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# From Gross Wages to Net Household Income: a Distributional Analysis of the Gender Wage Gap

Patricia Gallego-Granados\* and Johannes Geyer†

February 15, 2014

Numerous studies analyze gender wage differences focusing on gross hourly wages. The analysis of differences in gross wages allows statements on productivity differences between men and women and to quantify the unexplainable wage gap which is often attributed to discrimination. While there is plenty evidence that the gender (gross) wage gap is a persistent labor market phenomenon, less is known about its effects on the income distribution. In this paper, we therefore go a step further and ask how differences in gross wages – in particular the unexplained gap – show up in available income and its distribution. This is particularly relevant from a policy perspective because of its implications for income inequality and working incentives. The empirical analysis is carried out for West Germany with data from the GSOEP pooled for the years 2006 to 2011. Germany is an interesting case because it is one of the few countries with a system of joint taxation for married couples. This leads to high marginal tax rates for second earners and affects after-tax income differences between men and women.

**Keywords:** gender wage gap, labor supply, microsimulation, income distribution

**JEL Classification:** D31, J16, H23

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# 1. Introduction

The gender gap in gross wages is a persistent and pervasive phenomenon observable in virtually every country's labor market. The analysis of the gender pay gap and its determinants has been the focus of numerous studies. The central research question in this literature is whether the pay gap can be explained by observable characteristics or if women are disadvantaged on the labor market as compared to men. Empirically the observed wage gaps can be decomposed in differences in endowments and in unexplained differences which include different rewards for the same characteristics. In other words, this literature focuses on the relationship of productivity and labor prices.

A gap in gross hourly wages also leads to gaps in net income for most households. This is often part of the motivation of studies on the gender wage gap. However, little is known about the actual impact of this gross pay gap for disposable income. It is often argued that the pay gap might imply important behavioral consequences. *Ceteris paribus* it reduces labor supply incentives and also has also implications for the gender specific distribution of income within couple households and on the economic independence of women. In order to analyse these effects, it is necessary to know about the net income gap and its distribution. This paper is a first step in this direction. We contribute to the literature by developing a measure of the net gender wage gap and its distribution.

In order to derive a net gender pay gap we have to combine gross hourly wages, the hours distribution and the tax-benefit system. Taking into account the tax and benefit system is also interesting because of its implicit gender specific impacts. In our empirical analysis we choose Germany as a case study because it has a system of joint taxation of married couples which leads to high marginal tax rates for second earners who are mostly female. Thus the implicit gender specific impact is lower labor supply incentives for women as compared to a system of individual taxation. In addition, the gender pay gap is relatively large in Germany. Therefore, the unexplained part of the income difference between men and women (despite differences in working hours) might increase negative labor supply incentives that result from joint taxation. But other features of the tax and benefit system are relevant as well. For example, depending on the actual shape of the unexplained gap across the income distribution, income redistribution might mitigate disadvantageous labor market treatment of women with low household income.

Our empirical strategy consists mainly of three steps. First, we determine the part of the gender pay gap that cannot be explained by differences in individual characteristics. Since we aim to identify the effect of gross wage differences on after-tax income, we do not focus on mean differences but on the whole income distribution. We estimate conditional

quantile regressions and apply the decomposition method proposed by [Machado and Mata \(2005\)](#). One important finding is that the unexplained gap is smallest in the lower part of the distribution and increases with gross earnings. The low unexplainable gap in the lower part of the distribution deviates from other studies on Germany. However, a comparison is difficult because we use a broader sample than most other studies on Germany.

In order to derive a counterfactual net household income distribution, we first simulate gross hourly wages in the absence of an unexplainable wage gap. The semi-parametric decomposition method results in characteristics of two distributions but not in counterfactual wages for each individual. Here we assume that the intra-quantile rank of (female) individuals in the counterfactual distribution would prevail with respect to the baseline distribution. Furthermore, this choice of counterfactual wages assumes that the unexplained gap to which women are exposed depends only on their position along the gross hourly wage distribution. This allows to increase female wages by a mark-up that accounts for the unexplained gap. Using observed working hours, we can further derive a counterfactual gross monthly earnings distribution. Our results indicate a strong correlation between gross hourly wages and monthly earnings. However, results for the earnings gap differ in magnitude. For instance, the median unexplained gap in the lower end of the distribution is close to 10 percent, whereas in terms of hourly wages the unexplained gap for this part of the distribution was statistically insignificant.

In a last step, we use the microsimulation model STSM (for details, see [Steiner et al., 2012](#)) to simulate household net income in the base scenario and the counterfactual scenario. The difference in household income can be interpreted as the representation of the unexplainable gap in hourly wages. We present two measures that shall facilitate the interpretation of our simulation exercise. The first one describes by how much the equivalised household net income would increase following a rise of female gross earnings. This is interesting because we want to examine the distributional consequences of gross wage differences. The second measure relates the increase in household net income to women's own labor earnings. This allows us to compute the marginal effective tax rate to which each woman is exposed and relate this to the wage gap.

The empirical analysis is carried out for West Germany with data from the German Socio-Economic Panel (SOEP) study for the years 2006 to 2011.

The paper proceeds as follows. The next section provides a brief overview of earlier studies of the gender wage gap. Here we focus on studies for Germany. Section 3 describes the data and provides descriptive statistics. Our methodological approach is detailed in section 4. Section 5 presents the results for each step of the simulation. Section 6

concludes.

## 2. Previous findings

The extensive literature on the gender wage gap typically focuses on determinants of gross wage gaps. We provide a brief review of findings for Germany. We are not aware of studies that combine the analysis of the gross gender wage gap and after tax income.

Departing from the seminal work of [Oaxaca \(1973\)](#) and [Blinder \(1973\)](#), several studies have conducted mean decompositions of the gender wage gap for (West) Germany (e.g. [Busch and Holst \(2008\)](#) and [Anger and Schmidt \(2010\)](#), among others). In this literature, the estimates of the overall gap range from 23% to 29% and an unexplained part that amounts to 13% to 16% depending on the estimation sample, dataset and chosen time period.

A second strand of literature applies semi- and non-parametric techniques that enable to go beyond the mean decomposition and analyses the gender wage gap across the whole wage distribution (see, e.g., [Machado and Mata \(2005\)](#), [Melly \(2005\)](#), [DiNardo et al. \(1996\)](#), [Fortin and Lemieux \(1998\)](#)). For Germany, [Fitzenberger and Kunze \(2005\)](#) analyze the gender wage gap with respect to occupational mobility, making use of administrative data that contains full employment records for the period 1975 to 2001. The authors find that the gender wage gap is highest in the lowest part of the earnings distribution. [Heinze \(2010\)](#), who uses linked employer-employee data for the year 2002, also finds that the overall gender gap is highest at the lowest part of the distribution. [Antonczyk et al. \(2010\)](#), who analyze the gender wage gap with regard to collective bargaining agreements, perform a quantile-based decomposition of the log hourly wage for full-time workers with data from the German Structure of Earnings Survey (Gehalts- und Lohnstruktur-erhebung) and find (for 2006) an increasing overall and unexplained gap across the earnings distribution.

Some studies aim to identify institutional causes for gender wage gaps and conduct cross-country comparisons. For instance, [Arulampalam et al. \(2007\)](#), using the European Community Household Panel for the years 1995 to 2001, study the existence of “sticky floors” and “glass ceilings” in several European countries. These two concepts describe the shape of the gender wage gap at the bottom and top of the wage distribution. “Sticky floors” refer to a higher wage gap at the lower tail of the distribution, which implies less career opportunities for women as compared to men. “Glass ceilings” refer to obstacles for women to advance their career in the upper part of the distribution. For Germany, the authors find a “glass ceiling” for women in the private sector. [Christofides et al. \(2013\)](#),

who use EU-SILC for 2007 find both a “sticky floor” and a “glass ceiling” for Germany.

While most of the studies mentioned above concentrate on full-time workers, there is a smaller part of the literature that focuses on the role of part-time work as explanatory factor behind wage differentials. [Wolf \(2002\)](#) finds negative wage differentials for part-time workers in Germany on the basis of a simultaneous wage-hours model. [Matteazzi et al. \(2013\)](#) point out that part-time employment explains a larger share of the gender wage gap in Germany compared to other European countries. In addition, they argue that other factors such as occupational segregation of women play an even more important role. A similar conclusion is reached in [Bardasi and Gornick \(2008\)](#).

Complementing this literature, there are many articles that concentrate on solving methodological problems related to selectivity issues of the full-time working sample. [Beblo et al. \(2003\)](#) estimate selectivity-corrected average wage gaps for several European countries, but obtain inconclusive results for Germany. [Albrecht et al. \(2009\)](#) propose an adaptation of the [Machado and Mata \(2005\)](#) method to account for selection issues. However, the selection correction in the semi-parametric model is problematic as emphasized by [Huber and Melly \(2012\)](#). [Kerm \(2013\)](#) proposes a fully parametric method of accounting for selectivity issues when decomposing the gender wage gap across the distribution.

Parallel to the body of gender wage research, a seemingly unrelated literature examines the gender aspects of tax-benefit systems. Even though nowadays tax-benefit systems in Western countries do not contain any gender-specific rule, the very fact that their outcome depends (among other factors) on earnings, and earnings differ systematically for men and women, leads to a *de facto* gender dimension of tax-benefit systems. This branch of scholarship examines the role of tax-benefit systems on several objects of interest such as the intra-couple distribution of earnings (see [Sutherland \(1997\)](#), [Figari et al. \(2011\)](#)), working (dis)incentives ([Immervoll et al. \(2011\)](#)), as well as optimal (gender-based) taxation ([Alesina et al. \(2011\)](#)).

### 3. Data and Descriptive Statistics

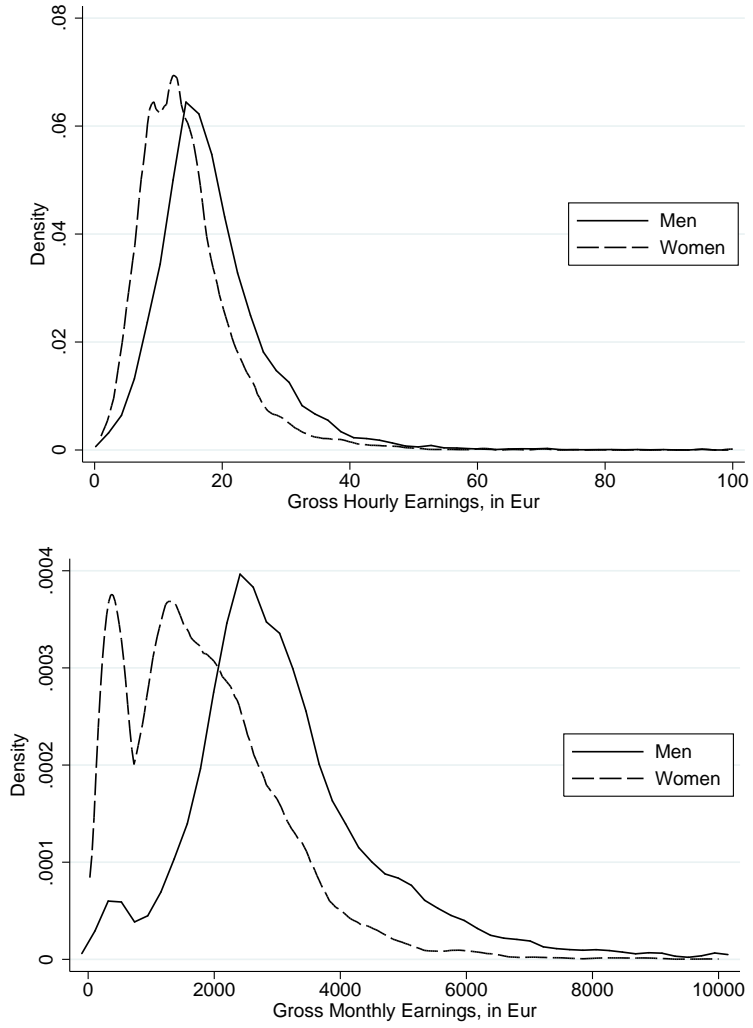
We use data from the German Socio-Economic Panel (SOEP) study from 2006 to 2011 for West Germany. The main advantage of the SOEP for our research question is the availability of information at the household level that is relevant for the tax-benefit system (e.g. earnings of the spouse, dependent children, other household income). Our estimation sample for the wage regression comprises all working individuals aged between 15 and 64 years, except for the self-employed, those in vocational training, students,

pensioners and those doing the military service. We have excluded all observations with missings in any of the variables entering our wage model. Furthermore, we have excluded observations earning less than 1 Euro and more than 100 Euro per hour. We have not imposed any exclusion based on working hours, so that our estimation sample includes part- and full-time workers. This yields a total number of 38,610 observations, of which 18,950 are females and 19,660 are males.

Our dependent variable is the log of the gross hourly wage. Since the distribution of working hours differs between men and women, Figure 1 shows density plots for hourly and monthly earnings. In all three plots one can see that male earnings distributions are shifted to the right in comparison to female earnings distributions. As expected, the income difference is larger in gross monthly earnings, since men work in general longer hours and earn higher wages. In terms of gross monthly earnings, one can observe stark bunching of women around 400 euro per month. This is the income threshold for marginal employment for which no taxes or social security contributions have to be paid. As explained above, the system of joint taxation implies high tax rates for second earners and thus high incentives to take up marginal employment for women. The net monthly earnings distribution is narrower than for gross monthly earnings, which shows the redistributive effect of the tax-benefit system.

Descriptive statistics of the variables entering the wage model can be found in Tables 5 and 6 in the Appendix. In our sample, men are on average slightly older than women, have significantly more work experience and longer tenure. The share of women working in the public sector is higher than for men. And whereas 44% of women work part-time (defined as less than 30 hours), only 5.5% of men do.

Figure 1: Density Plots, pooled data for 2006-2011



Source: own calculations and SOEP, pooled data for 2005-2010, sample weights used



## 4. Methodology

### 4.1. Wage model and decomposition method

Our starting point is an extended Mincer-type linear wage regression model, which we estimate separately for men and women:

$$w_g = X_g\beta_g + u_g, \quad g = f, m \quad (1)$$

where  $w_g$  denotes log hourly wages,  $X_g$  is a set of covariates (same for women and men),  $\beta_g$  are regression coefficients,  $u_g$  represents the error term, and the subindices  $f$  and  $m$  denote female and male, respectively. Our set of covariates,  $X_g$ , consists of age (linear and squared), experience (linear and squared), tenure (linear and squared), a set of education dummies, a set of industry dummies, a set of occupation dummies, a set of size of firm dummies, a part-time dummy, and year dummies.

We start with a simple linear decomposition before we describe the semi-parametric model. The decomposition approach proposed by [Oaxaca \(1973\)](#) and [Blinder \(1973\)](#) (hereinafter OB) consists of decomposing the difference in mean wages between men and women into a component that comprises differences in endowments or labor skills (the “Xs” in the wage equation) and differences in the returns to these skills (the “ $\beta$ ”s in the wage equation). We choose counterfactual wages for women that would result from their observed labor skills being paid as if they would be men, which we denote as  $w_C = X_f\beta_m$ .<sup>1</sup> The sample expression of the OB for our choice of counterfactual reads:

$$\bar{w}_m - \bar{w}_f = \bar{X}_f (\hat{\beta}_m - \hat{\beta}_f) + (\bar{X}_m - \bar{X}_f) \hat{\beta}_m \quad (2)$$

where the first term on the right hand side is the unexplained effect and the second one the effect explained by differences in the covariates. We take men wages to be the reference wages in order to produce results that are comparable to the existing literature. What is a “fair” (discrimination- and favouritism-free) wage is an empirical question that cannot be answered via a decomposition exercise. While most of the literature on gender pay differences uses men wages as a benchmark, some studies (e.g. [Black and Strahan, 2001](#)) show that, at least for certain economic sectors, women wages responded more accurately to their productivity while men wages were indeed overpaid.

While equation (2) yields an estimated mean gender wage gap, we are also interested in the gap along the earnings distribution. The quantile equivalent to the OB decomposition

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<sup>1</sup>One alternative would be to compute counterfactual wages in which women would have men’s characteristics but still would be paid “female” returns (cf. [Antonczyk et al., 2010](#)).

principle reads:

$$\hat{Q}_\theta(w_m) - \hat{Q}_\theta(w_f) = \left[ \hat{Q}_\theta(w_m) - \hat{Q}_\theta(w_C) \right] + \left[ \hat{Q}_\theta(w_C) - \hat{Q}_\theta(w_f) \right] \quad (3)$$

where the first term on the right hand side is the component explained by differences in covariates and the second term is the unexplained component.

We follow the procedure proposed by [Machado and Mata \(2005\)](#) in order to obtain estimates for unconditional quantiles that are consistent with our conditional quantile regression model. First, we estimate the conditional quantile regression coefficients  $\beta_{m,\theta}$  and  $\beta_{f,\theta}$  for all percentiles  $\theta \in (0, 1)$  from the model:<sup>2</sup>

$$Q_\theta(w_g|X) = X_g\beta_{g,\theta} + u_g, \quad g = f, m, \theta \in (0, 1)$$

Based on these estimates we repeat the following procedure 5,000 times: draw  $\theta$  from a standard uniform distribution (between 1 and 99, corresponding to the percentiles), sample  $X_m$  and  $X_f$  from their observed distributions, predict  $Q_\theta(w_m|X_m) = x_m\beta(m, \theta)$ ,  $Q_\theta(w_f|X_f) = x_f\beta(f, \theta)$  and  $Q_\theta(w_C|X_f) = x_f\beta(m, \theta)$  for the sampled  $X_m$  and  $X_f$  with the  $\beta$  coefficients corresponding to the drawn percentile,  $\theta$ . The simulation results in three new samples  $\{x_m\beta(m, \theta)\}_{i=1}^{i=5000}$ ,  $\{x_f\beta(f, \theta)\}_{i=1}^{i=5000}$  and  $\{x_f\beta(m, \theta)\}_{i=1}^{i=5000}$  for which we can compute unconditional quantiles  $\hat{Q}_\theta(w_m)$ ,  $\hat{Q}_\theta(w_f)$  and  $\hat{Q}_\theta(w_C)$ .<sup>3</sup> In order to compute standard errors, we have bootstrapped the procedure described above with 500 replications.<sup>4</sup>

## 4.2. Counterfactual wages

In order to examine the distributional consequences of the unexplained wage gap, we need a counterfactual wage for each woman in order to calculate the counterfactual net income. We do this by assigning a given value of the unexplained gap to each woman. This results in counterfactual wages for women without an unexplained gender gap which are consistent with our wage model described above. To this end, we first evaluate in which quantile of the estimated marginal (unconditional) distribution their

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<sup>2</sup>We would ideally like to also account for selection issues in the quantile regression setup. Unfortunately, the main estimator available for this purpose, developed by [Buchinsky \(1998\)](#), is only consistent when the slope coefficients are equal for all quantiles or when selection is randomly determined (see, for instance, [Huber and Melly, 2012](#)).

<sup>3</sup>As explained by [Machado and Mata \(2005\)](#), the validity of this procedure relies on the probability integral transformation theorem.

<sup>4</sup>We use pooled data for our analysis. We have run the decomposition exercise separately for each wave and found the same shape for the overall, explained and unexplained gap.

observed wages are located, and then we add to them the unexplained gap found for that particular quantile.<sup>5</sup> Counterfactual wages for men equal their status quo wages.

$$w_{i,C} = \begin{cases} w_{i,f} + [\hat{Q}_\theta(w_C) - \hat{Q}_\theta(w_f)] \\ w_{i,m} \end{cases}$$

In order to map the results for the counterfactual wage distribution to individual wages we have to make some assumptions. The decomposition method chosen results in characteristics of the two distributions but not in counterfactual wages for each individual. Here we assume that the intra-quantile rank of (female) individuals in the counterfactual distribution would prevail with respect to the old distribution. And secondly, this choice of counterfactual wages assumes that the unexplained gap to which women are exposed depends only on their position along the gross hourly wage distribution.<sup>6</sup>

### 4.3. Net (Unexplained) Gender Gap

On the basis of the counterfactual wage rates calculated above, we can derive gross monthly earnings for each individual under the status quo and the counterfactual scenario, denoted by  $E_i$ :

$$E_i = \begin{cases} \exp(w_i) \cdot h_i & \text{under the status quo} \\ \exp(w_{i,C}) \cdot h_i & \text{under the counterfactual} \end{cases} \quad (4)$$

where  $h_i$  are hours worked per month.

We construct a measure of net gap that captures the change in (equivalised) net household income responding to the increase in female gross wages implied by our counterfactual exercise. It follows that we only compute net gaps for females (or, alternatively, that net gaps for men are zero). The level of analysis of net income is the household.<sup>7</sup> For women living in single-person households, the change in net income refers to their own net income. For women living with their partner, the change in net income refers to the change in the joint net income of both spouses. For each household, the absolute difference in net income,  $D_i$ , can be expressed as:

<sup>5</sup>Note that the gap determined in the decomposition exercise can be interpreted as percentage from actual wages. Given that we work with log wages, we add the gap as quantile-specific lump-sum to log wages. In absolute terms, the gap takes a different value for each value of status quo hourly wage

<sup>6</sup>This implies, for instance, that the unexplained gap is only job specific to the point that different jobs pay wage rates that are in different sectors of the distribution. Table 10 in the appendix shows descriptive statistics of the estimated unexplained gap for several individual characteristics of our wage model.

<sup>7</sup>Each household for which we compute the net gender gap comprises an adult woman and, if applicable, her partner (married or not) and dependent children.

$$D_i = N(E_{i,C}, HH_i) - N(E_i, HH_i) \quad (5)$$

where  $E_i$  are household gross labor earnings,  $HH_i$  a vector of household characteristics relevant for the tax-benefit system, and  $N(E_{i,C}, HH_i)$  and  $N(E_i, HH_i)$  are net household income for counterfactual and status quo monthly earnings, respectively. Since  $N(\cdot)$  is a highly complex non-linear function capturing the rules of the tax-benefit system, household net income is obtained via microsimulation.<sup>8</sup>

In order to give  $D_i$  a better interpretation, we provide two different representations:

$$g_i = \frac{N(E_{i,C}, HH_i) - N(E_i, HH_i)}{N(E_i, HH_i)/S_i} \quad (6)$$

and

$$g_i^* = \frac{N(E_{i,C}, HH_i) - N(E_i, HH_i)}{E_i, f} \quad (7)$$

where  $S_i$  is the household size according to the new OECD equivalence scale. Equation (6) describes by how much the equivalised household net income would increase following the increase of female gross earnings. Whereas one can easily stretch this interpretation of  $g_i$  for single women as the (percentage) increase in their own disposable income ( $S_i$  will be equal to 1 in this case, thereby implying that equivalised household net income equals individual net income), this is not the case for married women. In particular it is important to note that in the case of multi-person households, the denominator has no direct link to women's own labor earnings. Hence, its interpretation as the woman's net disposable income is based on the assumption of income pooling within the couple. The interpretation of  $g_i$  is by how much households would profit from such an increase in women's gross earnings.<sup>9</sup>

The second measure in equation (7),  $g_i^*$ , relates the increase in household net income to women's own labor earnings but arguably becomes a somewhat more abstract construct. However, as a positive side effect, the comparison of  $g_i^*$  with  $w_{i,C} - w_i$  allows us to compute the marginal effective tax rate to which each woman is exposed.<sup>10</sup>

<sup>8</sup>We use the STSM Microsimulation Model for Germany. Based on variables drawn from the SOEP, gross earnings, the taxable income, the amount of income taxes, all important transfers and finally the disposable net income can be derived at the household level. See [Steiner et al. \(2012\)](#) for a detailed description of the model.

<sup>9</sup>The assumption of income pooling might appear to be too strong and has been questioned in the literature [Browning et al.](#) (see, e.g., [1994](#)) and [Lundberg et al. \(1997\)](#)) However, in our case it is only used for illustrative purposes of the change in disposable income at the household level. Further effects on intra household income allocation are most likely but beyond the scope of this paper.

<sup>10</sup>By "tax" we mean the outcome of the whole tax-benefit system (as opposed to a particular tax like

Further remarks on our approach: First, we follow a static approach. The counterfactual net household income is computed under the assumption that the change in wages does not cause any adjustment on the labor supply of any individuals. We consider these effects as first-round effects before behavioral adjustments. Furthermore it is a partial analysis and we abstract from general equilibrium effects. Second, our assumptions allow us to describe the distributional impacts of the gender wage gap without resorting to compute individual net incomes. Third, there are some mechanical links between gross and net gender gap. For example, conditional on the position in the gross hourly earnings distribution, the progressivity of the tax-benefit system will provide for net gender wage gaps that decrease the more hours women work. This is true for women both in the individual as well as the joint taxation regime, although the net gender wage gap will increase quicker with hours for non-married than for married women. In addition, following this definition of net gender gap, a woman exposed to a very high taxation will have a very small net gender gap independently of how big the unexplained gap allocated to her is. This brings us to the last, but not least, point. The measure of net gender gap presented here does not attempt to capture how big the unexplained gap (or discrimination) truly is – this can only be done in the decomposition exercise. What it does capture, and this is our contribution, is the magnitude and distribution of the material/financial consequences for women and households.

## 5. Results

### 5.1. Decomposition Results

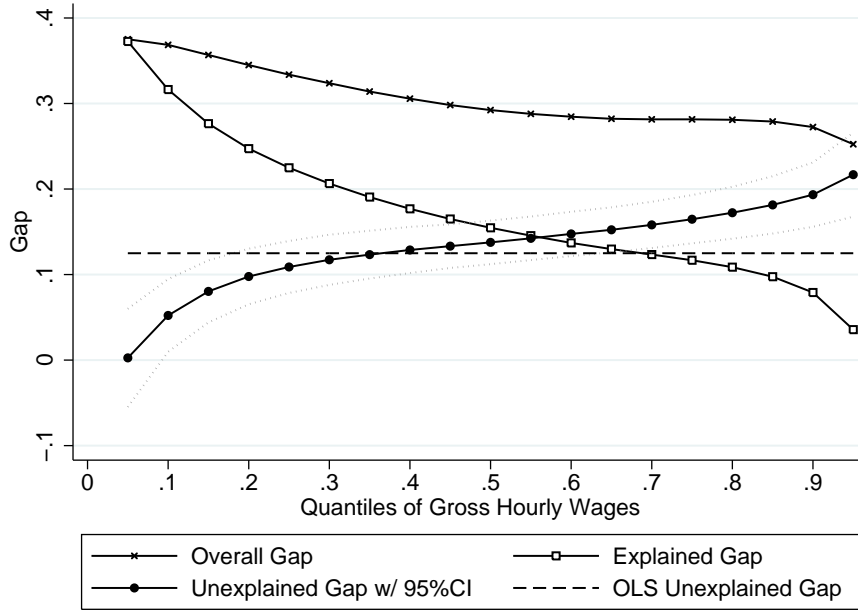
Figure 2 below offers a graphical representation of the results of the decomposition exercise described in section 4 (see Table 9 in the Appendix for the exact estimates with standard errors). The y-axis depicts the absolute gap between the quantiles of two logarithmic gross hourly earnings distributions and can be roughly interpreted as the relative gap between the quantiles of the exponentiated distributions. We find that the overall gap,  $\hat{Q}_\theta(w_m) - \hat{Q}_\theta(w_f)$ , is highest in the lowest part of the distribution (at around 37 percentage points) and decreases with wage rates (reaching 25 percentage points at the upper end of the distribution). Differences in covariates (explained gap),  $\hat{Q}_\theta(w_m) - \hat{Q}_\theta(w_C)$ , explain almost fully the wage gap at the lower end of the distribution and loose explanatory power as the wage increases. The unexplained gap,  $\hat{Q}_\theta(w_C) - \hat{Q}_\theta(w_f)$ , starts from being statistically insignificant at the fifth percentile and increases up to being slightly

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the personal income tax). Thus, we would refer as “negative tax” to the outcome of the tax-benefit system of a person that is net recipient of transfers.

above 20 per cent at the top of the distribution. The average unexplained gap resulting from a standard OB decomposition based on an OLS regression amounts to roughly 12 per cent. Compared to other studies for Germany, the mean gap is rather low. However, it is difficult to meaningfully compare our decomposition results quantitatively with the existing literature because of the different estimation samples, datasets and time periods used.

Figure 2: Decomposition Results



As explained in section 4.2, we assign a specific value for the unexplained gap to each woman in our sample and compute counterfactual wages that would result from the abolishment of the unexplained gap. The density plot of the new counterfactual wages for women (see Figure 5 in the Appendix) show how it shifts women’s wage density to the right. The assignment of a mark-up to each woman’s wage allows us to get an impression of how the unexplained gap correlates with relevant labor market characteristics. Thus, our results show that, on average, the unexplained gap increases with age, education and experience, and that is lower for part-time workers than for full-time workers (see Table 10 in the Appendix).

## 5.2. Gender Gap and Gross Monthly Wages: the Distribution of Working Hours

Before we analyse the gender pay gap after taxes and transfers we have to consider working hours. First, we analyse how the unexplained gap is distributed across gross monthly earnings of women. We do this by multiplying the counterfactual hourly wage rates by the observed number of working hours for each woman in our sample. Note that for each woman, if we added a mark-up for the unexplained gap to the hourly wage (x percent) the relative mark-up in terms of her gross monthly earnings would be the same (x percent). What makes this analysis interesting is the fact that women may be sorted in a different order in the hourly wage distribution than in the monthly wage distribution. Empirically we observe women with high hourly wage rates that have low monthly wages because they work few hours. Alternatively, we also observe women with very low wage rates that still reach female median gross monthly earnings by working many hours.

Figure 3: Unexplained Gap against Gross Monthly Earnings

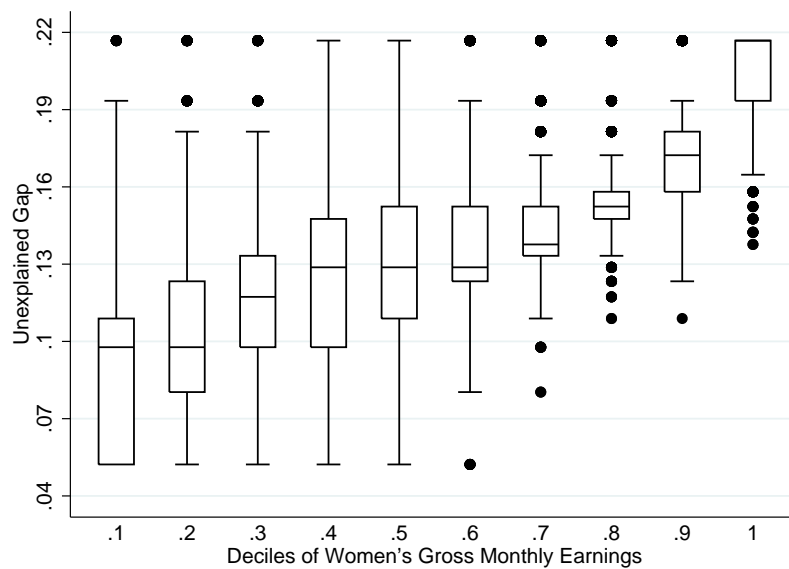


Figure 3 shows an increasing trend of the unexplained gap by gross earnings that indicates a quite strong correlation between gross hourly wages and monthly earnings. Nonetheless, we observe a level effect with respect to Figure 2. For instance, the median unexplained gap in the lower end of the distribution is close to 10 percent, whereas in terms of hourly wages the unexplained gap for this part of the distribution was statistically insignificant.

Table 1 characterises the gross monthly earnings distributions under the status quo and the counterfactual scenario. The three first columns from the left show the upper thresholds of the deciles of the men’s and women’s distributions separately. We want to emphasize three results at this stage of our analysis: (1) the distribution of monthly earnings for women is much more dispersed than that of men, (2) the differences between the male and the female distribution are largest at the lower part of the distribution and (3) the abolishment of the unexplained gender gap in hourly wages would, as suggested here, lead to an increase in the earnings inequality among women (which can be seen from the quotients at the bottom of Table 1). The distribution of hours worked is responsible for (1) and (2), since none of these features are observed in the distributions of hourly wages. The three columns to the right refer to the (male-female) joint distribution of gross monthly income. It shows that women are highly concentrated in the lower deciles of the distribution. In this case, the counterfactual distribution stretches the tails of the distribution (the quotient P90/P10 increases) while slightly concentrates the more central parts of the distribution (the P75/P25 decreases by 0.10).

Table 1: Effects on Gross Monthly Income Distributions

Deciles	Gender-Specific Distributions			Joint Distribution		
	Men	Women	Women	Proportion of		
	Status quo	Status quo	Counterfactual	Status quo	Counterfactual	Women in Decile
1	1651	413	433	597	619	91.92%
2	2167	750	825	1254	1406	92.86%
3	2425	1135	1281	1733	1857	85.63%
4	2683	1412	1588	2084	2270	58.29%
5	2992	1702	1959	2427	2579	35.12%
6	3302	2049	2343	2751	2889	25.26%
7	3611	2373	2760	3095	3302	20.36%
8	4212	2837	3345	3611	3818	20.48%
9	5283	3508	4198	4574	4829	17.73%
P90/P10	3.20	8.50	9.70	7.66	7.80	
P75/P25	1.73	2.63	2.77	2.24	2.14	

Source: own calculations, SOEP

Comments:

### 5.3. Net Gender Gap: the role of the tax-benefit system

This section displays the results obtained for the measures of net gender gaps described in section 4.3. Table 2 below shows by how much households’ equalised net income



would increase in the absence of the unexplained gap. The gain (as percentage) increases with higher net income. In addition, the variation of the net gap strongly increases with higher household net income. According to our results, the lowest decile gains the least, which is consistent both with the fact that the unexplained gap was the lowest in that part of the distribution and with the fact that some of the households in the lower part of the distribution experience a (partial or total) withdrawal of transfers in response to an increase of gross earnings. This explains why for the lower third of the distribution the average equalised household income stays nearly constant at around 7 per cent.

Table 2: Net Gender Gap (% of eq- household net income)

Deciles of eq. HH net income	Mean	P25	P50	P75
1	06.95	00.00	00.89	05.03
2	06.34	00.63	05.91	09.70
3	06.96	01.37	06.67	10.64
4	08.08	03.02	08.64	11.36
5	08.18	02.93	08.73	12.05
6	08.73	03.94	08.43	12.65
7	09.90	04.96	09.36	14.26
8	09.84	04.92	09.12	15.66
9	10.86	04.86	08.89	16.24
10	11.35	04.03	10.34	17.75

Source: own calculations, SOEP and STSM

Comments: Calculations made for households that are affected by the counterfactual exercise (i.e. with a woman in our estimation sample). Pooled data for 2005-2010.

Sample weights used.

As explained in section 4.3, the representation  $g_i^*$  of the net gap allows us to indirectly infer the effective marginal tax rate that applies to each female individual. This can be seen in Figure 4. If women were not subject to a tax-benefit system, then all points of the scatterplot would find themselves in the 45 degree line. Since this is not the case, these figures show that the majority of women are subject to positive taxation (i.e. they are above the 45 degrees line, which implies that in case of an increase of their gross earnings, they have to pay a part of it as taxes or social security contributions). Interestingly, Figure 4 shows that the variation in the degree of effective taxation to which women are exposed is wider for married than for single women. There are several factors that explain this result, including the distribution of working hours and the existence of a joint taxation regime.

Figure 4: Pre- vs Post-Tax Gaps (in % of Gross Monthly Earnings)

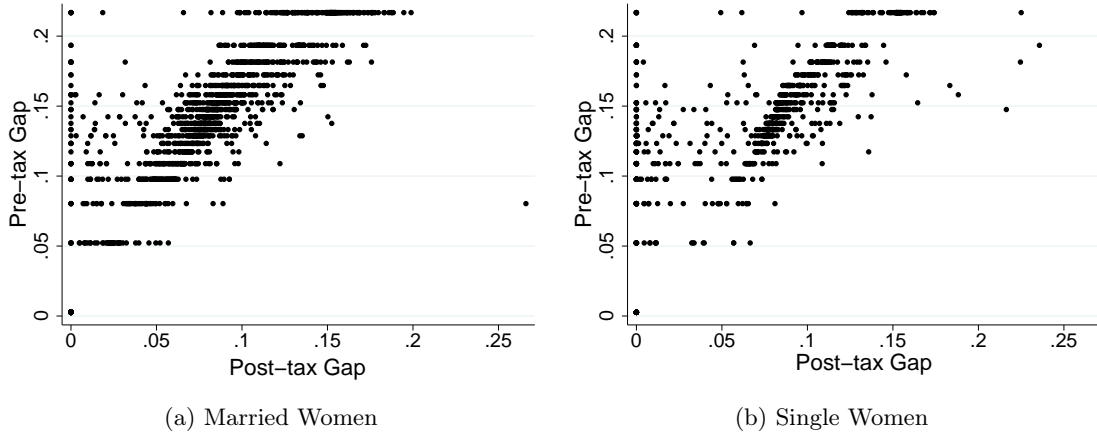


Table 3 summarizes the net effects of the counterfactual exercise. The pre-tax gap indicates by how much gross monthly earnings of women were increased. On average, this was a 14% increase, which in absolute terms implied an increase of the monthly gross wage by 340 Euro per month. In terms of disposable income, though, the average increase for the affected households would amount to roughly 178 Euro. It is interesting to note that post-tax gap's figures are systematically lower than pre-tax gap figures, but that the dispersion of the magnitude of the increase is much higher in terms of net monthly income than in terms of gross monthly earnings. Thus, whereas the quotient P75/P25 of the absolute change in gross monthly income is approximately 3.6, the equivalent figure for the absolute change in net monthly income is roughly 7.3.

Table 4 illustrates how inequality and poverty measures would react to such an increase in women's gross monthly wages. The three inequality measures presented in the upper panel indicate that under the counterfactual wage distribution equalised household inequality would slightly rise. This phenomenon is driven by the fact that the unexplained gap is higher among women with very high hourly wage rates and so the gains of balancing out the unexplained gap concentrate on this group of women. Poverty measures also display a significant increase, which can be explained by the higher increase of median net income (around 3.3 %) with regard to the lowest parts of the distribution (with 0.3% and 1.4% growth in the first second deciles, respectively; for more details see Table 11 in the Appendix).

Table 3: Summary Table

	Mean	P25	P50	P75
<b>Pretax Gap</b> (% of gross monthly income)	13.55	10.89	13.76	16.47
<b>Posttax Gap <math>g_i</math></b> (% of eq. household net income)	08.72	02.04	07.78	12.39
<b>Posttax Gap <math>g_i^*</math></b> (% of gross monthly income)	07.27	04.70	07.84	09.84
<b><math>\Delta</math> Gross Monthly Income</b> (in Eur)	338.93	126.51	261.74	457.86
<b><math>\Delta</math> Net Monthly Income</b> (in Eur)	177.66	32.00	134.12	232.77

Source: own calculations, SOEP and STSM

Comments: Calculations for households affected by our counterfactual exercise.  
Pooled data for 2005-2010. Sample weights used.

Table 4: Effects on Inequality and Poverty Measures

Deciles	Status Quo	Counterfactual	
	Level (x 100)	Level (x 100)	Rel. Change
Inequality Measures			
Gini	27,71	28,32	2,22%
MLD	13,39	14,00	4,51%
Atkinson	28,89	29,91	3,53%
Poverty Measures			
AQ	15,01	15,44	2,86%
AA	3,82	4,06	6,22%
AI	1,54	1,65	7,26%

Source: own calculations, STSM and SOEP

## 6. Conclusion

The aim of this paper is to provide a net measure of the unexplained part of the gender wage gap. To the best of our knowledge, our study is the first that attempts to relate the outcome of a gross wage decomposition to net household income. We argue that it is important to quantify the distributional impact of the gender wage gap in terms of disposable income. From a policy perspective this is potentially highly relevant for female labor supply, gender-specific distribution of income within couple households as well as the economic independence of women.

We use quantile regressions to obtain a measure of the gender wage gap across the whole wage distribution. We find a low or not significant unexplained gender wage gap at the bottom of the distribution, which contradicts the existence of “sticky floors”. In order to map the results of the counterfactual wage distribution to individual wages, we assume (female) individuals’ intra-quantile rank preservation. Our choice of counterfactual implies that the unexplained gap to which women are exposed depends only on their position along the gross hourly wage distribution.

The construction of individual counterfactual wages enables us to derive a gender gap both in terms of gross monthly earnings and in terms of net household income. As opposed to the hourly wage analysis, taking into account the working hours distribution reveals a larger (and statistically significant) earnings gap for most low income women. As expected, households’ equivalised net income rises in the absence of the unexplained gap. This increase is larger for high income households than for lower income households. The reason for this is twofold: higher unexplained gaps at the top of the wage distribution, and the tax-benefit system (the latter effect seems to work through a combination of transfer withdrawal for low income households in response to rising gross earnings, as well as the joint taxation regime).

Finally, we would like to issue a word of caution on the results presented in this paper and hint at possible directions for future research. Our approach so far is mainly static and thus we abstract from labor supply adjustments and general equilibrium effects. The integration of possible labor supply reactions should be at the core of the future research agenda. In addition, the assumptions behind counterfactual wages could be relaxed and we believe it is promising to experiment with different definitions of “true” reference wages.

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## A. Tables



Table 5: Descriptives of the Estimation Sample

	Mean			Standard Deviation		
	Men	Women	Total	Men	Women	Total
<b>Age</b>	42.7215	41.9123	42.3303	10.6535	10.8033	10.7337
<b>Experience</b>	20.1052	16.4073	18.3174	11.3189	10.2899	10.9900
<b>Tenure</b>	12.6406	9.7731	11.2543	10.8881	9.2871	10.2462
<b>Public Sector</b>	0.2188	0.2936	0.2549	0.4134	0.4554	0.4358
<b>Part-time</b>	0.0550	0.4383	0.2403	0.2280	0.4962	0.4273
<b>Education:</b>						
Primary School	0.1150	0.1169	0.1159	0.3190	0.3213	0.3201
Sec./Midd Vocational	0.4988	0.5288	0.5133	0.5000	0.4992	0.4998
Upper Sec./High Voc.	0.1605	0.1708	0.1654	0.3670	0.3763	0.3716
University Degree	0.2258	0.1835	0.2053	0.4181	0.3871	0.4040
<b>Occupation:</b>						
occl	0.1603	0.1764	0.1681	0.3669	0.3812	0.3739
Non-skilled Worker	0.2033	0.0377	0.1232	0.4025	0.1905	0.3287
Skilled Worker	0.0691	0.0097	0.0403	0.2536	0.0978	0.1968
High Skilled Worker	0.0240	0.0786	0.0504	0.1531	0.2692	0.2188
Non-skilled Employee	0.0446	0.1580	0.0995	0.2065	0.3648	0.2993
Middle-Skilled Empl.	0.1852	0.3653	0.2723	0.3885	0.4815	0.4451
Skilled Empl.	0.2208	0.1118	0.1681	0.4148	0.3151	0.3740
Lower Civil Servant	0.0315	0.0143	0.0232	0.1746	0.1185	0.1504
Upper Civil Servant	0.0612	0.0482	0.0549	0.2397	0.2142	0.2278
<b>Industrial Branch:</b>						
Electronics	0.1907	0.0765	0.1355	0.3929	0.2657	0.3423
Mining, Energy	0.0168	0.0057	0.0114	0.1286	0.0753	0.1064
Chemical Industry	0.0737	0.0480	0.0613	0.2613	0.2137	0.2398
Construction Sector	0.0822	0.0134	0.0489	0.2746	0.1150	0.2157
Heavy Industry	0.0762	0.0188	0.0484	0.2653	0.1358	0.2147
Textile Sector	0.0049	0.0093	0.0070	0.0700	0.0961	0.0837
Trade and Retail	0.0956	0.1737	0.1334	0.2941	0.3788	0.3400
Transports, Post	0.0698	0.0314	0.0512	0.2548	0.1744	0.2205
Public Services	0.2122	0.3892	0.2978	0.4089	0.4876	0.4573
Private Services	0.1091	0.1646	0.1360	0.3118	0.3709	0.3428
Others	0.0600	0.0655	0.0627	0.2375	0.2475	0.2424
Agriculture	0.0086	0.0039	0.0064	0.0925	0.0627	0.0795
<b>Size of Firm:</b>						
Up to 5 Employees	0.0473	0.1009	0.0732	0.2123	0.3012	0.2605
5-200 Employees	0.4265	0.4818	0.4532	0.4946	0.4997	0.4978
200-2000 Employees	0.2491	0.2066	0.2285	0.4325	0.4049	0.4199
2000+ Employees	0.2771	0.2106	0.2450	0.4476	0.4078	0.4301

Source: own calculations, SOEP

Table 6: Descriptives Statistics Conditional on Earnings Quartiles

	First Quartile		Second Quartile		Third Quartile		Fourth Quartile	
	Men	Women	Men	Women	Men	Women	Men	Women
<b>Age</b>	37.74	40.50	42.35	40.69	44.85	42.38	47.86	44.15
<b>Experience</b>	15.51	13.83	20.59	15.41	22.52	17.64	23.54	18.78
<b>Tenure</b>	6.86	6.03	13.12	8.27	15.76	11.42	17.01	13.50
<b>Public Sector</b>	.1516	.1346	.2276	.2202	.3133	.4015	.2695	.4231
<b>Part-time</b>	.1237	.6037	.0197	.4323	.0209	.3548	.0418	.3627
<b>Education:</b>								
Primary School	.1712	.1943	.1333	.1514	.1155	.0846	.0374	.0338
Sec./Midd Vocational	.6424	.6080	.6079	.5999	.4752	.5473	.2317	.3632
Upper Sec./High Voc.	.1141	.1190	.1619	.1656	.2032	.2223	.1637	.1746
University Degree	.0722	.0786	.0969	.0831	.2061	.1458	.5672	.4284
<b>Occupation:</b>								
occ1	.3301	.3827	.1659	.2020	.0852	.0904	.0160	.0348
Non-skilled Worker	.2752	.0524	.2923	.0422	.1931	.0377	.0581	.0233
Skilled Worker	.0403	.0093	.0906	.0093	.0967	.0123	.0394	.0076
High Skilled Worker	.0501	.1765	.0146	.0808	.0072	.0311	.0031	.0174
Non-skilled Employee	.0788	.1921	.0436	.2415	.0297	.1396	.0070	.0585
Middle-Skilled Empl.	.1295	.1640	.1995	.3386	.2403	.5253	.1386	.4299
Skilled Empl.	.0482	.0117	.1031	.0611	.2005	.1043	.5762	.2709
Lower Civil Servant	.0324	.0028	.0583	.0120	.0423	.0257	.0058	.0168
Upper Civil Servant	.0154	.0086	.0319	.0124	.1052	.0336	.1559	.1407
<b>Industrial Branch:</b>								
Electronics	.1354	.0646	.1592	.0662	.1884	.0793	.2421	.0933
Mining, Energy	.0091	.0030	.0144	.0016	.0243	.0044	.0250	.0129
Chemical Industry	.0589	.0370	.0746	.0401	.0739	.0451	.0736	.0738
Construction	.1109	.0152	.1312	.0115	.0690	.0196	.0306	.0083
Heavy Industry	.0757	.0093	.0890	.0163	.0886	.0260	.0607	.0239
Textile Sector	.0070	.0134	.0074	.0124	.0031	.0038	.0026	.0075
Trade and Retail	.1575	.2324	.1098	.2628	.0672	.1323	.0394	.0676
Transports, Post	.1032	.0205	.0758	.0325	.0580	.0421	.0447	.0294
Public Services	.1449	.2613	.1947	.3516	.2787	.4711	.2894	.4759
Private Services	.1079	.2395	.0753	.1395	.0924	.1312	.1411	.1506
Others	.0634	.0986	.0583	.0585	.0512	.0442	.0483	.0542
Agriculture	.0261	.0052	.0103	.0071	.0052	.0010	.0026	.0026
<b>Size of Firm:</b>								
Up to 5 Employees	.0953	.1930	.0427	.1236	.0288	.0518	.0122	.0359
5-200 Employees	.6023	.5824	.4746	.5268	.3363	.4410	.2732	.3789
200-2000 Employees	.1582	.1239	.2499	.1750	.3091	.2766	.2725	.2551
2000+ Employees	.1442	.1007	.2329	.1746	.3259	.2307	.4420	.3301

Source: own calculations, SOEP

Table 7: Wage Regression Output, Males

	OLS	q10	q25	q50	q75	q90
<b>Constant</b>	1.641***	0.934***	1.601***	1.973***	2.108***	2.409***
<b>Age</b>	0.0150***	0.0246***	0.00942*	0.00427	0.00916**	0.00292
<b>Age (sq)</b>	-0.0132***	-0.0271***	-0.00718	0.000198	-0.00472	0.00594
<b>Experience</b>	0.0177***	0.0234***	0.0194***	0.0186***	0.0165***	0.0139***
<b>Experience (sq)</b>	-0.0354***	-0.0442***	-0.0401***	-0.0404***	-0.0356***	-0.0350***
<b>Tenure</b>	0.0179***	0.0220***	0.0183***	0.0148***	0.0118***	0.0122***
<b>Tenure (sq)</b>	-0.0279***	-0.0349***	-0.0288***	-0.0226***	-0.0160***	-0.0179***
<b>Part-time Work</b>	-0.0568***	-0.388***	-0.246***	-0.108***	0.0906**	0.322***
<b>Public Sector</b>	-0.0480***	-0.0103	-0.0205*	-0.0266***	-0.0685***	-0.108***
<b>Education:</b>						
Sec./Midd Vocational	0.0191*	0.00184	-0.00688	0.0262***	0.0271**	0.0180
Upper Sec./High Voc.	0.0670***	0.0734***	0.0584***	0.0768***	0.0715***	0.0610**
University Degree	0.219***	0.220***	0.201***	0.218***	0.203***	0.175***
<b>Occupation:</b>						
Non-skilled Worker	0.179***	0.203***	0.180***	0.143***	0.117***	0.122***
Skilled Worker	0.275***	0.286***	0.271***	0.244***	0.210***	0.211***
High Skilled Worker	-0.0472	-0.0862	-0.0910*	-0.0523	-0.0530	-0.0168
Non-skilled Employee	0.131***	0.127***	0.137***	0.112***	0.0774***	0.0798**
Middle-Skilled Empl.	0.317***	0.338***	0.328***	0.283***	0.264***	0.267***
Skilled Empl.	0.582***	0.559***	0.553***	0.524***	0.539***	0.590***
Lower Civil Servant	0.168***	0.229***	0.167***	0.125***	0.0928***	0.0830***
Upper Civil Servant	0.409***	0.359***	0.365***	0.361***	0.372***	0.356***
<b>Industrial Branch:</b>						
Mining, Energy	-0.0274	-0.0661	-0.0166	-0.0330**	-0.0267*	0.00433
Chemical Industry	0.00530	-0.00250	0.00293	0.0118	0.0183	0.0106
Construction Sector	-0.0477***	-0.0137	-0.0462***	-0.0660***	-0.0616***	-0.101***
Heavy Industry	0.0231*	0.0179	0.0174*	0.0120	0.0277**	0.00336
Textile Sector	-0.112**	-0.184**	-0.187***	-0.202***	-0.169***	-0.0297
Trade and Retail	-0.139***	-0.182***	-0.166***	-0.153***	-0.135***	-0.125***
Transports, Post	-0.103***	-0.160***	-0.139***	-0.113***	-0.0698***	-0.0454**
Public Services	-0.0709***	-0.0790***	-0.0938***	-0.0991***	-0.0531***	-0.0204
Private Services	-0.0577***	-0.102***	-0.103***	-0.0607***	-0.00561	0.0419*
Others	-0.0679***	-0.0887***	-0.0788***	-0.0628***	-0.0409**	-0.0334*
Agriculture	-0.259***	-0.304***	-0.298***	-0.221***	-0.222***	-0.216***
<b>Size of Firm:</b>						
5-200 Employees	0.167***	0.277***	0.194***	0.118***	0.0825***	0.0377*
200-2000 Employees	0.274***	0.414***	0.309***	0.215***	0.170***	0.116***
2000+ Employees	0.319***	0.457***	0.349***	0.262***	0.222***	0.157***
<b>Year Dummies:</b>						
2005	-0.0376***	-0.0543***	-0.0448**	-0.0346***	-0.0397***	-0.00121
2006	-0.0369***	-0.0346*	-0.0485***	-0.0417***	-0.0426***	-0.0107
2007	-0.0268**	-0.0287*	-0.0394***	-0.0380***	-0.0327***	-0.00526
2008	-0.0204*	-0.0325*	-0.0236*	-0.0191*	-0.0191	-0.00105
2009	-0.0123	-0.0107	-0.0230*	-0.0157*	-0.0121	0.0197
Observations	19660	19660	19660	19660	19660	19660

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ 

Source: Own calculations, SOEP

Table 8: Wage Regression Output, Females

	OLS	q10	q25	q50	q75	q90
<b>Constant</b>	1.538***	0.862***	1.348***	1.607***	1.825***	2.042***
<b>Age</b>	0.0158***	0.0296***	0.0143***	0.0134***	0.0133***	0.0151*
<b>Age (sq)</b>	-0.0198***	-0.0391***	-0.0191***	-0.0161***	-0.0151***	-0.0175*
<b>Experience</b>	0.0131***	0.0131***	0.0155***	0.0114***	0.0129***	0.0117***
<b>Experience (sq)</b>	-0.0179***	-0.0157	-0.0242***	-0.0162***	-0.0196***	-0.0147*
<b>Tenure</b>	0.0146***	0.0194***	0.0155***	0.0165***	0.0130***	0.00890***
<b>Tenure (sq)</b>	-0.0238***	-0.0356***	-0.0248***	-0.0292***	-0.0214***	-0.0115***
<b>Part-time Work</b>	0.00803	-0.109***	-0.0591***	-0.0112	0.0345***	0.0961***
<b>Public Sector</b>	0.0408***	0.0678***	0.0667***	0.0412***	0.0272***	0.0139
<b>Education:</b>						
Sec./Middle Vocational	0.0177	0.00471	0.0175	0.0167	0.0303***	0.0582***
Upper Sec./High Voc.	0.0807***	0.0902***	0.105***	0.0799***	0.0793***	0.0818***
University Degree	0.213***	0.159***	0.200***	0.210***	0.253***	0.318***
<b>Occupation:</b>						
Skilled Worker	0.225***	0.204***	0.235***	0.220***	0.237***	0.254***
High Skilled Worker	0.301***	0.282***	0.264***	0.271***	0.281***	0.266***
Non-skilled Employee	0.0536***	0.00251	0.0386	0.0712***	0.0898***	0.0815***
Middle-Skilled Empl.	0.237***	0.264***	0.263***	0.263***	0.233***	0.190***
Skilled Empl.	0.416***	0.461***	0.446***	0.430***	0.400***	0.353***
Highly-Skilled Empl.	0.651***	0.634***	0.621***	0.639***	0.651***	0.610***
Lower Civil Servant	0.429***	0.424***	0.398***	0.393***	0.403***	0.432***
Upper Civil Servant	0.614***	0.577***	0.554***	0.600***	0.634***	0.611***
<b>Industrial Branch:</b>						
Mining, Energy	0.0769*	0.155	0.0804*	0.0841*	0.0267	0.0605
Chemical Industry	-0.0329	-0.148***	-0.0323	0.00315	0.0161	-0.00494
Construction Sector	-0.103***	0.0157	-0.0604**	-0.127***	-0.147***	-0.210***
Heavy Industry	0.0706**	0.124	0.127***	0.0891***	0.0465	0.0660*
Textile Sector	-0.176***	-0.0680	-0.136***	-0.184***	-0.156***	-0.236***
Trade and Retail	-0.183***	-0.188***	-0.162***	-0.190***	-0.225***	-0.232***
Transports, Post	-0.0866***	-0.137***	-0.0898***	-0.113***	-0.0892***	-0.0963**
Public Services	-0.0907***	-0.0610*	-0.0717***	-0.101***	-0.138***	-0.144***
Private Services	-0.0907***	-0.118***	-0.102***	-0.0952***	-0.0822***	-0.0619***
Others	-0.145***	-0.202***	-0.152***	-0.142***	-0.138***	-0.115***
Agriculture	-0.232***	-0.251*	-0.231***	-0.227***	-0.288***	-0.261***
<b>Size of Firm:</b>						
5-200 Employees	0.166***	0.204***	0.190***	0.174***	0.148***	0.119***
200-2000 Employees	0.271***	0.357***	0.307***	0.268***	0.215***	0.174***
2000+ Employees	0.319***	0.369***	0.336***	0.323***	0.295***	0.248***
<b>Year Dummies:</b>						
2005	-0.0592***	-0.0644***	-0.0499***	-0.0521***	-0.0512***	-0.0685***
2006	-0.0489***	-0.0487**	-0.0390**	-0.0493***	-0.0496***	-0.0716***
2007	-0.0516***	-0.0540*	-0.0483***	-0.0535***	-0.0499***	-0.0661***
2008	-0.0249*	-0.0308*	-0.0287*	-0.0322**	-0.0270**	-0.0301
2009	-0.0238*	-0.00778	-0.0191	-0.0252*	-0.0238	-0.0549**
Observations	18950	18950	18950	18950	18950	18950

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ 

Source: Own calculations, SOEP

Table 9: Decomposition Results

Quantiles	Overall Gap		Explained Gap		Unexplained Gap	
	Coeff.	Std.Error	Coeff.	Std.Error	Coeff.	Std.Error
0.05	.3704	.0259	.3761	.0278	-.0059	.0282
0.10	.3653	.0197	.3180	.0203	.0473	.0213
0.15	.3544	.0160	.2778	.0171	.0765	.0178
0.20	.3430	.0144	.2482	.0150	.0948	.0161
0.25	.3321	.0135	.2258	.0138	.1063	.0150
0.30	.3223	.0129	.2078	.0128	.1145	.0142
0.35	.3128	.0126	.1917	.0123	.1211	.0137
0.40	.3047	.0123	.1778	.0122	.1269	.0133
0.45	.2977	.0122	.1659	.0121	.1318	.0132
0.50	.2920	.0121	.1558	.0122	.1362	.0130
0.55	.2875	.0120	.1467	.0123	.1408	.0128
0.60	.2840	.0122	.1380	.0125	.1460	.0127
0.65	.2817	.0125	.1308	.0130	.1510	.0127
0.70	.2805	.0128	.1240	.0134	.1566	.0128
0.75	.2803	.0131	.1169	.0140	.1634	.0137
0.80	.2794	.0137	.1085	.0148	.1709	.0147
0.85	.2771	.0146	.0974	.0158	.1797	.0160
0.90	.2696	.0165	.0792	.0180	.1904	.0188
0.95	.2493	.0218	.0356	.0244	.2137	.0253

Source: own calculations and SOEP. Standard errors obtained by bootstrapping (500 replications)

Table 10: Average unexplained gaps

	Mean	Std. Deviation	N
<b>Age:</b>			
15 to 25 years	0.099	0.049	1170
26 to 35 years	0.130	0.048	3584
36 to 50 years	0.136	0.053	8978
51 to 64 years	0.141	0.054	5267
<b>Education:</b>			
Primary School	0.107	0.051	2112
Secondary/Middle Vocational	0.123	0.051	9604
Upper Second/Higher Vocational	0.140	0.044	3253
University Degree	0.169	0.047	4030
<b>Experience:</b>			
0 to 5 years	0.109	0.054	2546
6 to 10 years	0.129	0.053	2642
11 to 17 years	0.133	0.053	4230
18 to 25 years	0.141	0.051	4071
more than 26 years	0.148	0.048	3906
<b>Occupation:</b>			
Non-skilled Workers	0.092	0.051	2929
Skilled Worker	0.114	0.049	548
High Skilled Worker	0.131	0.042	113
Non-skilled Employee	0.091	0.053	1508
Middle-Skilled Empl.	0.117	0.044	2835
Skilled Empl.	0.146	0.040	7360
Highly-Skilled Empl.	0.176	0.037	2093
Lower Civil Servant	0.158	0.038	319
Upper Civil Servant	0.183	0.038	1294
<b>Industry Branche:</b>			
Electronics	0.141	0.052	1411
Mining, Energy	0.172	0.044	122
Chemical Industry	0.137	0.058	840
Construction	0.131	0.045	291
Heavy Industry	0.140	0.047	316
Textile Sector	0.113	0.050	138
Trade and Retail	0.111	0.049	3029
Transports, Post	0.138	0.049	616
Public Services	0.147	0.046	7930
Private Services	0.125	0.060	2949
Others	0.115	0.059	1266
Agriculture	0.102	0.059	91
<b>Parttime Work:</b>			
No	0.144	0.045	10029
Yes	0.122	0.058	8970

Source: Own calculations and SOEP

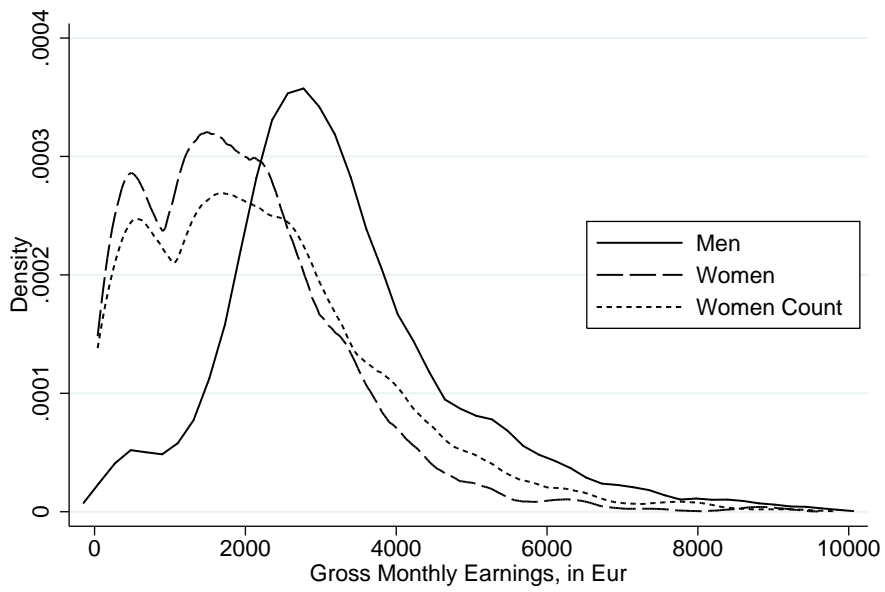
Table 11: Distributional Effects on Equivalised Household Net Income

Deciles	Status Quo	Counterfactual	Relative change
	Mean	Mean	
1	648	650	0.30%
2	990	1004	1.41%
3	1233	1257	1.93%
4	1430	1475	3.16%
5	1623	1676	3.28%
6	1828	1896	3.73%
7	2061	2144	4.00%
8	2343	2450	4.58%
9	2772	2915	5.15%
10	4200	4406	4.91%
Total	1912	1986	3.87%

Source: own calculations, STSM and SOEP

## B. Figures

Figure 5: Status Quo vs Counterfactual Density Plots



Source: own calculations, SOEP.  
Comments: Density conditional on positive earnings. Pooled data 2005–2010. Sample weights used.