

Gender and recession

SUMMARY

The Great Recession has strongly influenced employment patterns across skill and gender groups in EU countries. We analyse how these changes in workforce composition might distort comparisons of conventional measures of gender wage gaps via non-random selection of workers into EU labour markets. We document that male selection (traditionally disregarded) has become positive during the recession, particularly in Southern Europe. As for female selection (traditionally positive), our findings are twofold. Following an increase in the labour-force participation of less-skilled women, due to an added-worker effect, these biases declined in some countries where new female entrants were able to find jobs, whereas they went up in other countries which suffered large female employment losses. Finally, we document that most of these changes in selection patterns were reversed during the subsequent recovery phase, confirming their cyclical nature.

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The changing nature of gender selection into employment over the great recession

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1. INTRODUCTION

There has been an extensive debate both in the academic literature and the media about the effects of the Great Recession on household income inequality. Yet, its impact on gender wage inequality remains far less explored.¹ This is somewhat surprising since

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¹ See, for example, [Jenkins *et al.* \(2012\)](#).

industries which differ markedly in their relative use of male and female labour have experienced quite unequal fluctuations in employment and labour-force participation (LFP), both of which could affect male and female wages unequally through their effects on the workforce composition. In particular, these changes have been very relevant in some EU Member States, where the recession was longer and more severe than in the United States and other high-income countries.² Consequently, the EU provides an interesting laboratory to analyse how gender wage gaps react to differences in the way men and women self-select into labour markets when faced with large shifts in labour demand (LD) and labour supply (LS), like those taking place during the Great Recession.³

To account for non-random selection by gender over the business cycle, it is important to distinguish between the *raw* gender gap (RG), i.e. the difference between observed wages of male and female employees and the *potential* gender gap (PG), i.e. the difference that would be observed if all men and women of working age were employed. In effect, when comparing wages across two population groups, non-random selection into employment implies that RGs could be above or below PGs, depending on the sign of the selection biases. The literature typically assumes no selection whatsoever for the majority group (white, natives, men, etc.), while both positive or negative selection is considered for the minority. As a result, a large body of research on gender gaps has stressed that accounting for selection is paramount to obtain less distorted measures of the gender gaps. Hence, the need to pay growing attention to PGs rather than just report RGs.⁴

When looking at the EU, our focus on selection is further dictated by the available evidence highlighting their key role in explaining differences in RGs in the recent past, prior to the crisis. For example, relying on imputed wage distributions for the male and female working-age populations, Olivetti and Petrongolo (2008) have documented that PGs in Southern Mediterranean countries (*Southern EU*, hereafter) were considerably larger than RGs from the mid-1990s to the early 2000s, whereas these differences were fairly small in other EU countries (*Rest of EU*, henceforth) and the United States. Olivetti and Petrongolo (2008) rationalize this finding by convincingly arguing that, while male LFP rates are high everywhere, the historically lower female LFP rates in Southern EU countries are often related to positive selection among participating women, as those who work often have relatively high-wage characteristics. By contrast, selection issues become irrelevant in the Rest of the EU and the United States since most of these countries exhibit rather high female LFP rates. Accordingly, lower RGs in Southern EU are

2 This is so since the Great Recession in most of the EU not only covers the global financial crisis in 2008–9, but also the subsequent sovereign debt crisis in the Euro area from late 2009 to mid-2012.

3 More precisely, the gender wage gap is defined in the sequel as the difference between male and female hourly wages in log points.

4 See, *inter alia*, Heckman (1979), Johnson *et al.* (2000), Neal (2004), Mulligan and Rubinstein (2008), Olivetti and Petrongolo (2008) and Arellano and Bonhomme (2017).

mainly explained by positive selection in their female workforces which increases the average wage among female employees, relative to other countries where female selection is not a relevant issue. The main finding of this influential paper is that, once selection-bias corrections are implemented, the previous ranking gets reversed, leading to higher PGs in Southern EU than in the Rest of the EU.

In view of these considerations, the aim of this article is to explore whether the above regularities on gender non-random sorting into the EU labour markets have changed as a result of the Great Recession, as well as to check to what extent the subsequent recovery phase has led to a reversal of those changes. To address this issue, use is made of the EU-SILC longitudinal dataset on wages, which is available for several EU Member States covering periods before and after the global financial crisis. To estimate how selection biases behave over the relevant subsamples, we estimate changes in PGs from a wide range of imputations for non-observed wages, and then proceed to compare them with the observed changes in RGs, whose evolution over this period is taken as given.⁵ We argue that, as a result of changes in workforce composition during the slump, male selection has become more important than previously thought, whereas female selection may have become stronger or weaker, depending on the economic forces at play. We refer to this phenomenon as ‘the *changing nature*’ of selection by gender during the Great Recession.⁶

Our main insight for the emergence of positive male selection is that, following massive job destruction in sectors intensive in low-skilled male workers (e.g. in the construction and manufacturing sectors in some EU economies), the distribution of observed male wages has become a censored version of the imputed distribution. This would lead to a higher average wage of male employees, implying that RGs would be larger than PGs, rather than the opposite. As regards female selection, two contrasting effects are at play. First, it is likely that the existence of a so-called ‘added-worker’ effect (AWE) during the crisis – whereby less-skilled women who were previously inactive enter the labour market to help restore household income levels as male breadwinners become jobless – has increased female LFP at the bottom of the wage distribution, therefore reducing female positive selection biases. In line with previous findings by [Bentolila and Ichino \(2008\)](#), [Bredtmann et al. \(2018, table 2\)](#) have recently shown that this effect is particularly strong in Southern Mediterranean countries, probably due to their less generous

5 A number of recent reports, most notably [OECD \(2014\)](#), have documented that RGs have continued to narrow in most EU countries during the Great Recession. Potential explanations of this fact could be women’s over-representation in the public sector (where gender gaps are generally lower) and the widespread use of early retirement policies (mainly affecting elderly male employees with long professional careers and high wages).

6 To the best of our knowledge, [Arellano and Bonhomme \(2017\)](#) are the only paper that documents positive male selection into the labour market. Their focus is on the United Kingdom prior to the Great Recession.

welfare states.⁷ If new female entrants from the bottom of the skill distribution succeed in finding jobs during the slump, male and female selection would change in different directions (male up, female down), so that the difference between RGs and PGs would become larger. However, even under an increasing female LFP, if LD for both male and female less-skilled workers experienced large adverse shifts during the downturn, it could well be the case that both male and female selection may have become more positive, so that the sign of the difference between RG and PG would be ambiguous. We argue that this rise in female selection characterizes well the experience of some Southern EU countries with high shares of temporary contracts (dual labour markets) since women are over-represented in fixed-term jobs (e.g. in the services sector) which were massively destroyed during the slump due to having much lower termination costs than open-ended contracts.

In sum, while unskilled men's employment has been subject to a large negative LD shift, women's employment patterns have been subject to both supply and demand shifts, and depending on which dominates, female selection may have moved in line or in opposite direction to male selection. Moreover, insofar as these phenomena are driven by a cyclical collapse in LD, one should observe a reversal of the changing patterns in selection once the recovery started, an issue on which we also provide evidence.

Two empirical strategies are used to construct PG in EU countries. Following [Olivetti and Petrongolo \(2008\)](#), we first apply the sample selection correction methodology advocated by [Johnson et al. \(2000\)](#) and [Neal \(2004\)](#). This approach imputes missing wages for non-employed workers relative to the median (rather than the actual level of missing wages). An advantage of this approach is that it avoids arguable exclusion restrictions often invoked in the standard econometric (Heckit) approach to extrapolate the wage distribution below the reservation wage.⁸ However, a potential drawback of this procedure is that the reliability of its results hinges strongly on the plausibility of assumptions underlying the imputation rules. Therefore, to check how robust our findings are under a more conventional control-function approach, we also report results based on [Arellano and Bonhomme's \(2017\)](#) estimation procedure of quantile wage regressions by gender subject to selectivity corrections. Notice that, besides being suitable for median regression, the main reason for using a quantile approach is that our rationalization of changes in the gender wage gap relies on the different behaviour of male and female workers with different skills, namely, those at the bottom and other parts of the wage distribution.

7 [Bredtmann et al. \(2018\)](#) – using the same database (EU-SILC; see Section 3) and a similar sample period as ours – find evidence of a high responsiveness of women's labour supply to their husband's loss of employment. Given that this evidence is based on the same panel dataset we use here and for a similar sample period (2004–13), in the sequel we take the 'added-worker' effect as a given stylized fact for this set of countries.

8 For example, this might be the case regarding number of children or being married (as proxies for household chores). Such variables are often assumed as only affecting labour-market participation via reservation wages. However, one could argue that they might as well affect effort at market-place work, and therefore productivity and wages.

Our empirical findings broadly support the mechanisms outlined above. First, we document that the traditional assumption of no male selection prior to the crisis may not be valid during the Great Recession. Strong evidence of positive male selection is found for several EU countries, particularly in Southern EU. Second, we show that patterns of female selection are mixed. On the one hand, we document that a significant rise of less-skilled female LFP in some EU countries has reduced female selection relative to what was found before the slump. On the other hand, in those countries where the rise in female LFP has not translated into new jobs and female unemployment rates have also surged (particularly in dual labour markets), female selection has become stronger than before the crisis.

1.1. Related literature

This paper contributes to a vast literature on gender outcomes in developed (and developing) countries; cf. [Blau et al. \(2013\)](#) and [Goldin \(2014\)](#) for comprehensive overviews. While most of this research analyses the determinants of secular trends in gender wage gaps (typically using RGs), our paper complements this approach by focusing on their behaviour at particularly relevant business cycle phases, like those taking place during the Great Recession and the subsequent recovery.

There is some previous research on this topic that is worth highlighting. For example, the issue of how male hourly real wages change over the US business cycle has been addressed in a well-known paper by [Keane et al. \(1988\)](#) which uses the standard [Heckman \(1979\)](#)'s techniques to correct for non-random selection.⁹ We differ from this forerunner in several respects. First, we focus on gender wage gaps instead of exclusively on male wages. Second, our evidence refers to a cross-country comparison of gender wage gaps in EU countries which have been subject to much less research than the United States ([Blau et al., 2013](#)). Third, we identify new channels on how the Great Recession in particular and business cycles in general effect selection by gender. Lastly, while most of the papers on this topic apply a conventional Heckit approach, our results rely on the two alternative econometric techniques mentioned earlier, which are less problematic in correcting for selection biases.

The rest of the paper is organized as follows. Section 2 provides some theoretical underpinning of the main mechanisms at play and derives testable implications in terms of signs of changes in selection biases and LFP/employment rates by gender. Section 3 describes the EU-SILC longitudinal dataset used throughout the paper. Section 4 explains our two empirical approaches (imputation rules around the median and quantile selection models) to compute the potential wage distributions and correct for selectivity biases. Section 5 presents the empirical results yielded by both econometric

9 See also [Bowlus \(1995\)](#) and [Gayle and Golan \(2012\)](#) for further examples in the gender gap literature accounting for the dynamics of employment selection over the business cycle.

procedures. Section 6 interprets the main empirical findings of the paper in light of the hypotheses outlined in Section 2. Finally, Section 7 concludes. An Appendix provides further details on the model (Appendices A and B) and on the construction of hourly wages (Appendix C), while an [Online Appendix](#) gathers additional results on alternative imputation procedures and further descriptive statistics for the 13 European countries included in our sample.

2. A SIMPLE THEORETICAL FRAMEWORK

2.1. The basic model

To provide some simple theoretical underpinning for the main mechanisms at play, we start by reviewing the basic effects of selection on the measurement of gender wage gaps. Following [Mulligan and Rubinstein \(2008\)](#), we consider a conventional *mincerian* equation for the determination of the (logged) hourly *potential wage*:

$$w_{it} = \mu_t^w + g_i \gamma_t + \varepsilon_{it} \quad (1)$$

where w_{it} denotes individual i 's potential hourly wage in year t , g_i is a gender indicator variable (males have $g = 0$, females have $g = 1$), μ_t^w represents (an index of) the determinants of wages that are common to *all* workers, while γ_t captures those determinants of female wages common to all women but not applicable to men (including discriminatory practices by employers). Finally, ε_{it} is an error term normalized to have a unit variance (for both males and females) such that $m(\varepsilon_{it} | \mu_t^w, g_i) = 0$, where $m(\cdot)$ denotes the (conditional) *median* function.¹⁰

If potential wages were available for all individuals in the working-age population, then the *potential* median gender wage gap at year t , PG_t , would be defined as:

$$PG_t \equiv m(w_{it} | g_i = 0) - m(w_{it} | g_i = 1) = -\gamma_t, \quad (2)$$

where one would expect that $PG_t > 0$ (i.e. $\gamma_t < 0$) on historical grounds ([Olivetti and Petrongolo, 2016](#)).

However, to the extent that selection into employment is not a random outcome of the male and female populations, the observed (raw) gender gap in median wages, RG_t , in a sample restricted to *employed* individuals will differ from the PG_t , namely¹¹:

10 Consistent with the empirical section, our focus in this section is on median rather than mean gender gaps. This choice is without loss of generality since the results can be rewritten in terms of mean gaps and selection biases. As is well known, in this case the latter become functions of the inverse Mill's ratio, as in [Mulligan and Rubinstein \(2008\)](#).

11 The discussion below reproduces the well-known arguments on selection biases in the seminal work by [Gronau \(1974\)](#) and [Heckman \(1979\)](#), albeit based on gaps in median wages rather than on average wages, as these authors consider.

$$\begin{aligned}
 RG_t &\equiv m(w_{it}|g_i = 0, L_{it} = 1) - m(w_{it}|g_i = 1, L_{it} = 1) \\
 &= -\gamma_t + m(\varepsilon_{it}|g_i = 0, L_{it} = 1) - m(\varepsilon_{it}|g_i = 1, L_{it} = 1), \\
 &= PG_t + \underbrace{b_t^m - b_t^f}_{\text{selection bias differential}}
 \end{aligned}
 \tag{3}$$

where L_{it} is an indicator for whether individual i is employed in year t , and $b_t^m = m(\varepsilon_{it}|g_i = 0, L_{it} = 1)$ and $b_t^f = m(\varepsilon_{it}|g_i = 1, L_{it} = 1)$ are the (median) selection biases of males and females, respectively. These two terms differ from zero to the extent that non-employed males and females have different potential wages than the employed ones. As discussed above, Olivetti and Petrongolo (2008) argue that: (i) the inequality $b_t^m < b_t^f$ holds in Southern EU countries prior to the Great Recession, so that $RG_t < PG_t$; and (ii) $b_t^m \simeq b_t^f$ held in Rest of EU countries and the United States, implying that $RG_t \simeq PG_t$.

Using Equation (3), the change (Δ) in the observed RGs over time becomes:

$$\Delta RG_t = \Delta PG_t + \Delta b_t^m - \Delta b_t^f.
 \tag{4}$$

Equation (4) has three terms. The first one ($\Delta PG_t = -\Delta\gamma_t$) is the change in the gender-specific component of wages, which may exist due to changes in gender wage discrimination, relative market valuation of skills or relative human capital accumulation when considering *all* men and women. The second and third terms in Equation (4) capture in turn the changes in the selection biases of males and females, respectively, which constitute the main focus of this paper.¹²

Traditionally, this set-up has been used to predict which females are employed using a potential market wage equation determining w_{it} , as in Equation (1), plus an additional equation determining the reservation wage, r_{it} , such that individuals would accept a job if $w_{it} > r_{it}$. We extend this conventional framework by adding an extra equation determining productivity, x_{it} , to capture labour-demand constraints that could affect both men and women. This leads to the following three-equation model (where Equation (1) is repeated below in Equation (5) for convenience):

$$w_{it} = \mu_t^w + g_t\gamma_t + \varepsilon_{it}
 \tag{5}$$

$$x_{it} = \mu_t^x + u_{it}
 \tag{6}$$

12 Note that, had we allowed for changes in the variance in the error term ε_{it} , an additional term would appear in Equation (4), namely $(b_t^m - b_t^f)\Delta\sigma_t^e$, where σ_t^e is its time-varying standard deviation. This term captures changes in the dispersion of wages which has been shown to play an important role in explaining female selection in the United States (Mulligan and Rubinstein, 2008). Yet, these changes are ignored in the sequel. The reason is that, as shown in Figure A1 in the Online Appendix where wage dispersion is measured by the logarithm of the ratio between wages at the 90th and 10th percentiles, no major trends seem to be present over 2004–12, with the possible exceptions of Greece and Portugal.

$$r_{it} = g_i(\mu_t^f + v_{it}), \quad (7)$$

such that μ_t^x in Equation (6) represents (an index of) the determinants of the average productivity of a worker, μ_t^r in Equation (7) captures the determinants of female reservation wage (notice that the male reservation wage is normalized to zero in Equation (7), since $g_i = 0$ for men), u_{it} is a productivity shock, and v_{it} is a reservation-wage shock. The normalization $r_{mt} = 0$ is used as a shortcut to capture the fact that male LFP rates are very high everywhere. Furthermore, since the shock in the wage Equation (5) should mainly reflect unexpected productivity changes, it is assumed for simplicity that,

$$u_{it} = (1 + \rho)\varepsilon_{it},$$

with $\rho > 0$. Therefore, a productivity shock of size $(1 + \rho)\varepsilon_{it}$ only shifts the wage by the lower amount ε_{it} , reflecting some wage rigidity.¹³ This assumption allows us to capture the fact that some individuals sorting themselves into the labour market during a recession may not be able to find jobs when wages are partially rigid, as it has been the case in several EU countries. Finally, whereas ε_{it} has a continuous support, to simplify matters we constrain the female reservation-wage shock to only take two values: a high one, \bar{v} , with probability $p \in (0, 1)$ and a low one, \underline{v} , with probability $1 - p$. This simplified two-mass distribution suffices to capture the lower LFP rate of less-skilled women by assuming that $\bar{v} > \underline{v}$.

Accordingly, individual i works at time t if her/his reservation wage is higher than her/his potential market wage (LS condition), i.e. $w_{it} > r_{it}$, and if her/his productivity is greater than the wage, leaving a positive surplus for the firm (LD condition), i.e. $x_{it} - w_{it} > 0$. As a result, there are LS and LD threshold values of the productivity shock ε_{it} , determining whether the worker participates and the firm creates/destroys jobs. In the sequel, these cut-off values will be, respectively, labelled $a_t^{LS}(g_i)$ and $a_t^{LD}(g_i)$, and their derivation can be found in Appendix A. Since the worker's decision to participate and the firm's decision to create a job imply that ε_{it} should exceed a given cut-off value, notice that the LD and LS conditions will be the binding ones whenever $a_t^{LS}(g_i) < a_t^{LD}(g_i)$ and $a_t^{LD}(g_i) < a_t^{LS}(g_i)$, respectively.

The main implications of this simple model can be summarised as follows. First, the LD constraint $a_t^{LD}(g_i = 0)$ is the only binding one for men, due to the assumption that they always participate ($r_m = 0$). Second, as regards women, the LD constraint $a_t^{LD}(g_i = 1)$ binds (i.e. $a_t^{LD} > a_t^{LS}$) whenever: (i) their potential wage ($\mu_t^w + \gamma_t$) is larger than the reservation wage (μ_t^r) but it is below their expected productivity (μ_t^x), implying that they would like to participate but firms do not create new female jobs and would even

13 This is particularly the case in most European countries, where unions play a more important role in wage setting than in the United States. Our model implies symmetry in wage response to positive and negative productivity shocks, although it could be easily generalized to allow for asymmetric responses.

terminate existing ones; and (ii) wages are more rigid, i.e. ρ is large. Conversely, whenever female productivity is high, their reservation wage is low and wages are more flexible, the LS constraint becomes the binding one ($a_i^{LD} < a_i^{LS}$). For example, in more traditional societies (such as those in Southern EU), where the average female reservation wage is high due to cultural and social norms, and the surplus is small due to lower productivity in these countries, the LS condition becomes the binding one. On the contrary, in more modern societies (such as in the Rest of the EU), where the average female reservation wage is low and the surplus is high, the LD condition turns out to be the binding constraint. Moreover, the LS constraint is also more likely to bind for lower-educated women in all countries given that they are often more heavily involved in household chores than higher-educated women.

Finally, in [Appendix B](#), we derive comparative statics of male and female observed median wages with respect to changes in μ_i^x and μ_i^f . The former captures changes in productivity due to business cycle fluctuations, whereas the latter captures changes in (female) outside-option values due to, for example, AWEs. The main findings here are as follows:

- i. male and female median wages go down as μ_i^x falls (e.g. in a recession); this leads to growing positive selection for both genders as low-productivity (low-wage) workers are the ones more likely to lose their jobs during a downturn (i.e. $\Delta b_i^m > 0$ and $\Delta b_i^f > 0$ in expression (4) above), and
- ii. female median wages go down as μ_i^f falls. This is because less-skilled (married) women, who were not participating before the recession, are the ones who start searching for jobs during the slump as their reservation wages fall due to the large job losses suffered by their less-skilled partners (i.e. $\Delta b_i^f < 0$ in [Equation \(4\)](#)).

Summing up, the main implication of the previous analysis is that, while the male median wage is bound to increase in a downturn, the female median wage may increase or decrease, depending upon which of the two opposite forces (LD and LS constraints) dominates as a result of the recession. The opposite effects would prevail during expansions.

2.2. Gender-gap scenarios over the Great Recession

The implications of the previous analysis result in a range of hypotheses about gender gaps that can emerge (individually or jointly), depending on how employment and LFP rates change by gender. The Great Recession has had two key effects for our purposes. On the one hand, there was a large shedding of unskilled low-paid jobs; this increase in job destruction has not only affected *male* labour-intensive industries but also *female* workers in some countries as well. On the other hand, as documented by [Bredtmann et al. \(2018\)](#), the slump led to a rise in less-skilled female LFP (particularly in Southern EU labour markets), as a response to a decline in the employment rate of less-skilled men.

When the LS constraint binds, then the AWE implies that new less-skilled female entrants in the labour market will succeed in finding jobs; by contrast, when LD is the binding constraint, the rise in less-skilled female LFP would not translate into new jobs, and even some of those who were already working may become dismissed, resulting in higher female unemployment rates. Denoting employment rates at time t by E_t^{ij} , where $i = f, m$ denotes gender and $j = u, s$ whether the individual is unskilled or skilled, we can then outline the main testable implications of our analysis as follows:

- Hypothesis I: *Gender differences in job destruction rates among less-skilled workers.*
 - Hypothesis I_m : If the recession has mainly hit low-paid jobs in *male* labour-intensive industries, this implies that $\Delta E_t^{mu} < 0$, while $\Delta E_t^f = \Delta E_t^{ms} \approx 0$. As a result, male selection becomes positive during the slump ($\Delta b_t^m > 0$), while female bias does not change ($\Delta b_t^f = 0$). From Equation (4), this implies that $\Delta RG_t > \Delta PG_t$.
 - Hypothesis I_f : If the recession has mainly hit low-paid jobs in *female* labour-intensive industries, then it holds that $\Delta E_t^{fu} < 0$, while $\Delta E_t^m = \Delta E_t^{fs} = 0$. As a result, female selection becomes even more positive ($\Delta b_t^f > 0$) during the slump, while male selection does not change ($\Delta b_t^m = 0$). Thus, from Equation (4), $\Delta RG_t < \Delta PG_t$.
- Hypothesis II: *Added-worker effect and creation/destruction of female less-skilled jobs.*
 - Hypothesis II_f . When less-skilled female LFP increases and LS is the binding constraint for this type of women (as in the AWE), they will enjoy job gains, i.e. $\Delta E_t^{fu} > 0$. Thus, female selection becomes *less* positive ($\Delta b_t^f < 0$) during the slump. Moreover, if Hypothesis I_m also holds ($\Delta E_t^{mu} < 0$), male selection (previously absent) becomes positive ($\Delta b_t^m > 0$). Hence, from Equation (4), $\Delta RG_t \gg \Delta PG_t$.
 - Hypothesis II_{fu} . When less-skilled female LFP increases and LD is the binding constraint for this type of women, they will experience job losses, i.e. $\Delta E_t^{fu} < 0$. Thus, female selection becomes even *more* positive ($\Delta b_t^f > 0$) during the slump. Moreover, if Hypothesis I_m also holds ($\Delta E_t^{mu} < 0$), male selection remains positive ($\Delta b_t^m > 0$), and therefore ΔRG_t could be larger or smaller than ΔPG_t , depending on the relative sizes of the positive changes in selection.

Notice that, while Hypothesis I can be seen as an individual hypothesis regarding whether job destruction affects mostly either men (subscript m) or women (f), Hypotheses II + I_m are a joint hypothesis that combines male job destruction in both instances with either female employment gains ($f\ell$) or higher female unemployment (fu) in response to an increase in female less-skilled LFP rates. Two key conclusions arise from this analysis. First, if the adverse employment shock during the Great Recession translated into large job losses among less-skilled men, positive male selection appears as a distinct possibility that should be taken into account when computing PGs. Second, the relative pattern of

RGs and PGs during the crisis is highly contextualized, depending on both the differential LD responses for men and women and their (endogenous) LS decisions.

3. DATA

In order to compute both RGs and PGs, we use the European Statistics on Income and Living Conditions (EU-SILC) data set.¹⁴ This is an unbalanced household-based panel survey which has replaced the European Community Household Panel Survey (ECHPS) as the standard data source for many gender wage gap studies in Europe, including the aforementioned [Olivetti and Petrongolo \(2008\)](#). It collects comparable multidimensional annual micro-data on a few thousand households per country, starting in 2004. Our core sample focuses on the Great Recession and covers the period 2007–12, where 2007 captures the pre-crisis situation. However, data for a longer period (2012–6) will be used to check how our main theoretical implications change once the recovery phase started.

The countries in our sample are classified in two groups: (i) ‘Southern EU’: Greece, Italy, Portugal and Spain, and (ii) ‘Rest of EU’: Austria, Belgium, Denmark, Finland, France, Ireland, the Netherlands, the United Kingdom and Norway. Within the latter, in some instances, we distinguish among three blocks: *Continental* EU (Austria, Belgium, France and the Netherlands), *Nordic* (Denmark, Finland and Norway) and *Anglo-Saxon* (Ireland and the United Kingdom).¹⁵

We restrict our sample to individuals aged 25–54 as of the survey date, and we use self-defined labour market status to exclude those in self-employment, full-time education and military service.¹⁶ To derive hourly wages, we follow a similar methodology to [Engel and Schaffner \(2012\)](#). A detailed account of this procedure is provided in [Appendix C](#).

The educational attainment categories (no college and college) correspond to ISCED 0-4 and 5-7, respectively. Descriptive statistics are reported in [Online Appendix A](#).

14 Existing literature using EU-SILC data for international comparisons of gender gaps includes [Christofides et al. \(2013\)](#), who use OLS and quantile regressions to document the differences in the gender gap across the wage distribution in a number of countries.

15 It is noteworthy that Germany is not included in our sample due to lack of longitudinal information in EU-SILC on several key variables affecting wages. Moreover, though Norway is only an associated member of the EU, for simplicity we will refer to it and the remaining full member states as EU countries,

16 One of the shortcomings of the EU-SILC data is that income information is only available for the income reference period, while labour market status and additional variables are recorded at the moment of the interview during the survey year, which for most countries does not cover the same period. In fact, the income reference period corresponds to the previous calendar year for all countries except the United States (where the income reference period is the current year) and Ireland (where the income reference period is the 12 months preceding the interview).

Finally, throughout the empirical analysis, observations are weighted using population weights when available.¹⁷

Before proceeding to the results, it is convenient to consider gender differences in the LFP and employment responses to the downturn. As shown in Figure 1a – where changes in female LFP rates (in percentage point (pp.), vertical axis) during the crisis are plotted against changes in male LFP rates (in pp., horizontal axis) – most EU countries exhibit a much larger rise in female LFP than men's since 2007 (i.e. at the beginning of the recession), with Finland and Ireland being the exceptions. Yet, as stressed earlier, higher LFP by women may not necessarily translate into female employment gains during the recession. According to Figure 1b – where changes in female employment rates (in pp., vertical axis) are displayed against the corresponding changes in male employment rates (in pp., horizontal axis) – both turn out to be negative in almost half of the countries under consideration.¹⁸ As can be seen, Greece, Ireland, Portugal and Spain exhibit much larger drops in male, as compared to female, employment rates (points above the 45° line), capturing large job destruction in their male-intensive industries. However, even within Southern EU countries, there are interesting diverging patterns. For example, employment changes in Italy are more muted than in the other three members of this block. By contrast, the Rest of EU countries exhibits much fewer male and female job losses (with the exception of Denmark and Ireland, which also experienced the bursting of housing bubbles).

When LFP and employment changes are analysed by workers' educational attainment (for males in Figures 2a and 3a and for females in Figures 2b and 3b), it becomes clear that the fall in employment among less-educated (no-college) male workers has been much more pronounced. This has been particularly the case not only in Ireland and Spain, as a result of the collapse of their real estate sectors, but also in Greece, following the sovereign debt crisis this country suffered. Likewise, regarding participation, it can be seen that most of the gains in LFP in Southern EU countries are due to married females with lower educational attainments, in line with the added-worker hypothesis outlined above. Overall, we take this preliminary evidence as providing considerable support to the mechanism underlying Hypothesis II in Section 2.2.

4. ECONOMETRIC METHODS

In this section, we describe the two econometric procedures used to test the main hypotheses discussed above on how changes in selection biases by gender have translated

17 Specifically, we use personal base weights, PB050. For Denmark, Finland, Sweden and the Netherlands, income data are only available for selected respondents. We use personal base weights for selected respondents, PB080, for these countries. Personal weights are not available for Norway and Ireland.

18 Employment rates are defined as the ratios between employment and the labour force.

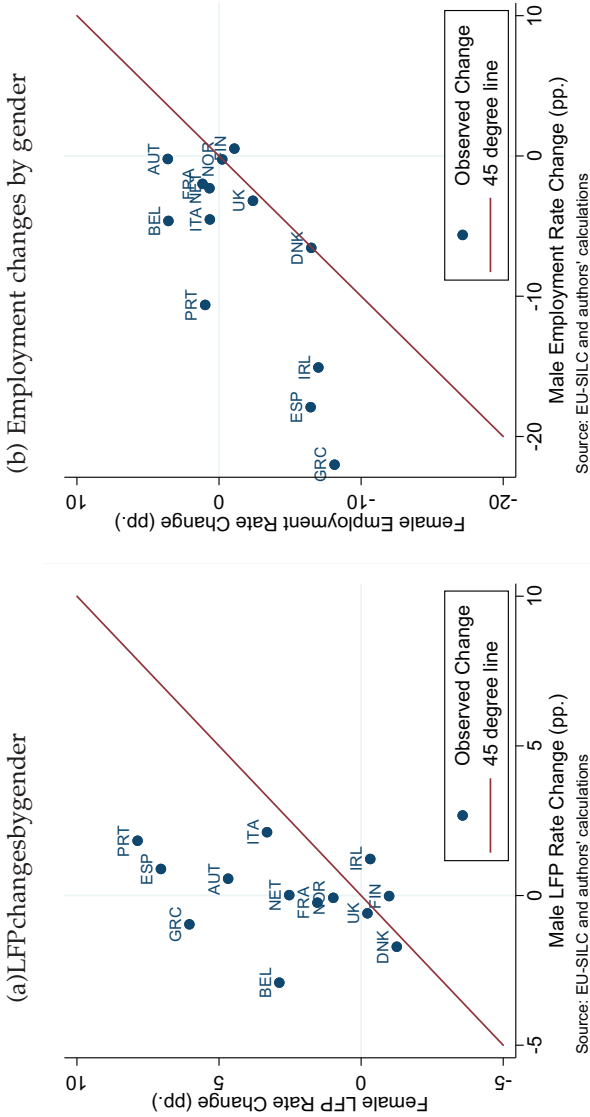


Figure 1. Labour market attachment by gender, 2007–12.

Notes: (a) LFP changes by gender. (b) Employment changes by gender.

Sources: EU-SILC and authors' calculations

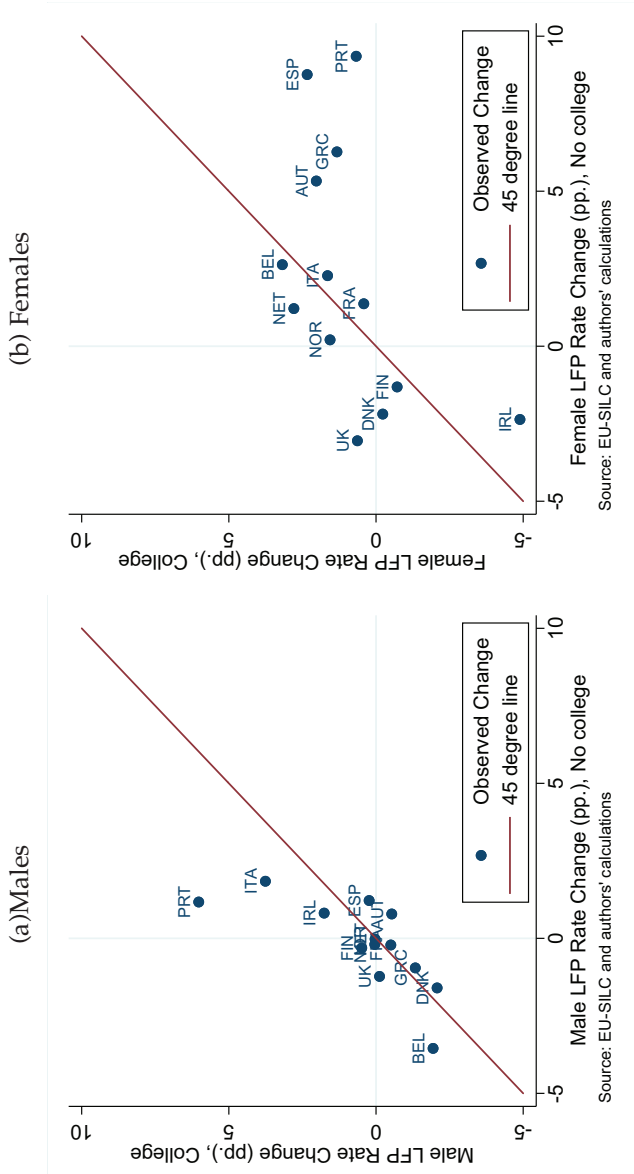


Figure 2. Changes in LFP by gender and education, 2007–12.

Notes: (a) Males. (b) Females.

Sources: EU-SILC and authors' calculations.

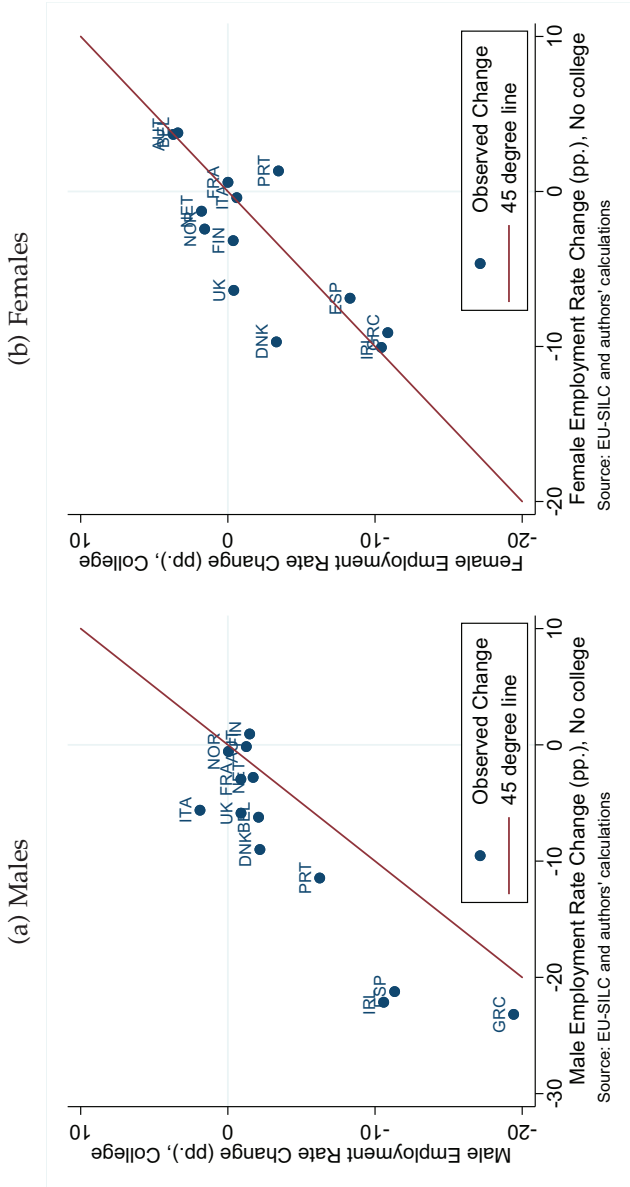


Figure 3. Changes in employment rates by gender and education, 2007–12.

Notes: (a) Males. (b) Females.

Sources: EU-SILC and authors' calculations.

into changes in RGs and PGs during the downturn and the subsequent recovery. Both procedures provide corrections for the selection biases which arise in the estimation of standard wage *mincerian* regressions based on reported employees' wages, as in Equation (1), when those who are employed exhibit different potential wage distributions than the non-employed ones.

4.1. Imputation around the median

As discussed in Olivetti and Petrongolo (2008), the imputation around the median estimator uses a transformed dependent variable which equals w_{it} for those who are employed at time t , $L_{it} = 1$, and some arbitrary (low or high) imputed value, \underline{w}_t and \overline{w}_t , respectively, for those in the non-employment, $L_{it} = 0$.¹⁹ The main insight behind this procedure is that, contrary to the mean, the observed median of the distribution of observed and imputed wages yields an unbiased estimator of the true median of potential wages insofar as the missing observations are imputed on the correct side of the median.²⁰

A small number of observable characteristics, X_i , is used to make assumptions about the position of the imputed wage with respect to the median of the gender-specific wage distribution. We define a threshold value for X_i below which non-employed workers would earn wages below the gender-specific median, and another threshold value above which individuals would earn above-median wages.

Specifically, our core specification relies on standard human capital theory and, therefore, uses both observed *educational* attainment and labour market *experience* ('Imputation on EE') to predict the position of the missing wages. The imputed dependent variable is set to equal a low value, \underline{w}_t , if an individual has low education and limited labour market experience, and a high value, \overline{w}_t , when an individual is highly educated and has extensive labour market experience.²¹ In addition, to take into account non-employed individuals with low (high) education and long (limited) experience, we follow Olivetti and Petrongolo (2008) in fitting a probit model for the probability that the wage of employed individual lies above the gender specific median, based on education, experience (and its square) and the interaction of both variables. In this way, predicted probabilities for the

19 As noted earlier, this approach is closely related to Johnson *et al.* (2000) and Neal (2004).

20 To simply illustrate this property, suppose that the true realization of the wage for five individuals (ranked in increasing order) is $\{1, 3, 5, 6, 10\}$ and that the first and last observations (i.e. 1 and 10) happen to be missing. If imputations for these missing values are equal to 2 and 29, the new estimated median will remain unbiased ($=5$) whereas the mean will be severely biased (changing from 5 to 8).

21 This methodology implies a trade-off between the likelihood of imputing an individual's wage correctly (which increases with the number of covariates) and the share of observations for which we cannot ascertain the position relative to the mean (which also increases with the number of covariates). Following Olivetti and Petrongolo (2008), we only use two explanatory variables, which provide a reasonable compromise. We performed robustness tests with a larger number of covariates as discussed in Table A4 in the Appendix.

non-employed are obtained. An imputed sample using all individuals in the sample is then constructed using these predicted probabilities as sample weights.

Since these imputation methods for missing wages follow an educated guess, we provide two procedures to assess their goodness of fit. Following [Olivetti and Petrongolo \(2008\)](#), the first procedure (Goodness Method 1) makes use of wage information for non-employed individuals from other waves in the panel in which individuals report having received a wage. In this way, it is possible to check whether the relative position as regards the median of imputed wages using information of the aforementioned demographics corresponds to the actual one when the wage is actually observed. We propose a second method (Goodness Method 2) which considers all employed workers and computes the fraction of those with wage observations on the correct side of the median as predicted by the imputation rule.

Finally, as an alternative imputation method which does not rely on using somewhat arbitrary assumptions based on observable characteristics, as above, we follow [Olivetti and Petrongolo \(2008\)](#) in exploiting the panel nature of the data. In particular, for all those not employed in year t , we recover their wages from the nearest wave, t' . The identifying assumption is that the wage position with respect to the median when an individual is not employed can be proxied by the observed wage in the nearest wave. While this procedure, labelled 'Imputation on Wages from Other Waves' ('WOW') relies exclusively on wages, and therefore has the advantage of incorporating selection on time-invariant unobservables, it has the disadvantage of not providing any wage information on individuals who never worked during the sample period. Thus, this method will be relatively conservative in assessing the effects of positive selection in the countries with a relatively low labour market attachment of females. Moreover, since the panel dimension of our data set is relatively short, this procedure yields less satisfactory results in terms of goodness of fit.²² Consequently, we relegate its results to the [Online Appendix](#).

4.2. Quantile selection models

As acknowledged above, estimation of selection biases using imputations of missing values around the median wage may be problematic in a context of short panels (like ours) and a large fraction of people who never worked throughout the panel. Hence, it seems convenient to compare the results yielded by the imputation rules with those stemming from a more conventional control-function approach which takes advantage of the longitudinal structure of the data.

Recalling that the key ingredients of our theoretical argument are that male job destruction and changes in female LFP and employment have mostly affected less-skilled

22 The longitudinal component of EU-SILC allows to follow each household for 4 years, with the exception of France, where each household is followed for eight consecutive years.

workers (i.e. those in the lower part of the wage distribution), it seems natural to implement selection corrections in a *quantile* regression framework. If our interpretation is correct, the insight behind this approach is that we should observe more positive selection biases at the lower quantiles of the observed male wage distribution than at the other quantiles. By the same token, selection bias should be more positive in the female wage distribution if the adverse shifts in LD dominate the favourable shifts in LS (due to the AWE) or, conversely, less positive when LS acts as the binding constraint. To do so, we apply the methodology recently developed by [Arellano and Bonhomme \(2017\)](#) (hereafter, AB).

In AB's (2017) quantile model, sample selection is modelled via a bivariate cumulative distribution function, or *copula*, of the errors in the wage and the selection equations. In particular, the following selection model is considered for the latent (potential) wage of each individual of gender g ($g = m, f$), labelled as w^{*g} , and their decision to accept a job:

$$w^{*g} = X^{g'} \beta^g(U), \quad (8)$$

$$D^g = 1\{V \leq p(\zeta^g)\}, \quad (9)$$

$$w^g = w^{*g} \text{ if } D^g = 1, \quad (10)$$

where $\beta^g(U)$ in [Equation \(8\)](#) is increasing in a random variable uniformly distributed on the unit interval, U , independent of the set of covariates determining wages, X^g , such that $Q(\tau, X^g) = X^{g'} \beta^g(\tau)$ is the τ -th conditional quantile of w^{*g} given X^g . Moreover, [Equation \(9\)](#) represents the selection equation where $1\{\cdot\}$ is an indicator function, while $\zeta^g = (X^g, B^g)$, such that B^g are those extra covariates which appear in the participation equation but not in the wage equation; finally, V is the rank of the error term in this equation, which is also uniformly distributed on the support $(0, 1)$. Assuming that (U, V) is jointly statistically independent of ζ^g given X^g , denoting the c.d.f. of (U, V) as $C(u, v)$, and finally defining $p(\zeta^g) = \Pr(D^g = 1 | \zeta^g) > 0$, the presence of dependence between U and V is the source of the sample selection bias. In particular, this dependence is captured by $G(\tau, p; \rho^g) = C(\tau, p; \rho^g)/p$ which is the conditional copula of U given V , defined on $(0, 1) \times (0, 1)$. In this respect, notice that a negative copula means positive selection since individuals with higher wages (higher U) tend to participate more (lower V) and, conversely, a positive copula implies negative selection. Then, [AB \(2017\)](#) show that

$$\beta^g(\tau) = \arg \min_{b(\tau)} E\left[D^g (G_{\tau, \zeta^g}(w^g - X^{g'} b^g(\tau))^+ + (1 - G_{\tau, \zeta^g})(w^g - X^{g'} b^g(\tau))^- \right],$$

where $a^+ = \max(a, 0)$, $a^- = \max(-a, 0)$ and $G_{\tau, \zeta^g} = G(\tau, F^{-1}(\zeta^{g'} \gamma^g); \rho^g)$ denotes the rank of $X^{g'} \beta^g(\tau)$ in the selected sample $D^g = 1$, conditional on $\zeta^g = \zeta^g$. Since the above optimization problem is a linear programme, given γ^g and ρ^g , the parameters $\beta^g(\tau)$ can be estimated in a τ -by- τ fashion by solving linear programmes, just like with the

conventional check function in standard quantile regressions (Koenker and Bassett, 1978). The only difference is that, in quantile regressions, τ replaces $G_{\tau Z^g}$; in other words, correcting for selection in quantile regressions implies that one needs to rotate the check function depending on Z^g . AB (2017) suggest two previous steps in order to compute $\beta^g(\tau)$: estimation of the propensity score $p(Z^g)$ in Equation (9) (e.g. via a probit model) and estimation by means of a grid-search Generalized Method of Moments (GMM) of the degree of selection (i.e. the copula parameter ρ^g) using a Frank copula, though they also cover more general cases.

5. EMPIRICAL RESULTS

In this section, we present the main results from the two econometric approaches discussed above: (i) imputations around the median, and (ii) selection bias corrections in quantile regressions. For brevity, in (i) we focus exclusively on the evidence drawn from imputation on EE, which yields the best goodness-of-fit results (see below). The corresponding results for the imputation rule based on WOW can be found in the [Online Appendix](#).

5.1. Imputation around the median wage

[Table 1](#) presents the results for our EE imputation method. Recall that two education categories are being considered: those individuals with upper secondary education or less are considered to be ‘less-educated’, while those with some tertiary education are defined as ‘high-educated’. Similarly, we define as ‘low (high) experienced individuals’ those with less than (at least) 15 years of work experience.

[Table 1](#) presents the results for the four Southern EU and the nine Rest of EU countries split into the three blocks as defined above (Anglo-Saxon, Continental EU and Nordic). In the left panel, we report the RGs and PGs in levels (log. points), as well as the selection biases and employment rates by gender in 2007 (at the onset of the Great Recession).²³ Selection biases are measured as pp. changes in the median wage once missing wages are imputed. The right panel in turn shows the corresponding changes of these variables between 2007 and 2012 (during the Great Recession) with asterisks denoting the statistical significance of changes in selection biases.²⁴ To help interpret

23 In the [Online Appendix](#) (see [Table A2](#) in section A), we present evidence on how female LFP rates have increased in the four Southern EU economies and in a few Rest of EU countries, and that this rise has been much higher among less-educated women everywhere.

24 To test for the null of no selection changes between 2007 and 2012, we run a gender-specific median quantile regression of both latent and raw wages on a constant, a dummy for latent wages, a dummy for 2012 and an interaction of the two. The standard errors are bootstrapped and clustered by year, and population weights are used in the regression. The *t*-ratio on the interacted coefficient tests for the null of no changes in selection biases. The same procedure is applied in [Table 2](#) to test the null hypothesis of no change between 2012 and 2016.

Table 1. Median wage gaps under imputation on education and experience, 2007–12

Country	Levels in 2007						Changes over 2007–12					
	Raw wage gap	Potential wage gap	Selection bias		Employment rate		Raw wage gap	Potential wage gap	Selection bias		Employment rate	
			M	F	M	F			M	F	M	F
Greece	0.182	0.445	0.025	0.288	0.887	0.540	-0.089	-0.067	0.059***	0.081**	-0.220	-0.081
Italy	0.035	0.277	0.034	0.276	0.863	0.559	0.051	0.024	0.010	-0.017	-0.045	0.006
Portugal	0.172	0.223	0.036	0.087	0.875	0.707	-0.059	-0.105	0.024**	-0.021*	-0.106	0.010
Spain	0.131	0.248	0.017	0.134	0.889	0.638	-0.020	0.002	0.066***	0.088***	-0.179	-0.064
Southern	0.130	0.298	0.028	0.196	0.879	0.611	-0.030	-0.037	0.040	0.033	-0.138	-0.032
Austria	0.189	0.300	0.012	0.124	0.893	0.695	0.015	-0.007	-0.007	-0.029	-0.002	0.036
Belgium	0.074	0.142	0.022	0.090	0.897	0.732	-0.019	-0.060	0.003	-0.038***	-0.046	0.036
France	0.114	0.161	0.008	0.055	0.917	0.808	0.005	-0.019	0.010	-0.014*	-0.020	0.012
The Netherlands	0.158	0.199	0.004	0.044	0.963	0.823	-0.048	-0.038	-0.001	0.009	-0.023	0.007
Continental	0.133	0.201	0.011	0.079	0.917	0.765	-0.012	-0.031	0.001	-0.018	-0.023	0.023
Ireland	0.170	0.303	0.020	0.153	0.862	0.674	-0.039	-0.069	0.003	-0.026**	-0.151	-0.070
United Kingdom	0.247	0.301	0.011	0.065	0.934	0.804	-0.064	-0.045	0.009**	0.028*	-0.032	-0.024
Anglo-Saxon	0.208	0.302	0.015	0.109	0.898	0.739	-0.052	-0.057	0.006	0.001	-0.091	-0.047
Denmark	0.116	0.126	-0.002	0.009	0.966	0.905	-0.036	-0.048	-0.012	-0.023***	-0.066	-0.065
Finland	0.203	0.221	0.016	0.035	0.862	0.831	-0.049	-0.086	0.015	-0.022**	0.005	-0.011
Norway	0.154	0.161	0.006	0.013	0.969	0.931	0.020	0.003	0.006	-0.023***	-0.002	-0.002
Nordic	0.158	0.170	0.007	0.019	0.932	0.889	-0.022	-0.044	-0.001	-0.023	-0.021	-0.026

Notes: Selection bias = an increase in observed wage due to selection. Wage imputation rule: impute wage < median when non-employed and education ≤ upper secondary and experience < 15 years; impute wage > median when non-employed and education ≥ higher education and experience ≥ 15 years. All raw and potential wage gaps are significant at the 1% level. *, ** and *** denote statistical significance at 10%, 5% and 1% levels. Bold values correspond to averages of countries in each block.

Sources: EU-SILC and authors' calculations.

Table 2. Median wage gaps under imputation on education and experience, 2012–6

Country	Changes over 2012–6					
	Raw wage gap	Potential wage gap	Selection bias		Employment rate	
			M	F	M	F
Greece	-0.030	-0.130	-0.026	-0.126***	0.013	0.021
Italy	-0.028	0.063	0.000	0.091**	-0.003	-0.011
Portugal	0.000	0.027	-0.050***	-0.023**	0.060	0.039
Spain	-0.047	-0.078	-0.040***	-0.072***	0.050	0.075
Southern	-0.026	-0.029	-0.029	-0.032	0.030	0.031
Austria	-0.004	-0.026	-0.005	-0.027	-0.005	0.019
Belgium	0.017	0.028	-0.012*	-0.001	0.018	0.022
France	-0.006	0.007	-0.003	0.010*	-0.012	0.002
The Netherlands	0.073	0.051	0.001	-0.021**	-0.005	-0.008
Continental	0.020	0.015	-0.005	-0.010	-0.001	0.009
Ireland	-0.054	-0.117	0.021***	-0.042***	-0.711	-0.604
United Kingdom	-0.005	-0.024	-0.008*	-0.027	0.040	0.002
Anglo-Saxon	-0.030	-0.071	0.007	-0.034	-0.335	-0.301
Denmark	0.026	0.017	0.029***	0.019**	0.009	0.071
Finland	-0.021	-0.015	-0.011*	-0.004	-0.029	-0.009
Norway	-0.013	-0.013	0.002	0.002*	-0.004	0.004
Nordic	-0.003	-0.004	0.007	0.006	-0.008	0.022

Notes: Selection bias = an increase in observed wage due to selection. Wage imputation rule: impute wage < median when non-employed and education ≤ upper secondary and experience > 15 years; impute wage > median when non-employed and education ≥ higher education and experience ≥ 15 years. *, **, and *** denote statistical significance at 10%, 5% and 1% levels. Bold values correspond to averages of countries in each block.

Sources: EU-SILC and authors' calculations.

our findings, it is useful to recall from Equation (4) that changes in PG equal changes in RG plus changes in the female bias minus changes in the male bias, i.e. $\Delta PG_t = \Delta RG_t + \Delta b_t^m - \Delta b_t^f$.

In agreement with the findings of Olivetti and Petrongolo (2008), the left panel of Table 1 shows that, before the slump, Southern EU countries exhibited on average a much lower RGs (13 pp.) than PGs (30 pp.), as well as higher gender employment gaps in favour of men than the Rest of EU countries. With regard to RGs, it can be seen that only the Continental EU countries exhibit a similar gap to the one in Southern EU countries while, in relation to PG, only the Anglo-Saxon countries fare similarly. As a result, the most salient features of this evidence can be summarized as follows: (i) the difference $PG - RG$ is much higher (17 pp.) in Southern EU than in the Rest of the EU (5 pp. on average), (ii) the female selection bias is also much higher in Southern EU (19.6 pp.), broadly explaining the difference of 17 pp. between PGs and RGs, as it is also the case for male selection biases, which are almost three times larger in the South than elsewhere (2.8 pp. against 1.1 pp.), in agreement with the lower aggregate employment rates in this block of countries.

The right panel of Table 1 indicates that, in line with the evidence in OECD (2014), RGs declined in most countries over the Great Recession, with Italy being the noticeable exception. However, our findings indicate that the slump also involved considerable changes in selection which triggered an even larger drop in PGs for a majority of countries. Hence, in relative terms, this means that changes in RGs overestimate changes in PGs over the downturn, which contrasts with the results reported by Olivetti and Petrongolo (2008) before the recession, when PGs exceeded RGs in several EU countries. Two findings explain this new pattern. First, the male selection bias became more positive, notably in Southern EU where it rose by almost 6.6 pp.²⁵ The largest increases in male selection seem to have taken place in those countries where the decline in male employment was largest. Second, the evolution of female selection varies across countries. We can observe two different patterns, with two-thirds of the countries exhibiting a reduction in female selection and the remaining one-third experiencing an increase. These differences are clearly illustrated within the Southern EU block. Female selection biases experienced substantial reductions in Portugal (−2.1 pp.) and to a lesser extent in Italy (−1.7 pp. but not statistically significant), the only two countries in the South where female employment rates fared relatively well during the crisis. On the other hand, female employment rates plummeted in Greece and Spain (by −8.1 pp. and −6.4 pp., respectively) leading to growing (more positive) female selection biases (changes above 8 pp.). Another country where female selection bias has increased markedly is the United Kingdom (2.8 pp.), due to its drop in employment being largely driven by the dismissals

25 There are a few exceptions, notably Denmark and Norway, where male selection fell.

of young, and hence below median wage workers.²⁶ These differences indicate the importance of the supply and demand forces discussed above for female selection. Consequently, the evolution of the PG depends on which of these dominates, as we can see in the contrasting findings between Portugal, where the PG fell by 10 pp., and Spain, where it remained stable. Further details on the differences between these two countries will be discussed further below.

Table 2 presents the changes in the variables reported in Table 1 during the recovery period (2012–6). It should be noticed that, due to the sovereign debt crisis, recovery was delayed by one or two years in some of the Southern EU countries (see the case of Portugal below). As can be observed, RGs and PGs decrease in most countries, with the exception of the Continental EU block and Denmark where they go up. The most salient finding, however, is that the increase in male selection during the slump is partially reversed during the subsequent recovery, particularly in Southern EU. This is explained by a higher demand for less-skilled male labour once growth took off.²⁷ Likewise, female selection biases that had grown in these countries during the crisis, now decline, being fuelled by higher demand for less-skilled female labour during the upturn. A notable exception is Portugal, where positive female selection declined both during the crisis and the recovery. This indicates that the higher demand for less-skilled women during the crisis remained strong when it was over (see discussion further below), whereas in other countries a parallel rise in the demand for high-skilled women took place. Notwithstanding this exception, we take the reversed signs of selection biases from the downturn to the upturn as supportive evidence of their business-cycle nature. Male selection is countercyclical, increasing in the downturn and falling in the upturn, while female selection also follows the business cycle, although its sign depends on the interplay between LS and LD.

To provide a graphical illustration of how the LS and LD constraints operate, we focus on the experiences of Portugal and Spain, the two neighbouring Iberian countries badly hit by the recession. The left panels in Figures 4 and 5 display the estimated selection biases by gender in each country from 2007 to 2016. For comparison, the right panels present employment rates by gender. As can be seen, male selection biases (dashed lines) surged in both countries during the Great Recession (i.e. the LD constraint binds for men). Yet, striking differences appear as regards female selection biases: while the positive female selection declines in Portugal (the LS constraint binds for women), it goes up in Spain (the LD constraint binds for women). These contrasting patterns are

26 Male employment changes in the United Kingdom over the recession have been characterized by both a decline in youth male and female employment, that tended to increase positive selection among men and women, and job destruction in the male-dominated and high-paid financial sector; see Bell and Blanchflower (2010). The joint effect of these two forces is a negligible change in male selection and an increase in female selection.

27 Note that there is no reversal in France, where the lack of change in male employment is accompanied by a small and insignificant change in male selection.

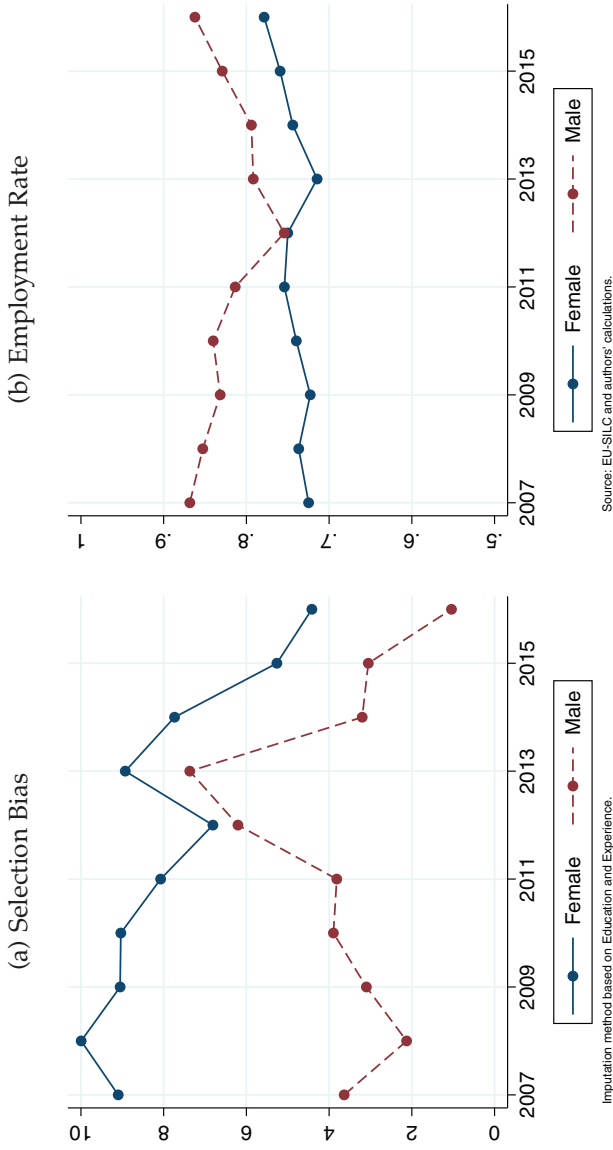


Figure 4. Selection bias and employment rates by gender, Portugal, 2007–12.

Notes: (a) Selection Bias. Imputation method based on education and experience. (b) Employment Rate (Sources: EU-SILC and authors' calculations).

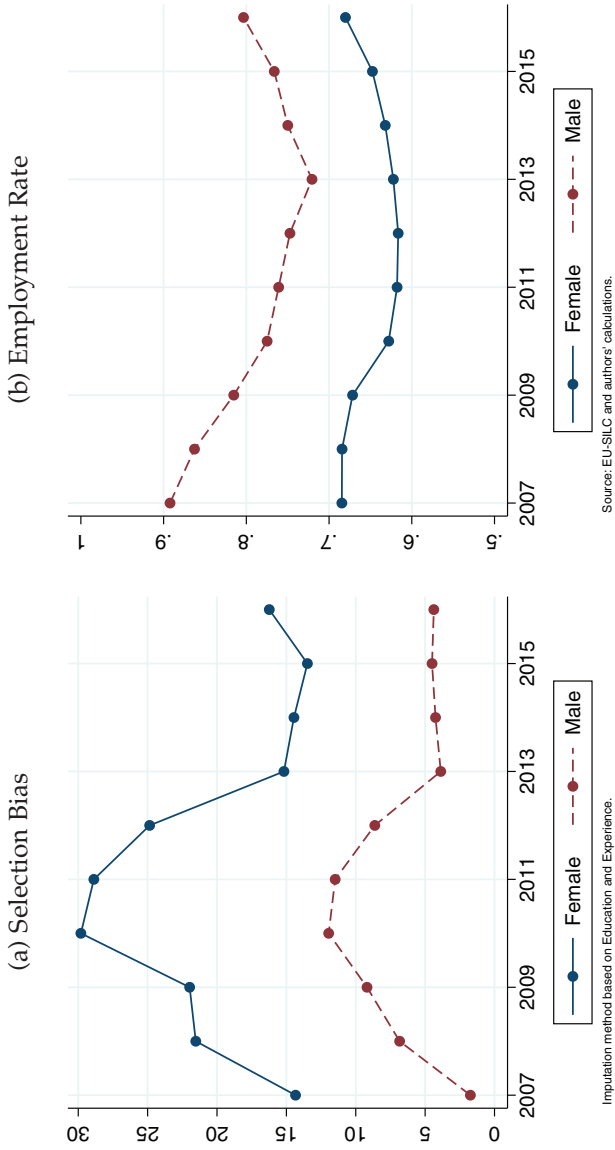


Figure 5. Selection bias and employment rates by gender, Spain, 2007–12.

Notes: (a) Selection bias. Imputation method based on education and experience. (b) Employment rate (Sources: EU-SILC and authors' calculations).

related to the fact that, while only male employment fell in Portugal, job destruction hit both female and male jobs in Spain. The worse performance of the Spanish labour market during the downturn can be attributed to two factors. First, before the crisis, Spain had less wage flexibility and more generous unemployment benefits than Portugal (Bover et al., 2000). Second, Spain had a much higher rate of female temporary workers (above 30% of employees), most of which were massively destroyed once the crisis hit. The much higher rate of fixed-term contracts in Spain than in Portugal had to do both with its much larger weight of employment in the construction and ancillary sectors (reaching 15% of total employment in 2007) and a higher gap between firing costs (including red-tape costs) for workers under permanent (open-ended) and temporary contracts, which inhibited direct hiring of workers under permanent contracts and *temp-to-perm* contract conversions in this country (Dolado, 2016). As already pointed out above, once the recovery started, these selection patterns changed. Male selection biases declined in both countries as a result of the recovery of unskilled male employment (the LD constraint was less binding for men), particularly in the hospitality and retail sectors. Female selection biases went down drastically in Spain (signalling that the LD constraint for women became weaker as well), while they follow a non-monotonic pattern in Portugal: first up and then down (as during the downturn). The initial hike in female selection in Portugal was due to greater hiring of more educated women at the beginning of the upturn, which later on was more than offset by a much higher demand for less-skilled women as a result of a boom in tourism resulting from political instability in competing destination countries located in Northern Africa (which also occurred in Spain).

Lastly, a brief comment is due to the reliability of the results obtained by using the imputation on EE rule. Table 3 reports results on our two above-mentioned measures of goodness of fit, computed for men and women separately, for the years 2007, 2012 and 2016. We report both the imputation rates for each year and the share of imputations that place the individual on the correct side of the median. As can be inspected, both measures indicate a satisfactory fit for about 75% of the individuals of either gender in our sample. Furthermore, there is no indication that we do a better job in imputing female than male missing wages.²⁸

5.2. Quantile regressions

Using the AB's (2017) method described above, we estimate wage quantile regressions separately for male and female wages, allowing for sample selection using EU-SILC unbalanced panel data for 2007–12. The dependent variable is the log-hourly wage, covariates X^g contain experience and its square, marital status, the two education indicators mentioned earlier, a set of dummies for region of residence (NUTS) in each country and

28 In order to check the robustness of our imputation method, the Online Appendix B reports estimates based on a probit model. The results are qualitatively similar to our findings in Table 1.

Table 3 Rate and goodness of imputation on education and experience

Country	2007				2012				2016									
	Imputation rate		Goodness Method 1		Goodness Method 2		Imputation Rate		Goodness Method 1		Goodness Method 2		Imputation rate		Goodness Method 1		Goodness Method 2	
	M	F	M	F	M	F	M	F	M	F	M	F	M	F	M	F	M	F
Greece	0.42	0.69	0.88	0.88	0.84	0.85	0.37	0.57	0.78	0.78	0.80	0.79	0.38	0.54	0.85	0.70	0.80	0.83
Italy	0.53	0.73	0.82	0.72	0.70	0.69	0.52	0.71	0.82	0.76	0.73	0.73	0.62	0.72	0.78	0.77	0.71	0.74
Portugal	0.38	0.55	0.59	0.61	0.71	0.76	0.44	0.43	0.63	0.53	0.65	0.77	0.34	0.46	0.73	0.51	0.81	0.86
Spain	0.39	0.63	0.66	0.70	0.75	0.79	0.54	0.65	0.72	0.65	0.73	0.77	0.39	0.61	0.46	0.73	0.76	.75
Southern	0.43	0.65	0.74	0.73	0.75	0.77	0.47	0.59	0.74	0.68	0.73	0.76	0.43	0.58	0.70	0.68	0.77	.79
Austria	0.32	0.51	0.85	0.76	0.76	0.81	0.32	0.48	0.77	0.70	0.83	0.80	0.42	0.55	0.73	0.84	0.81	0.81
Belgium	0.42	0.56	0.86	0.84	0.80	0.80	0.50	0.60	0.84	0.77	0.78	0.82	0.54	0.65	0.81	0.85	0.83	0.83
France	0.42	0.58	0.83	0.77	0.80	0.79	0.46	0.61	0.76	0.72	0.81	0.80	0.52	0.61	0.75	0.74	0.80	0.78
The Netherlands	0.34	0.58	0.77	0.83	0.81	0.75	0.46	0.58	0.80	0.76	0.81	0.79	0.42	0.52	0.49	0.62	0.87	0.82
Continental	0.38	0.56	0.83	0.80	0.79	0.79	0.43	0.57	0.79	0.74	0.81	0.80	0.47	0.58	0.70	0.76	0.83	0.81
Ireland	0.37	0.53	0.85	0.80	0.83	0.81	0.39	0.45	0.70	0.68	0.73	0.76	0.46	0.46	0.57	0.65	0.73	0.75
United Kingdom	0.40	0.51	0.54	0.70	0.75	0.74	0.42	0.55	0.89	0.75	0.75	0.71	0.59	0.55	0.81	0.64	0.75	0.74
Anglo-Saxon	0.39	0.52	0.69	0.75	0.79	0.77	0.41	0.50	0.80	0.71	0.74	0.73	0.52	0.51	0.69	0.64	0.74	0.74
Denmark	0.23	0.46	0.55	0.82	0.67	0.76	0.37	0.28	0.09	0.64	0.69	0.68	0.41	0.41	0.78	0.85	0.78	0.80
Finland	0.60	0.41	0.80	0.73	0.75	0.78	0.53	0.45	0.67	0.60	0.76	0.75	0.50	0.45	0.84	0.53	0.74	0.72
Norway	0.37	0.38	0.66	0.70	0.75	0.79	0.35	0.41	0.72	0.65	0.73	0.77	0.39	0.45	0.46	0.73	0.76	0.75
Nordic	0.40	0.42	0.67	0.75	0.73	0.78	0.42	0.38	0.49	0.63	0.72	0.73	0.43	0.44	0.70	0.70	0.76	0.76

Notes: Wage imputation rule: impute wage < median when non-employed and education <= upper secondary and experience <15 years; impute wage > median when non-employed and education >= higher education and experience >= 15 years. Imputation Rate = proportion of imputed wage observations in total non-employment. Goodness Method 1 = proportion of imputed wage observations on the same side of the median as wage observations from other waves in the panel. Goodness Method 2 = proportion of employed workers on the same side of the median as predicted by the imputation rule. Bold values correspond to averages of countries in each block.

Sources: EU-SILC and authors' calculations.

Table 4. Quantile regression estimates corrected for selection

Country Quantile	Changes in Selection Bias over 2007–12					
	20		50		80	
	M	F	M	F	M	F
Greece	0.178	0.151	0.068	0.093	0.088	0.063
Italy	0.009	−0.004	0.004	−0.001	−0.003	0.001
Portugal	0.031	−0.021	0.026	0.005	0.033	−0.005
Spain	0.113	0.086	0.082	0.058	0.050	0.039
Southern	0.083	0.053	0.045	0.039	0.042	0.025
Austria	0.018	0.011	0.000	0.016	−0.003	0.035
Belgium	0.007	−0.034	0.002	−0.018	−0.014	−0.044
France	−0.011	−0.002	0.003	−0.007	0.001	−0.009
Continental	0.005	−0.008	0.002	−0.003	−0.005	−0.006
Ireland	0.001	0.048	0.047	−0.006	0.035	−0.038
United Kingdom	0.036	0.026	0.032	0.027	0.037	−0.002
Anglo-Saxon	0.019	0.037	0.040	0.010	0.036	−0.020

Notes: Covariates in the participation equation are described in the main text. Matlab code at: https://drive.google.com/file/d/0B13ohL0_ULTDaDE2N0d1ZnEzZ1U/view. Bold values correspond to averages of countries in each block.

Sources: EU-SILC and authors' calculations.

year effects. As for B^e (determinants of participation that do not affect wages directly), we take the number of children in six age brackets and their interaction with marital status, non-labour income and a dummy variable of whether the corresponding spouse lost his/her job in the previous year interacted with marital status (AWE). Notice that, if the latter effect holds, we would expect a positive effect of this variable on the probability of participating in the labour market. Unfortunately, as discussed earlier (in footnote 16), the AWE indicator is not available for Nordic countries and the Netherlands, since information on labor market experience in both countries is restricted to a single member of the household and not for both spouses. Thus, these countries are omitted in this subsection.

Table 4 presents evidence for the nine remaining EU countries where the information requirements to run these quantile regressions is available. For brevity, the reported results correspond to the male and female selection biases for three relevant quantiles at the bottom, centre and upper part of the wage distribution: $\tau = 0.2, 0.5$ and 0.8 .

As with the previous approach, the increase in male selection appears relevant in most countries, being stronger at $\tau = 0.2$ than for the other higher quantiles, in line with the much higher job destruction rate for the less-skilled workers than for other higher-skilled groups. The exception to this rule is the Anglo-Saxon block, where the rise in male selection is stronger at $\tau = 0.5$, and 0.8 , possibly due to the dismissals of many young, and hence relatively lower-paid, workers in high-pay sectors such as the banking and financial industries. Moreover, in agreement with the evidence reported in Table 1, this rise in male selection is much stronger in Southern EU countries (except Italy) than in the other countries where the decline in male employment rates was much less intense. Second, in contrast to the strong rise in Greece and Spain and to a lesser

Table 5. Quantile regression estimates corrected for selection

Country	Copula		corr(U, V)	
	M	F	M	F
Greece	-4.78***	-3.13***	-0.63	-0.46
Italy	-0.12*	-0.70**	-0.02	-0.12
Portugal	-0.91***	-1.42***	-0.15	-0.23
Spain	-2.19***	-0.86***	-0.34	-0.14
Southern	-2.00	-1.53	-0.28	-0.24
Austria	-1.37***	-1.37***	-0.22	-0.22
Belgium	-0.06	-0.30**	-0.01	-0.05
France	-0.12*	-0.36**	-0.02	-0.06
Continental	-0.52	-0.68	-0.08	-0.11
Ireland	-0.06	-0.42**	-0.01	-0.07
United Kingdom	-0.30**	-0.06	-0.05	-0.01
Anglo-Saxon	-0.18	-0.24	-0.03	-0.04

Notes: Covariates in the participation equation are described in the main text. *, ** and *** denote statistical significance at 10%, 5% and 1% levels. Replication codes at: https://drive.google.com/open?id=0B13ohL0_ULTDMVhBN0s1OXhldWc. Bold values correspond to averages of countries in each block.

Sources: EU-SILC and authors' calculations.

extent in the Anglo-Saxon block, female selection goes down in Portugal (particularly at $\tau = 0.2$) and in Belgium, supporting the findings on this issue presented in Table 1.

Table 5 reports the estimated copulas and correlations between the error terms in the wage and participation equations, denoted as $\text{corr}(U, V)$. As can be seen, all copulas and correlations are negative over the Great Recession period and, in most instances, copulas turn out to be statistically significant. As discussed earlier, negative copulas imply positive selection which takes place both among men and women. Notice that female selection remains positive by the end of the recession, even in countries where it experienced a sizeable reduction (like in Italy and Portugal), the reason being that it was initially (in 2007) very high and positive.

Finally, two additional empirical findings are worth discussing, though they are not reported for the sake of brevity. First, we have checked how selection patterns have changed over time by estimating copulas using cross-section quantile regressions with selection corrections for three specific years: 2007, 2012 and 2016. In general, we find that the male copulas are more negative in 2012 than in 2007, while they are less negative in 2016 than in 2012. This agrees with our earlier evidence regarding an increase of male selection during the recession period and a reduction over the recovery period. As for female selection, the results vary in line with the evidence reported in Table 1. In countries, like Greece, Spain and the United Kingdom where female employment went severely down over the downturn, female copulas are more negative in 2012 than in 2007, while the opposite happens for countries like Italy, Portugal, Ireland and those in the Nordic block. Second, we find that the estimated coefficient on AWE in the participation probit equations for men is often negative and statistically insignificant in most countries. By contrast, the corresponding coefficient for women is positive and highly

Table 6. Summary of findings over the Great Recession

Country	Consistent hypotheses			
	I_m	I_f	Π_{fe}	Π_{fu}
Southern				
Greece	✓			✓
Italy	✓		✓	
Portugal	✓		✓	
Spain	✓			✓
Continental				
Austria			✓	
Belgium			✓	
France	✓		✓	
The Netherlands	✓			
Anglo-Saxon				
Ireland	✓		✓	
United Kingdom	✓			✓
Nordic				
Denmark	✓		✓	
Finland	✓		✓	
Norway			✓	

Notes: Hypothesis I_m (I_f): higher job destruction rate among low-skilled *male* (*female*) workers. Hypothesis Π_{fe} : AWE with female employment *gains*. Hypothesis Π_{fu} : AWE with female employment *losses*.

significant, particularly in Southern countries and Ireland, meaning that male job losses triggered higher female LFP. In line with the evidence presented by [Bredtmann et al. \(2018\)](#), this is seemingly consistent with the conjectured AWE for less-educated married women. Overall, we take these results as being fairly in agreement with the previous evidence based on median imputation methods.

6. INTERPRETING THE FINDINGS

In view of the previous empirical evidence drawn from the two chosen selection-correction methods, we complete our analysis by providing an overview of how these results fit in the theoretical scenarios laid out in Section 2.2 about the main potential drivers of gender wage gaps in the EU during the Great Recession. Relying on the results in [Tables 1 and 4](#) and [Figures 2 and 3](#), we summarize our interpretation of the evidence in [Table 6](#).

The first conclusion to be drawn is that neither the male (Hypothesis I_m) nor the female version (Hypothesis I_f) of Hypothesis I (i.e. destruction of less-skilled jobs) hold *per se* for any of the countries in our sample. This is because our evidence points to sizeable changes in both male and female selection in parallel, perhaps with the exception of Norway. Hence, from this finding, one can infer that the estimated selection biases and the observed employment changes in EU countries should be rationalized through a combination of the individual hypotheses listed in Section 2.2.

Within Southern EU, the patterns for Italy and Portugal conform neatly to the implications of the combined Hypotheses $I_m + II_{fe}$ (i.e. AWE plus large losses in unskilled male employment losses with no major changes in female employment rates), which jointly lead to a substantial reduction (resp. increase) in female (resp. male) selection, so that $\Delta RG > \Delta PG$. By contrast, the patterns in Greece and Spain seem to be better rationalized by the combined Hypotheses $I_m + II_{fu}$ (i.e. AWE plus a collapse in both male and female unskilled employment rates), leading to a simultaneous rise in the selection biases for both genders. Since our evidence points out to a larger increase in the female bias than in the male bias, this would imply that $\Delta PG > \Delta RG$ in these two countries.

Among the Rest of EU countries, where employment losses have been much more muted than in Southern EU – except in Denmark and Ireland – we find two distinct patterns. On the one hand, several countries in the Continental EU block provide nice examples of Hypothesis II_{fe} , i.e. AWE plus unskilled female employment gains, leading to a reduction in female selection. Likewise, the substantial drop in male unskilled employment and in the female selection biases in Finland seems best explained by the combined Hypotheses $I_m + II_{fe}$ (AWE with female employment gains and male employment losses). Lastly, the findings for the Anglo-Saxon block are more ambiguous. While the Irish pattern is akin to the one for Italy and Portugal, and so rationalized by more positive male and less positive female selection (the combined Hypotheses $I_m + II_{fe}$), the rationalization for the UK experience seems to fit better with a milder version of the more positive selection for both genders (combined Hypotheses $I_m + II_{fu}$) that were previously applied to Greece and Spain, albeit at a much lower scale.

Overall, the existence of positive male selection emerges as a uniform and robust finding in most countries, despite being much more pronounced in Southern EU than in Rest of EU. In relation to positive female selection, depending on whether LD or LS shifts dominate, we find instances where it has gone up and others where it goes down. Consequently, rationalization of these contrasting patterns in female selection calls for a combination of factors. Among the Southern EU countries most badly hit by the crisis, it seems that in those economies where female LFP was higher to start with (e.g. in Portugal, whose female LFP rate was close to those prevailing in Continental EU before the crisis), or where crisis has been milder (e.g. Italy or some of the Continental EU countries), the female selection bias has declined. Conversely, countries where female LFP was initially lower and had more dualized labour markets (Greece and Spain) have witnessed a further rise in the female selection bias. Nonetheless, the case of the United Kingdom stands out as an exception to this rule, since the female selection bias has increased despite having high female LFP in 2007. Yet, as argued earlier, a potential explanation of this finding is the fact that unemployment in the United Kingdom hit young women particularly hard.

7. CONCLUSIONS

This paper analyses how the conventional patterns of female and workers' self-selection into EU labour markets have exhibited relevant changes as a result of the large shifts in LD and LS brought about by the Great Recession. Based on a large body of empirical evidence, it has been traditionally assumed that male selection biases were negligible before the crisis, due to high male LFP rates everywhere. By contrast, due to their lower LFP rates (particularly in southern Europe), working women were favourably selected since not many unskilled women worked. Our main hypothesis here is that, if the large job losses experienced during the crisis have mainly affected unskilled male-dominated sectors, then male selection may have become significantly positive over that period. In addition, if non-participating unskilled women had increased their LFP rates due to an AWE during the recession, then female selection should have become less positive than prior to the crisis. However, the overall impact the downturn on the change in the female bias could be a priori ambiguous, since the rise in female LS could have been more than offset by adverse LD shifts during the recession, in which case the female selection bias could become even more positive than it was before.

Using an imputation technique for the wages of non-participating individuals in EU-SILC datasets for a large group of EU countries, as well as quantile wage regressions corrected for selection biases, our findings yield strong support for the hypothesis of a rise in male selection during the recession. This has been especially the case in the Southern EU economies, and to a lesser extent in France and the United Kingdom, where there have been considerable male employment losses in response to the decline of low-productivity industries during the slump. With regard to female selection, our results are mixed. We find that, in line with the AWE, female selection has become less positive (particularly in the Continental EU and Nordic blocks, and in Italy and Portugal), while in other instances (most notably Greece and Spain, but also the United Kingdom) it has become even more positive because widespread job destruction has also meant substantial reductions in female employment rates, either for less-educated or less-experienced women.

Our results highlight the importance of correcting for male selection in computing gender wage gaps. For example, according to the EE imputation rule for missing wages, the potential gender gap (PG) in Spain barely changes (0.2 pp.) over the Great Recession once male selection is taken into account. However, had we ignored male selection and only corrected for female selection, as it is traditionally done, the estimated PG would have *increased* by 6.8 pp. Hence, future research about measuring gender gaps might require corrections for the two gender groups.

Given the cyclical nature of changes in selection into the workforce, we also provide evidence about whether changes in PG have reversed over the subsequent recovery period (2012–16). We find that the positive male selection bias during the downturn goes down in most countries during the recovery, as the less-skilled workers who were laid off during the slump regained jobs when employment growth picked up. By the same token,

in those countries where the female selection bias has increased (decreased) during the crisis, we find that this bias goes down (up) during the recovery, pointing to a favourable LD shift for less-skilled (skilled) women, especially in those countries where either group of women faced big employment losses during the slump. Overall, the decrease in the female selection bias is likely to be a long-lasting phenomenon since female LFP is likely to rise in the future at both tails of the skills distribution, in line with the job polarization hypothesis documented by [Autor and Dorn \(2013\)](#) for the United States and [Goos et al. \(2009\)](#) for some EU countries.

Discussion

Libertad González

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The Great Recession that started in 2008 led to large increases in unemployment in many countries, driven by job destruction across multiple sectors. Understanding how the crisis affected earnings and income inequality is an important research question. In particular, given the pre-existing inequalities, it seems relevant to study the effects of the Great Recession on employment and wages by gender.

This paper analyses empirically the changes in male and female selection into the labour force during and after the Great Recession, across European countries. Their main conclusion appears to be that, due to large job destruction among men, the recession led to positive selection into employment for men, particularly in Southern European countries. The changes in selection were more mixed for women, who became more positively selected into employment in some countries, but less so in others.

It has been shown previously that women tend to be positively selected into employment, and the degree of selection is higher in countries with lower female labour force participation. Selection is smaller among men, since their participation is very high. It has also been documented before that the raw gender wage gap fell in Europe during the recession. This fall may be due in part to differential changes in selection into employment, given the large destruction of jobs during the crisis. This is an important question to explore, and exactly what this paper tackles.

On top of the relevance of the question, I have two main comments and several smaller ones.

The storyline

I feel like the main message of the paper could be streamlined. The main result, again, seems to be that male selection into employment became positive during the recession,

mostly in Southern European countries, while the degree of positive selection among women increased in some countries and decreased in others. This was clear from the introduction and conclusions, but I got somewhat lost during the presentation of the actual results in Section 5.

I also would have liked the authors to go back and reconcile these results (in Section 7) with the starting point of the paper (in Section 1): the observed changes in the gender wage gap during the recession. In particular, the raw gender gap is observed to fall. How can their findings help understand this decline? At first sight, it would seem that the lower participation of low-wage men would lead the raw wage gap to increase, not fall. What am I missing?

Interpretation of coefficients

My second comment refers to the interpretation of point estimates in the text. The main results of the paper are presented in tables that do not show standard errors. The text then compares averages and coefficients across countries. However, the reader does not know whether the highlighted differences are statistically significant or not. This makes the results hard to interpret. Table 1, for example, seems to present the main results of the paper. No standard errors are shown, and significance levels are only indicated in two of the columns.

From looking at Table 1, the main pattern that emerges seems to be a small reduction in both raw and potential gender wage gaps during the recession, of similar magnitudes across EU countries, except perhaps Italy. But this is not what the text highlights. Other than that, it's hard to see a consistent picture or a simple story emerging from this table. There seems to be a lot of cross-country variation, even within groups of countries, and the lack of standard errors makes it hard to know whether differences are significant versus mostly noise.

Smaller comments

i) The authors could be more explicit in explaining why we (should) care about raw gaps and/or potential gaps, and why.

ii) It would also be useful to discuss which factors could affect the gender gap during the recession, other than changes in composition (selection). In other words, why is the potential gap changing?

iii) Men and women who are self-employed or in education are excluded from the analysis sample. I feel like something should be said regarding potential changes in selection into education and self-employment during the recession.

iv) I found section 6 hard to follow. It would help to rephrase the different hypotheses in words again, since it is hard to remember what they were from the earlier section.

Overall, I enjoyed the paper and found it to be an informative analysis of a relevant question.

Dominik Sachs

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This paper analyses how the great recession affected the gender wage gap in different EU countries and extends an earlier paper by [Olivetti and Petrongolo \(2008\)](#). The authors distinguish the raw gender wage gap (RG), which is implied directly by observed wages of males and females and the potential gender wage gap (PG), which accounts for the fact that both females and males may be non-randomly selected into employment. In countries where female labour force participation is low, females are typically quite positively selected and therefore we have $PG \gg RG$. This is, for example, true for Greece, Italy, Portugal and Spain. By contrast, in Scandinavian countries, labour force participation for females is very high and there is no big difference between RG and PG.

This paper asks how these empirical regularities have changed during and after the great recession. On the one hand, of course, PG could have changed. More importantly, the difference in RG and PG may have changed due to (large) changes in employment for both males and females.

A basic labour demand mechanism is that selection should increase for both males and females, because employment decreases due to less labour demand and the selection out of employment is not random. Lower qualified individuals are more likely to get dismissed during recessions. In case this, effect is stronger for males than for females, the ratio RG/PG increases: the average ability of employed men increases stronger than for employed women. If it is stronger for females, the ratio RG/PG decreases because the average ability of employed women increases more strongly than for men.

However, as the authors point out, there is an important second effect – the added worker effect: as many individuals lose their job due to the labour demand shock, this increases the willingness to work of their partner. If the labour force participation of men is higher than for women, this typically means that the woman is the added worker. Hence, female employment may increase due to labour supply effects. This, in turn, should imply an increase in the ratio RG/PG because the average ability of employed women decreases. Why? Because those women that so far did not work but only start due to their partner losing their job are very likely to be of lower ability than those women that did work in any case.

The authors then empirically evaluate these channels using two different empirical approaches to account for selection. Their primary approach is imputation around the median as was also used by [Olivetti and Petrongolo \(2008\)](#) but they also show how their results extend to quantile selection models.

As expected, the authors find that male selection into employment has been increasing during the great recession due to the increase in unemployment. For females, the evidence

is mixed. Furthermore, among the southern countries (Greece, Italy, Portugal and Spain), which are rather similar pre-crisis, effects differ. In Greece and Spain, the labour demand effect for women dominates and female selection increases. In Italy and Portugal, the added worker effect dominates and therefore female selection decreases. The comparison between Spain and Portugal is of particular interest since these two countries were very similar in terms of female employment as well as RG and PG before the crisis.

The analysis is very convincing and I very much appreciated the short theory section that greatly explains the different hypotheses. In addition, this paper provides an excellent overview of employment changes and gender wage gaps for major European countries for the period 2007–16.

Given that so many countries are considered, the authors cannot discuss in detail the results of all countries, so some questions remain. The authors provide a discussion about the differences between Portugal and Spain. The differences are that female selection declined (increased) in Portugal (Spain) and therefore the labour supply (labour demand) constraint was binding if one interprets the findings in line with the theoretical section. Providing more information about the reasons, the authors mention the inflexible wage setting in Spain and the large number of temporary jobs for women. Were the Portuguese employment protection laws so strict that firms were severely restricted in dismissing workers during the Great Recession? A more general question that clearly goes beyond the scope of the paper is why the added worker effect is so strong in Portugal? Is there a structural difference between Portugal and Spain in terms of the occupation structure of female employment that could also explain the differences?

A similar comparison to that which the authors provide for Portugal and Spain, would be interesting for Greece and Italy. As with Portugal and Spain, Greece and Italy were quite similar in terms of pre-crisis employment rates and selection biases. What are the reasons for their different development? Is it mainly that Greece was hit more severely, also in the following sovereign debt crisis? Or does family structure, culture or occupation structure of female employment play important roles?

To conclude, this is a very interesting contribution that enriches the current literature on gender inequality. Understanding selection is key and knowledge about how selection interacts with the business cycle is one important aspect to be understood.

SUPPLEMENTARY DATA

Supplementary data are available at *Economic Policy* online.

APPENDIX A: DERIVATION OF LD AND LS CONSTRAINTS

Given the wage, productivity and outside value equations in system (5)–(7) in the main text, we derive here the values of the relevant thresholds of the productivity thresholds determining LS and LD decisions.

LS cut-off values

As for the LS thresholds, men participate when $w_{it} > r_{it}$. Since the male reservation wage has been normalized to zero, Equations (5) and (7) with $g_i = 0$ imply that their productivity shock ε_{it} has to exceed the LS cut-off value, $a_t^{LS}(g_i = 0)$, given by:

$$a_t^{LS}(g_i = 0) = -\mu_t^w, \tag{A1}$$

where, for simplicity, it is assumed that the inequality $\varepsilon_{it} > a_t^{LS}(g_i = 0)$ always holds. This implies that that men would always wish to participate in the labour market and, as a result, that their LS constraint does not bind.

As regards women, their LS condition, $w_{it} > r_{it}$, is satisfied iff ε_{it} exceeds the following two LS thresholds, depending on the value of the reservation-wage shock, v_{it} :

$$a_t^{LS}(g_i = 1, v_{it} = \bar{v}) \equiv \bar{a}_t = \mu_t^r + \bar{v} - \mu_t^{iw} - \gamma_t, \tag{A2a}$$

$$a_t^{LS}(g_i = 1, v_{it} = \underline{v}) \equiv \underline{a}_t = \mu_t^r + \underline{v} - \mu_t^{iw} - \gamma_t. \tag{A2b}$$

LD cut-off values

With regard to the LD condition to create/maintain a job, $w_{it} < x_{it}$, it holds iff ε_{it} exceeds the following LD threshold:

$$a_t^{LD}(g_i) \equiv \frac{\mu_t^{iw} + g_i \gamma_t - \mu_t^x}{\rho}. \tag{A3}$$

for $g_i = 1, 0$.

The conditions above yield gender-specific lower bounds for ε_{it} implying that *only one* of the two constraints above binds.

Notice that the previous assumption on zero male reservation wage implies that the LD threshold $a_t^{LD}(g_i = 0)$ is the only one that binds for them. By contrast, both LD and LS constraints may be binding for female workers. For example, concerning women with a high reservation-wage shock, the LD constraint would be binding iff: $a_t^{LS}(g_i = 1, v_{it} = \bar{v}) < a_t^{LD}(g_i = 1)$ or equivalently:

$$\frac{\mu_t^x - (\mu_t^{iw} + \gamma_t)}{\bar{a}_t} < \rho, \tag{A4}$$

whereas for women with low reservation-wage shock, the corresponding LD condition becomes²⁹:



29 Note that, since $\underline{a}_t < \bar{a}_t$, the LD condition is more likely to be the binding one for women with a high reservation-wage shock than for women with a low reservation-wage shock.

$$\frac{\mu_t^x - (\mu_t^w + \gamma_t)}{\underline{a}_t} < \rho. \quad (A5)$$

Intuitively, Equations (A4) and (A5) hold when: (i) the potential female wage is high relative to productivity, i.e. when the numerator $\mu_t^x - (\mu_t^w + \gamma_t)$ in Equation (A5) is small; (ii) the reservation wage is low relative to potential wage, i.e., when the denominators in Equation (A5) \underline{a}_t and \bar{a}_t are high; and (iii) the surplus is high, i.e., when ρ is much larger than zero. By contrast, when $\mu_t^x - (\mu_t^w + \gamma_t)$ is high, \underline{a}_t and \bar{a}_t are low and ρ is close to unity, it is likely that $a_t^{LD} < a_t^{LS}$, so that the LS constraint would be the binding one.

APPENDIX B: COMPARATIVE STATICS

Male participation

In order to examine male LFP, for illustrative purposes, we make use of the following result concerning the median of a (standardized) normal distribution which is truncated from below (Johnson et al., 1994). Assuming $\varepsilon_{it} \sim \mathcal{N}[0, 1]$ and denoting the c.d.f. of the standardized normal distribution by $\Phi(\cdot)$, then the median, $\underline{m}(a)$, of the truncated from below distribution of ε_{it} , such that $a < \varepsilon_{it}$, is given by:

$$\underline{m}(a) = \Phi^{-1} \left[\frac{1}{2} (1 + \Phi(a)) \right].$$

Using this result, the observed male wage, for which the LD constraint binds, $a_t^{LS}(g=0) < a_t^{LD}(g=0)$, has the following closed-form solution:

$$\begin{aligned} w_t^m &\equiv m(w_{it}|g_i = 0, L_{it} = 1) = m(w_{it}|g_i = 0, a_t^{LD}(g=0) < \varepsilon_{it}) (a_t^{LD}(g=0)). \\ &= \mu_t^w + \underline{m} \end{aligned}$$

then, given the properties of $\Phi(\cdot)$, it holds that the $\underline{m}(\cdot)$ term is a non-negative increasing function of $a_t^{LD}(g=0)$ which measures the strength of the male selection bias, namely, $b_t^m = m(\varepsilon_{it}|g_i = 0, L_{it} = 1) = \underline{m}(a_t^{LD}(g=0))$.

Next, the response of w_t^m with respect to a change in μ_t^x is given by:

$$\frac{dw_t^m}{d\mu_t^x} = \frac{\partial \underline{m}}{\partial a_t^{LD}(g=0)} \times \frac{\partial a_t^{LD}(g=0)}{\partial \mu_t^x} < 0, \quad (B1)$$

since $a_t^{LD}(g=0)$ is decreasing in μ_t^x . Hence, if we identify the Great Recession as a drop in expected productivity, $\Delta \mu_t^x < 0$, then the median of the observed male wage distribution increases, due to a stronger positive selection of males into employment,

$\Delta b_t^m > 0$.³⁰ In other words, less-skilled male workers with lower wages will not show up in the observed wage distribution because they become unemployed, leading to a rise in the median wage for employed men.

Female participation

Under our assumption on the female reservation-wage shocks v_{it} , it is easy to check that the median of female wages, $m(a(v))$, of the truncated from below distribution of ε_{it} , such that $a(v) < \varepsilon_{it}$, is given by:

$$\underline{m}(a(v)) = \Phi^{-1} \left[\frac{1}{2} \left(1 + p\Phi(\bar{a}) + (1 - p)\Phi(\underline{a}) \right) \right].$$

Mutatis mutandis, the female wage among the employed workers is given by:

$$\begin{aligned} w_t^f &\equiv m(w_{it}|g_i = 1, L_{it} = 1) = m(w_{it}|g_i = 1, a_t^f(v) < \varepsilon_{it}) \\ &= \mu_t^w + \gamma_t + \underline{m} \left(a_t^f(v) \right) \\ &\equiv \begin{cases} a_t^{LS}(g = 1; v) & : a_t^{LS}(g = 1; v) > a_t^{LD}(g = 1) \\ a_t^{LD}(g = 1) & : a_t^{LS}(g = 1; v) < a_t^{LD}(g = 1) \end{cases} \end{aligned}$$

Thus, the observed female wage will depend on which of the LS and LD constraints is binding. Again, the strength of the selection bias for females is measured by the $m(\cdot)$ term, that is, $b_t^f = m(\varepsilon_{it}|g_i = f, L_{it} = 1) = m(a_t^f(v))$. If the binding constraint is LD, i.e. $a_t^{LS}(g = 1; v) < a_t^{LD}(g = 1)$, then a reduction in labour productivity ($d\mu_t^x < 0$) during the Great Recession will have the same impact on observed female wages as the one discussed before for male wages, namely:

$$\frac{da_t^f}{d\mu_t^x} = \frac{\partial \underline{m}(a_t^f(v))}{\partial a_t^{LD}(g = 1)} \times \frac{\partial a_t^{LD}(g = 1)}{\partial \mu_t^x} < 0. \tag{B2}$$

That is, observed female median wages will increase due to an even stronger positive selection of women into employment when productivity goes down, since those at the bottom of the wage distribution are the ones losing their jobs.

30 Note that the converse argument could be used to model the effects of a rise in early retirement. Because older male workers have longer experience and this typically leads to higher wages, early retirement would imply stronger negative selection, $\Delta b_t^m < 0$.

However, if the LS constraint is the binding one, $a_i^{LS}(g = 1; v) > a_i^{LD}(g = 1)$, then:

$$\frac{\frac{da_i^f}{d\mu_i^f} = \partial m(a_i^f(v))}{\partial a_i^{LS}(g = 1; v) \times \frac{\partial a_i^{LS}(g=1;v)}{\partial \mu_i^f}} > 0. \quad (B3)$$

Hence, insofar as the downturn has generated an AWE among previous female non-participants in the less-skilled segment of the labour market, this would translate into a reduction in the reservation wage, $\Delta\mu_i^f < 0$. This results in a reduction of the observed female wage due to a less positive selection, $\Delta b_i^f < 0$, since less-skilled women entering the labour market would get jobs.

APPENDIX C: DERIVING HOURLY WAGES

The main challenge in deriving hourly wages is to combine annual income (PY010) and monthly economic status information (PL210A-PL210L up to 2009 and PL211A-PL211L onwards) for the previous calendar year with the number of hours usually worked per week (PL060) at the date of the interview.

To do this, we combine the longitudinal files from the period 2005–17 and use the imputed annual hours of work

$$hours_{annual} = months_{annual} \times 4.345 \times hours_{week}$$

to compute hourly wages. The following sequential set of rules are used to impute missing annual hours of work during the previous calendar year:

1. For those workers who have only one employment spell (with no changes in full-time/part-time status), we use the number of months of this spell and the number of hours from the previous survey.
2. For those workers who have only one employment spell (with no changes in full-time/part-time status), we use the number of months of this spell and the number of hours declared at the date of the interview if the person has not changed job since last year (PL160).

In the case of the United Kingdom, we only use the number of hours at the date of the interview since the income reference period coincides with the year of the interview.

3. For those workers who have only one employment spell (with no changes in full-time/part-time status), we use the number of months of this spell and approximate the number of hours by the year-gender-full-time/part-time status-specific mean.
4. For those workers who have multiple employment spells, we use the number of months of each spell and the number of hours for each spell approximated by the year-gender-full-time/part-time status-specific mean.

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