The Changing Nature of Gender Selection into Employment over the Great Recession *

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Abstract

The Great Recession has strongly influenced employment patterns across skill and gender groups in EU countries. We analyze how the resulting changes in non-employment by gender during the slump have affected male and female selection patterns into EU labour markets. Male selection (traditionally disregarded) has become positive, particularly in Southern Europe. Female section (traditionally positive) exhibits two different patterns. Following an increase in labour force participation of less-skilled women, due to an *added-worker effect*, it becomes less positive in those countries where new female entrants found jobs¿ Conversely, it increases in those other countries where female employment went down. Finally, we document that most of these changes are reversed during the subsequent recovery period, confirming their cyclical nature.

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1 Introduction

While there has been extensive discussion in the academic literature and the media about the effects of the Great Recession on household income inequality, its impact on gender wage inequality remains less explored.[1] This is somewhat surprising since industries which differ markedly in their relative use of male and female labour have experienced quite unequal fluctuations in employment and labour-force participation, both of which could affect male and female wages in different ways through their effects on the workforce composition. In particular, this has been the case in some of the European Union (EU) economies where the last recession has been longer and more severe than in the US and other high-income countries.[2] Thus, the EU provides an interesting laboratory where to analyze 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 and labour supply, like those taking place during the Great Recession.

A number of recent reports, most notably OECD (2014), have documented that *raw* gender wage gaps (i.e. those based on reported wages by employees which have not been adjusted for characteristics; termed in short *RG* hereafter) have narrowed in most EU countries during the Great Recession.[3] There are several explanations for this finding. For example, a decreasing RG could be the outcome of women being over-represented in the public sector (where gender gaps are generally lower) and under-represented in industries subject to much higher job destruction, where men tend to earn well. Likewise, it could be argued that the intensive use of early retirement policies in some EU countries – to alleviate social pressure against collective dismissals during the slump – could have decreased RG, since men are a majority among elderly workers with long professional careers and higher wages. However, a drawback of these potential rationalizations is that they lack a systematic analysis of how changes in observed RG relate to relevant shifts in patterns of non-random selection by gender, as those caused by intense and prolonged business cycle fluctuations.

In effect, when comparing wages across two groups, non-random selection into employment can imply that measured RG differ considerably from the gaps that one would obtain if the two populations had experienced the same employment fluctua-

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

[2] This is so since the Great Recession in most of the EU not only covers the global financial crisis in 2008-09, 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.

tions. The observed RG can be larger or smaller than the *potential* wage gap (termed *PG* in the sequel), depending on the sign of selection. The literature usually assumes no selection of the majority group (white, natives, men, etc.) and considers both positive and negative selection of the minority. As a result, a large body of literature on this topic has documented that accounting for selection is key to obtain a corrected measure of RG that better reflects PG.[4]

Indeed our focus on selection issues is dictated by existing evidence about its key role in explaining EU cross-country differences in RG before the last recession. Indeed, Olivetti and Petrongolo (2008) argue that, from the mid 1990s to the early 2000s, PG in Southern Mediterranean countries (*Southern EU*, hereafter), based on imputed wage distributions for the working age population, were considerably higher than RG, based on reported wages for employees. In contrast, both gaps were fairly similar in other EU countries (*Rest of EU*, henceforth) and the US. The historically low female labour-force participation (LFP) rate in Southern EU is often related to positive selection among participating women, since those who work often have relatively high-wage characteristics. This is, however, not the case in other EU countries and the US where selection is considered irrelevant because male and male LFP rates are uniformly high. Accordingly, in the absence of selection-bias corrections, Olivetti and Petrongolo (2008) convincingly conclude that, while measured RG in Southern EU appear as being much lower than in the Rest of EU, PG would be higher once selection corrections are implemented.

In view of these considerations, the aim of this paper is to explore whether the above diagnosis on gender sorting before the slump could have changed as a result of the Great Recession, and to explore whether 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.

Specifically, against the previous assessment, we conjecture that male selection during the Great Recession has become more important than prior to it, 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.[5] The main insight for the emergence of positive male selection is that, following massive job destruction in sectors intensive in

[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).

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

low-skilled male workers (e.g., in the construction sector in some EU economies), the distribution of observed male wages has become a censored version of the imputed distribution. As for female selection, two contrasting effects are at play. First, it is likely that the existence of a so-called "added-worker" effect 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. 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 welfare states.[6] If new female entrants from the bottom of the skill distribution succed in finding jobs, this would imply that male and female selection would move in different directions, with important implications for gender gaps. Second, in those countries where, despite the rise in female LFP, labour demand for both male and female for less-skilled workers has experienced large adverse shifts, the slump would not only push male selection upwards but also female selection. 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, women's employment patterns have been subject to both supply and demand forces, 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 labour demand, one shoud observe a reveseral of the changing patterns in selection once the recovery started, a feature on which we also provide evidence.

Two empirical strategies are used to correct for non-random selection in measuring gender wage gaps 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 distribution below

[6] 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 labor 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 stylised fact for this set of countries.

the reservation wage.[7] 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 provide results based on Arellano and Bonhomme's (2017) estimation procedure of quantile wage regressions by gender subject to selectivity corrections. Note that, besides being amenable 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.

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 a 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 has led female selection to become less positive than 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 even more positive.

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 analyzes the determinants of secular trends in gender wage gaps, our paper complements this approach by focusing on their behaviour at particularly relevant business cycle phases, such as the Great Recession and the following recovery.

The issue of how hourly real wages vary over the business cycle, taking into account differences between observed and unobserved characteristics of male workers moving in and out of the labor force during downturns and upturns has been studied by Keane et al. (1988) for the US using the standard Heckman (1979)'s techniques to correct for self-selection.[8] We differ from this forerunner in several respects. First,

[7]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.

[8]See also Bowlus (1995) and Gayle and Golan (2012) for further examples in the gender-gap litera-

we focus on gender wage gaps instead of exclusively on male wages. Second, our evidence refers to a cross-country comparison of RG in EU countries, where gender gaps have been subject to much less research than in the US (see e.g., Blau et al., 2013). Third, we provide new channels on how the Great Recession in particular and business cycles in general affect selection by gender. Lastly, while these authors apply the conventional Heckit approach, we make use of 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 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 procedures. Section 6 interprets the main empirical findings of the paper in the light of the hypotheses outlined in Section 2. Finally, Section 7 concludes. An Appendix provides further details on the model (parts A and B) and on the construction of hourly wages, while an Online Appendix reports 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*:

$$w_{it} = \mu_t^w + g_i\gamma_t + \varepsilon_{it} \tag{1}$$

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

ture accounting for the dynamics of employment selection over the cycle.

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.[9]

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:

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

where one would $PG_t > 0$ (i.e., $\gamma_t < 0$) on historical grounds (see 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, namely:[10]

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

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 employed ones. As discussed above, Olivetti and Petrongolo (2008) argue that: (i) the inequality $b_t^m < b_t^f$ held 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 US, implying that $RG_t \simeq PG_t$.

Using (3), the change (Δ) in the observed RG 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 (4)

[9]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).

[10]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.

capture in turn the changes in the selection biases of males and females, respectively, which constitute the main focus of this paper.[11]

Traditionally, this setup has been used to predict which females are employed using a potential market wage equation determining w_{it}, as in (1), plus an additional equation determining the reservation wage, r_{it},such that individuals 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 (5) for convenience):

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

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

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

such that μ_t^x in (6) represents (an index of) the determinants of the average productivity of a worker, μ_t^r in (7) captures the determinants of female reservation wage (notice that the male reservation wage is normalized to zero in (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, we assume for simplicity that,

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

with $\rho > 0$. Thus, a productivity shock of size $(1 + \rho)\varepsilon_{it}$ translates into a lower change of size ε_{it} in the wage, reflecting some wage rigidity.[12] 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 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, $\overline{v}$, with probability $p \in (0, 1)$ and a low one, $\underline{v}$, with probability $1 - p$. This

[11]Note that, had we allowed for changes in the variance in the error term ε_{it}, an additional term would appear in (4), namely $(b_t^m - b_t^f)\Delta\sigma_t^\varepsilon$, where σ_t^ε 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 US (see 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 2004-2012, with the possible exceptions of Greece and Portugal.

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

simplified two-mass distribution captures the lower LFP rate of less-skilled women by assuming that $\overline{v} > \underline{v}$.

Accordingly, individual i works at time t if her/his reservation wage is higher than her/his potential market wage (labour supply condition), i.e. $w_{it} > r_{it}$, and if her/his productivity is greater than the wage, leaving a positive surplus for the firm (labour demand condition), i.e. $x_{it} - w_{it} > 0$. As a result, there are labour supply (LS) and labour demand (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 implies 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 is below their expected productivity (μ_t^x), implying they would like to participate but firms do not create new female jobs and would even terminate existing ones ; and (ii) wages are more rigid, i.e. ρ is large. Conversely, when female productivity is high, their reservation wage is low and wages are more flexible, the LS constraint becomes the binding one ($a_t^{LD} < a_t^{LS}$) . 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 will be 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 is 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_t^x and μ_t^r. 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, added- worker effects. The main findings here are as follows:

(i) male and female median wages increase when μ_t^x falls (e.g. in a recession), leading to increasing positive selection as low-productivity (low-wage) workers are the ones more likely to lose their jobs during a downturn (i.e. $\Delta b_t^m > 0$ and $\Delta b_t^f > 0$ in expression (4) above), and

(ii) female median wages decrease when μ_t^r falls since e.g. less-skilled married women who were not participating in upturns are the ones who will start searching for jobs during slumps as their reservation wages fall when their less-skilled partners become unemployed (i.e. $\Delta b_t^f < 0$ in (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 hold 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 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 occurred both in *male* labour-intensive industries and, in some countries, among *female* workers 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 added-worker effect implies that new less-skilled female entrants in the labour market will be successful in finding jobs; by contrast, when LD is the binding constraint, the increase in less-skilled female LFP does not translate into new jobs, and those who were already working may even 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 rate 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 ($\Delta b_t^m > 0$) 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, it then 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 (4), $\Delta RG_t < \Delta PG_t$.

- **Hypothesis II**: *Added-worker effect and creation/destruction of female less-skilled jobs*.
  - **Hypothesis II$_{fe}$.** When less-skilled female LFP increases and LS is the binding constraint for this type of women (as in the added-worker effect), they will enjoy job gains, i.e. $\Delta E_t^{fu} > 0$. Thus, female selection becomes *less* positive ($\Delta b_t^f < 0$). 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 (4), $\Delta RG_t \gg \Delta PG_t$..
  - **Hypothesis II$_{fu}$.** When less-skilled female LFP increases and LD is the binding constraint for thus type of women, they will experience job losses, i.e. $\Delta E_t^{fu} < 0$. Thus, female selection becomes even *more* positive ($\Delta b_t^f > 0$). 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$_m$ is a joint hypothesis that combines male job destruction in both instances with either female employment gains (fe) or higher female unemployment (fu) in response to an increase in female less-skilled LFP. 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 potential gender gaps. Second, the relative evolution of the RG and PG during the crisis is highly contextualised, depending on both the differential labour demand responses for men and women and their (endogenous) labour supply decisions.

3 Data

In order to measure both RG and PG, we use the European Statistics on Income and Living Conditions (EU-SILC) data set.[13] This is an unbalanced household-based

[13]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

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 2007-2012, where 2007 captures the pre-crisis situation. However, data for a longer period (2012-2016) will be used to check how our main theoretical implications change once the recovery 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, UK, and Norway. Within the latter, in some instances we will distinguish among three blocks: *Continental* EU (Austria, Belgium, France, and The Netherlands), *Nordic* (Denmark, Finland and Norway), and *Anglosaxon* (Ireland and the UK).[14]

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.[15] To derive hourly wages, we follow a similar methodology to Engel and Schaffner (2012). A detailed account of this procedure is provided in the Appendix C.

The educational attainment categories (no college and college) correspond to ISCED 0-4 and 5-7, respectively. Descriptive statistics are reported in the Online Appendix A. Finally, throughout our empirical analysis, observations are weighted using population weights when available.[16]

Before proceeding to the results, let us consider gender differences in the LFP and employment responses to the recession. As shown in Figure 1a–where changes in female LFP rates (in pp., vertical axis) during the crisis are plotted against changes in male LFP rates (in pp., horizontal axis)–, most EU countries (Finland is the exception)

gender gap across the wage distribution in a number of countries.

[14]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 estates as EU countries,

[15]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 UK (where the income reference period is the current year) and Ireland (where the income reference period is the 12 months preceding the interview).

[16]Specifically, we use personal base weights, PB050. For Denmark, Finland, Sweden and The Netherlands, income data is 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.

Figure 1: Labour market attachment by gender, 2007-2012.

(a) LFP changes by gender

(b) Employment changes by gender

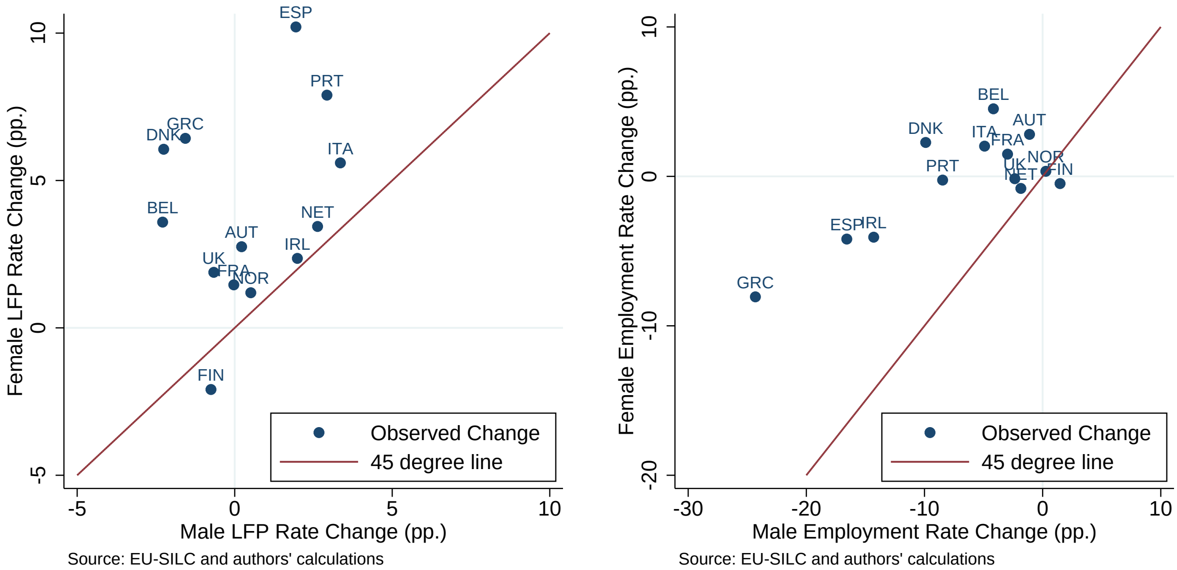


exhibit a much larger rise in female LFP than men's since 2007 (i.e., at the beginning of the recession) . Yet, as stressed earlier, higher LFP by women may not necessarily translate into female employment gains during a recession. According to Figure 1b– where changes in female employment rates (in 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.[17] 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^o line), capturing large job destruction in male-intensive industries. However, even within Southern EU countries, there are 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 exhibit much fewer male and female job losses (with the exception of Denmark and Ireland, which also experienced the bursting of housing bubbles).

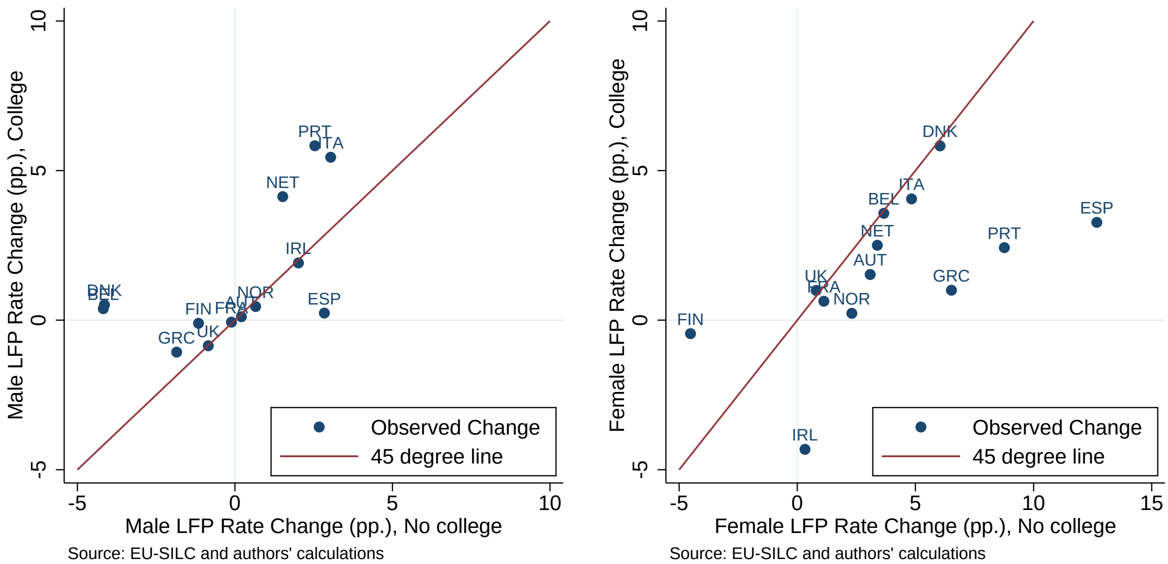
When LFP and employment changes are analyzed by workers' educational attainment (for males in Figure 2a and 3a and for females in Figure 2b and 3b), it becomes clear that the fall in employment among less-educated (no-college) male workers has been much more pronounced. This has been particularly the 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. Likewise, regarding participation, it can be seen that most of the gains in LFP in Southern EU countries are due to married females with

[17]Employment rates are defined as the ratios between employment and the labour force.

lower educational attainments, in line with the added-worker hypothesis. Overall, we take this preliminary evidence as providing considerable support to the mechanism underlying Hypotheses II in Section 2.2.

Figure 2: Cross-country changes in LFP by gender and skill, 2007-2012.

(a) Males (b) Females



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

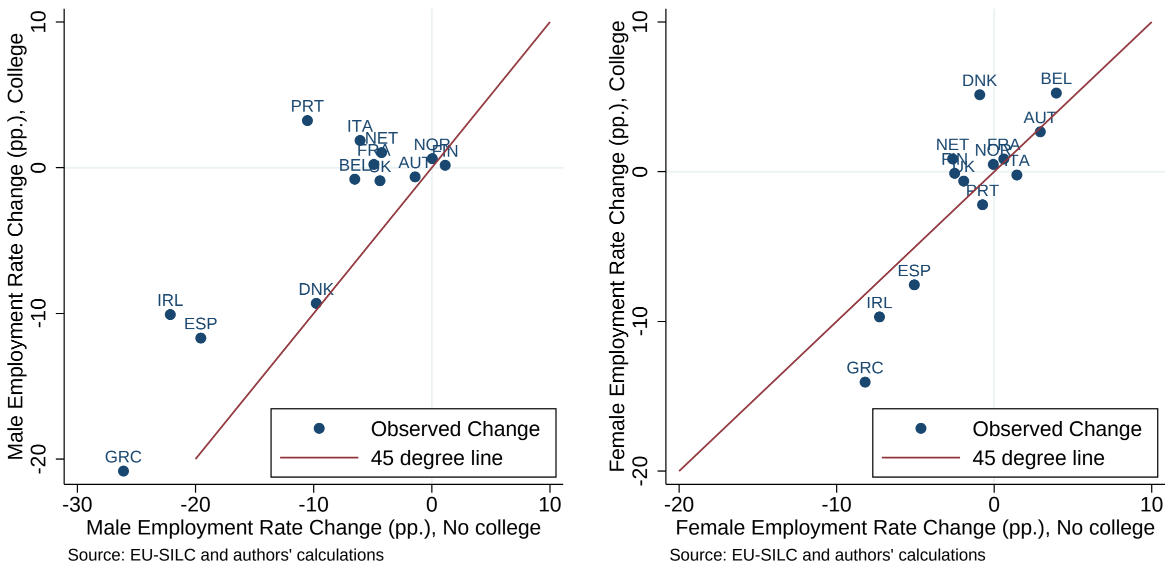
4.1 Imputation around the median

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, $L_{it} = 0$.[18] The main insight behind

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

Figure 3: Cross-country changes in employment rates by gender and skill, 2007-2012.

(a) Males (b) Females



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.[19]

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 for X_i below which non-employed workers would earn wages below the gender-specific median, and another threshold 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.[20] In addition, to take

[19]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).

[20]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

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 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 of missing wages follow an educated guess, two procedures are used 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 regard the median of imputed wages using information of the aforementioned demographics corresponds to the actual one when the wage is 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.[21] Consequently, we relegate its results to the Online Appendix.

in Table A4 in the Appendix.

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

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 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 workers (i.e., those in the lower part of the wage distribution), it is natural to implement selection corrections in a *quantile* regression framework. If our interpretation is correct, the insight 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 added-worker effect) 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; AB hereafter).

In AB's (2017) quantile model, sample selection is modeled 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 ($g = m, f$), labeled as w^{*g}, and their decision to accept a job:

$$\begin{aligned} w^{*g} &= X^{g'}\beta^{g}(U), && (8)\\ D^{g} &= \mathbf{1}\{V \leq p(Z^{g})\}, && (9)\\ w^{g} &= w^{*g} \text{ if } D^{g} = 1, && (10) \end{aligned}$$

where $\beta^{g}(U)$ in (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, (9) represents the selection equation where $\mathbf{1}\{\cdot\}$ is an indicator function, while $Z^{g} = (X^{g}, B^{g})$, 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 Z^{g} given X^{g}, denoting the c.d.f. of

(U, V) as $C(u, v)$, and finally defining $p(Z^g) = \Pr(D^g = 1|\ Z^g) > 0$, 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 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

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

where $a^+ = \max(a, 0)$, $a^- = \max(-a, 0)$, and $G_{\tau Z^g} = G(\tau, F^{-1}(z^{g\prime}\gamma^g); \rho^g)$ denotes the rank of $X^{g'}\beta^g(\tau)$ in the selected sample $D^g = 1$, conditional on $Z^g = z^g$. Since the above optimization problem is a linear program, given γ^g and ρ^g, the parameters $\beta^g(\tau)$ can be estimated in a τ-by-τ fashion by solving linear programs, just like with the conventional check function in standard quantile regressions (see 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 (9) (e.g., via a probit model) and estimation by means of a grid-search 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 wages from other waves can be found in the Online Appendix.

5.1 Imputation around the median wage

Table 1 presents 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: Median Wage Gaps under Imputation on Education and Experience 2007-2012

	Levels in 2007						Changes over 2007-2012					
	Raw Wage Gap	Potential Wage Gap	Selection Bias M	Selection Bias F	Employment Rate M	Employment Rate F	Raw Wage Gap	Potential Wage Gap	Selection Bias M	Selection Bias F	Employment Rate M	Employment Rate F
Greece	.182	.445	.025	.288	.853	.542	-.089	-.067	.059***	.081***	-.257	-.118
Italy	.035	.277	.034	.276	.849	.558	.051	.024	.010*	-.017*	-.041	.000
Portugal	.172	.223	.036	.087	.838	.708	-.059	-.105	.024**	-.021**	-.131	-.002
Spain	.131	.248	.017	.134	.881	.674	-.020	.002	.066***	.088***	-.161	-.084
Southern	**.130**	**.298**	**.028**	**.196**	**.855**	**.621**	**-.030**	**-.037**	**.040**	**.033**	**-.147**	**-.051**
Austria	.189	.300	.012	.124	.881	.711	.015	-.007	-.007	-.029**	.001	.013
Belgium	.074	.142	.022	.090	.866	.742	-.019	-.060	.003	-.038**	-.034	.031
France	.114	.161	.008	.055	.917	.816	.005	-.019	.010*	-.014*	-.039	-.004
Netherlands	.158	.199	.004	.044	.933	.802	-.048	-.038	-.001	.009	-.033	.001
Continental	**.133**	**.201**	**.011**	**.079**	**.899**	**.768**	**-.012**	**-.031**	**.001**	**-.018**	**-.026**	**.010**
Ireland	.170	.303	.020	.153	.851	.668	-.039	-.069	.003	-.026**	-.142	-.074
UK	.247	.301	.011	.065	.942	.806	-.064	-.045	.009	.028**	-.036	-.023
Anglosaxon	**.208**	**.302**	**.015**	**.109**	**.896**	**.737**	**-.052**	**-.057**	**.006**	**.001**	**-.089**	**-.048**
Denmark	.116	.126	-.002	.009	.985	.941	-.036	-.048	-.012*	-.023**	-.080	-.064
Finland	.203	.221	.016	.035	.897	.864	-.049	-.086	.015*	-.022**	-.032	-.049
Norway	.154	.161	.006	.013	.975	.913	.020	.003	-.006	-.023**	-.005	.013
Nordic	**.158**	**.170**	**.007**	**.019**	**.952**	**.906**	**-.022**	**-.044**	**-.001**	**-.023**	**-.039**	**-.033**

Source: EU-SILC and authors' calculations. Note: Selection bias = an increase in observed wage due to selection. Wage imputation rule: Impute wage $<$ median when non-employed and education $\leq$ upper secondary and experience $<$ 15 years; impute wage $>$ median when non-employed and education $\geq$ higher education and experience $\geq$ 15 years. All raw and potential wage gaps are significant at the 1% level. *, **, *** denotes statistical significance at 10, 5 and 1 percent levels.

Table 1 presents the results for the four Southern EU and the nine Rest of EU countries split into three blocks defined above (Anglosaxon, Continental EU and Nordic). In the left panel we report the RG and PG in levels (log. points), as well as the selection biases and employment rates by gender in 2007 (at the onset of the Great Recession).[22] 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 statistical significance of changes in selection biases.[23] To help

[22] 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.

[23] 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, an dummy for latent wages, a year=2012 dummy and an interaction of the two. The t-ratio on the latter coefficient tests for the null of no changes in selection biases. The same procedure is applied in Table 2 below to test for a similar null hypothesis between 2012 and 2016.

Table 2: Median Wage Gaps under Imputation on Education and Experience 2012-2016

	Changes over 2012-2016					
	Raw Wage Gap	Potential Wage Gap	Selection Bias		Employment Rate	
			M	F	M	F
Greece	-.030	-.130	-.026**	-.126***	.061	.046
Italy	-.028	.063	.000	.091***	-.008	-.012
Portugal	.000	.027	-.050***	-.023**	.108	.029
Spain	-.047	-.078	-.040***	-.072***	.056	.064
Southern	**-.026**	**-.029**	**-.029**	**-.032**	**.054**	**.032**
Austria	-.004	-.026	-.005	-.027**	-.013	.044
Belgium	.017	.028	-.012*	-.001	.011	.008
France	-.006	.007	-.003	.010*	.000	-.006
Netherlands	.073	.051	.001	-.021**	-.023	.028
Continental	**.020**	**.015**	**-.005**	**-.010**	**-.006**	**.018**
Ireland	-.054	-.117	.021**	-.042***	.073	.052
UK	-.005	-.024	-.008	-.027**	.062	.007
Anglosaxon	**-.030**	**-.071**	**.007**	**-.034**	**.068**	**.030**
Denmark	.026	.017	.029**	.019*	-.038	.016
Finland	-.021	-.015	-.011*	-.004	-.006	-.002
Norway	-.013	-.013	.002	.002	-.005	-.002
Nordic	**-.003**	**-.004**	**.007**	**.006**	**-.016**	**.004**

Source: EU-SILC and authors' calculations. Note: Selection bias = an increase in observed wage due to selection. Wage imputation rule: Impute wage $<$ median when non-employed and education $\leq$ upper secondary and experience $<$ 15 years; impute wage $>$ median when non-employed and education $\geq$ higher education and experience $\geq$ 15 years. *, **, *** denotes statistical significance at 10, 5 and 1 percent levels.

interpret 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. $\Delta PG_t = \Delta RG_t + \Delta b_t^f - \Delta b_t^m$.

In agreement with the conclusions of Olivetti and Petrongolo (2008), the left panel of Table 1 shows that, prior to the recession, Southern EU countries exhibited on average lower RG (13 pp.), higher PG (30 pp.), and higher gender employment gaps in favour of men than the Rest of EU countries. With regard to RG, only the Continental EU countries exhibit a similar gap while, in relation to PG, only the Anglosaxon countries fare similarly. As a result, the most salient findings are that; (i) the difference *PG-RG* is much higher (17 pp.) in the South than in the Rest of the EU (5 pp. on average), and (ii) the female selection bias is also highest the South (19.6 pp.), broadly explaining the previous difference of 17 pp. between PG and RG. Notice that male biases are also higher in the Southern EU countries (2.8 pp.) than elsewhere (on average 1.1 pp.), a finding which agrees with the lower aggregate employment rates in those countries.

Furthermore, in line with the available evidence in OECD (2014), we find that the Great Recession led to a reduction in RG (right panel of Table 1). However, our findings indicate that the slump also involved considerable changes in selection, which triggered an even larger drop in PG. Two findings are noteworthy in this respect. The first one is that the male selection bias has become more positive in most countries, particularly in Southern EU.[24] The second finding is that, while female selection has gone down, especially in Continental EU and Nordic countries, it has increased on average by 3.3 pp. in Southern EU. However, the patterns in the South differ in interesting ways. On the one hand, in line with the Rest of EU, female selection biases experience substantial reductions in Portugal (-2.1 pp.) and to a lesser extent in Italy (-1.7 pp.), the only two countries in the South where female employment rates fared well. On the other hand, female employment rates have plummeted in Greece and Spain (by -11.8 pp and -8.4 pp., respectively) leading to growing (more positive) female selection biases (above 8 pp). Another country where female selection bias has gone up is the UK (2.8 pp.), due to its drop in employment being largely driven by the dismissals of young, and hence below-median workers.[25]

Table 2 presents changes of the variables reported in Table 1 during the recovery period (2012-2016). 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. As can be observed, RG and PG decrease in general (except in the Continental EU block where they go up) but by less than over the recession period. The most salient finding, however, is that the increasing male selection during the slump, now goes down, particularly in the Southern EU and Anglosaxon countries. This is explained by a higher demand for less-skilled male labour once economies recovered. Likewise, the female selection bias declines in those countries where it had grown during the crisis, fuelled by higher demand for less-skilled female labour during the recovery. A noticeable exception, however, is Portugal, where female selection declined both during the crisis and most of the recovery. This indicates that the higher demand for less-skilled women remained strong after the slump (see further below), whereas

[24] There are a few exceptions (Nordic countries and The Netherlands) where male selection does not increase. Yet, the changes are very small and stastistically non-significant and 10% level.

[25] Male employment changes in the UK over the recession have been characterised 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 negligeable change in male selection and an increase in female selection.

Figure 4: Selection bias and employment rates by gender, Portugal, 2007-2012.

(a) Selection Bias

(b) Employment Rate

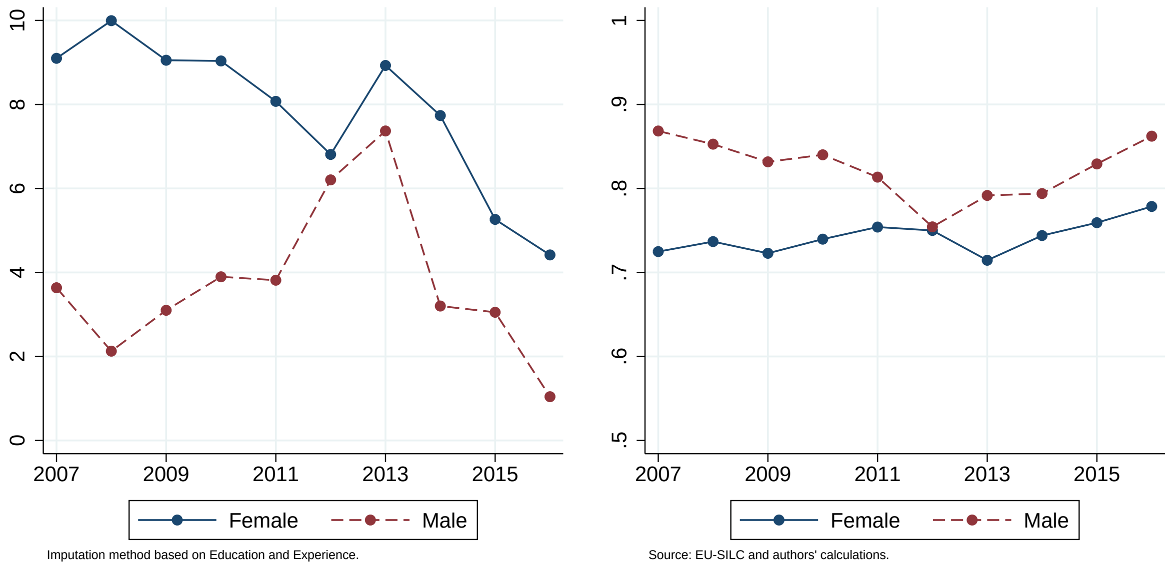
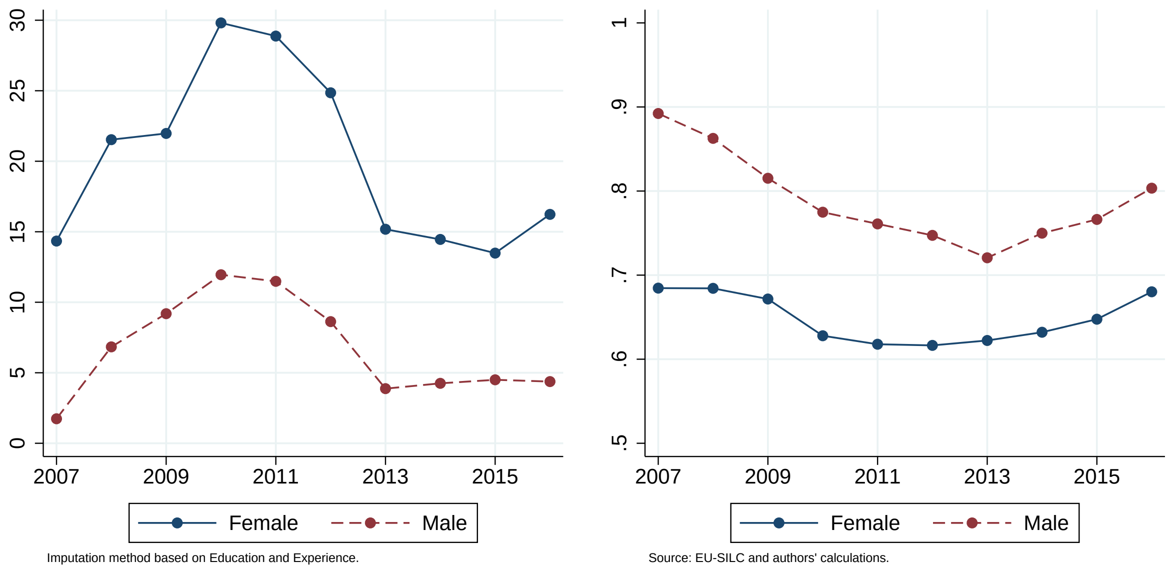


Figure 5: Selection bias and employment rates by gender, Spain, 2007-2012.

(a) Selection Bias

(b) Employment Rate



in other countries a parallel rise in the demand for high-skilled women took place. Notwithstanding, we take the reversed signs of selection biases from the downturn to the upturn as supportive evidence of their business-cycle nature.

To provide a graphical illustration of how the LS and LD constraints operate in practice, 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 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) surge in both countries during the crisis (i.e. the LD constraint binds for men). Yet, while female selection declines in Portugal (the LS constraint binds for women), it goes up in Spain (the LD constraint is the binding one). These different patterns are related to the fact that both female and male employment rates collapsed in Spain, while only male employment declined in Portugal. The worse performance of the Spanish labour market can be attributed to its lower wage flexibility prior to the wage-setting reform in 2012, as well as to a much higher rate of female temporary jobs before the recession, most of which were massively destroyed once the crisis hit (see Dolado, 2016). These patterns changed as the recovery started. Male biases declined in Spain and Portugal as male employment picked up (the LD constraint was less binding). Female selection biases drastically decreased in Spain (the LD constraint becomes weaker as well) and went temporarily up in Portugal to later decline by a larger amount than what it did during the downturn. The initial hike in female selection in the latter country could be due to larger hiring of more educated women at the beginning of the recovery which afterwards was more than offset by a much higher demand for less-skilled women as a result of the boom in tourism (also in Spain) following political instability in competing destination countries.

Table 3: Rate and Goodness of Imputation on Education and Experience

	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	.42	.69	.88	.88	.84	.85	.37	.57	.78	.78	.80	.79	.38	.54	.85	.70	.80	.83
Italy	.53	.73	.82	.72	.70	.69	.52	.71	.82	.76	.73	.73	.62	.72	.78	.77	.71	.74
Portugal	.38	.55	.59	.61	.71	.76	.44	.43	.63	.53	.65	.77	.34	.46	.73	.51	.81	.86
Spain	.39	.63	.66	.70	.75	.79	.54	.65	.72	.65	.73	.77	.39	.61	.46	.73	.76	.75
Southern	**.43**	**.65**	**.74**	**.73**	**.75**	**.77**	**.47**	**.59**	**.74**	**.68**	**.73**	**.76**	**.43**	**.58**	**.70**	**.68**	**.77**	**.79**
Austria	.32	.51	.85	.76	.76	.81	.32	.48	.77	.70	.83	.80	.42	.55	.73	.84	.81	.81
Belgium	.42	.56	.86	.84	.80	.80	.50	.60	.84	.77	.78	.82	.54	.65	.81	.85	.83	.83
France	.42	.58	.83	.77	.80	.79	.46	.61	.76	.72	.81	.80	.52	.61	.75	.74	.80	.78
Netherlands	.34	.58	.77	.83	.81	.75	.46	.58	.80	.76	.81	.79	.42	.52	.49	.62	.87	.82
Continental	**.38**	**.56**	**.83**	**.80**	**.79**	**.79**	**.43**	**.57**	**.79**	**.74**	**.81**	**.80**	**.47**	**.58**	**.70**	**.76**	**.83**	**.81**
Ireland	.37	.53	.85	.80	.83	.81	.39	.45	.70	.68	.73	.76	.46	.46	.57	.65	.73	.75
UK	.40	.51	.54	.70	.75	.74	.42	.55	.89	.75	.75	.71	.59	.55	.81	.64	.75	.74
Anglosaxon	**.39**	**.52**	**.69**	**.75**	**.79**	**.77**	**.41**	**.50**	**.80**	**.71**	**.74**	**.73**	**.52**	**.51**	**.69**	**.64**	**.74**	**.74**
Denmark	.23	.46	.55	.82	.67	.76	.37	.28	.09	.64	.69	.68	.41	.41	.78	.85	.78	.80
Finland	.60	.41	.80	.73	.75	.78	.53	.45	.67	.60	.76	.75	.50	.45	.84	.53	.74	.72
Norway	.37	.38	.66	.70	.75	.79	.35	.41	.72	.65	.73	.77	.39	.45	.46	.73	.76	.75
Nordic	**.40**	**.42**	**.67**	**.75**	**.73**	**.78**	**.42**	**.38**	**.49**	**.63**	**.72**	**.73**	**.43**	**.44**	**.70**	**.70**	**.76**	**.76**

Source: EU-SILC and authors' calculations. Note: Wage imputation rule: Impute wage $<$ median when non-employed and education $\leq$ upper secondary and experience $<$ 15 years; impute wage $>$ median when non-employed and education $\geq$ higher education and experience $\geq$ 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.

Finally, a brief comment is due on the reliability of the results using the imputation on EE rule. Table 3 reports results on our two 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.[26]

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 2007-2012. 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 year effects. As for B^g (determinants of participation that do not affect wages directly), we take the number of children in 6 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 (added-worker effect or AWE in short). Note that, if the latter effect holds, we would expect a positive effect of this variable on the probability of participating. Unfortunately, as discussed earlier in foonote 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 both. Thus, these countries are omitted in this sub-section.

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.

The main findings are as follows. First, the increase in male selection appears again as a relevant feature in most countries, being stronger at $\tau = 0.2$ following the much higher destruction rate of less-skilled male jobs during the recession. The exception is the Anglosaxon 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

[26] 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 4: Quantile Regression Estimates Corrected for Selection

Quantile	Changes in Selection Bias over 2007-2012					
	20		50		80	
	M	F	M	F	M	F
Greece	.178	.151	.068	.093	.088	.063
Italy	.009	-.004	.004	-.001	-.003	.001
Portugal	.031	-.021	.026	.005	.033	-.005
Spain	.113	.086	.082	.058	.050	.039
Southern	**.083**	**.053**	**.045**	**.039**	**.042**	**.025**
Austria	.018	.011	.000	.016	-.003	.035
Belgium	.007	-.034	.002	-.018	-.014	-.044
France	-.011	-.002	.003	-.007	.001	-.009
Continental	**.005**	**-.008**	**.002**	**-.003**	**-.005**	**-.006**
Ireland	.001	.048	.047	-.006	.035	-.038
UK	.036	.026	.032	.027	.037	-.002
Anglosaxon	**.019**	**.037**	**.040**	**.010**	**.036**	**-.020**

Source: EU-SILC and authors' calculations. Covariates in the Participation eqn. are described in the main text. Matlab code at: `https://drive.google.com/file/d/0B13ohL0_ULTDaDE2N0d1ZnEzZ1U/view`

lower-paid, workers in high-pay sectors, such as the banking and financial industries. Moreover, in line 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 reduction in male employment rates was much lower. Second, in contrast to the strong rise in Greece and Spain and to a lesser extent in the Anglosaxon block, female selection goes down in Portugal (particularly at $\tau = 0.2$) and in Belgium, yielding the same evidence as in Table 1.

Next, Table 5 reports the estimated copulas and correlations between the error terms between the wage and participation equations, corr (U, V). As can be observed, all copulas and correlations are negative over the Great Recession period and, in most instances, copulas turn out to be statistically significant. As discussed before, negative copulas imply positive selection which takes places both among men and women. The insight for why female selection remains negative , even if it experienced a sizeable reduction (like in Italy, Portugal, and some Nordic countries), is that it was very positive initially (in 2007) so that it still remains positive by the end of the recession (in 2012).

Table 5: Quantile Regression Estimates Corrected for Selection

	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
UK	-0.30**	-0.06	-0.05	-0.01
Anglosaxon	**-0.18**	**-0.24**	**-0.03**	**-0.04**

Source: EU-SILC and authors' calculations. Covariates in the Participation eqn. are described in the main text. *, **, *** denotes statistical significance at 10, 5 and 1 percent levels. Replication codes at: `https://drive.google.com/open?id=0B13ohL0_ULTDMVhBN0s1OXhldWc`.

Finally, though not reported for the sake of brevity, there we are two additional sets of results which are worth discussing. First, we have also 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 2007. This agrees with the increase of male selection during the recession period and its 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 UK, female copulas are more negative in 2012 than in 2007, and 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 non-significant in most countries. By contrast, the corresponding coefficient for women is positive and highly significant, particularly in Southern countries and Ireland, meaning that male job losses trigger higher female LFP. In line with the evidence presented by Bredtmann et al. (2018), this is seemingly consistent with the conjectured added-worker effect for less-educated married women. Hence, 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 our findings fit 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 is that neither the male (Hypothesis $\mathbf{I_m}$) nor the female version (Hypothesis $\mathbf{I_f}$) of Hypothesis I (destruction of less-skilled jobs) hold *per se* for any country in our sample. This is because our evidence points to sizeable changes in both male and female selection simultaneously, perhaps with the exception of Norway. Hence, one can infer that the estimated selection biases and the observed employment changes in EU countries should be rationalized by a combination of the hypotheses listed in Section 2.2.

Within Southern EU, the patterns for Italy and Portugal conform neatly to the implications of the combined Hypotheses II_{fe}+I_m (added-worker effect with large male employment losses and female employment gains or small losses), which jointly leads 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 explained by the combined Hypotheses $\mathrm{II}_{\mathbf{fu}}$+$\mathrm{I}_{\mathbf{m}}$, with a collapse in both male and female (unskilled) employment rates (despite higher female LFP) and a simultaneous rise in selection biases for both genders. Since our evidence points out to a larger increase in the female bias, this would lead to $\Delta PG > \Delta RG$ 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 plus Norway represent in general nice illustrations of Hypothesis II_{fe} on its own (a significant decline in female selection and stability of or a mild increase in male selection, together with female employment gains and small employment losses or even gains by men). Likewise, the substantial drop in male unskilled employment and in the female selection biases in Finland seem better explained by $\mathrm{I}_{\mathbf{m}}$+$\mathrm{II}_{\mathbf{fe}}$. On the other hand, the findings for the Anglosaxon block are ambiguous. While the Irish

Table 6: Summary of Findings over the Great Recession

	Consistent Hypotheses			
	I_m	I_f	II_{fe}	II_{fu}
Southern				
Greece	✓			✓
Italy	✓		✓	
Portugal	✓		✓	
Spain	✓			✓
Continental				
Austria			✓	
Belgium			✓	
France	✓		✓	
Netherlands	✓			
Anglosaxon				
Ireland	✓		✓	
United Kingdom	✓			✓
Nordic				
Finland	✓		✓	
Denmark	✓		✓	
Norway			✓	

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

pattern is akin to the one for Italy and Portugal, and so rationalized by the combined Hypotheses $\mathbf{I_m}$+$\mathbf{II_{fe}}$, the UK pattern is a milder version of the one found for Greece and Spain and thus Hypotheses $\mathbf{I_m}$+$\mathbf{II_{fu}}$ is a better choice.

Overall, the increase in male selection emerges as a robust finding in most countries, although it has been much more pronounced in Southern EU than in Rest of EU. As for women, depending on whether LD or LS shifts dominate, we find instances where these changes have led to a larger or smaller reduction in PG than in RG. There does not seem to clear patterns that can explain which effects dominates but rather 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 before the recession (e.g. in Portugal, with a female LFP rate close to those in Continental EU) or where crisis has been milder (Italy or some of the Continental EU countries), the female selection bias has declined. Conversely, the opposite has happened in those countries where female LFP was lower and had more dualized labour markets (Greece and Spain). The case of the UK stands out, since despite high female participation in 2007, the female bias has increased. As argued earlier, a possible explanation is the fact the unemployment hit particularly hard young women.

7 Conclusions

This paper analyzes if the conventional patterns of workers' self-selection into EU labour markets have changed as a result of the large shifts in labour demand and labour supply that took place during the Great Recession. Based on a large body of empirical evidence, it has been traditionally assumed that male selection biases were negiglible before the crisis due to high male LFP rates. By contrast, due to their lower LFP rates (particularly in southern Europe), women were favourably selected. Our working hypothesis is that, if the large job losses experienced during the crisis have mainly affected unskilled male-dominated sectors, then male selection may have become positive. Moreover, if non-participating women had increased their participation rates due to an added-worker effect, then female selection may have become less positive. However, the overall impact on the female bias is a priori ambiguous, since adverse female labour demand shifts during the recession could have offset the rise in female labour supply, in which case female selection changes would have been more muted or even become more positive.

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 support to an increase in male selection, which has become positive during the recession. This has been especially the case in the Southern EU economies, and to a lesser extent in France and Finland, where there have been considerable male job losses in response to the decline of low-productivity industries. With regard to female selection, our results are mixed we find that, in line with the added-worker effect, female selection has become less positive (particularly in the Continental EU and Nordic blocks, and in Italy and Portugal), in other instances (most notably Greece and Spain, but also the UK) it has become even more positive because widespread job destruction has also led to substantial reductions in female employment rates, either for low-education or low-experience workers.

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 PG in Spain barely changes (0.2 pp) during the Great Recession. Had we ignored male selection and only corrected for female selection, as is traditionally done, the measured PG would have *increased* by 6.6 pp. Hence, future work measuring gender gaps might require corrections for the two gender groups.

Given the cyclical nature of these changes in selection, we also provide evidence about how they have fared over the subsequent recovery period (2012-16). We find male selection goes down in most countries as most of those less-skilled workers who were laid off during the slump regain their jobs when employment growth picks up. For the same reason, we find that, in those countries where female selection went up over the crisis period, it goes down during the recovery. By contrast, in those countries where the female selection bias went down, it either goes up in a few instances (e.g. in Italy) , pointing out to a favourable effect of the recovery on the relative demand for high-skilled women, or more generally it continues falling but at a slower pace than during the slump. Overall, the decrease in female selection is likely to be long-lasting since increasing female LFP seems to be a persistent trend at both ends of skills distribution, in line with the job polarization phenomenon documented by Autor and Dorn (2013) for the US and Goos et al. (2009) for some EU countries.

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Appendix

A Derivation of LD and LS constraints

Given the wage, productivity and outside value equations in system (5) to (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, (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, so that men always participate and their LS constraint does not bind.

As regards women, likewise the labour supply (LS) condition, $w_{it} > r_{it}$ is satisfied if and only if ε_{it} exceeds the following two LS thresholds, depending on the value of v_{it}:

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

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

* LD CUT-OFF VALUES.

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

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

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. As for men, the previous assumption on their reservation wage implies that the LD threshold $a_t^{LD}(g_i = 0)$ is the only one that binds. By contrast, both LD and LS constraints may be binding for female workers. For example, as regards women with a high reservation-wage shock, the LD constraint would be binding if and only if: $a_t^{LS}(g_i = 1, v_{it} = \overline{v}) < a_t^{LD}(g_i = 1)$ or:

$$\frac{\mu_t^x - (\mu_t^w + \gamma_t)}{\overline{a}_t} < \rho. \tag{A4}$$

whereas for women with low reservation wage shock, the corresponding LD condition becomes:[27]

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

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 (A5) is small; (ii) the reservation wage is low relative to potential wage, i.e., when the denominators in (A5) $\underline{a}_t$ and $\overline{a}_t$ are high; (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 $\overline{a}_t$ 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.

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 (see 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 a closed-form solution:

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

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 selection bias, $b_t^m = m(\varepsilon_{it}|g_i = 0, L_{it} = 1) = \underline{m}(a_t^{LD}(g=0))$.

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

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

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

[27] Note that, since $\underline{a}_t < \overline{a}_t$, 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.

distribution increases, due to a stronger positive selection of males into employment, $\Delta b_t^m > 0$.[28] In other words, less-skilled male workers with lower wages will not show up in the observed wage distribution because they become unemployed, and so the median wage for men will rise.

* Female Participation

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

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

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

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

$$a_t^f(v) \equiv \begin{cases} a_t^{LS}(g=1;v) & : a_t^{LS}(g=1;v) > a_t^{LD}(g=1) \\ a_t^{LD}(g=1) & : a_t^{LS}(g=1;v) < a_t^{LD}(g=1) \end{cases}$$

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 $\underline{m}(\cdot)$ term, that is, $b_t^f = m(\varepsilon_{it}|g_i = f, L_{it} = 1) = \underline{m}(a_t^f(v))$. 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:

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

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.

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

$$\frac{dw_t^f}{d\mu_t^r} = \frac{\partial \underline{m}(a_t^f(v))}{\partial a_t^{LS}(g=1;v)} \times \frac{\partial a_t^{LS}(g=1;v)}{\partial \mu_t^r} > 0. \tag{B3}$$

Hence, insofar as the downturn has generated an added-worker effect among previous female non-participants in the less-skilled segment of the labour market,

[28]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, $\Delta b_t^m < 0$.

this would translate into a reduction in the reservation wage, $\Delta\mu_t^r < 0$. This results in a reduction of the observed female wage due to a less positive selection, $\Delta b_t^f < 0$, since less-skilled women enter the labour market and are able to find a job.

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 2005-2017 and use the imputed annual hours of work

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

to calculate hourly wages. The following set of rules are used sequentially 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 hasn't changed job since last year (PL160).

In the case of 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.