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

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Abstract

The aim of this paper is to evaluate the role played by selectivity issues induced by nonemployment in explaining gender wage gap patterns in the EU since the onset of the Great Recession. We show that male selection into the labour market, traditionally disregarded, has increased. This is particularly the case in peripheral EU countries, where dramatic drops in male unskilled jobs have taken place during the crisis. As regards female selection, traditionally positive, we document mixed findings. While it has declined in some countries, as a result of increasing female LFP due to an added-worker effect, it has become even more positive in other countries. This is due to adverse labour demand shifts in industries which are intensive in temporary work where women are over-represented. These adverse shifts may have more than offset the rise in unskilled female labour supply.

JEL code: J31.
Keywords: Sample selection, gender wage gaps, gender employment gaps.

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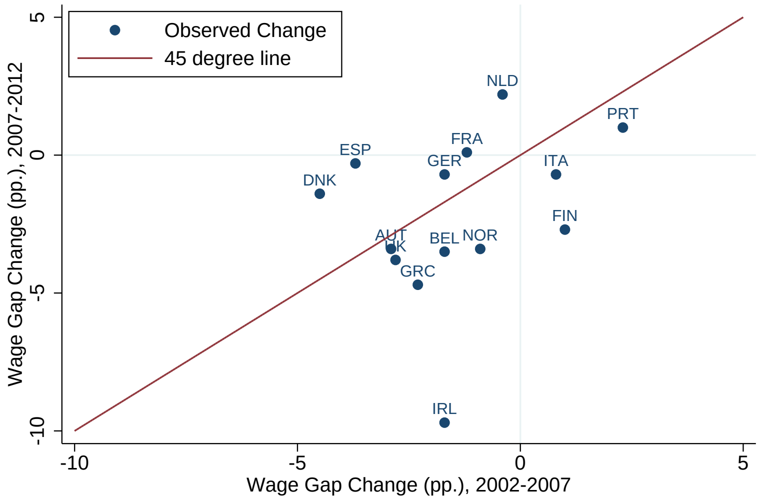
1 Introduction

In this paper we look at how changes in the way men and women have self-selected into the labour market during the Great Recession (henceforth, denoted as GR in short) may have affected gender (hourly) wage gaps in a representative sample of European countries.[1] We focus on Europe and the GR because the scale of employment adjustments during the last slump has been larger in several member states of the European Union (EU) than in other developed areas of the world economy, and these shifts are the ones that often underlie participation decisions into the labour market.[2]

Figure 1: Changes in the median gender wage gap before and after the GR.



Source: OECD data and authors' calculations.
Note: The median gender wage gap is unadjusted.

A number of recent reports, most notably OECD (2014), have documented that raw (unadjusted for characteristicss) gender wage gaps (denoted in short as RG in the sequel) have narrowed during the GR in several EU countries between 2007 and 2012. This is illustrated in Figure 1 where percentage point (pp.) changes in *median* RG between 2007 and 2012 (the latest available date in the OECD reports) in several EU economies (vertical axis) are plotted against their corresponding changes between 2002 and 2007 (horizontal axis), i.e., prior to the GR. As can be inspected, reductions in RG that took place in several European countries before the crisis have continued afterwards.[3] Furthermore, as OECD (2014) also documents, gender convergence has

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

[2]This is so since the GR in most of Europe 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]Finland, Italy and Portugal are the exceptions before the GR, whereas France and The Netherlands

not only taken place in wage terms: gender gaps in employment and unemployment have also narrowed down substantially during this period, relative to longer-term convergence trends since the postwar period.

Several explanations have been put forward to rationalize these time patterns. For example, Bettio et al. (2012) argue that reductions in RG are largely the result of a "levelling down" of male wages, as well as of the rise in male unemployment, rather than of actual gains made by women. They point out that the extra wage components (bonuses and premiums) often included in pay packages are the ones first to be foregone in a recession and that this variable pay component often accrues disproportionately to men. Likewise, it is been argued that, while women are over-represented in the public sector (where gender wage gaps are generally lower), they are under-represented in other sectors that have shed much more labour and where men tend to earn well. Finally, it is also mentioned that some European countries have implemented early retirement policies, mainly as a way to alleviate social pressure against collective dismissals and to facilitate youth employability. Since men are a majority among elderly workers with long professional careers, these policies may be also behind lower observed male hourly wages.

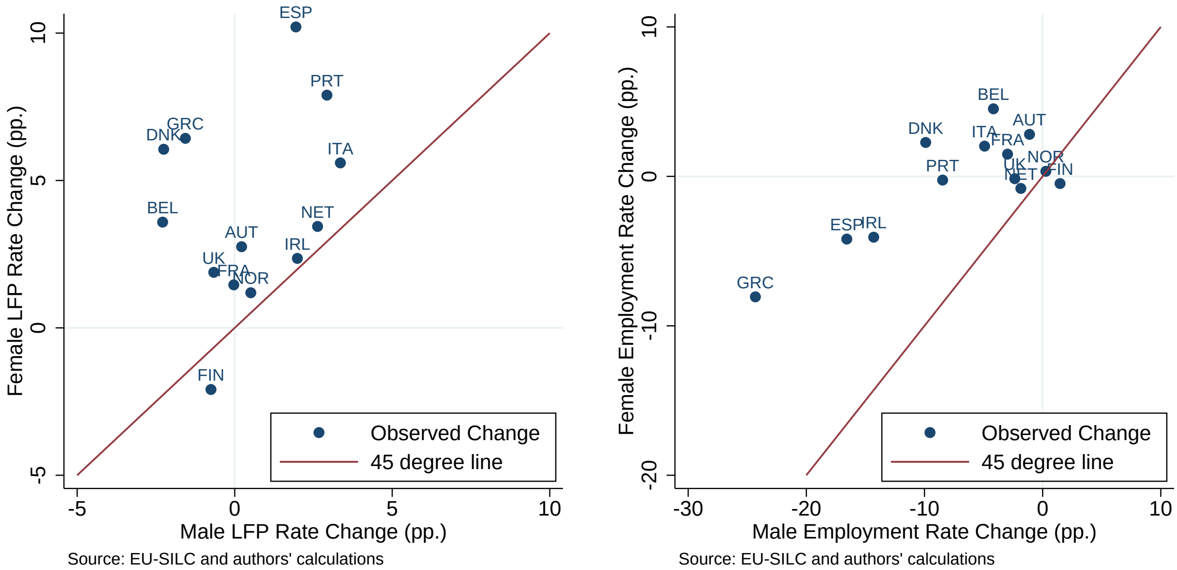
All these hypotheses raise interesting questions about potential factors behind gender wage equalization since the GR. However, they often ignore the possibility of major changes in non-random selection of workers into employment. To the extent that these changes differ by gender, they could have large effects on gender gaps based on the observed distribution rather than on the potential distribution of wages.

One of the main reasons why analyzing changes in selection over the recent slump could be interesting is that in the past selection has played a key role in explaining European cross-country patterns. In effect, in a forerunner of this paper, Olivetti and Petrongolo (2008) document that, before the GR (from the mid 1990s to the early 2000s), gender wage gaps in southern Europe on imputed (rather than on reported) wage distributions were quite higher than those based on reported wages. By contrast, both gaps yield fairly results in Anglosaxon and central-northern European countries. The insight for this difference is twofold. On the one hand, the historically lower female labour force participation (LFP hereafter) in the olive-belt countries implies more positive selection among participating women, as they often have relatively high-wage characteristics. On the other hand, given that female LFP is higher in Anglosaxon and central-northern Europe and that LFP happens to be uniformly high everywhere (implying no concerns about selectivity issues among men), observed medians of male and female wage distributions accurately represent their

happen to be so during the crisis.

Figure 2: Labour market attachment by gender, 2007-2012.

(a) LFP changes by gender (b) Employment changes by gender



population counterparts in this group of countries. Hence, lacking selection-bias corrections, RG in Mediterranean countries would seemingly appear as being much lower than in the rest of Europe. Yet, they would not provide good predictors of the potential gender wage gaps (PG hereafter) were all women to participate in countries with lower female LFP.

In view of these considerations, our goal here is to contribute to this strand of the literature by exploring whether Olivetti and Petrongolo (2008)'s diagnosis on gender sorting into employment may have changed as a result of the intensity of the GR in several European countries. In particular, following the above-mentioned changes in employment and LFP by gender, we conjecture that, in contrast with the traditional view on this issue, selection may have become more relevant among men and less so among women.[4] Moreover, these changes in selection are more likely to have taken place in the peripheral countries than in the rest of Europe. One plausible explanation of this *changing nature* of selection by gender is that the crisis has led to a much more intensive shedding of male unskilled jobs, either in construction (Ireland, Spain), services (Greece or Italy) or in less-skilled employment outsourced by the public sector (Portugal), than in other economies less badly hit in the downturn.

Following a massive job shedding among the less or middle-skilled workers, the distribution of observed male wages is bound to have become a censored (to the left)

[4]To 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 GR.

version of the imputed distribution. On the contrary, female LFP may have increased to help restore household income in those countries where male breadwinners lost their jobs. In effect, there is strong empirical evidence by Bredtmann et al. (2014)– using the same database (EU-SILC; see Section 3) and a similar sample period as ours– documenting the high responsiveness of women's labor supply (either at the extensive or intensive margins) to their husband's loss of employment, i.e., the so -called "added-worker" effect.[5] These authors show that this effect is particularly strong in Mediterranean countries, due to their less generous welfare states, and among less-educated women. Combining male job destruction with a rise in female LFP and employment, both among the less skilled, would lead to a lower (resp. larger) difference between observed RG and PG among females (resp. males) during the GR than prior to it.

As shown in Figure 2a, where changes in female LFP rates (in pp., vertical axis) during the GR are plotted against changes in male LFP rates (in pp., horizontal axis), most European countries (albeit Finland) have exhibited a much larger rise in female LFP since 2007 than earlier. Nonetheless, it should be acknowledged that higher LFP by women does not necessarily translate into female employment gains. In effect, according to Figure 2b, 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 are negative in almost half of the countries under consideration.[6] For example, Greece, Portugal and Spain (together with Ireland) exhibit much larger drops in male than in female employment (points above the 45^o line), capturing large job destruction in male-intensive industries. However, even within the peripheral countries, there are different experiences. For instance, employment changes in Italy have been much more muted than in the other southern EU countries. Northern and central EU countries in turn have followed rather different employment patterns, experiencing much lower male and female job losses.

When LFP and employment changes are analysed distinguishing by educational attainment (for males in Figure 3a and 4a, and for females in Figure 3b and 4b) it becomes noticeable that the fall in employment has been more pronounced among less-educated (no-college) male workers. This has been especially the case in Ireland and Spain, as a result of the bursting of their respective housing bubbles, as well as in Greece due to the sovereign debt crisis. Likewise, as regards LFP, it can be inspected that most of the gains in participation in the peripheral countries are due to females

[5]Given that this evidence is based on the same panel dataset we use here and for a similar sample period, in the sequel we take the "added-worker" effect as a given stylised fact, and therefore abstain from providing further empirical evidence on this issue

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

with lower educational attainments.

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

(a) Males

(b) Females

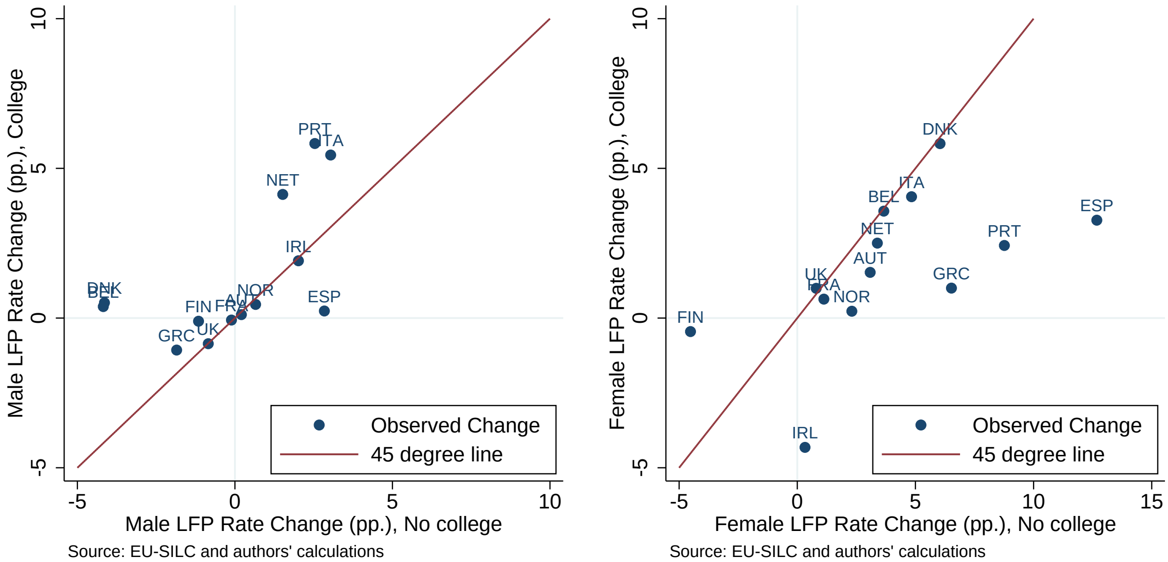
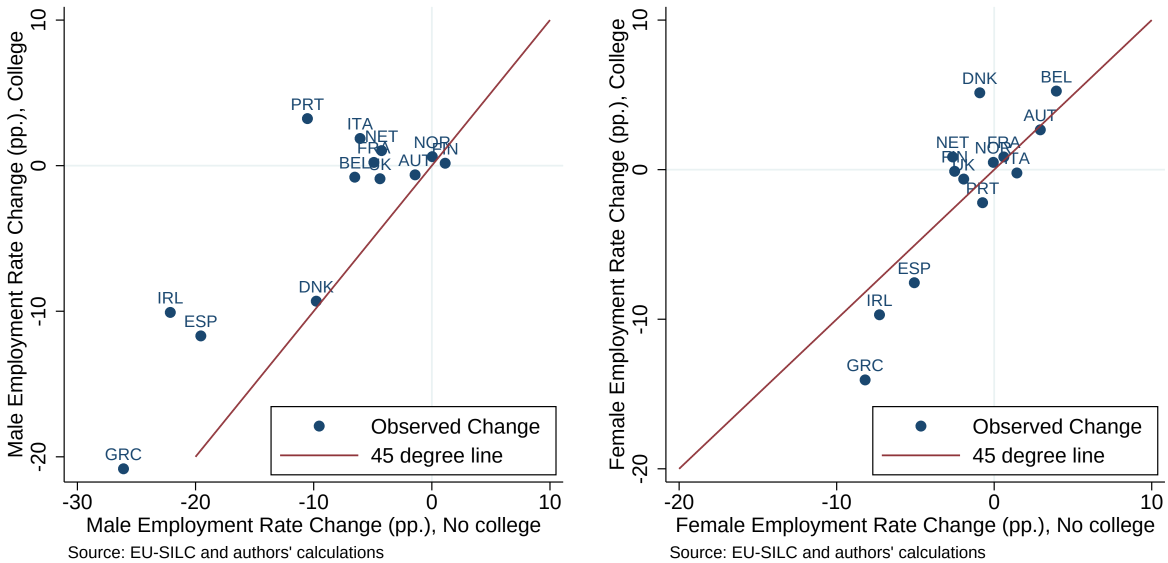


Figure 4: Cross-country changes in employment rates by gender and skill, 2007-2012.

(a) Males

(b) Females



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 the literature documents historical trends, our paper complements this approach by providing evidence on how sizeable changes in gender gaps are shaped at particularly relevant business cycle phases, as is the case of the GR. The issue of how real wages vary over the business cycle, taking into account that the observed and unobserved characteristics of workers moving in and out of the work force over the cycle may differ systematically from those who stay in, has been studied by Keane et al. (1988) by means of the well-known Heckman (1979)'s self-selection correction techniques.[7]

We differ from these authors in three main respects. First, we focus on gender wage gaps rather than exclusively on male wages, as Keane et al. (1988) do in their paper. Second, while their data correspond to the US, ours refers to a cross-country comparison across European countries, where the evolution and causes of gender gaps has been subject to much less research than in the US (see e.g., Blau et al., 2013). Lastly, we also depart from these authors in that, instead of using Heckman's control function approach, we adopt the alternative sample selection correction methodology advocated by Johnson et al. (2000) and Neal (2004), which is also the one used by Olivetti and Petrongolo (2008) in their closely related paper to ours.

In particular, by simply requiring assumptions on the position of imputed wages for non-employed workers relative to the median (rather than the actual level of missing wages), this imputation procedure avoids arbitrary exclusion restrictions often invoked in two-stage Heckman model.[8] Thus, rather than relying on doubtful exclusion restrictions to extrapolate the distribution below the reservation wage, our chosen imputation method allows to assess the impact of selection into work on gender gaps by providing several estimates of the differences between the distributions of RG and PG under alternative imputation rules. Notice that, as pointed out by Olivetti and Petrongolo (2008), the goodness of fit of these imputation rules can be assessed by treating observed wages in the available sample as missing observations and then check how well these rules fare in assigning those wages on either side of the median of the observed wage distribution. As explained below in Section 5, we follow these authors in considering selection on unobservables for individuals who have worked in some year of our panel data sample, and on matching observable characteristics of individuals who have never worked during the sample period with those who have worked. Combining this evidence with LFP and employment gaps (aggregate and by skill and age), allows us to analyse how changes in selection biases– either on their

[7]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 cycle.

[8]For example, this is the case of 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, they might as well affect effort at market-place work and therefore productivity and wages.

own or combined with some of the hypotheses discussed at the beginning of this section– are able to shed more light on the interpretation of the changing patterns in gender wage gaps experienced in Europe during the GR.

The rest of the paper is organized as follow. Section 2 provides a theoretical underpinning of the main mechanisms at play and derives their testable implications in terms of changes in selection biases and employment by gender. Section 3 describes the EU-SILC longitudinal dataset used throughout the paper. Section 4 explains the different imputation procedures we use to construct potential wage distributions. Section 5 discusses the main results in the light of the implications of the various mechanisms explored earlier. Finally, Section 6 concludes. An Appendix provides further details on the construction of hourly wages, measures of goodness of alternative imputation procedures and further descriptive statistics for the 13 European countries in our sample.

2 A Simple Theoretical Framework

To provide some theoretical underpinning of the mechanisms at play, we start by briefly reviewing the basic effects of selection on the measurement of gender gaps. Following Mulligan and Rubinstein (2008), let us consider the following equation for 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 represents gender (males have $g = 0$, females have $g = 1$), μ_t^w represents 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). In addition, 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.

If we were able to measure potential wages for all men and women, then *potential* (median) gender wage gap at year t (PG_t) would be:

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

where we expect $PG_t > 0$, since $\gamma_t < 0$ on historical grounds (see Olivetti and Petrongolo, 2016).[9]

[9]Consistently with the empirical section, our focus is on median rather than mean gender gaps. The choice is without loss of generality: the results can be rewritten in terms of mean gaps and biases. In such case, as it is well known selection bias becomes a function of the inverse Mill's ratio, similarly to Mulligan and Rubinstein (2008).

However, given that selection into employment is not a random outcome of the male and female populations, the observed raw gender gap in median (RG_t) is calculated by aggregating equation (1) by gender among *employed* individuals:[10]

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

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, which 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 in northern EU countries $b_t^m \simeq b_t^f$ and therefore $RG_t \simeq PG_t$, whereas in southern EU countries $b_t^m < b_t^f$, and thus $RG_t < PG_t$.

Using (3), the change in the observed gender gap over time can be expressed as:

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

Equation (4) has three terms. The first one ($\Delta PG_t = -\Delta\gamma_t$) is the change in the gender-specific component of net labor demand, which may occur due to changes in gender wage discrimination / relative market valuation of skills / relative human capital accumulation when considering *all* men and women. In addition, the second and third terms in (4) capture the changes in the selection bias of males and females, respectively, which constitute our main focus in the sequel.[11]

2.1 Scenarios over the GR

To identify which of the arguments (hinging on selection or not) laid out in the Introduction are more likely to hold in different areas of Europe, we propose the following three hypotheses (individually or jointly) and derive their main testable implications:

[10]The discussion below echoes 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 do.

[11]Notice 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, we ignore these changes in the sequel because, as shown in Figure 7 in Appendix B, where wage dispersion is measured by logarithm of the ratio between wages at 90th and 10th percentiles, no major trends seem to to present over 2004-2012, with perhaps the exceptions of Greece and Portugal.

- **Hypothesis I**: *Reduction in bonuses and performance pay.*

  As argued by Bettio et al. (2012), wages fell during the GR because of a reduction in variable pay component. Insofar as male employees are more prone to receive this type of compensation (see de la Rica et al., 2015), then Hypothesis I implies that, absent selection issues, RG should decline, while no substantial changes in male (E_m) and female (E_f) employment rates should have taken place. As a result, (4) implies that $\Delta RG_t = \Delta PG_t < 0$, due to $\Delta\gamma_t > 0$, and $\Delta E^m \simeq \Delta E^f \simeq 0$, for this hypothesis.

- **Hypothesis II**: *Higher job destruction rate of low-skilled jobs.*

  - **Hypothesis II$_m$**: If the GR has largely resulted in the shedding of unskilled low-paid jobs in male labour-intensive industries, then we would expect a positive male selection bias ($\Delta b_t^m > 0$). Using (4), this implies that $\Delta RG_t > \Delta PG_t \simeq 0$. The employment patterns consistent with this hypothesis would be a decline in employment of unskilled male workers, i.e. $\Delta E_t^{mu} < 0$, and no changes in either skilled male or overall female employment, i.e., $\Delta E_t^{ms} = \Delta E_t^f = 0$ respectively.
  - **Hypothesis II$_f$.** Same as Hypothesis II$_m$ except that now the focus is on changes in female employment. It may be more pronounced in countries with dual labour markets where temporary jobs (in which females are over-represented) can be easily terminated at low cost. It then holds that $\Delta E_t^{fu} < 0$.

- **Hypothesis III**: *Higher LFP of less-skilled women as a result of the added-worker effect.*

  As argued by Bredtmann et al. (2014), the GR has pushed less able women to rise their participation in the labor market. It implies female selection has become less positive, that is, $\Delta b_t^f < 0$, and hence $\Delta RG_t > \Delta PG_t \simeq 0$. One should expect an increase in employment of unskilled female workers, i.e. $\Delta E_t^{fu} > 0$, without noticeable changes in female skilled and overall male employment, that is, $\Delta E_t^{fs} = \Delta E_t^m = 0$.

However, some combinations of these hypotheses might be relevant in practice. For instance, it is plausible that Hypothesis II$_f$ and III could have operated in conjunction. In effect, although female LFP may have risen, a decline in labour demand for female workers could have more than offset this increase, leading to lead to a drop in E_f. In particular, this could have been again the case in EU countries with dual labour markets, where job shedding has concentrated on temporary jobs in services sectors in which women are typically disproportionately represented.

2.2 The Model

In this section we propose a simple model that rationalizes the main implications derived above. To do so, we extend the setup in Mulligan and Rubinstein (2008) to predict which workers are employed (consisting of a potential market wage equation (1) and a reservation wage equation, r_{it}) by adding a productivity equation, x_{it}, to capture labour-demand constraints:

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

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

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

where μ_t^x is the average productivity of a worker, μ_t^r is the female reservation wage (male reservation wage is normalized to zero), ε_{it} is a productivity shock, and v_{it} is a reservation-wage shock. We assume that $\rho > 1$ to capture the fact that wages do not fully respond to productivity shocks, ε_{it}, because they are not totally flexible. Notice that the productivity equation appears in the model to capture labour demand constraints, namely the fact that some individuals who sort themselves into the labour market may not be able to find a job when wages are not perfectly flexible. Finally, whereas ε_{it} has a continuous support, for expositional simplicity it is assumed that the shock v_{it} in the reservation wage equation is equal to zero for males and only takes two values for females: a high one, $\overline{v}$, with probability $p \in (0, 1)$ and a low one, $\underline{v}$, with probability $1 - p$.

Individual i works at time t if her/his reservation wage is higher than her/his potential market wage (labour supply condition), $w_{it} > r_{it}$, and her/his productivity is greater than the wage, leaving a positive surplus for the firm (labour demand condition), $x_{it} - w_{it} > 0$. We assume that the male reservation wage is equal to zero, implying that men participate if $\mu_t^w > 0$ and that they generate a surplus, $\mu_t^x - \mu_t^w > 0$, at any period t.

For women, the labour supply (LS) condition, $w_{it} > r_{it}$, is satisfied if and only if ε_{it} exceeds the following labour supply thresholds:

$$a_t^{LS}(g_i = 0) = -\mu_t^w, \tag{8}$$

$$a_t^{LS}(g_i = 1, v_{it} = \overline{v}) \equiv \overline{a}_t = \mu_t^r + \overline{v} - \mu_t^w - \gamma_t, \tag{9}$$

$$a_t^{LS}(g_i = 1, v_{it} = \underline{v}) \equiv \underline{a}_t = \mu_t^r + \underline{v} - \mu_t^w - \gamma_t. \tag{10}$$

The labour demand (LD) condition, $w_{it} < x_{it}$, holds if and only if ε_{it} exceeds the following labour demand threshold:

$$a_t^{LD}(g_i) \equiv \frac{\mu_t^w + g_i\gamma_t - \mu_t^x}{(\rho - 1)}. \tag{11}$$

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. Because of the zero male-reservation wage, the LS condition for men always holds, and therefore the LD threshold $a_t^{LD}(g_i = 0)$ is the only binding one. For women with a high reservation-wage shock, the LD condition is binding if and only if $a_t^{LS}(g_i = 1, v_{it} = \overline{v}) < a_t^{LD}(g_i = 1)$ or:

$$\frac{\mu_t^x - (\mu_t^w + \gamma_t)}{\overline{a}_t} < \rho - 1. \tag{12}$$

whereas for women with low reservation wage shock, the corresponding condition becomes:[12]

$$\frac{\mu_t^x - (\mu_t^w + \gamma_t)}{\underline{a}_t} < \rho - 1. \tag{13}$$

Intuitively, equations (12) and (13) hold when: (i) the potential female wage is high relative to productivity, i.e. when $\mu_t^x - (\mu_t^w + \gamma_t)$ is low; (ii) the reservation wage is low relative to potential wage, i.e. when $\underline{a}_t$ and $\overline{a}_t$ are high; (iii) the surplus is high, i.e. when ρ is much larger than unity. 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 condition would be the binding one. For example, in more traditional societies (like those in southern Europe), where the average female reservation wage is high due to cultural norms and the surplus is low reflecting lower productivity, the LS condition will be binding. Conversely, in a more modern society (like in northern-central Europe), where the average female reservation wage is low and the surplus is high, the LD condition is the binding one. Moreover, the LS condition is more likely to affect lower-educated women in all countries because it is often thought that, relative to their distribution of offered wages, they have a higher reservation wages than higher-educated ones because they more subject to traditional social norms on the distribution of household taks.

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

2.2.1 Male Participation

In what follows 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 $a_t^{LS}(g=0) < a_t^{LD}(g=0)$, 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 in the median sense, $b_t^m = m(\varepsilon_{it}|g_i = 0, L_{it} = 1) = \underline{m}(a_t^{LD}(g=0))$.

Then, the comparative statics formula of w_t^m with respect to μ_t^x is given by:

$$\frac{dw_t^m}{d\mu_t^x} = \frac{\partial \underline{m}}{\partial a_t^{LD}(g=0)} \times \frac{\partial a_t^{LD}(g=0)}{\partial \mu_t^x} < 0, \tag{14}$$

since $a_t^{LD}(g=0)$ is decreasing in μ_t^x. Hence, if the GR has generated a drop in productivity, $\Delta\mu_t^x < 0$, the median of the observed male wage distribution will increase due to a stronger positive selection of males into employment, $\Delta b_t^m > 0$.

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

2.2.2 Female Participation

In the case of women, under the above-mentioned assumption on the reservation-wage shocks v_{it}, it is easy to check that 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:

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

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

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

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 $\underline{m}(\cdot)$ 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, $a_t^{LS}(g = 1; v) < a_t^{LD}(g = 1)$, a reduction in labour productivity will have the same effect on observed female wages as for male wages, namely:

$$
\frac{dw_t^f}{d\mu_t^x} = \frac{\partial \underline{m}(a_t^f(v))}{\partial a_t^{LD}(g = 1)} \times \frac{\partial a_t^{LD}(g = 1)}{\partial \mu_t^x} < 0. \tag{15}
$$

As predicted by Hypothesis III when LD binds, the previous expression shows that, as for males, observed female wages will increase due to a stronger positive selection of women into employment when productivity goes down.

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

$$
\frac{dw_t^f}{d\mu_t^r} = \frac{\partial \underline{m}(a_t^f(v))}{\partial a_t^{LS}(g = 1; v)} \times \frac{\partial a_t^{LS}(g = 1; v)}{\partial \mu_t^r} > 0. \tag{16}
$$

Hence, if the GR has generated an added-worker effect among previous non participants, this translates 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, $\Delta b_t^f < 0$, which is the main prediction of Hypothesis III when LS binds.

In sum, depending upon which of the two opposite forces (LD and LS) dominates, the observed female wage may go up or down as a result of the GR.

2.2.3 An illustration of the mechanisms at play: Portugal *vs.* Spain

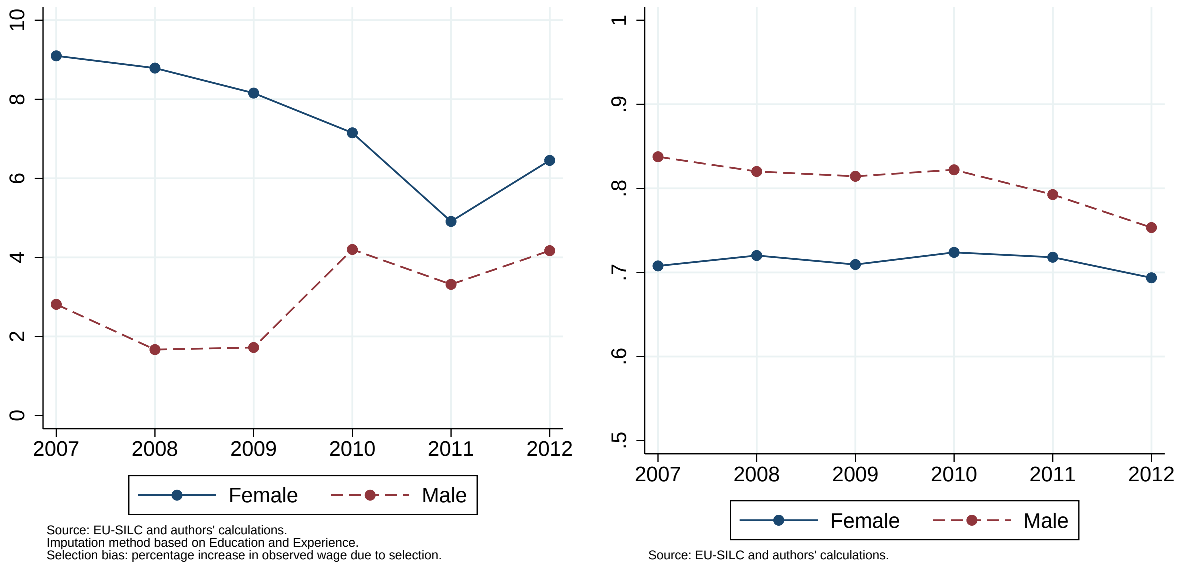
To provide a brief preview of how the previous contrasting LS and LD effects operate in practice, let us focus on the cases of Portugal and Spain, two neighbouring Mediterranean countries badly hit by negative shocks during the GR.[13] As can be observed in Figures 3 and 4, while less-skilled male workers suffered massive job losses, non-participating less-educated women increasingly searched for jobs in both countries, in line with the arguments given above on how the GR could have impinged on the nature of gender selection into the labour market. However, in parallel with a rise

[13]Details on the data and methods are provided below.

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

(a) Selection Bias

(b) Employment Rate



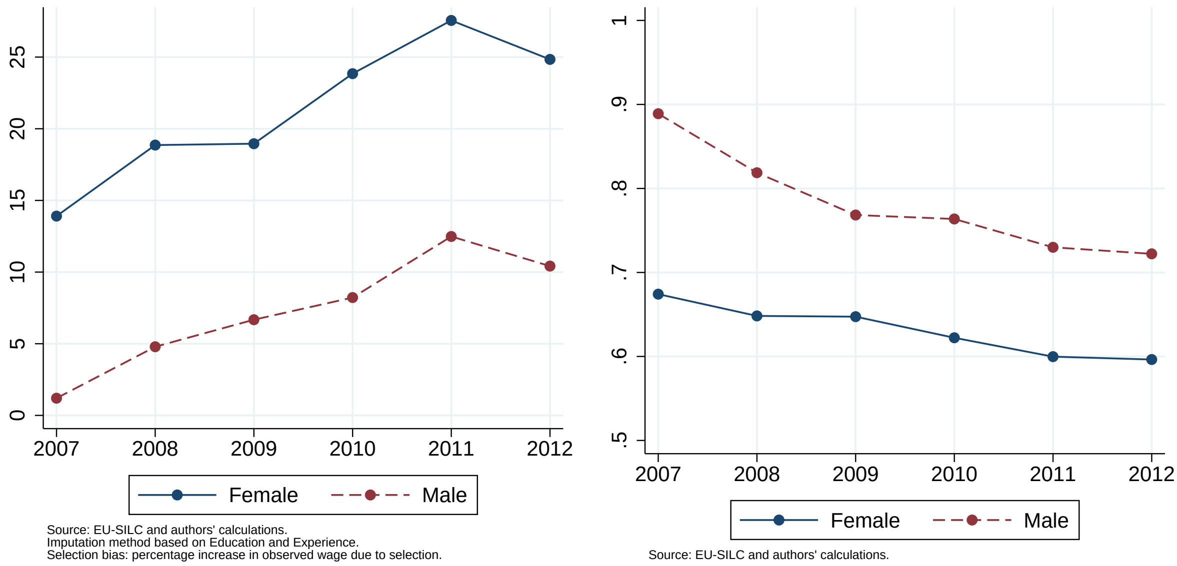
in labour supply, it is well known that many unskilled jobs were destroyed during the slump, particularly in Spain where the unemployment rate went up from 9% in 2008 to 26% in 2012. This implies that, while only adverse LD shifts (i.e., higher job destruction) apply to males, both LD and LS considerations are likely to have been relevant for women.

This is illustrated by the left-hand-side (LHS) panels in Figures 5a and 6a, which present selection biases for males and females in Portugal and Spain, respectively, from 2007 to 2012, computed according to the best performing imputation method discussed in Section 4 below. Selection biases are measured as a percentage decrease in the median wage once wages of those nonemployed are imputed. For comparison, the RHS panels of these two Figures display employment rates (shares of occupied in the population of working age) for these countries. As can be inspected, male selection (dashed line) in both countries increases drastically during the slump. Yet, while female selection declines in Portugal, it goes up in Spain.

The different behaviour of female selection biases between these two countries is probably due to the fact that, while both female and male employment rates collapsed in Spain, only male employment declined in Portugal. The better performance of the Portuguese labour market is likely to be related to its larger wage flexibility prior to 2012, as well as to a less dualized labour market (see Dolado, 2016). At any rate, given that employment adjustment in Spain was mainly borne by the termination of temporary contracts (where women are over-represented), this evidence seemingly

Figure 6: Selection bias and employment rates by gender, Spain, 2007-2012.

(a) Selection Bias (b) Employment Rate



indicates that the rise of female LFP (a positive LS shift) has been offset by an even larger reduction in female employment (a negative LD shift). Thus, to the extent that those women who retained their jobs were favourably selected, an increasing, rather than decreasing, female selection bias arises in this country.[14]

3 Data

To measure both RG and PG, we use the European Statistics on Income and Living Conditions (EU-SILC) data set.[15] 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 gap studies in Europe, including the aforementioned Olivetti and Petrongolo (2008). It collects comparable multidimensional annual micro-data on a few thousands households per country starting from 2004 until 2012, that is, a sample period which covers years before and after the GR .

The countries in our sample are Austria, Belgium, Denmark, Finland, France,

[14]As will be discussed further below in Section 5, similar patterns hold in Greece, a country whose cumulated collapse in GDP of more than 25% during the GR meant even more dramatic employment losses than in Spain. Finally, as a counterexample of these dramatic changes, evidence will also be provided showing that changes in selection patterns by gender are much less pronounced in northern and central EU countries and in the UK, where employment changes over this period have been much more muted than in the peripheral economies.

[15]Existing literature using EU-SILC data for international comparisons of gender gaps include 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.

Greece, Ireland, Italy, The Netherlands, Portugal, Spain, UK, and Norway.[16] It is noteworthy that some big EU countries, such as Germany are not included in our sample due to lack of longitudinal information on several key variables affecting wages.

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.

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 do not capture the same period. In effect, 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). We follow a methodology similar to Engel and Schaffner (2012) to derive hourly wages. A detailed account of this procedure is provided in Appendix A.

The educational attainment categories used (no college and college), correspond to ISCED 0-4 and 5-7, respectively. Spouse income is calculated as annual labor income for spouses of respondents. Descriptive statistics are reported in Appendix B. Finally, throughout our empirical analysis observations are weighted using population weights when available.[17]

4 Empirical Methodology

As mentioned earlier, median wage regressions are used to estimate parameters μ_t^w and γ_t in equation (1). However, wages w_{it} are only observed for the employed and are missing for the rest of the sample. As shown in equation (3), running the median wage regression on the observed wages will result in a bias to the extent that $m(\varepsilon_{it}|g_i, L_{it} = 1) \neq 0$, i.e. employed males and females have have different potential wage distributions than employed ones.

As discussed in Olivetti and Petrongolo (2008), the median estimator on 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

[16] Note that although Norway is not an EU member state, we use this labelling for simplicity. Together with Denmark, we use this country as a representative gender patterns in the Nordic countries.

[17] 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.

those in the non-employment, $L_{it} = 0$, will result in an unbiased estimator of the median gap in potential wages as long as the missing wage observations are imputed on the right side of the median. To understand this procedure, let us consider the following illustrative linear wage equation:

$$\omega = \beta_0 + \beta_1 g + \epsilon, \tag{17}$$

where ω is the (logged) potential wage of an (atomistic) agent in a very large (continuous) sample of individuals, β_0 is an intercept, β_1 is the parameter capturing the pay gap, g_i is a gender dummy, and ϵ_i is a disturbance term with support (-∞, $+\infty$) and c.d.f. $F(\cdot)$, such that $m(\epsilon|g) = 0$. Let $\widehat{\beta} = (\widehat{\beta}_0, \widehat{\beta}_1)'$ be the hypothetical least absolute deviations (LAD) regression estimators based on potential wages, namely, $\widehat{\beta} \equiv$ arg min $\int_{-\infty}^{\infty} |\omega - \beta_0 - \beta_1 g| dF(\epsilon)$. Suppose now that wages are only observed for the employed, while the missing wages for the nonemployed fall completely below the median regression line, i.e., $\omega < \widehat{\omega} \equiv \widehat{\beta}_0 + \widehat{\beta}_1 g$, that is, $F(m|g, L = 0) = 1$.[18] Then, defining a transformed dependent variable y such that it equals the observed wage w_i for $L = 1$ and an arbitrarily low value $\underline{w}$ (with $\underline{w} < \widehat{\omega}$) for $L = 0$, the LAD estimator of the median of y, denoted as $\widehat{y}$, verifies:[19]

$$\widehat{y} = \arg\min_{\widehat{y}} \left[\int_{-\infty}^{\underline{w}} |\underline{w} - \widehat{\omega}| dF(\epsilon) + \int_{\underline{w}}^{\widehat{y}} |w - \widehat{\omega}| dF(\epsilon_i) + \int_{\widehat{y}}^{\infty} |w - \widehat{\omega}| dF(\epsilon) \right].$$

Using Leibniz's rule to differentiate this object function w.r.t. $\widehat{y}$ yields the following f.o.c:

$$[F(\underline{w}) + F(\widehat{y}) - F(\underline{w})] - [1 - F(\widehat{y})] = 0,$$

that is, $F(\widehat{y}) = 0.5$, whereas the f.o.c. for the LAD estimator of the median of potential wages verifies $F(\widehat{\omega}) = 0.5$. Hence, it follows that $\widehat{y} = \widehat{\omega}$.

In the sequel we use this procedure and compute median gender gaps as well as the effects of selection into non-employment, based on wage imputations that require only assumptions on the position of the imputed wage with respect to the median of the gender-specific wage distribution.[20]

[18] Similar arguments as below would apply if all the missing observations happen to be above the median regression lines, with y being defined as $\overline{w}$ when $L = 0$.

[19] See Bloomfield and Steiger (2012)

[20] This approach is closely related to Johnson et al. (2000) and Neal (2004).

4.1 Imputation on Observables

We use a small number of observable characteristics, X_i, 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 nonemployed workers would earn wages below the gender-specific median, and another threshold above which individuals would earn above-median wages.

Specifically, our first specification is based on standard human capital theory and uses observed educational attainment and labour market *experience* (labelled in short as Imputation on EE) to predict the position of the missing wages. In this case, as explained earlier, the imputed dependent variable is set to equal a low value, $\underline{w}_t$, if an individual has little education and little labour market experience and a high value, $\overline{w}_t$, if an individual is highly educated and has a significant amount of labour market experience. In addition, to also take into account nonemployed individuals with low (high) education and long (short) experience, we follow Olivetti and Petrongolo (2008) in fitting a probit model for the probability that the wage of employed individual is above the gender specific median, based on education, experience and its square, to obtain predicted probabilities for the nonemployed. An imputed sample using all individuals in the sample is then constructed using these predicted probabilities as sample weights. The reference wage is calculated on the base sample with wage observations from adjacent waves.

As regards our second specification, we exploit the hypothesis of assortative mating which implies a positive correlation between *spousal incomes* within the household (denoted in short as Imputation on SI). Further details on the precise rules of imputation we use are provided below.

These methods of imputation of missing wages follow an educated guess. Two procedures are used to assess the goodness of alternative guesses. The first one (Goodness Method 1) follows Olivetti and Petrongolo (2008) and uses wage information for non-employed individuals from other waves in the panel when such individuals report receiving 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. Notice that this procedure is accurate to the extent 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, an assumption that may not hold during the Great Recession. The second method (Goodness Method 2) takes all employed workers and computes the proportion of those with the relevant personal characteristics and wage observations on the correct side of the median as predicted by the imputation rule.

4.2 Imputation on Wages from Other Waves

As an alternative imputation method which does not rely on using arbitrary assumptions based on observable characteristics, as above, we exploit the panel nature of our data so that, for all those not employed in year t, we recover their wages from the nearest wave, t'. As argued by Olivetti and Petrongolo (2008), 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 (denoted as Imputation on 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 relatively low labour market attachment of females (like e.g. in Austria, Belgium or the peripheral countries). In addition, there are no simple ways of assessing the accuracy of such imputations.

Another caveat is that the panel dimension of our data set is relatively short. The longitudinal component of EU-SILC allows to follow each household for four years.[21] Proportions of imputed wage observation over the total non-employed population are reported in Table 8: the imputation rates are generally lower than in Olivetti and Petrongolo (2008) who benefit from a much longer panel . Also, the male imputation rate is almost 50% higher than the female one in southern Europe. As mentioned earlier, one way to increase these imputation rates is to estimate probabilistic models based on observables, like education and experience, which we will use as robustness checks for the results obtained from the more standard imputation methods.

5 Results

5.1 Imputation on employment and experience

Table 1 presents our core Imputation EE method based on education and experience. As discussed earlier, two education categories are defined: those with upper secondary education or less are considered low-education and those with some tertiary education are defined as high-education. Similarly, we define as low (high)

[21] With the exception of France, where each household is followed for 8 consecutive years.

experience individuals with less than (at least) 15 years of work experience. We then proceed to impute a wage below the median for those with low education and low experience and above the median for those with high education and high experience.

Table 1: Median Wage Gaps under Imputation on Education and Experience

	Levels in 2007						Changes over 2007-2012					
	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
Southern Europe:												
Greece	.182	.450	.016	.283	.853	.542	-.076	-.036	.069	.109	-.257	-.111
Italy	.035	.266	.029	.260	.849	.558	.053	.017	.008	-.028	-.057	.002
Spain	.132	.254	.012	.134	.889	.674	-.027	-.021	.087	.094	-.167	-.078
Portugal	.172	.229	.030	.087	.838	.708	-.038	-.067	.011	-.018	-.084	-.014
Mean	**.130**	**.300**	**.022**	**.191**	**.857**	**.620**	**-.022**	**-.027**	**.044**	**.039**	**-.141**	**-.050**
Rest of Europe:												
Austria	.192	.299	.009	.117	.879	.711	.012	-.021	.000	-.033	.003	.011
Belgium	.074	.142	.021	.089	.866	.742	-.019	-.063	.004	-.040	-.034	.031
Ireland	.170	.296	.029	.155	.851	.668	-.040	-.064	.002	-.022	-.139	-.076
United Kingdom	.247	.302	.009	.063	.942	.806	-.065	-.049	.010	.026	-.035	-.025
Netherlands	.158	.190	.003	.034	.933	.802	-.054	-.043	-.001	.010	-.031	-.018
France	.114	.159	.006	.051	.917	.816	.005	-.015	.008	-.012	-.034	.000
Finland	.203	.209	.013	.019	.897	.864	-.072	-.072	.003	.003	-.020	-.038
Denmark	.116	.121	.001	.006	.985	.941	-.072	-.064	-.001	.007	-.126	-.045
Norway	.154	.161	.002	.009	.975	.913	.027	.014	-.003	-.016	-.015	.004
Mean	**.158**	**.209**	**.010**	**.060**	**.916**	**.807**	**-.031**	**-.042**	**.003**	**-.008**	**-.048**	**-.017**

Source: EU-SILC and authors' calculations. Note: Selection bias = an increase in observed wage due to selection. Wage imputation rule: Impute wage $<$ median when nonemployed and education $\leq$ upper secondary and experience $<$ 15 years; impute wage $>$ median when nonemployed and education $\geq$ higher education and experience $\geq$ 15 years.

The upper panel of Table 2 presents results for the four southern EU economies, while the lower panel gives those for the rest of countries in our sample (denoted as Rest of Europe in the sequel). We report both RG and PG in levels, selection biases and employment rates by gender in 2007, at the onset of the GR, and the corresponding change between 2007 and 2012. In line with the results of Olivetti and Petrongolo (2008), southern EU countries exhibit a greater employment gap and a much stronger female bias than the Rest of Europe. For example, the average female bias in the former group of countries amounts to 19 pp. out of the 30 pp. yielded by PG (i.e., 60%), whereas it amounts to only 6.0 pp. out of 21 pp. (i.e., 27%) in the latter. In general, female selection biases are fairly small in Rest of Europe counties (bottom panel). The exceptions are Belgium, Austria and, particularly, Ireland, having all of them the lowest female employment rates (between 65% and 75%) among Rest of Europe countries. In spite of having similar average selection biases (2.2 pp. against 1.0 pp.), male biases are also higher in southern countries, a finding which is again compatible with the lower aggregate employment rates in this group of countries.

As regards changing patterns in selection biases since 2007, two findings are noteworthy. The first one is that the female selection bias has increased on average by 3.9

pp. in southern Europe while it has hardly moved in Rest of Europe (-0.8 pp.). However, patterns among southern countries differ in interesting ways. On the one hand, female selection biases experience substantial reductions in Italy and Portugal, where the fall in female employment is small or non-existent. Given the strong reduction in male employment rates (-5.7 pp. and -8.4pp.), this finding is not only consistent with the added-worker hypothesis but also is clearly indicative that increases in female LFP in these two countries have been matched by similar increases in female labour demand. Conversely, female employment has fallen sharply in Greece and Spain (and also in Ireland), implying that a downward shift in male and female labour demand is the dominant force in these countries. Hence both selection biases become stronger (more positive).

As reported in the Appendix (see Table 10 in Appendix B), female LFP rates have increased in the four olive-belt countries and, in general, these changes have been stronger among low-educated workers. It is worth noticing, however, that the largest drops in female selection in our sample of countries have taken place in Austria and Belgium (bottom panel), which are the two central EU countries where female employment rates have risen the most. In the case of Belgium, the increase in female employment is associated with an equally large decline in male employment which has affected both high- and low-educated women. In Austria, we find evidence of an added-worker effect too, which in this case may reflect assortative matching in couples. For example, Table 9 in the Appendix indicates that, while college educated Austrian males (females) experienced an increase (no change) in employment, employment rates among low-educated individuals moved in opposite directions, falling for men and rising for women.

Table 1 also indicates that male selection bias has increased on average by much more in southern Europe (4.4 pp.) than in Rest of Europe (+0.3 pp.). Among the Mediterranean economies, the rise in male selection is largest in Greece and Spain (in line with large drops in less-skilled male employment of 27.6 pp. and 19.2 pp., respectively), whereas in Portugal, wage flexibility imposed by the memorandum of understanding with the 'Troika' and out-migration have reduced job shedding of less-skilled men. Note that amongst the Rest of Europe, only the UK exhibits a sizeable increase (see Arellano and Bonhomme, 2017).

When we focus on changes in wage gaps over the GR, it is found that RG has fallen by 2.2 pp. and 3.1 pp. in Southern Europe and Rest of Europe, respectively, and that accounting for selection accentuates the decline by about 0.5 pp. and 1.0 pp., respectively. Note, however, that while northern-central countries share similar patterns in RG, there are substantial variations among southern countries. For example, as discussed in Section 2, accounting in Portugal for selection implies a much larger reduction of PG than in RG, namely, 7.6 pp. vs. 3.8 pp, since selection has become more positive for men and less positive for women. Similar but weaker results also hold for Italy. Hence, Italy and Portugal are good examples of labour markets where the binding constraint is LS. Conversely, accounting for selection makes no difference for the changing patterns of RG and PG in Greece and Spain, since selection bias has increased in similar ways for both genders due to adverse labour demand shifts. These have not only meant big job losses for men, but also have offset the rise in female labour supply. Thus, these two countries provide the best illustrations of labour markets where the binding constraints is LD.

Table 2: Rate and Goodness of Imputation on Education and Experience

	2007						2012					
	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
Southern Europe:												
Greece	.43	.71	.93	.86	.84	.85	.45	.63	.72	.80	.83	.82
Italy	.54	.74	.81	.74	.70	.69	.51	.70	.85	.75	.72	.74
Spain	.41	.66	.79	.71	.75	.80	.73	.73	.70	.69	.73	.77
Portugal	.39	.54	.63	.56	.71	.77	.29	.40	.68	.60	.74	.80
Mean	**.44**	**.66**	**.79**	**.72**	**.75**	**.78**	**.50**	**.61**	**.74**	**.71**	**.76**	**.78**
Rest of Europe:												
Austria	.34	.57	.89	.70	.76	.80	.33	.54	.80	.70	.83	.80
Belgium	.39	.58	.81	.88	.79	.80	.47	.64	.82	.78	.77	.81
Ireland	.41	.54	.92	.87	.83	.81	.40	.45	.73	.65	.73	.78
United Kingdom	.42	.50	.36	.62	.74	.74	.41	.55	.94	.61	.76	.70
Netherlands	.39	.64	.55	.94	.81	.75	.50	.59	.92	.91	.82	.77
France	.44	.64	.85	.79	.80	.79	.44	.70	.68	.67	.79	.80
Finland	.58	.47	.95	.85	.76	.78	.54	.45	.74	.70	.78	.73
Denmark	.21	.43	.63	.75	.66	.76	.23	.57	.13	1.00	.72	.77
Norway	.40	.40	.79	.71	.75	.80	.33	.45	.70	.69	.73	.77
Mean	**.40**	**.53**	**.75**	**.79**	**.77**	**.78**	**.41**	**.55**	**.72**	**.75**	**.77**	**.77**

Source: EU-SILC and authors' calculations. Note: Wage imputation rule: Impute wage $<$ median when nonemployed and education $\leq$ upper secondary and experience $<$ 15 years; impute wage $>$ median when nonemployed and education $\geq$ higher education and experience $\geq$ 15 years. Imputation Rate = proportion of imputed wage observations in total nonemployment. 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.

Table 2 reports results on our two measures of goodness of fit for the years 2007 and 2012. 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. Recall that Method 1 compares our imputation with the positioning implied by looking at the wage observed for the individual in other waves, while Method 2 computes the proportion of employed workers which are on the same side of the median as would be implied if we applied our imputation rule to them. All measures are computed for men and women separately. As expected, imputation rates are higher for women (between 40% and 74%) than for men (between 21% and 73%) and somewhat larger in southern countries than in Rest of Europe. Both measures indicate a satisfactory goodness of 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 missing wages than males.

Table 6 in Appendix B reports estimates based on a probit model. The imputation technique proceeds in two steps. First, we estimate a probit model for the probability of earning a wage below the gender-specific median, controlling for education dummies, experience, and its square. The estimated probabilities, $\hat{P}_i$, are then used as sampling weights to impute the wages of the nonemployed individuals. Specifically, each nonemployed individual appears twice in the imputed sample: with a wage above the median and a weight $\hat{P}_i$, and with a wage below the median and a weight $1 - \hat{P}_i$. To account for a bias in the reference median wage in the first step, we enlarge our base sample with wage observations from other waves. The results are qualitatively similar to our findings in Table 1.[22]

5.2 Imputation on spousal income

As mentioned above, under the assumption of assortative matching in marriages, spousal income could become a good proxy for an individual's earning capacity. Hence, we impute a wage below (above) the median to those who are non-employed and whose spouses have earnings that are in the bottom (top) quartile of the gender and year specific earnings distribution. Table 3 presents the results of this imputation method. The main findings of Imputation on SI echo those based on Imputation on EE, although they tend to be less strong, probably due to a weaker performance of Imputation SI in terms of goodness of fit.[23] As before, in 2007 we observe a larger selection in southern EU countries than in Rest of Europe, and that this selection is particularly strong for women. The changes that have occurred during the GR are similar across the four peripheral economies with some differences: male selection has increased in all of them; female selection has increased in Greece and, very slightly, in Spain, while it has declined in Italy and Portugal. For the Rest of Europe, we find again little change in female selection, while the average increase in male

[22]The conclusions from a probabilistic model are robust to a more general specification that includes marital status, the number of children, and the position of spouse income in their gender-specific distribution.

[23]Table 7 in Appendix B indicates both a lower imputation rate and worse goodness of fit.

Table 3: Median Wage Gaps under Imputation on Spousal Income

	Levels in 2007				Changes over 2007-2012			
	Raw Wage Gap	Potential Wage Gap	Selection Bias M	Selection Bias F	Raw Wage Gap	Potential Wage Gap	Selection Bias M	Selection Bias F
Southern Europe:								
Greece	.182	.321	.016	.154	-.076	-.039	.049	.086
Italy	.035	.107	.013	.085	.053	.032	.011	-.010
Spain	.132	.179	.007	.054	-.027	-.057	.033	.003
Portugal	.172	.205	.026	.059	-.038	-.073	.021	-.014
Mean	**.130**	**.203**	**.015**	**.088**	**-.022**	**-.034**	**.028**	**.016**
Rest of Europe:								
Austria	.192	.221	.012	.041	.012	.013	-.001	.000
Belgium	.074	.093	.013	.032	-.019	-.036	.004	-.013
Ireland	.170	.235	.031	.096	-.040	-.071	.074	.044
United Kingdom	.247	.268	.014	.035	-.065	-.052	.009	.023
Netherlands	.158	.151	.003	-.003	-.054	-.052	.005	.006
France	.114	.127	.004	.018	.005	-.007	.003	-.009
Finland	.203	.202	.004	.003	-.072	-.062	.003	.013
Denmark	.116	.115	.001	.000	-.072	-.071	.006	.007
Norway	.154	.155	.000	.001	.027	.025	.007	.005
Mean	**.158**	**.174**	**.009**	**.025**	**-.031**	**-.035**	**.012**	**.008**

Source: EU-SILC and authors' calculations. Note: Selection bias = an increase in observed wage due to selection. Wage imputation rule: Impute wage $<$ median when nonemployed and spouse income in bottom quartile; impute wage $>$ median when nonemployed and spouse income in top quartile.

selection is 1.2 pp., mainly driven by its large rise in Ireland.

5.3 Imputation on wages from other waves

Our third imputation method attributes to non-employed individuals who are observed as having been employed in other waves of the panel their wage in the nearest year for which it is available. Unfortunately, the panel dimension of our data is rather short and we have only a limited number of available observations to impute.[24] Low imputation rates imply that a lower gap is found between the southern countries and the Rest of Europe as regard female selection in 2007. Changes in selection biases since the onset of the GR are smaller than those obtained under the previous imputation methods. This is especially the case for female selection, except in Greece. This smaller variation is not surprising since, e.g., in Spain the imputation rates for 2007 and 2012 are 23% and 30%, while they were 66% and 73% with Imputation EE. Yet, as with the other imputation methods, we still document a sizeable increase in male selection in southern countries, making this finding rather robust.

[24] As can be seen from table 7 in Appendix B, we impute around a third of observations and, particularly, few women in Southern Europe. These figures are much lower than those in Olivetti and Petrongolo (2008), who have a longer panel.

Table 4: Median Wage Gaps under Imputation Based on Wages from Other Waves

	Levels in 2007				Changes over 2007-2012			
	Raw Wage Gap	Potential Wage Gap	Selection Bias M	Selection Bias F	Raw Wage Gap	Potential Wage Gap	Selection Bias M	Selection Bias F
Southern Europe:								
Greece	.182	.191	.010	.019	-.076	-.086	.018	.008
Italy	.035	.046	.008	.019	.053	.048	.011	.006
Spain	.132	.152	.003	.023	-.027	-.049	.024	.002
Portugal	.172	.173	.006	.008	-.038	-.049	.015	.004
Mean	**.130**	**.141**	**.007**	**.017**	**-.022**	**-.034**	**.017**	**.005**
Rest of Europe:								
Austria	.192	.211	.003	.023	.012	.003	.007	-.002
Belgium	.074	.078	.006	.010	-.019	-.026	.004	-.003
Ireland	.170	.184	.012	.026	-.040	-.055	.000	-.014
United Kingdom	.247	.253	.000	.006	-.065	-.080	.006	-.008
Netherlands	.158	.160	.005	.007	-.054	-.050	.002	.006
France	.114	.126	.004	.016	.005	-.007	.001	-.011
Finland	.203	.199	.011	.008	-.072	-.066	-.005	.002
Denmark	.116	.117	.001	.003	-.072	-.074	-.001	-.003
Norway	.154	.160	.002	.009	.027	.023	.003	-.001
Mean	**.158**	**.165**	**.005**	**.012**	**-.031**	**-.037**	**.002**	**-.004**

Source: EU-SILC and authors' calculations. Note: Selection bias = an increase in observed wage due to selection. Wage imputation rule: Impute wage from other waves when nonemployed.

5.4 Interpreting the findings

In view of the previous evidence on the plausibility of our alternative imputation methods, it seems that Imputation on EE is the procedure that provides better goodness of fit. Furthermore, the qualitative results from this imputation method remain fairly robust under the other two alternative procedures. Although in principle we could expect imputation based on wages from other waves to be more precise, the nature of our data makes is de facto a poorer approach, as we have few observations per individual and the nature of the GR implies that they stay out of work and hence have no observable wages for various years. Thus, in the sequel, we will concentrate on summarizing the main findings drawn from the results in Table 1.

Comparing this evidence with the theoretical scenarios laid out in section 2.1 on the different implications of the main drivers of gender wage gaps over the crisis, the following findings stand out. They are summarized in Table 5.

- Hypothesis I on its own (a similar reduction in RG and PG, due to a drop in performance pay affecting men, without major changes in employment and selection of either gender) does not seem to hold in the majority of countries. This is because, though there are similar drops in observed and potential gaps in several instances (Spain, among southern countries, and Denmark, Finland,

Table 5: Summary of Findings over the Great Recession

	Consistent Hypotheses
Southern Europe:	
Greece	I + II_m + II_f
Italy	II_m + III
Spain	I + II_m + II_f
Portugal	I + II_m + III
Rest of Europe:	
Austria	III
Belgium	I + II_m + III
Ireland	I + II_m + III
United Kingdom	I + II_m + II_f
Netherlands	I + II_m + II_f
France	I + II_m + III
Finland	I + II_m + II_f
Denmark	I + II_m + II_f
Norway	II_m + III

Ireland, The Netherlands and the UK, among Rest of Europe), either sizeable changes in selection biases or in employment rates have also taken place.

- As regards Hypothesis II, no country in our sample satisfies the predictions of Hypothesis II_m on its own (only male selection increases). The reason is that, although male selection has become increasingly positive in most countries, female selection changes have often been even larger, especially in southern Europe. By the same token, given the non-negligible changes in male selection, it also follows that no country satisfies the corresponding predictions of Hypothesis II_f on its own (only female selection increases).

- Hypothesis III (decline in female selection bias as a result of an added-worker effect, and no change in male selection, with large employment gains for women and no major changes for men's), seems to hold in Austria, while it is only partially verified by Italy in the first group, and Belgium, Ireland, Norway and The Netherlands in the second group. Notice that in all these countries, despite fulfilling the predicted changes in selection by gender, there are sizeable drops in male employment.

From the previous discussion, one can infer that the observed selection and employment changes could be rationalized by combining some of the individual hypotheses.

- Among southern EU countries, Portugal becomes the best example of the combination of Hypotheses I+II$_m$+III, which jointly lead to a reduction in both PG and PG, a decline (increase) in female (male) selection, a large drop in male employment (especially unskilled) and a rise in female employment. Italy exhibits somewhat similar patterns, except that RG, and to a lesser extent PG, have shot up. This could rationalized by a combination of Hypotheses II$_m$+II$_f$. By contrast, the Greek and Spanish patterns seem to be better explained by Hypotheses I+II$_m$+II$_f$, with an increase in both male and female selection biases and a collapse in both (unskilled) male and female employment rates.

- Among Rest of Europe, as already mentioned, Austria provides a good illustration of Hypothesis III on its own, whereas the findings for Belgium, France, and Ireland fit with Hypotheses I+II$_m$+III; finally, the evidence for Denmark, Finland, The Netherlands and the UK are better rationalized by I+II$_m$+II$_f$.

Overall, our main conclusions from the previous discussion is that changing patterns in male and female selection have been much more pronounced in southern Europe than in Rest of Europe. Depending on whether LD or LS shifts dominate, we find cases where these changes have led to a larger or smaller reduction in PG than in RG. Yet, a fairly robust case for an increase in male selection can be made. Furthermore, among those EU countries most badly hit by the crisis, it seems that in those where female LFP was higher before the crisis (Ireland and Portugal), female selection bias corrections have gone down, while the opposite has happened in those where female participation was lower (Greece and Portugal)

6 Conclusions

This paper has analyzed whether conventional patterns of selection of workers into EU labour markets have changed as a result of the large variations in labour demand and labour supply brought in by the Great Recession (GR). Based on a large body of empirical evidence, it has been traditionally assumed that, because of their high labour force participation rates, there were no relevant differences between the observed and potential male wage distributions prior to the crisis. In contrast, due to their lower participation rates (especially in southern Europe), favourable labour market selection has operated among women. Our working hypothesis is that, if the big job losses brought about by the GR have mainly affected unskilled male-dominated sectors, then male selection may have become positive. Moreover, if non-participating women have increase their labour force participation due to an added-worker effect, then female selection may have become less positive, unless adverse labour demand shifts have more than offset the rise in female labour supply. In this case female selection changes would have been more muted or even become more positive.

Using alternative imputation methods for wages of non-participating individuals in EU-SILC datasets for a large group of European countries, our findings support the conjecture that male selection corrections have become more relevant in most instances. This has been especially the case in some southern EU economies, where large male job losses have taken place in response to the bursting of real estate bubbles. In effect, their dysfunctional labour markets, characterized by labour contract dualism or wage rigidity, have incentivized adjustment to negative shocks via dismissals rather than through wage cuts. Spain provides the best illustration of this changing pattern. With regard to female selection, we find mixed results: while there are cases where, in line with the added-worker effect, female selection has gone down significantly (Austria, Belgium, Ireland, Italy and Portugal), in other instances (Greece and Spain) it has gone up because of widespread job destruction that has prevented new female entrants into the labour market from finding jobs.

We conjecture that, once the GR is over and employment growth picks up, it is likely that the increase in male selection will remain relevant. This is so since those men who lost their jobs during the crisis (mostly concentrated in construction and other low-value added industries) are likely to become long-term unemployed and hence non-employable. Likewise, the decrease in female selection is likely to stay. This is so since increasing female labour force participation is 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. Hence, if these predictions were to be correct, everything else equal, we may see in the future increases in actual, rather than in potential, gender wage gaps.

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A 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 2005-2013 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.

B Additional Tables and Figures

Table 6: Median Wage Gaps under Imputation on Education and Experience - Probabilistic Model

	Levels in 2007				Changes over 2007-2012			
	Raw Wage Gap	True Wage Gap	Selection Bias M	Selection Bias F	Raw Wage Gap	True Wage Gap	Selection Bias M	Selection Bias F
Southern Europe:								
Greece	.182	.413	.016	.247	-.076	-.088	.067	.056
Italy	.035	.184	.014	.163	.053	.027	.013	-.013
Spain	.132	.207	.010	.085	-.027	-.026	.035	.036
Portugal	.172	.219	.012	.059	-.038	-.061	.016	-.007
Mean	**.130**	**.256**	**.013**	**.138**	**-.022**	**-.037**	**.033**	**.018**
Rest of Europe:								
Austria	.192	.266	.009	.084	.012	-.016	.001	-.027
Belgium	.074	.143	.021	.090	-.019	-.060	.000	-.041
Ireland	.170	.273	.042	.145	-.040	-.019	.037	.059
United Kingdom	.247	.262	.010	.025	-.065	-.040	.009	.035
Netherlands	.158	.175	.004	.021	-.054	-.044	.003	.012
France	.114	.144	.005	.035	.005	-.012	.009	-.008
Finland	.203	.200	.013	.010	-.072	-.066	.002	.008
Denmark	.116	.119	.000	.003	-.072	-.073	.007	.006
Norway	.154	.156	.002	.004	.027	.023	.004	.000
Mean	**.158**	**.193**	**.012**	**.046**	**-.031**	**-.034**	**.008**	**.005**

Source: EU-SILC and authors' calculations. Note: Selection bias = an increase in observed wage due to selection. Wage imputation rule: Impute wage $<(>)$ median with probability $\hat{P}_i$ (respectively, $1-\hat{P}_i$) if nonemployed, where $\hat{P}_i$ is the predicted probability of earning a wage below the gender-specific median, as estimated from a probit model including education dummies, experience and its square on an enlarged base sample with wage observations from other waves.

Table 7: Rate and Goodness of Imputation on Spousal Income

	2007						2012					
	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
Southern Europe:												
Greece	.27	.63	.56	.29	.55	.61	.30	.56	.56	.58	.57	.61
Italy	.30	.52	.64	.53	.55	.59	.32	.52	.73	.62	.54	.61
Spain	.32	.56	.74	.70	.62	.66	.35	.49	.65	.63	.62	.65
Portugal	.36	.62	.61	.59	.60	.62	.41	.50	.65	.55	.65	.65
Mean	**.31**	**.58**	**.64**	**.53**	**.58**	**.62**	**.35**	**.52**	**.65**	**.59**	**.59**	**.63**
Rest of Europe:												
Austria	.36	.53	.71	.69	.60	.67	.33	.50	.78	.60	.54	.60
Belgium	.30	.45	.86	.67	.56	.62	.27	.47	.78	.85	.62	.62
Ireland	.41	.53	.88	.53	.57	.60	.53	.55	.80	1.00	.56	.60
United Kingdom	.51	.59	.32	.69	.56	.60	.47	.57	.70	.58	.56	.61
Netherlands	.19	.47	1.00	.22	.49	.55	.29	.42	.57	.63	.55	.56
France	.35	.51	.52	.66	.63	.62	.31	.51	.63	.45	.58	.63
Finland	.23	.47	.73	.84	.61	.60	.26	.50	.72	.71	.61	.61
Denmark	.47	.39	1.00	.68	.60	.63	.16	.34	1.00	1.00	.68	.63
Norway	.25	.40	.74	.70	.62	.66	.42	.50	.65	.63	.62	.65
Mean	**.34**	**.48**	**.75**	**.63**	**.58**	**.62**	**.34**	**.48**	**.74**	**.72**	**.59**	**.61**

Source: EU-SILC and authors' calculations. Note: Wage imputation rule: Impute wage $<$ median when nonemployed and spouse income in bottom quartile; impute wage $>$ median when nonemployed and spouse income in top quartile. Imputation Rate = proportion of imputed wage observations in total nonemployment. 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.

Table 8: Rate of Imputation Based on Wages from Other Waves

	2007		2012	
	M	F	M	F
Southern Europe:				
Greece	.23	.11	.32	.17
Italy	.28	.14	.35	.16
Spain	.42	.26	.46	.30
Portugal	.60	.59	.62	.62
Mean	**.38**	**.28**	**.44**	**.31**
Rest of Europe:				
Austria	.31	.36	.33	.28
Belgium	.22	.14	.30	.16
Ireland	.18	.12	.09	.08
United Kingdom	.16	.17	.15	.14
Netherlands	.25	.16	.30	.20
France	.46	.43	.49	.34
Finland	.52	.48	.24	.36
Denmark	.47	.60	.23	.28
Norway	.55	.64	.32	.32
Mean	**.35**	**.34**	**.27**	**.24**

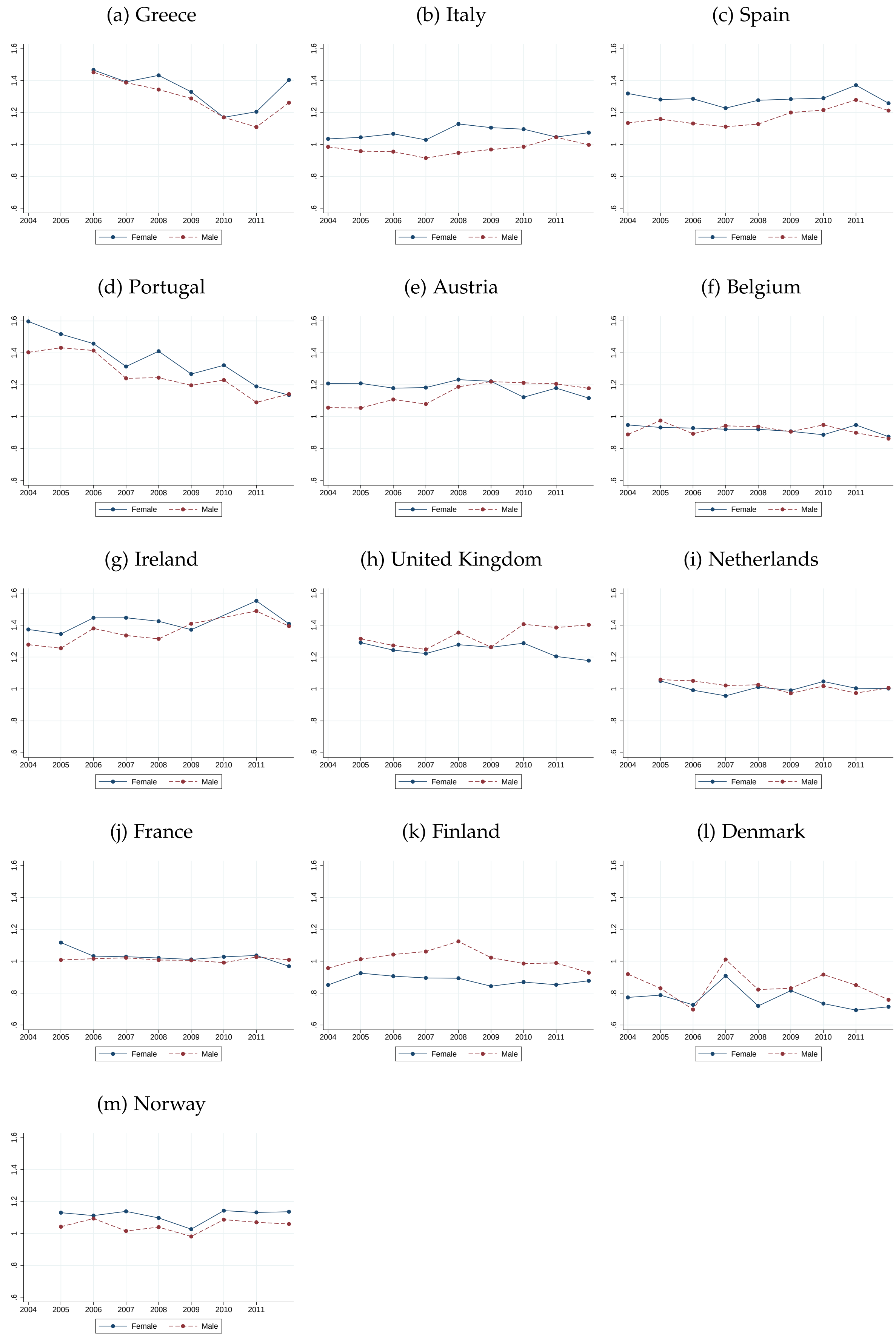
Source: EU-SILC and authors' calculations. Note: Wage imputation rule: Impute wage from other waves when nonemployed. Imputation Rate = proportion of imputed wage observations in total nonemployment.

Table 9: Employment Rates by Education

	Employment Rate in 2007				Changes over 2007-2012			
	College		No college		College		No college	
	M	F	M	F	M	F	M	F
Southern Europe:								
Greece	.977	.681	.965	.567	-.213	-.142	-.276	-.114
Italy	.946	.673	.944	.618	.009	.001	-.068	-.003
Spain	.977	.810	.964	.730	-.122	-.081	-.192	-.098
Portugal	.946	.835	.936	.788	-.074	-.009	-.088	-.025
Mean	**.962**	**.750**	**.952**	**.676**	**-.100**	**-.058**	**-.156**	**-.060**
Rest of Europe:								
Austria	.962	.768	.944	.752	.020	.001	-.003	.014
Belgium	.950	.849	.914	.768	-.038	.028	-.034	.022
Ireland	.973	.721	.965	.607	-.107	-.122	-.210	-.104
United Kingdom	.979	.816	.972	.797	-.008	-.014	-.065	-.057
Netherlands	.950	.853	.957	.815	.004	.003	-.059	-.038
France	.988	.886	.977	.856	-.011	.004	-.049	-.012
Finland	.988	.888	.987	.913	-.015	-.025	-.030	-.067
Denmark	.995	.955	.990	.952	-.144	-.003	-.114	-.086
Norway	.982	.921	.988	.933	-.017	.008	-.014	-.002
Mean	**.974**	**.851**	**.966**	**.821**	**-.035**	**-.013**	**-.064**	**-.037**

Source: EU-SILC and authors' calculations.

Figure 7: Cross-country wage inequality, 2007-2012.



Notes.— Wage inequality is measured by logarithm of the ratio between wages at 90th and 10th percentiles. Source: EU-SILC and authors' calculations.

Table 10: LFP Rates by Education

	LFP Rate in 2007				Changes over 2007-2012			
	College		No college		College		No college	
	M	F	M	F	M	F	M	F
Southern Europe:								
Greece	.977	.681	.965	.567	.005	.011	-.024	.053
Italy	.946	.673	.944	.618	.043	.052	.025	.024
Spain	.977	.810	.964	.730	.002	.040	.025	.079
Portugal	.946	.835	.936	.788	-.005	.051	.039	.073
Mean	**.962**	**.750**	**.952**	**.676**	**.011**	**.038**	**.016**	**.057**
Rest of Europe:								
Austria	.962	.768	.944	.752	.009	-.013	.010	.022
Belgium	.950	.849	.914	.768	.009	.031	-.008	.039
Ireland	.973	.721	.965	.607	.016	-.067	.014	-.027
United Kingdom	.979	.816	.972	.797	-.002	-.005	-.019	-.025
Netherlands	.950	.853	.957	.815	.040	.029	.014	.020
France	.988	.886	.977	.856	.005	.006	-.004	.008
Finland	.988	.888	.987	.913	-.004	-.003	-.007	-.057
Denmark	.995	.955	.990	.952	-.004	.028	-.043	.024
Norway	.982	.921	.988	.933	-.002	.011	-.005	.015
Mean	**.974**	**.851**	**.966**	**.821**	**.007**	**.002**	**-.005**	**.002**

Source: EU-SILC and authors' calculations.

Table 11: Descriptive Statistics of Samples Used

	2007						2012					
	Males			Females			Males			Females		
	N	M	SD	N	M	SD	N	M	SD	N	M	SD
Greece												
Employed	1799	.85	.35	2320	.54	.50	1205	.60	.49	1559	.43	.50
Unemployed	1799	.11	.31	2320	.11	.31	1205	.35	.48	1559	.27	.45
Inactive	1799	.04	.19	2320	.35	.48	1205	.05	.22	1559	.30	.46
Annual Earnings	1651	21.63	15.73	1383	16.10	10.44	839	17.38	12.58	729	14.26	9.05
Annual Hours	1587	2073	506	1322	1770	575	810	1891	565	707	1707	597
Log(hourly wage)	1587	2.02	.57	1322	1.90	.56	810	1.80	.49	707	1.72	.53
Age	1799	38.80	8.42	2320	38.92	8.43	1205	38.77	8.50	1559	39.22	8.44
Educ1	1789	.27	.44	2311	.28	.45	1203	.21	.40	1555	.21	.41
Educ2	1789	.41	.49	2311	.35	.48	1203	.43	.50	1555	.38	.49
Educ3	1789	.26	.44	2311	.30	.46	1203	.28	.45	1555	.34	.47
Experience	1799	16.76	9.60	2320	10.19	9.08	1205	15.39	9.94	1559	10.24	9.19
Temporary	1580	.21	.41	1315	.23	.42	666	.15	.36	591	.17	.37
Spouse 1st quartile	1799	.36	.48	2320	.34	.47	1205	.37	.48	1559	.40	.49
Spouse 2nd quartile	1799	.08	.27	2320	.11	.31	1205	.05	.22	1559	.07	.26
Spouse 3rd quartile	1799	.09	.29	2320	.13	.34	1205	.07	.25	1559	.11	.31
Spouse 4th quartile	1799	.09	.28	2320	.16	.37	1205	.08	.27	1559	.12	.33
Italy												
Employed	7848	.85	.36	9534	.56	.50	4341	.79	.41	5311	.56	.50
Unemployed	7848	.09	.29	9534	.10	.30	4341	.17	.38	5311	.13	.33
Inactive	7848	.06	.24	9534	.35	.48	4341	.03	.18	5311	.31	.46
Annual Earnings	7068	19.05	8.90	6123	14.45	7.35	3851	19.02	10.64	3576	14.56	8.02
Annual Hours	6703	2089	436	5349	1716	521	3535	2011	449	3138	1716	506
Log(hourly wage)	6703	2.03	.42	5349	1.99	.46	3535	1.95	.50	3138	1.86	.52
Age	7848	39.68	8.21	9534	40.08	8.05	4341	40.40	8.20	5311	41.15	8.04
Educ1	7818	.44	.50	9500	.40	.49	4318	.39	.49	5298	.36	.48
Educ2	7818	.39	.49	9500	.38	.49	4318	.43	.50	5298	.43	.49
Educ3	7818	.13	.34	9500	.16	.37	4318	.15	.35	5298	.18	.38
Experience	7848	16.82	9.58	9534	11.54	9.18	4341	17.59	9.29	5311	13.36	9.19
Temporary	6487	.10	.30	5243	.14	.35	3336	.09	.29	2958	.12	.33
Spouse 1st quartile	7848	.36	.48	9534	.30	.46	4341	.35	.48	5311	.29	.46
Spouse 2nd quartile	7848	.08	.28	9534	.12	.32	4341	.09	.29	5311	.12	.32
Spouse 3rd quartile	7848	.08	.28	9534	.13	.34	4341	.08	.28	5311	.13	.34
Spouse 4th quartile	7848	.08	.27	9534	.15	.36	4341	.08	.28	5311	.16	.36
Spain												
Employed	5908	.89	.31	7022	.67	.47	3512	.72	.45	4129	.60	.49
Unemployed	5908	.08	.27	7022	.11	.31	3512	.27	.44	4129	.26	.44
Inactive	5908	.03	.17	7022	.22	.41	3512	.01	.11	4129	.15	.35
Annual Earnings	5506	17.47	8.93	5035	13.05	8.19	3029	16.66	11.10	2893	13.19	9.52
Annual Hours	5282	2107	489	4658	1760	597	2662	1931	576	2531	1652	642
Log(hourly wage)	5282	1.85	.48	4656	1.72	.54	2642	1.83	.61	2512	1.72	.63
Age	5908	38.36	8.29	7022	38.86	8.25	3512	39.81	8.08	4129	40.22	8.02
Educ1	5832	.41	.49	6908	.39	.49	3427	.42	.49	4020	.35	.48
Educ2	5832	.23	.42	6908	.25	.43	3427	.24	.43	4020	.24	.43
Educ3	5832	.35	.48	6908	.35	.48	3427	.34	.47	4020	.41	.49
Experience	5842	18.03	9.75	6964	13.05	9.23	3510	13.69	11.55	4125	9.76	10.45
Temporary	5028	.23	.42	4461	.28	.45	2464	.20	.40	2304	.24	.43
Spouse 1st quartile	5908	.33	.47	7022	.26	.44	3512	.33	.47	4129	.27	.45
Spouse 2nd quartile	5908	.10	.31	7022	.13	.34	3512	.11	.31	4129	.13	.33
Spouse 3rd quartile	5908	.10	.30	7022	.14	.35	3512	.10	.30	4129	.15	.36
Spouse 4th quartile	5908	.11	.31	7022	.17	.38	3512	.11	.32	4129	.18	.38

Source: EU-SILC and authors' calculations. Note: The descriptive statistics refer to the base samples, aged 25-54, excluding the self-employed, those in the military, and those in full-time education. Description of variables: Employed, unemployed, and inactive are self-defined. Educ1=1 if less than upper secondary education. Educ2=1 if upper secondary education completed. Educ3=1 if higher education. Married=1 if living in a couple.

Table 11: Descriptive Statistics of Samples Used

	2007						2012					
	Males			Females			Males			Females		
	N	M	SD	N	M	SD	N	M	SD	N	M	SD
Portugal												
Employed	1880	.84	.37	2250	.71	.45	1803	.75	.43	2124	.69	.46
Unemployed	1880	.10	.30	2250	.10	.30	1803	.22	.41	2124	.19	.39
Inactive	1880	.06	.24	2250	.19	.39	1803	.03	.17	2124	.12	.33
Annual Earnings	1658	10.91	7.10	1631	8.81	6.10	1458	11.15	6.91	1575	9.36	5.83
Annual Hours	1639	2092	431	1625	1863	505	1408	2096	553	1524	1926	514
Log(hourly wage)	1635	1.38	.51	1602	1.25	.58	1406	1.34	.49	1521	1.26	.49
Age	1880	38.45	8.73	2250	39.61	8.57	1803	40.50	8.32	2124	40.65	8.10
Educ1	1831	.72	.45	2185	.66	.47	1759	.63	.48	2073	.53	.50
Educ2	1831	.16	.37	2185	.15	.36	1759	.22	.41	2073	.23	.42
Educ3	1831	.11	.32	2185	.18	.39	1759	.15	.35	2073	.23	.42
Experience	1874	19.59	10.55	2247	17.18	10.63	1800	21.63	10.51	2124	18.92	10.11
Temporary	1556	.17	.38	1546	.21	.41	1260	.14	.35	1372	.14	.35
Spouse 1st quartile	1880	.31	.46	2250	.29	.46	1803	.33	.47	2124	.29	.45
Spouse 2nd quartile	1880	.10	.30	2250	.12	.32	1803	.13	.33	2124	.13	.34
Spouse 3rd quartile	1880	.10	.30	2250	.13	.34	1803	.13	.34	2124	.13	.34
Spouse 4th quartile	1880	.08	.28	2250	.16	.37	1803	.12	.33	2124	.15	.36
Austria												
Employed	2329	.88	.33	2647	.71	.45	1522	.88	.32	1769	.72	.45
Unemployed	2329	.07	.25	2647	.06	.23	1522	.08	.27	1769	.06	.24
Inactive	2329	.05	.22	2647	.23	.42	1522	.04	.20	1769	.22	.41
Annual Earnings	2176	36.11	21.83	2033	23.05	36.77	1348	43.29	31.89	1425	24.64	17.84
Annual Hours	2098	2118	430	1905	1623	626	1365	2108	491	1311	1605	598
Log(hourly wage)	2090	2.61	.50	1892	2.39	.56	1275	2.66	.64	1226	2.44	.58
Age	2329	40.40	8.16	2647	40.25	8.23	1522	40.74	8.70	1769	40.90	8.44
Educ1	2329	.09	.29	2647	.16	.37	1522	.10	.30	1769	.17	.38
Educ2	2329	.59	.49	2647	.50	.50	1522	.56	.50	1769	.48	.50
Educ3	2329	.21	.41	2647	.18	.39	1522	.22	.42	1769	.18	.39
Experience	2328	21.28	9.26	2646	16.63	9.56	1522	22.10	9.79	1768	17.66	9.63
Temporary	2084	.04	.19	1845	.06	.24	1342	.05	.21	1265	.06	.24
Spouse 1st quartile	2329	.37	.48	2647	.27	.44	1522	.34	.47	1769	.29	.45
Spouse 2nd quartile	2329	.12	.33	2647	.12	.33	1522	.15	.35	1769	.13	.34
Spouse 3rd quartile	2329	.11	.31	2647	.15	.36	1522	.10	.30	1769	.14	.35
Spouse 4th quartile	2329	.09	.28	2647	.17	.38	1522	.11	.31	1769	.15	.36
Belgium												
Employed	2458	.87	.34	2802	.74	.44	1517	.83	.37	1715	.77	.42
Unemployed	2458	.07	.25	2802	.08	.27	1517	.10	.30	1715	.08	.28
Inactive	2458	.07	.25	2802	.18	.39	1517	.07	.25	1715	.14	.35
Annual Earnings	2227	35.46	18.82	2140	25.38	13.26	1373	40.28	22.03	1387	30.77	17.25
Annual Hours	2152	2048	510	2001	1650	555	1332	2019	479	1301	1648	546
Log(hourly wage)	2150	2.64	.42	1962	2.54	.45	1332	2.69	.39	1292	2.63	.41
Age	2458	39.89	8.47	2802	39.97	8.61	1517	40.01	8.50	1715	39.95	8.74
Educ1	2373	.24	.43	2709	.22	.41	1502	.20	.40	1697	.18	.38
Educ2	2373	.37	.48	2709	.33	.47	1502	.34	.47	1697	.31	.46
Educ3	2373	.37	.48	2709	.43	.49	1502	.42	.49	1697	.48	.50
Experience	2443	18.38	9.94	2789	15.09	10.02	1497	16.50	9.86	1684	14.42	9.94
Temporary	2136	.05	.23	2046	.11	.31	1280	.07	.26	1309	.10	.30
Spouse 1st quartile	2458	.31	.46	2802	.25	.44	1517	.28	.45	1715	.25	.43
Spouse 2nd quartile	2458	.13	.34	2802	.14	.35	1517	.12	.33	1715	.14	.34
Spouse 3rd quartile	2458	.13	.33	2802	.16	.37	1517	.14	.34	1715	.15	.35
Spouse 4th quartile	2458	.12	.32	2802	.17	.37	1517	.12	.33	1715	.18	.38

Source: EU-SILC and authors' calculations. Note: The descriptive statistics refer to the base samples, aged 25-54, excluding the self-employed, those in the military, and those in full-time education. Description of variables: Employed, unemployed, and inactive are self-defined. Educ1=1 if less than upper secondary education. Educ2=1 if upper secondary education completed. Educ3=1 if higher education. Married=1 if living in a couple.

Table 11: Descriptive Statistics of Samples Used

	2007						2012					
	Males			Females			Males			Females		
	N	M	SD	N	M	SD	N	M	SD	N	M	SD
Ireland												
Employed	1326	.85	.36	1820	.67	.47	1269	.71	.45	1661	.59	.49
Unemployed	1326	.11	.32	1820	.03	.17	1269	.27	.44	1661	.10	.29
Inactive	1326	.04	.19	1820	.30	.46	1269	.02	.14	1661	.31	.46
Annual Earnings	1184	44.67	35.96	1283	27.34	21.69	945	47.03	112.74	1049	31.75	32.40
Annual Hours	1145	2015	543	1202	1467	633	896	1897	608	1006	1514	630
Log(hourly wage)	1141	2.80	.56	1193	2.64	.62	884	2.83	.61	995	2.70	.63
Age	1326	41.00	8.33	1820	41.26	8.28	1269	39.69	8.10	1661	39.30	8.13
Educ1	1293	.34	.47	1790	.30	.46	1213	.23	.42	1608	.17	.38
Educ2	1293	.23	.42	1790	.25	.43	1213	.23	.42	1608	.23	.42
Educ3	1293	.35	.48	1790	.35	.48	1213	.50	.50	1608	.49	.50
Experience	1313	20.69	9.69	1786	15.89	9.03	1260	18.15	9.40	1654	14.21	8.96
Temporary	1121	.04	.21	1192	.08	.28	865	.07	.26	959	.08	.27
Spouse 1st quartile	1326	.36	.48	1820	.31	.46	1269	.41	.49	1661	.35	.48
Spouse 2nd quartile	1326	.11	.31	1820	.10	.30	1269	.11	.32	1661	.11	.31
Spouse 3rd quartile	1326	.09	.29	1820	.13	.33	1269	.12	.32	1661	.11	.32
Spouse 4th quartile	1326	.12	.32	1820	.14	.35	1269	.11	.32	1661	.13	.33
United Kingdom												
Employed	2825	.94	.23	3748	.81	.40	3655	.91	.29	4434	.78	.41
Unemployed	2825	.03	.17	3748	.02	.12	3655	.06	.23	4434	.04	.19
Inactive	2825	.03	.16	3748	.18	.38	3655	.04	.19	4434	.18	.39
Annual Earnings	2638	47.77	35.88	3030	28.00	21.33	3206	42.46	43.13	3331	26.46	23.67
Annual Hours	2601	2267	509	2910	1694	663	3255	2236	560	3387	1709	671
Log(hourly wage)	2570	2.81	.55	2836	2.56	.60	3108	2.50	.59	3185	2.32	.54
Age	2825	40.09	8.01	3748	40.05	8.14	3655	39.91	8.29	4434	40.01	8.30
Educ1	2736	.08	.26	3646	.09	.28	3418	.09	.28	4199	.08	.27
Educ2	2736	.55	.50	3646	.57	.50	3418	.45	.50	4199	.44	.50
Educ3	2736	.33	.47	3646	.32	.47	3418	.46	.50	4199	.48	.50
Experience	1674	19.56	9.64	2368	15.97	9.04	3650	19.06	9.77	4423	17.08	9.91
Temporary	2562	.03	.17	2868	.04	.19	3173	.03	.17	3311	.03	.18
Spouse 1st quartile	2825	.32	.47	3748	.29	.45	3655	.35	.48	4434	.30	.46
Spouse 2nd quartile	2825	.15	.35	3748	.15	.35	3655	.12	.33	4434	.14	.35
Spouse 3rd quartile	2825	.14	.34	3748	.14	.35	3655	.12	.33	4434	.15	.36
Spouse 4th quartile	2825	.13	.34	3748	.16	.36	3655	.13	.34	4434	.16	.37
Netherlands												
Employed	2315	.93	.25	2712	.80	.40	1394	.90	.30	1689	.78	.41
Unemployed	2315	.02	.13	2712	.04	.19	1394	.07	.26	1689	.08	.28
Inactive	2315	.05	.22	2712	.16	.37	1394	.02	.15	1689	.13	.34
Annual Earnings	2267	44.00	33.61	2393	24.12	14.97	1362	46.48	23.87	1506	28.36	18.44
Annual Hours	2048	1949	367	2145	1358	477	1307	1939	393	1398	1385	467
Log(hourly wage)	2046	2.92	.48	2139	2.68	.58	1307	2.90	.50	1398	2.76	.52
Age	2315	40.32	8.41	2712	39.96	8.28	1394	40.73	8.45	1689	40.66	8.36
Educ1	2278	.18	.38	2663	.20	.40	1378	.15	.36	1681	.17	.38
Educ2	2278	.37	.48	2663	.42	.49	1378	.36	.48	1681	.42	.49
Educ3	2278	.42	.49	2663	.33	.47	1378	.44	.50	1681	.38	.49
Experience	2304	17.77	9.76	2672	14.00	8.65	1378	18.01	9.22	1665	15.04	8.66
Temporary	2133	.12	.33	2220	.14	.35	1244	.12	.33	1358	.14	.35
Spouse 1st quartile	2315	.30	.46	2712	.19	.40	1394	.30	.46	1689	.21	.41
Spouse 2nd quartile	2315	.15	.36	2712	.17	.38	1394	.15	.36	1689	.16	.37
Spouse 3rd quartile	2315	.13	.34	2712	.18	.38	1394	.15	.35	1689	.19	.39
Spouse 4th quartile	2315	.14	.35	2712	.22	.42	1394	.11	.32	1689	.19	.40

Source: EU-SILC and authors' calculations. Note: The descriptive statistics refer to the base samples, aged 25-54, excluding the self-employed, those in the military, and those in full-time education. Description of variables: Employed, unemployed, and inactive are self-defined. Educ1=1 if less than upper secondary education. Educ2=1 if upper secondary education completed. Educ3=1 if higher education. Married=1 if living in a couple.

Table 11: Descriptive Statistics of Samples Used

	2007						2012					
	Males			Females			Males			Females		
	N	M	SD	N	M	SD	N	M	SD	N	M	SD
France												
Employed	4121	.92	.28	4624	.82	.39	3426	.88	.32	3749	.82	.39
Unemployed	4121	.06	.24	4624	.07	.25	3426	.10	.29	3749	.08	.27
Inactive	4121	.02	.14	4624	.11	.32	3426	.02	.14	3749	.10	.30
Annual Earnings	3969	24.40	16.81	4098	16.64	10.53	3248	25.82	16.37	3375	18.48	11.63
Annual Hours	3783	2070	516	3732	1684	579	3086	2033	538	3025	1719	579
Log(hourly wage)	3779	2.25	.51	3704	2.09	.60	3084	2.27	.50	3022	2.11	.59
Age	4121	40.26	8.20	4624	40.50	8.31	3426	40.37	8.31	3749	40.69	8.33
Educ1	4117	.19	.39	4610	.22	.41	3415	.13	.34	3742	.14	.35
Educ2	4117	.49	.50	4610	.43	.50	3415	.52	.50	3742	.45	.50
Educ3	4117	.32	.47	4610	.35	.48	3415	.35	.48	3742	.40	.49
Experience	4105	19.08	9.91	4621	16.03	9.88	3410	19.16	9.66	3742	16.34	9.60
Temporary	3592	.10	.29	3644	.16	.36	2981	.11	.32	3032	.14	.35
Spouse 1st quartile	4121	.31	.46	4624	.25	.44	3426	.29	.45	3749	.24	.43
Spouse 2nd quartile	4121	.17	.37	4624	.16	.37	3426	.17	.37	3749	.17	.37
Spouse 3rd quartile	4121	.16	.36	4624	.18	.38	3426	.16	.37	3749	.17	.38
Spouse 4th quartile	4121	.15	.35	4624	.18	.39	3426	.14	.34	3749	.18	.39
Finland												
Employed	1128	.90	.30	1254	.86	.34	1299	.88	.33	1419	.83	.38
Unemployed	1128	.09	.29	1254	.04	.20	1299	.10	.31	1419	.05	.22
Inactive	1128	.01	.11	1254	.09	.29	1299	.02	.14	1419	.12	.33
Annual Earnings	1079	36.19	22.83	1176	25.69	14.12	1217	41.87	23.00	1317	31.86	17.59
Annual Hours	1017	1985	500	1035	1813	485	1125	1984	439	1125	1819	468
Log(hourly wage)	1005	2.74	.49	1031	2.54	.45	1114	2.78	.45	1120	2.66	.44
Age	1128	39.66	8.63	1254	40.00	8.65	1299	39.66	8.70	1419	40.11	8.58
Educ1	1116	.12	.32	1248	.11	.31	1282	.10	.30	1399	.05	.21
Educ2	1116	.49	.50	1248	.39	.49	1282	.48	.50	1399	.34	.47
Educ3	1116	.39	.49	1248	.50	.50	1282	.42	.49	1399	.60	.49
Experience	1071	16.59	9.84	1185	15.94	10.18	1273	16.93	9.79	1377	16.21	9.64
Temporary	1030	.11	.31	1072	.19	.39	1073	.08	.27	1059	.13	.33
Spouse 1st quartile	1128	.26	.44	1254	.21	.41	1299	.29	.46	1419	.21	.41
Spouse 2nd quartile	1128	.11	.32	1254	.14	.35	1299	.15	.36	1419	.14	.35
Spouse 3rd quartile	1128	.13	.34	1254	.16	.37	1299	.11	.31	1419	.15	.36
Spouse 4th quartile	1128	.13	.33	1254	.14	.35	1299	.11	.31	1419	.16	.36
Denmark												
Employed	1503	.98	.12	1762	.94	.23	565	.86	.35	636	.90	.30
Unemployed	1503	.01	.08	1762	.01	.12	565	.11	.31	636	.09	.28
Inactive	1503	.01	.09	1762	.04	.21	565	.03	.18	636	.02	.13
Annual Earnings	1434	47.98	26.57	1685	36.72	15.99	550	53.01	27.70	606	44.30	18.36
Annual Hours	1480	2064	409	1679	1829	362	535	1988	494	575	1799	381
Log(hourly wage)	1413	2.90	.69	1633	2.80	.61	528	3.01	.69	562	2.97	.38
Age	1503	40.07	8.17	1762	39.98	8.10	565	40.72	8.13	636	40.28	8.33
Educ1	1492	.19	.39	1753	.16	.37	557	.11	.31	628	.08	.27
Educ2	1492	.48	.50	1753	.41	.49	557	.50	.50	628	.43	.50
Educ3	1492	.34	.47	1753	.43	.49	557	.40	.49	628	.49	.50
Experience	1497	18.52	9.39	1758	16.05	9.52	561	19.15	10.13	629	17.44	10.06
Temporary	1431	.00	.00	1657	.00	.00	519	.08	.27	562	.05	.22
Spouse 1st quartile	1503	.19	.39	1762	.17	.37	565	.22	.41	636	.20	.40
Spouse 2nd quartile	1503	.15	.35	1762	.12	.33	565	.09	.29	636	.12	.32
Spouse 3rd quartile	1503	.12	.32	1762	.15	.36	565	.10	.29	636	.15	.35
Spouse 4th quartile	1503	.13	.33	1762	.19	.39	565	.12	.33	636	.19	.40

Source: EU-SILC and authors' calculations. Note: The descriptive statistics refer to the base samples, aged 25-54, excluding the self-employed, those in the military, and those in full-time education. Description of variables: Employed, unemployed, and inactive are self-defined. Educ1=1 if less than upper secondary education. Educ2=1 if upper secondary education completed. Educ3=1 if higher education. Married=1 if living in a couple.

Table 11: Descriptive Statistics of Samples Used

	2007						2012					
	Males			Females			Males			Females		
	N	M	SD	N	M	SD	N	M	SD	N	M	SD
Norway												
Employed	1379	.97	.16	1222	.91	.28	1698	.96	.20	1770	.92	.28
Unemployed	1379	.01	.10	1222	.02	.12	1698	.02	.14	1770	.02	.15
Inactive	1379	.02	.13	1222	.07	.26	1698	.02	.14	1770	.06	.24
Annual Earnings	1337	58.85	111.68	1176	35.52	19.94	1640	77.84	64.33	1681	50.81	26.40
Annual Hours	1330	2107	451	1090	1764	511	1629	2113	407	1624	1843	464
Log(hourly wage)	1296	3.04	.71	1077	2.80	.69	1590	3.31	.58	1595	3.04	.59
Age	1379	39.59	8.14	1222	39.79	8.23	1698	41.38	8.15	1770	41.14	7.90
Educ1	1328	.17	.37	1180	.13	.34	1670	.10	.30	1738	.11	.31
Educ2	1328	.43	.50	1180	.35	.48	1670	.39	.49	1738	.30	.46
Educ3	1328	.37	.48	1180	.48	.50	1670	.45	.50	1738	.57	.49
Experience	1379	18.02	9.66	1222	15.98	9.25	960	19.94	8.99	822	17.47	9.03
Temporary	1279	.05	.21	1122	.10	.30	891	.04	.20	770	.09	.28
Spouse 1st quartile	1379	.21	.41	1222	.18	.38	1698	.29	.45	1770	.25	.43
Spouse 2nd quartile	1379	.13	.33	1222	.14	.34	1698	.17	.38	1770	.18	.39
Spouse 3rd quartile	1379	.11	.31	1222	.12	.32	1698	.18	.39	1770	.20	.40
Spouse 4th quartile	1379	.10	.30	1222	.16	.37	1698	.18	.38	1770	.22	.41

Source: EU-SILC and authors' calculations. Note: The descriptive statistics refer to the base samples, aged 25-54, excluding the self-employed, those in the military, and those in full-time education. Description of variables: Employed, unemployed, and inactive are self-defined. Educ1=1 if less than upper secondary education. Educ2=1 if upper secondary education completed. Educ3=1 if higher education. Married=1 if living in a couple.