. C., and Freeman, R. (2016), 'It's Where You Work: Increases in the Dispersion of Earnings across Establishments and Individuals in the United States', *Journal of Labor Economics*, **34**(S2), S67–S97.

Bertrand, M. (2011), 'New Perspectives on Gender', in O. Ashenfelter and D. Card (eds), *Handbook of Labor Economics*, **4B**, Amsterdam, Elsevier, 1545–92.

Black, S. E., and Spitz-Oener, A. (2010), 'Explaining Women's Success: Technological Change and the Skill Content of Women's Work', *The Review of Economics and Statistics*, **92**(1), 187–94.

Blau, F. D., and Kahn, L. M. (2017), 'The Gender Wage Gap: Extent, Trends, and Explanations', *Journal of Economic Literature*, **55**(3), 789–865.

Borghans, L., ter Weel, B., and Weinberg, B. A. (2006), 'People People: Social Capital and the Labor-market Outcomes of Underrepresented Groups', Working Paper No. 11985, NBER.

Bursztyn, L., Fujiwara, T., and Pallais, A. (2017), '"Acting Wife": Marriage Market Incentives and Labor Market Investments', *American Economic Review*, **107**(11), 3288–319.

Card, D., Cardoso, A. R., and Kline, P. (2016), 'Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women', *Quarterly Journal of Economics*, **131**, 633–86.

Cortes, G. M., and Morris, D. M. (2019), 'Are Routine Jobs Moving South? Evidence from Changes in the Occupational Structure of Employment in the USA And Mexico', WIDER Working Paper 2020/11, Helsinki, UNU-WIDER.

— Jaimovich, N., and Siu, H. E. (2017), 'Disappearing Routine Jobs: Who, How and Why?', *Journal of Monetary Economics*, **91**, 69–87.

— — — (2018), 'The "End of Men" and Rise of Women in the High-skilled Labor Market', Working Paper No. 24274, NBER.

— — Nekarda, C. J., and Siu, H. E. (2020), 'The Dynamics of Disappearing Routine Jobs: A Flows Approach', *Labour Economics*, **65**, in press.

Cortes, P., and Pan, J. (2019*a*), 'When Time Binds: Substitutes for Household Production, Returns to Working Long Hours, and the Gender Wage Gap Among the Highly Skilled', *Journal of Labor Economics*, **37**(2), 351–98.

— — (2019*b*), 'Gender, Occupational Segregation, and Automation', Economics Studies at Brookings.

Delaney, J., and Devereux, P. J. (2019), 'Understanding Gender Differences in STEM: Evidence from College Applications', *Economics of Education Review*, **72**, 219–38.

Deming, D. J. (2017), 'The Growing Importance of Social Skills in the Labor Market', *The Quarterly Journal of Economics*, **132**(4), 1593–640.

Duncan, O. D., and Duncan, B. (1955), 'A Methodological Analysis of Segregation Indexes', *American Sociological Review*, **20**(2), 2010–17.

Flood, S., King, M., Rodgers, R., Ruggles, S., and Warren, J. R. (2018), Integrated Public Use Microdata Series (IPUMS), Current Population Survey: Version 6.0 [dataset].

Goldin, C. (2006), 'The Quiet Revolution that Transformed Women's Employment, Education, and Family', *American Economic Review, Papers and Proceedings*, **96**, 1–21.

— (2014), 'A Grand Gender Convergence: Its Last Chapter', *American Economic Review*, **104**(4), 1091–119.

Goldin, M. (1988), 'Marriage Bars: Discrimination Against Married Women Workers, 1920s to 1950s', Working Paper No. W2747, NBER.

Goos, M., Manning, A., and Salomons, A. (2009), 'Job Polarization in Europe', *American Economic Review Papers and Proceedings*, **99**(2), 58–63.

— — — (2014), 'Explaining Job Polarization: Routine-biased Technological Change and Offshoring', *American Economic Review*, **104**(8), 2509–26.

Lemieux, T. (2006), 'Increasing Residual Wage Inequality: Composition Effects, Noisy Data, Or Rising Demand for Skill?', *The American Economic Review*, **96**(3), 461–98.

Ngai, L. R., and Petrongolo, B. (2017), 'Gender Gaps and the Rise of the Service Economy', *American Economic Journal: Macroeconomics*, **9**(4), 1–44.

OECD (2017), OECD Labor Force Statistics, Retrieved from https://stats.oecd.org/Index.aspx?DatasetCode=AVE_HRS#

Olivetti, C., and Petrongolo, B. (2017), 'The Economic Consequences of Family Policies: Lessons from a Century of Legislation in High-income Countries', *Journal of Economic Perspectives*, **31**(1), 205–30.

Ortiz-Ospina, E., and Tzvetkova, S. (2017), 'Working Women: Key Facts and Trends in Female Labor Force Participation', Our World Data, retrieved from https://ourworldindata.org/female-labor-force-participation-key-facts#licence.

Pan, J. (2015), 'Gender Segregation in Occupations: The Role of Tipping and Social Interactions', *Journal of Labor Economics*, **33**(2), 365–408.

Petrongolo, B., and Ronchi, M. (2020), 'Gender Gaps and the Structure of Local Labor Markets', IZA Discussion Papers 13143, Institute of Labor Economics (IZA).

Webb, M. (2020), 'The Impact of Artificial Intelligence on the Labor Market', Stanford University Working Paper.