

Gallego-Granados, Patricia; Geyer, Johannes

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Distributional and behavioral effects of the gender wage gap

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Effects of the Gender Wage Gap**

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German Socio-Economic Panel Study (SOEP)

DIW Berlin

Mohrenstrasse 58

10117 Berlin, Germany

Contact: Uta Rahmann | soeppapers@diw.de

Distributional and behavioral effects of the gender wage gap*

Patricia Gallego-Granados[†] and Johannes Geyer[‡]

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Preliminary version

The gender wage gap is a persistent labor market phenomenon. Most research focuses on the determinants of these wage differences. We contribute to this literature by exploring a different research question: if wages of women are systematically lower than male wages, what are the distributional consequences (disposable income) and what are the labor market effects (labor supply) of the wage gap? We demonstrate how the gender gap in gross hourly wages shows up in the distribution of disposable income of households. This requires taking into account the distribution of working hours as well as the tax-benefit system and other sources of household income. We present a methodological framework for deriving the gender wage gap in terms of disposable income which combines quantile decomposition, simulation techniques and structural labor supply estimation. This allows us to examine the implications of the gender wage gap for income inequality and working incentives. We illustrate our approach with an application to German data.

Keywords: gender wage gap, quantile regression, wage decomposition, labor supply, microsimulation, income distribution, tax-benefit system

JEL Classification: D31, J31, J16, H23

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[†]DIW-Berlin, pgallego@diw.de

[‡]DIW-Berlin, jgeyer@diw.de

1. Introduction

In this paper we examine the distributional (available income) and behavioral (labor supply) consequences of the well-known gender wage gap. The gender gap in gross wages is a persistent and pervasive phenomenon observable in virtually every country's labor market. The [OECD \(2012, p.166\)](#) reported an average gender wage gap of 16% for full-time employees in its member countries in 2010. Numerous studies have analyzed its magnitude, determinants and development over time (see, for instance, [Bertrand \(2011\)](#) and [Blau and Kahn \(2003\)](#)). The influential decomposition literature, starting with the seminal work of [Oaxaca \(1973\)](#) and [Blinder \(1973\)](#), has sought to divide the observed differences between men's and women's wages into the effects of different human capital endowments and their returns. These studies find that observed wage differences can be only partly explained by observable productivity differences and that a large share remains unexplained.

Given the systematic and sizable gross wage differences between men and women the wage gap obviously affects disposable income and probably behavior as well. It is likely to impact female labor supply negatively, and women generally tend to react more elastically than men to changes of the wage rate. Depending on the distribution of the gender wage gap, it also affects the income distribution between and within households in a non-trivial way. To the extent that the gender wage gap affects the relative incomes of household members, it is likely to play an important role in most intra-household bargaining models (see, for instance, [Browning et al., 1994](#)). However, there is very little research on distributional or behavioral effects of the wage gap. We contribute to the literature by proposing a flexible approach to its effect on income distribution and labor supply. Our main contribution is to link the gender wage gap in gross hourly wages to net disposable income. Using a labor supply model, we estimate the effect of a reduction of the gender wage gap on female labor supply. Our suggested framework builds on the decomposition literature, which we combine with simulation of the tax-benefit system as well as structural estimation of labor supply. We provide a systematic discussion of each necessary step, underlying assumptions as well as data requirements.¹

The distribution of tangible financial consequences deriving from gender-based hourly wage differentials are, *a priori*, unknown – mainly for three reasons: First, the distribution of working hours needs to be factored in. Especially in countries where part-time work

¹In one of the few papers that focus on the behavioral effects of the gender wage gap, [Aizer \(2010\)](#) shows that a reduction of the gender wage gap had a negative effect on domestic violence in the United States. However, it is often difficult to find exogenous variation of the gender wage gap in order to identify a causal effect.

is widespread, the magnitude of the effect of a given (gross) wage differential in terms of gross earnings varies along the hours and the wage distribution. Second, the tax-benefit system is crucial for disposable income. Tax-benefit systems have an implicit gender dimension, which is best exemplified by schemes of joint taxation. But also implicit equivalence scales which underlie all tax-benefit systems often differ by household type and can thus produce different incentives for different household types. Third, to the degree that households share resources, the distributional impact depends on the income sharing rule within the household.

The presented framework for deriving the net gender pay gap involves four steps: (1) The first step is a quantile decomposition of hourly wage differences between men and women along the wage distribution. To this end, we estimate conditional quantile wage regressions and apply the decomposition method proposed by [Machado and Mata \(2005\)](#). We derive the explained and unexplained portion of the wage gap. (2) In the second step of our analysis, we simulate counterfactual gross hourly wages for women in the absence of gender wage gap (or a component thereof). The semi-parametric decomposition method provides a characterization of a counterfactual distribution for female wages but not the desired counterfactual wages for each individual. Therefore, we derive individual wages by assuming rank invariance of female individuals in the counterfactual distribution with respect to the baseline distribution. This allows us to increase individual female wage rates by a mark-up. On this basis, we can further derive the counterfactual gross monthly earnings distribution by accounting for hours worked. (3) The third step is the calculation of disposable income. At this stage, in addition to the counterfactual gross earnings obtained under step two, we require information on the household level (other own income, income from other household members, household characteristics relevant to the tax and transfer system such as number of children, etc.) which is then fed into a simulation model of the applying tax-benefit system (for details of the model, see [Steiner 2012](#)). The difference in household disposable income between the observed and the counterfactual scenario can be interpreted as the representation of the gender wage gap – originally estimated in hourly gross wages – in terms of household disposable income. However, the level of analysis is now the household and no longer the individual. In order to recover an individual measure of the net pay gap, information about an income sharing rule within the household is needed. Given that we do not observe this information, we use two common approaches in the literature, intra-household income pooling and proportional income sharing, which respectively yield a lower and upper bound of the net pay gap at individual level. (4) In a final step, we go beyond a static analysis and allow for labor supply adjustments. Using a discrete choice labor supply model we derive

net pay gaps with labor supply adjustments as well as aggregated labor supply effects resulting from the gender pay gap.

The empirical analysis is carried out using data from the German Socio-Economic Panel (SOEP) for West Germany. Analyzing the distributional impact of the gender pay gap in Germany is interesting for several reasons. First of all, the gender pay gap is relatively large and persistent in Germany: in 2010, the median wage gap of full-time working women was about 22% and has only slightly narrowed since 2000. Comparing female employees working full-time, several studies also suggest that the wage gap varies across the wage distribution in Germany (OECD, 2012; Christofides et al., 2013; Arulampalam et al., 2007). Secondly, the share of women working part-time is particularly high in Germany: in 2010, nearly 40% of all employed women worked part-time (OECD, 2012, p.161). Thirdly, Germany is one of the few remaining countries, together with France and the US, retaining a system of joint taxation of married couples. This leads to high marginal tax rates for the second earner which is typically the female spouse. On the other hand, income redistribution might mitigate disadvantageous labor market treatment of women with low household income.

We find that on average the unexplained household net gap is around 5.2% of household's equivalised net income and is higher for women living in single households (with or without children) than in couple households. Furthermore, within each of these two groups, the net financial consequences of the unexplained gap are higher for households without children. This pattern can be explained by larger earnings inequality of households with children. In particular, the share and level of female earnings in couple households with children are smaller than in households without children. At individual level, we can only identify bounds for the net pay gap. These range, on average, from 5.2% to 9.7%. The more (less) the actual sharing rule approaches perfect income pooling, the lower (higher) the net unexplained gap at individual level. When we allow for labor supply effects, we find a higher impact of closing the gender wage gap for women living in couple households than in single households, which is consistent with the higher labor supply elasticities of the first group. On the aggregate, we find the unexplained gap to be associated with the labor market non-participation of around 105,500 women and with a reduction of working hours of about 247,600 full-time equivalents.

The paper proceeds as follows: The next section provides an overview of the related literature. Our methodological approach is detailed in Section 3. Section 4 presents our application and findings. Section 5 concludes.

2. Previous findings

Empirical research on gender wage gaps is mainly focused on the identification of factors that explain systematic differences in gross wages of men and women. In this sense, [Blau and Kahn \(1996, 2003\)](#)'s cross-country studies find that wage-setting institutions (such as collective bargaining agreements) are associated with lower gender wage gaps. [Olivetti and Petrongolo \(2008\)](#) analyze the effect of women's non-random selection into employment on the gender wage gap of various OECD countries and find sizeable negative effects for southern EU countries. [Goldin \(2014\)](#), based on US data, points at wage penalties coming from part-time work as a major source of gender differences in wage rates. Most studies that analyze differences in wage rates between women and men use a standardized wage measure (e.g. gross hourly wage) to identify the factors that explain pay differences.

Studies on the gender wage gap show that observed wage differences can be only partly explained by observable productivity differences. A part of this literature uses decomposition approaches to explain differences between female and male wages (see [Fortin 2011](#) for an overview of the state of decomposition techniques in economics). Having its origins in the seminal work of [Oaxaca \(1973\)](#) and [Blinder \(1973\)](#), the decomposition literature has additionally developed semi- and non-parametric techniques that go beyond the mean decomposition enabling to analyze the gender wage gap across the whole wage distribution (see, e.g., [DiNardo et al., 1996](#); [Fortin and Lemieux, 1998](#); [Machado and Mata, 2005](#); [Melly, 2005](#)). The idea behind these techniques is that the wage gap might vary across the wage distribution. [Albrecht et al. \(2003\)](#), for example, argue that a small average wage gap might conceal "glass ceiling effects" at the top of the wage distribution and finds evidence for such an effect in Sweden. [Rica et al. \(2008\)](#) find both a glass ceiling and a "sticky floor" effect for Spain. [Arulampalam et al. \(2007\)](#), in a study on eleven European countries, find a glass ceiling effect for most analyzed countries. One key question in this literature is whether gender differences in the returns to labor market endowments that cannot be explained by differences in productivity are due to gender discrimination (e.g., [Hellerstein et al., 1999](#); [Black and Strahan, 2001](#)).

In our application we focus on Germany. Several studies find a relatively large gender pay gap for Germany that varies with estimation sample, dataset and year. The average raw gap in gross hourly wages lies between 23% and more than 30% (e.g., [Busch and Holst \(2008\)](#); [Anger and Schmidt \(2010\)](#); [OECD \(2012\)](#)). Decomposition exercises à la Oaxaca-Blinder show that a large part of this gap cannot be explained by differences in the labor-market skills of women and men (e.g., [Anger and Schmidt \(2010\)](#)). In addition,

most studies find some variation of the gender wage gap across the wage distribution although its estimated shape across the distribution differs depending on estimation sample, year and dataset used (see, e.g., [Fitzenberger and Kunze \(2005\)](#), [Heinze and Wolf \(2010\)](#), [Antonczyk et al. \(2010\)](#), [Arulampalam et al. \(2007\)](#)).

Parallel to the body of gender wage research and the decomposition of income inequality, a seemingly unrelated literature examines the gender aspects of tax-benefit systems. Even though nowadays tax-benefit systems in Western countries do not distinguish between men and women, the application of the same rules can have implicit gender specific effects ([Stotsky, 1996](#)). 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 [Figari et al., 2011](#)), working (dis)incentives ([Immervoll et al., 2011](#)), as well as optimal (gender-based) taxation ([Alesina et al., 2011](#); [Bastani, 2013](#)). Very relevant to the present paper is the issue of shifting the level of analysis from the individual to the household (and vice versa) – which becomes even more complex if the tax-benefit system is taken into account ([Bargain, 2008](#); [Sutherland, 1997](#)).

Lastly, there are some studies on income inequality which relate to our analysis. These focus on whether the secular increase in female labor force participation had an influence on the development of income inequality. The increase in female labor force participation was mainly driven by a higher participation rate of married women in many countries. [Cancian and Reed \(1998, 1999\)](#) discuss different methods to decompose inequality measures by sources of income. For the US, they find that female earnings reduced inequality compared to an income distribution without female earnings. Other studies found similar effects, e.g., [Del Boca and Pasqua \(2003\)](#) for Italy, and [Campos-Vázquez et al. \(2012\)](#) for Mexico. [Pasqua \(2002\)](#) uses the ECHP to analyze to what extent country differences in inequality can be attributed to differences in female employment rates. Pasqua shows that the effect on inequality depends mainly on the employment rate. In order to decompose the contribution of female earnings to income inequality, the common approach in these studies is a counterfactual distribution in which women have zero earnings.

3. Methodological approach

In the following, we describe the necessary steps to analyze the consequences of the gender wage gap for disposable income and labor market behavior. The first step is a quantile decomposition of hourly wage differences between men and women along the wage distribution. In the second step of our analysis, we simulate counterfactual gross hourly wages for women in which the unexplained gap is closed. The third step is the

simulation of disposable income. In a final step, we go beyond a static analysis and allow for labor supply adjustments to take place.

3.1. Wage model and decomposition method

The departing point is a standard decomposition of wage differences between women and men along the wage distribution. Departing from the work of [Oaxaca \(1973\)](#) and [Blinder \(1973\)](#) – hereinafter OB –, these decompositions aim at separating observed differences in wages (in our case between women and men) into a component that can be explained by differences in labor market endowments and another component that can be explained by differences in the returns to those labor market endowments.² The literature refers to these two components as explained and unexplained factors.

We follow [Machado and Mata \(2005\)](#) and apply the principle of the OB decomposition to differences in wage quantiles between women and men. Observed differences between male wages w_m and female wages w_f at the θ -percentile can be expressed as:

$$\hat{Q}_\theta(w_m) - \hat{Q}_\theta(w_f) = \left[\hat{Q}_\theta(w_m) - \hat{Q}_\theta(w_C) \right] + \left[\hat{Q}_\theta(w_C) - \hat{Q}_\theta(w_f) \right] \quad (1)$$

where w_C stands for a counterfactual wage distribution. The counterfactual distribution is not observed and we have to make an assumption about its shape. For the case in which the choice of counterfactual wage distribution consists of women’s labor market characteristics being paid as if they were men, the first term on the right hand side is the component explained by differences in covariates and the second term is the unexplained component – at each quantile of the wage distributions.³

We follow the algorithm proposed by [Melly \(2006\)](#) in order to obtain estimates for unconditional quantiles that are consistent with our conditional quantile regression model.⁴ First, we estimate the conditional quantile regression coefficients β_θ separately for men and women for a grid of 1000 percentiles, $\theta \in (0, 1)$, from the model:⁵

²See [Fortin et al. \(2011\)](#) for an in-depth discussion of the assumptions underlying decompositions of wage differentials.

³Alternatively, the counterfactual wage distribution could consist of men’s labor market characteristics being paid as if they would be women, in which case the correct interpretation of the two components would be the other way around.

⁴As explained in [Melly \(2006\)](#), this procedure is numerically identical to the procedure proposed by [Machado and Mata \(2005\)](#) when the number of simulations used approaches infinity.

⁵We 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](#)).

$$Q_\theta(w_g|X) = X_g\beta_{g,\theta} + u_g, \quad g = f, m, \theta \in (0, 1) \quad (2)$$

where X stands for relevant labor market characteristics entering the wage model, $g = f$ stands for females and $g = m$ for males.

Unconditional quantiles of \hat{w}_m , \hat{w}_f and $\hat{w}_C = X_f\hat{\beta}_m$ are then computed as:

$$\hat{Q}_\theta(w_g) = \inf \left\{ q : n^{-1} \sum \hat{F}_w(q|X_i) \geq \theta \right\}, \theta \in (0, 1) \quad (3)$$

where $\inf\{\dots\}$ picks the smallest value for which the condition in curly brackets is true. w_g stands for any of the three wage distributions \hat{w}_m , \hat{w}_f , \hat{w}_C and $\hat{F}_w(q|X_i)$ is the cumulative density of wages conditional on X and can be computed as $\hat{F}_w(q|X_i) = \sum 1(X_i\hat{\beta}(\tau_j) \leq q)$. This way, we obtain the characterization of the three wage distributions required in Equation (1) and can decompose the gender wage gap along the wage distribution. Point-wise and uniform standard errors of the overall gap as well as its two components can be computed via bootstrap as suggested in [Chernozhukov et al. \(2013\)](#).

3.2. Constructing individual counterfactual wages

In order to examine the distributional effect of the gender wage gap (and its components), a counterfactual wage for each woman in our sample is needed. However, the method described above results in the characteristics of three wage distributions (female, male and counterfactual) but not in counterfactual wages for each female observation. The mapping of these results to individual wages necessarily requires an additional assumption imposing rank invariance. At this stage, we have in principle two options: preserving the rank in the conditional or the unconditional wage distribution.⁶

Assuming rank invariance in the unconditional wage distribution implies that the gap to which each woman is exposed only depends on her rank in the observed distribution of gross hourly wages. Furthermore, under this assumption the unexplained gap is only job-specific to the point that different jobs pay wage rates that are in different segments of the distribution. This procedure can be understood as adding a mark-up to observed (predicted) female wages that “closes up” the gap found in the decomposition exercise. In particular, each observation is assigned the counterfactual wage rate corresponding to its quantile in the counterfactual distribution. The assumption of rank invariance in

⁶Note that this would also be the case if working with a mean decomposition. In this case, preserving the conditional rank would translate into computing female counterfactual wages as a regression-based prediction (with the beta coefficients of the male wage regression) while preserving the unconditional rank would boil down to adding the estimated gap to each status quo (observed or predicted) female wage.

the unconditional wage distribution allows to separately close the unexplained, explained and overall wage gap, thereby preserving a great deal of flexibility.

Alternatively, assuming rank invariance in the conditional wage distribution implies that the unexplained gap to which women are exposed will depend on their labor market relevant characteristics. In this case, counterfactual female wages will be computed as a prediction, using the β_θ -coefficients of the male (female) wage estimation applied to the values that the model covariates take on for each female (male) observation. This alternative yields counterfactual wages that respond to a hypothetical exercise: female (male) wages if women (men) would be paid as if they were men (women).

Whereas the assumption of rank invariance in the unconditional wage distribution allows to separately/sequentially close the unexplained, explained and overall wage gap, it also suggests that the used reference wage distribution is the "true" distribution (the wage distribution that would prevail in absence of labor market discrimination, which cannot be determined within the decomposition exercise). On the contrary, assuming rank invariance in the conditional wage distribution allows to abstract from a true reference wage distribution but restricts the possible counterfactuals to "women paid as men are currently paid" (or, vice versa, "men paid as women are currently paid"), thereby making it impossible to trace the net financial consequences from the explained and the overall gross gender wage gap. Although our measure of the net gender pay gap (derived in section 3.4) is technically compatible with both approaches, we believe that maintaining the rank in the unconditional wage distribution suits our research question and motivation for this paper best. Under both assumptions, counterfactual wages of men (the reference group) equal their status quo wages.

3.3. Simulation of net household income

In order to simplify the notation, from now on it will be assumed that the chosen reference wage distribution is that of men, and consequently counterfactual wages are being computed for women. In what follows, index i denotes individuals whereas index j denotes households. The superscript C stands for counterfactual.

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, which we denote $E_{i,f}$ and $E_{i,f}^C$, respectively. To this end, we multiply the (exponentiated) wage rate times observed working hours. The difference between the two can be expressed as $\Delta E_i^f = E_{i,f}^C - E_{i,f}^f = (\exp(w_i^C) - \exp(w_i)) h_i$.

The next step is computing households' net income under status quo and counterfactual earnings. Note that this is a necessary step, since under most tax-benefit systems in the

world it is not possible to compute an individual’s disposable income without applying a sharing rule to the previously computed household’s net income (except in the case of childless single-adult households). This is a data intensive step, as it requires very detailed information on the household (other household members, their demographic characteristics, their labor-market status, other income sources, among others).

We denote household net income as $N(E_j^C, X_j)$ (counterfactual) and $N(E_j, X_j)$ (observed), where E_j are gross labor earnings for household j and X_j is a vector of household characteristics (e.g., marital status, number of children) relevant for the tax-benefit system, which does not change between the status quo and the counterfactual scenario. 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.⁷

3.4. The net gender pay gap

This section presents our measures of the net gender wage gap. In the gender wage gap literature, it is often the case that gender differences are expressed in terms of women’s relative wages (to men). In the present exercise, however, we are interested in the net financial consequences of women’ relative income to a reference income that does not include the unexplained gross wage gap. As discussed above, in order to do so we need to shift the analysis level to the household. As a result, it is no longer meaningful (nor possible) to frame the resulting income gaps in terms of “relative incomes”. Instead, our measures of net pay gap will be based on the difference in terms of disposable income that each female would experience should her hourly wage gap be closed. Table 1 provides an overview of the measures presented below.

Net gender pay gap – in absolute values

We can express the difference in disposable income, ΔN_j , as:

$$\Delta N_j = N(E_j^C, X_j) - N(E_j, X_j) \quad (4)$$

From the static perspective, i.e., without labor supply adjustment, the only change between the status quo and counterfactual scenario is the increase in women’s wages. Therefore any change in net household income, ΔN_j , can be fully attributed to the

⁷We use the tax-transfer-simulation-model STSM for Germany. Based on variables drawn from the SOEP, gross earnings, the taxable income, income taxes, all important transfers and finally the disposable net income can be derived at the household level. See Appendix C and [Steiner et al. \(2012\)](#) for a detailed description of the model.

unexplained component of the gender wage gap.⁸

Net gender pay gap – relative to household income

Starting with the absolute difference ΔN_j , it is straightforward to obtain a measure of the (standardized) net gender gap relative to household net income:

$$\Omega_j = \frac{N(E_j^C, X_j)}{N(E_j, X_j)} - 1 \quad (5)$$

Ω_j describes the relative change of household net income following an increase of female gross wages for each household. The denominator of Equation (5) includes all income components of the household. This implies that the relative gender income gap is smaller the higher other income components are. There are also interactions with the tax-benefit system. For example, conditional on the position in the gross hourly earnings distribution, the progressivity of the tax-benefit system leads to net gender wage gaps that decrease the more hours women work. This is true for women both in an individual as well as in a joint taxation regime. Under joint taxation the net gender wage gap will increase slower with hours for married than for non-married women. In addition, following this definition of net gender gap, a woman exposed to a very high marginal tax will have a very small net gender gap independently of how big the unexplained gap allocated to her is.

Net gender pay gap – relative to female income

In addition to the household measure we quantify the relative change with respect to the female component of household income. This measure is better comparable to the gross wage gap which is also derived at the individual level. However, for non-single households determining the denominator in Equation 5 is not straightforward, since it requires further information on how net income is distributed within the household. This is due to the fact that many elements of the tax-benefit system are evaluated and determined at the household level. Furthermore, some income components can only be attributed to the household and not to its individual members. Therefore, any measure of individual net income necessarily implies a sharing rule within the household. A measure of the net gender gap in terms of female income would be constructed as:

⁸In section 3.5 we allow for adjustments in labor supply resulting from the existence of the gap. In this case, the difference in disposable income can capture – in addition to increased female hourly wage rates – changes in labor supply of both women and men. However, due to the fact that men's cross-elasticities of labor supply are very small, most of the change in disposable income is due to changes in female wages and women changing working hours or labor market participation.

$$\omega_i = \frac{\delta_i^C}{\delta_i} \frac{N(E_j^C, X_j)}{N(E_j, X_j)} - 1 \quad (6)$$

δ and δ^C represent the value of the sharing rule for the female household member under the status quo and the counterfactual female wage distribution, respectively. δ is bounded between zero and one, as it represents the proportion of household net income available to the female spouse. For single households, δ equals one in both cases, and ω_i equals Ω_j .

Given that we do not observe the true sharing rule in the households of our sample, in our application we use two opposite concepts of sharing rules: (1) perfect income pooling within the household and (2) proportional sharing of household net income. Under income pooling, female net income in couple households amounts to half of the overall household net income (regardless of the (in)existence or level of labor earnings of any other household member). In this case, $\delta = \delta^C = 1/2$ and as a result $\omega_i = \Omega_j$.

Under proportional income sharing, we let the share of female labor earnings (over total household labor earnings) determine the share of net household income available to the female spouse. Thus:

$$\delta_i = \frac{E_{i,f}}{E_{i,f} + E_{i,m}} \quad (7)$$

$$\delta_i^C = \frac{E_{i,f}^C}{E_{i,f}^C + E_{i,m}^C} \quad (8)$$

where $E_{i,k}$ denotes labor earnings earned by women ($k = f$) and men ($k = m$) within a household j .

While none of these two extreme sharing rules are (expected to be) realistic, we have chosen them so as to obtain a lower and upper bound of the net gender pay gap at individual level⁹. The assumption of perfect income pooling, although having been questioned in the literature (see, e.g., [Browning et al., 1994](#); [Lundberg et al., 1997](#)), yields a lower bound for the net gap because it fully “socializes” the gender gap within the household. On the opposite, the assumption of proportional sharing of household net income implies that women alone bear the whole financial consequences of the gap – providing thus an upper bound for our estimate of interest.

Given that, by construction, $E_{i,f}^C > E_{i,f}$ and $E_{i,m}^C = E_{i,m}$, the quotient δ_i^C/δ_i will equal one for single women and greater than one for partnered women. Thus, the net

⁹The estimation of the actual sharing rule is beyond the scope of this paper.

gap under income pooling will be by construction equal or smaller than the net gap under proportional sharing.

3.5. Labor supply effects of the net gender pay gap

We now go beyond a static wage gap decomposition and show how we can use a structural labor supply model to estimate net pay gaps that allow for behavioral changes. These estimates take into account labor supply adjustments derived from the existence of the gender wage gap itself. This relaxes the usual assumption of empirical studies on gender wage gaps that working hours and participation are not modified by the existence of a wage differential. Furthermore, such a model allows us to estimate aggregate labor supply responses from the gap in the intensive as well as in the extensive margin. The adjustment in terms of working hours is computed for each household by comparing the predicted number of working hours under the status quo and the counterfactual female wages. To calculate participation effects, we compare the probabilities of choosing working hours combinations.

We use a structural labor supply model as proposed by [van Soest \(1995\)](#) to estimate labor supply elasticities. In this model, households choose labor supply by maximizing a utility function that includes net income, leisure and other household characteristics (such as number of children in the household, age, health, etc.). The household utility level depends on the combination of working hours chosen. For couple households, males and females are assumed to choose among k and l alternatives of working hours (including non-employment in both cases), so that the household choice set includes $k \times l$ combinations of working hours. For single households, the choice set reduces to the own working hours categories. Under the assumption that the error term in the utility function is type I extreme-value distributed, the probability of choosing each given combination of working hours can be estimated via a conditional logit model ([McFadden, 1974](#)). For more details, see [Appendix C](#) and [Steiner et al. \(2012\)](#).

Once we have estimated the discrete choice model explained above, – both under status quo and counterfactual wage distributions – we can proceed to calculate household net incomes that allow for labor supply adjustments. We do so by multiplying the estimated probabilities of choosing the diverse working hours categories times the corresponding net income for each category – both under the status quo and the counterfactual wage distribution. The net pay gaps with behavioral reactions can be then expressed as:

$$\tilde{\Omega}_j = \frac{N(\tilde{E}_j^C, X_j)}{N(\tilde{E}_j, X_j)} - 1 \quad (5)$$

$$\tilde{\omega}_i = \frac{\tilde{\delta}_i^C}{\tilde{\delta}_i^S} \frac{N(\tilde{E}_j^C, X_j)}{N(\tilde{E}_j, X_j)} - 1 \quad (\tilde{6})$$

Under such formulation, adjustments in labor supply of men deriving from changes in female wages would theoretically show up in $\tilde{\Omega}_i$ and $\tilde{\omega}_i$, thereby not being able to claim any longer that all changes in $N(\cdot)$ can be exclusively traced back to the change in female wages (as it was the case in the static calculation). However, cross-elasticities of men are empirically very low and therefore not likely to play a major role (Steiner and Wrohlich, 2004).

Table 1: Summary of different representations of the gender wage gap in terms of disposable household income

Measure	Description
ΔN_j	<i>Absolute difference</i> in disposable household income between observed and counterfactual wages without labor supply adjustments
Ω_j	<i>Relative difference</i> in disposable household income between observed and counterfactual wages without labor supply adjustments (range between 0 and 1). Measured at the <i>household level</i> .
ω_i	<i>Relative difference</i> in disposable household income between observed and counterfactual wages without labor supply adjustments (range between 0 and 1). Measured at the <i>individual level</i> .
$\tilde{\Omega}_j$	<i>Relative difference</i> in disposable household income between observed and counterfactual wages with labor supply adjustments (range between 0 and 1). Measured at the <i>household level</i> .
$\tilde{\omega}_i$	<i>Relative difference</i> in disposable household income between observed and counterfactual wages with labor supply adjustments (range between 0 and 1). Measured at the <i>individual level</i> .

4. The unexplained net gap in West Germany

In this section we estimate the net wage gap for Germany applying the framework detailed in the previous section. Germany is a good example to study the distributional and behavioral consequences of the gender wage gap for several reasons: the gender pay gap in Germany is relatively large and persistent. In 2010, the median wage gap of full-time working women was about 22% and has only slightly narrowed since 2000. Comparing female employees working full-time, several studies also suggest that the

wage gap varies across the wage distribution in Germany (OECD, 2012; Christofides et al., 2013; Arulampalam et al., 2007). Secondly, the share of women working part-time is particularly high in Germany: in 2010, nearly 40% of all employed women worked part-time (OECD, 2012, p.161). Thirdly, the German tax-benefit system has an implicit gender dimension given its progressive tariff and the joint taxation regime for married couples. In the following, we show the consequences of the unexplained component of the gross hourly wage gap in terms of disposable income.¹⁰

We distinguish four different types of households to study the effect of the gross wage gap. We group women along household characteristics (partner in household and existence of children) that were identified in the literature to be important for either the level and distribution of gross wages, the level and distribution of working hours and participation behavior, and net household income: First of all, we differentiate between couples and women living alone because of different labor supply behavior. Estimated labor supply elasticities for women living in couples are usually higher than for female singles (see, e.g., Bargain et al., 2014). Furthermore, most couples are married and therefore taxed jointly which – compared to individual taxation – leads to lower average tax rates but higher marginal tax rates for the second earner, which is most often the female spouse. The high marginal tax rate for women entails negative labor supply incentives (e.g., Crossley and Jeon, 2007). Furthermore it increases incentives to take up low paid marginal employment which is exempted from social security contributions and tax free. Secondly, we differentiate women with and without children. Children have a negative impact on labor supply and are one important factor that leads to disadvantageous wage growth for women (e.g., Anderson et al., 2002, 2003; Meurs et al., 2010).

4.1. Data and Descriptive Statistics

Our study is based on data from SOEP which is a representative longitudinal micro database that provides a wide range of socio-economic information on private households in Germany. In 2012, the sample included about 21,000 respondents living in more

¹⁰We have chosen the unexplained component of the gender wage gap as the core of our application because of its relatively large magnitude in West Germany and since it is the main focus of many studies in this field and can be cautiously interpreted as a proxy for discrimination. It is difficult to identify and quantify discrimination based on the estimated residuals. If the unobservables are correlated with characteristics, the estimated betas are biased (Altonji and Blank, 1999). Even if there is no endogeneity, the residuals might include unobserved group differences related to productivity which would bias the estimated discrimination (Blau and Kahn, 2007). Conversely, observed characteristics could also be influenced by discrimination, e.g., vertical and horizontal occupational segregation.

than 12,000 households.¹¹ The SOEP provides information about employment status, earnings and working hours of individuals. Moreover, it includes detailed income information on the individual and household level and other demographic characteristics. One important feature of the data 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), which is not available in administrative data.

Sample for the Wage Decomposition

Our estimation sample for the wage regression comprises all working individuals aged between 15 and 64 years with residence in West Germany, except for the self-employed, people in vocational training or military service, students, and pensioners in line with the literature. We focus on West Germany because wage gap and female labor supply differ markedly between regions and the gap is particularly large in West Germany. We excluded observations earning less than 1.5 euro and more than 100 euro per hour, as well as observations with missing data in the variables entering the wage model.¹² We have not imposed any exclusion based on working hours, so that our estimation sample includes part-time and full-time workers. We pool data for the years 2008 to 2012 in order to have enough observations for our richly specified wage model. This yields a total number of 29,975 observations, of which 14,949 are females and 15,026 are males.

As Table 2 shows, women's hourly wages are on average about 15 euro – amounting to only 77% of male wages. It also shows that women work on average 11 hours per week less than men. Lower wages and lower working hours result in an average gross earnings difference per month of 1,355 euro. This represents 42% of male earnings. The unconditional difference of hourly wages increases in absolute and relative terms along the distribution of monthly earnings, reaching about 8 euro or 25% of the male average at the top quintile. In terms of working hours, the pattern we observe is the opposite. The difference is the highest at the bottom quintile of the distribution, where women work on average 22 hours per week less than men. Whereas working hours of men stay mostly steady around 40 hours per week along the gross earnings distribution, female work hours increase steeply, reducing the average difference in the top quintile to 5 hours per week.

The difference in the distribution of working hours between men and women is also

¹¹A description of the SOEP is provided by [Wagner et al. \(2007\)](#); more information is available at <http://www.diw.de/en/soep>.

¹²Variables included are polynomials in age, experience, and tenure, and sets of dummies that control for public sector, education, occupation, industry, firm size, and year effects.

Table 2: Average hourly wages and working hours by quintiles of gross monthly earnings

Quintiles of gross monthly earnings	Women		Men	
	Wage	Hours	Wage	Hours
1	8.36	13.55	9.91	35.97
2	11.72	25.87	14.53	40.37
3	13.60	33.23	17.50	40.76
4	16.37	36.80	21.66	41.04
5	23.95	38.98	31.84	44.20
Average	14.80	29.68	19.03	40.43
Gross monthly earnings	1,896		3,252	

Notes: Quintiles were calculated separately for the distribution of monthly gross earnings for men and women. Wages in euro. Hours worked per week. Weighted observations. Years 2008 through 2012.

Source: SOEP.v29.1, own calculations.

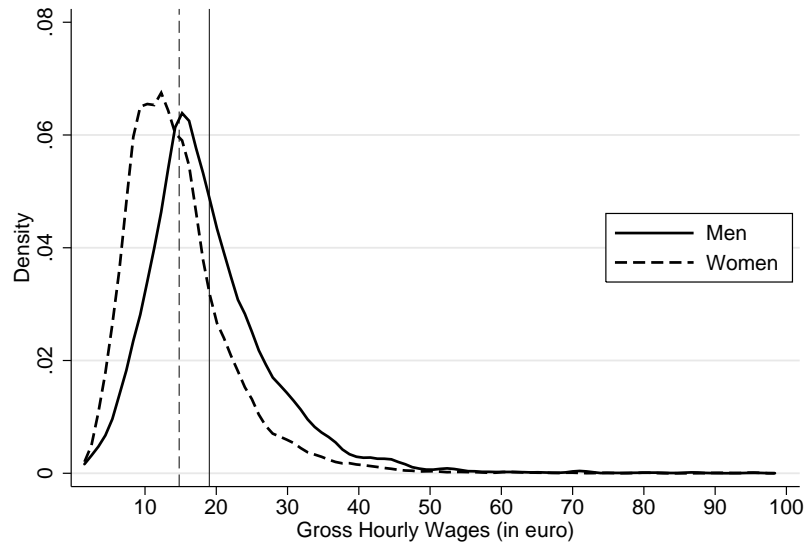
illustrated by Figure 1 below. The upper panel illustrates the differences in the distribution of hourly wages between men and women. The distribution of hourly wages of men is shifted to the right compared to the distribution of women's wages. The lower panel shows the differences in the distribution of gross monthly earnings. Since men work in general longer hours and earn higher wages, the average difference is larger as compared to hourly wages. But we also observe that monthly earnings of women follow a bimodal distribution. The bunching of women around 400 euro per month can be explained the existence of marginal employment. Up to this income threshold employees do not pay taxes or social security contributions. Women choose more often than men this type of employment.

Descriptive statistics of the variables entering the wage model can be found in Tables A1 and A2 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. There are no large differences in the level of education.

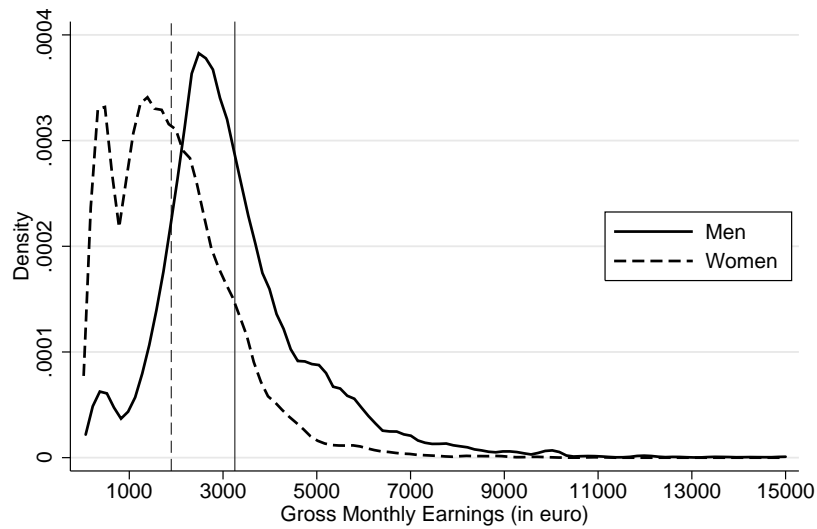
Sample for the estimation of net household income and labor supply effects

The simulation of net income and the estimation of labor supply is based on the year 2010. We choose only one year in order to keep the rules of the tax and benefit system constant. That is, all variation in the income distribution between the observed and the

Figure 1: Kernel densities of gross hourly wages and gross monthly earnings (2008-2012)



Note: kernel = epanechnikov, bandwidth = .95 (men) = .8129999999999999 (women)



Note: kernel = epanechnikov, bandwidth = 160.432 (men) = 157.085 (women)

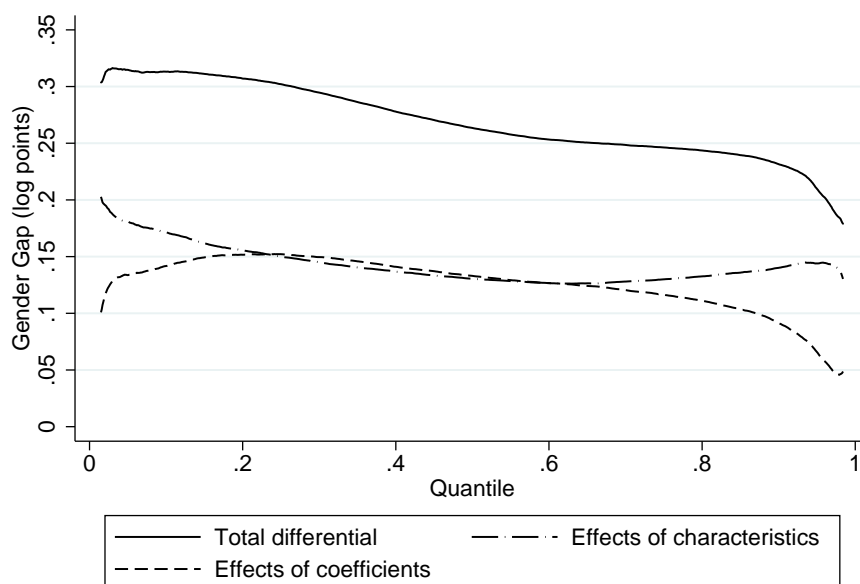
Source: SOEP.v29.1, own calculations.

counterfactual scenarios are related to our simulation and not induced by changes in tax rates, social security contributions or transfers. For this part of the analysis, we restrict our sample to households with a woman of working age (working or not working) and thereby those households that may be directly affected by the existence of a gender wage gap. A detailed description of the imputation procedure of wages for non-working women can be found in Appendix B. This leaves us with a total of 3,063 households, of which 2,174 are couple households and 889 are single households.

4.2. Gross gender wage gap: decomposition results

In this section, we report the results of our decomposition exercise, which is based on counterfactual female wages that would result from rewarding female labor market skills with male skill prices. This implies that we take male wages as the reference return to labor market characteristics.¹³

Figure 2: Decomposition results



Source: SOEP.v29.1, own calculations. Weighted observations.

Figure 2 presents the results of the decomposition exercise (see Table A5 in the Ap-

¹³Besides the straightforward alternative of using the betas estimated for female wages as reference returns to labor market skills, further alternatives explored by the literature – though only in the context of mean decompositions – consist of reference returns to skills constructed with the variation in the wage regressors of the two groups (e.g. Fortin, 2008; Neumark, 1988) and using the shares of women and men in the population to construct a weighted distribution (Oaxaca and Ransom, 1994).

pendix for the exact point estimates and standard errors). The y-axis depicts the absolute gap between the quantiles of two logarithmic gross hourly wage distributions and is approximately the relative gap between the quantiles of the exponentiated distributions.

The overall gap shows a decreasing shape from nearly 32 log points in the lower tail of the distribution down to approximately 18 log points at the upper end. The unexplained component displays a slight inverted u-shape. It starts at about 10 log points and increases up to 15 log points at the twentieth percentile. From there on, it decreases steadily and reaches the 5 log points at the top of the distribution. The explained component has a weak u-shape. It starts from about 20 log points, decreases until the third quintile to 12 and increases again to nearly 15 log points in 95-percentile.

A comparison to previous findings from other studies is difficult because samples, data, and year of the analysis are in general different. In terms of the raw gender wage gap, some studies find a similar decreasing trend (e.g., [Fitzenberger and Kunze \(2005\)](#); [Hübler \(2005\)](#); [Heinze and Wolf \(2010\)](#)). Nevertheless, other studies like [Arulampalam et al. \(2007\)](#), [Antonczyk et al. \(2010\)](#), and [Christofides et al. \(2013\)](#) show either a u-shaped overall gap or a gap that increases over the distribution.

As explained in [Section 3.3](#), the next step consists of assigning a specific value for the unexplained gap to each woman's observed wage in the sample. In order to do so, we assume rank invariance in the unconditional hourly wage distribution. Allocating an unexplained gap to each individual woman enables us to conduct a distributional analysis of the unexplained gap by household types. However we do not find large differences by household type with respect to the unexplained gap in hourly wages. This is consistent with our observation that households are distributed evenly across observed hourly wages. Note that the height of the gap is solely determined by the rank in the observed wage distribution.

Next, it is analyzed how the unexplained gap is distributed across gross monthly earnings of women. Empirically, we do observe women with high hourly wage rates who have low monthly wages because they work few hours. Alternatively, we also observe women with very low wage rates who still reach female median gross monthly earnings by working many hours. To the extent that women are ranked differently in the hourly wage distribution than in the monthly earnings distribution, the shape of the unexplained gap across the monthly earnings distribution is an open empirical question.

We assume the number of working hours to be constant between the status quo and the counterfactual scenario and multiply the counterfactual hourly wage rates by the observed number of working hours for each woman in our sample. [Table 3](#) depicts our results. The unexplained gap as percentage of gross monthly earnings is decreasing by

Table 3: Unexplained gross monthly gaps (in % and absolute values) by quintiles of gross earnings and household type

Quintiles	Couples		Single		All
	without children	with children	without children	with children	
% of female monthly gross earnings					
1	15.1	14.6	14.6	15.1	14.8
2	15.0	13.9	15.5	15.1	14.6
3	14.2	12.9	15.3	14.2	14.2
4	13.3	11.4	13.7	12.9	13.2
5	10.6	8.8	10.6	10.6	10.4
Average	13.6	13.3	13.3	14.0	13.4
Absolute difference (in Euro)					
1	61	60	62	51	60
2	160	143	171	161	154
3	244	219	262	251	244
4	322	270	332	302	318
5	379	346	373	356	372
Average	234	157	297	210	229

Notes: Unexplained Gaps represented as % of gross monthly earnings. Quintiles of the overall predicted female monthly gross earnings distribution in 2010.

Source: SOEP.v29.1, own calculations. Weighted observations.

earnings quintiles. It is lowest at the upper end of the earnings distribution for each type of household. This corresponds to the results of the decomposition which showed a decreasing gap at the top of the wage distribution. However, in absolute values, the gap is increasing. The unexplained gap amounts to 60 euro on average in the lowest quintile to 372 euro in the top quintile. We find the wage gap in most quintiles to be smaller for households with children.

Table 4 shows that for a given quantile of monthly earnings, households with children reach an average hourly wage that is above the wage of households without children. In other words, they work fewer hours and reach the same income as their childless counterparts in the same quantile. Given the results of the decomposition, higher wages correspond to lower unexplained wage gaps (see Table 3).

Table 4: Hourly wages and working hours by earnings quintiles and household type

Quintiles	Couples		Single		All
	without children	with children	without children	with children	
Median Hourly Wages					
1	7.8	8.2	7.5	7.8	7.8
2	11.4	13.2	9.2	10.8	11.5
3	13.8	15.1	11.0	14.4	12.9
4	14.9	19.9	14.2	16.6	14.9
5	19.9	25.5	19.5	19.2	20.1
Average	13.6	13.5	14.2	13.4	13.8
Median Working Hours per Week					
1	9.1	8.6	8.6	8.6	8.6
2	25.7	15.6	27.7	20.2	25.7
3	26.7	25.7	38.8	27.7	27.7
4	38.3	25.7	38.8	34.1	38.8
5	38.8	38.3	38.8	38.8	38.8
Average	26.7	15.6	38.8	27.7	27.7

Notes: Median hourly wages in Euro. Quintiles of the overall predicted female monthly gross earnings distribution in 2010.

Source: SOEP.v29.1, own calculations. Weighted observations.

4.3. Static net gender pay gap: the role of the tax-benefit system

Due to the tax-benefit system, the change in gross monthly earnings will have very different consequences in terms of net household income depending on the characteristics of each household.

Table 5: Static net gender pay gap by income quintiles and household type

Quintiles	Couples		Singles		All
	without children	with children	without children	with children	
% of household disposable income, Ω_j					
1	6.6	3.1	7.5	4.5	5.6
2	4.4	2.6	9.9	6.7	5.8
3	3.4	2.1	9.7	6.8	5.0
4	4.8	2.6	9.3	6.4	5.8
5	3.9	1.9	7.1	2.7	4.0
Average	4.4	2.4	8.9	5.5	5.2
Absolute difference (in Euro), ΔN_j^{hh}					
1	96	86	92	75	88
2	107	66	123	125	100
3	107	71	151	139	110
4	142	99	172	162	141
5	146	78	186	152	138
Average	126	79	141	102	116

Notes: Gaps presented as % of net household income. Quintiles of overall equivalized net household income. Weighted observations.

Source: SOEP.v29.1, own calculations.

Table 5 presents results for net gender pay gap, Ω_j , at the household level. Observations are sorted by quintiles of household equivalised¹⁴ disposable income. On average, the unexplained gap accounts for 5.2% of households' net income. This figure stays fairly constant along the income distribution, only slightly decreasing at the top quintile.

If we look at the results disaggregated by household types, differences in net gender gaps along the income distribution become more pronounced. For couple households without children the net gender gap is highest at the lowest income quintile – more than 6% – and decreases at higher income quintiles, where it amounts nearly 4%. For

¹⁴We use the new OECD-equivalence scale that assigns a value of 1 to the first adult in the household, a value of 0.5 to each further member of the household above the age of 14, and a value of 0.3 to children in the household below the age of 14.

single households without children, the net gender gap is highest at the middle of the income distribution, with gaps ranging between 9.3% and 9.9%, and decreases at both distribution ends, though not as strongly as for couple households. Households with children show lower average gaps in each quintile.

On average, household equivalized income increase by about 116 euro per month in our counterfactual scenario. We find that the absolute difference increases monotonically across income quintiles for household without children and singles but shows a heterogeneous pattern for couples with children. This pattern can be explained by a larger intra-household earnings inequality of households with children. In particular, the share and level of female earnings in couple households with children are smaller than in households without children.

Table 6: Different measures of the average net gender pay gap by household type

	Couples		Singles		All
	without children	with children	without children	with children	
PANEL A: Measures without labor supply adjustment					
Household level					
Ω_j	4.4	2.4	8.9	5.5	5.2
Individual level					
$\omega_i^{inc\ pool}$	4.4	2.4	8.9	5.5	5.2
$\omega_i^{ind\ inc}$	10.7	10.0	9.2	6.0	9.7
PANEL B: Measures with labor supply adjustment					
Household level					
$\tilde{\Omega}_j$	5.5	3.3	9.9	6.3	6.2
Individual level					
$\tilde{\omega}_i^{inc\ pool}$	5.5	3.3	9.9	6.3	6.2
$\tilde{\omega}_i^{ind\ inc}$	14.32	14.20	10.32	6.9	12.6

Notes: Gaps presented as % of net household income in the case of Ω_j and $\tilde{\Omega}_j$, and as % of female individual income in the case of ω_i and $\tilde{\omega}_i$. Weighted observations.

Source: SOEP.v29.1, own calculations.

As explained in Section 3, a point-identification of the net unexplained gap in terms of female net income for couple households is not possible without information on the actual sharing rule within the household. However, by choosing opposite sharing rules we can produce bounds for the estimate of interest. These are reported in Panel A of Table 6.

Our calculations suggest that the the average net pay gap for women in couple households lies between 5.2% and 9.7% depending on the actual sharing rule of the household. The closer the household is to income pooling (proportional sharing), the more (less) the financial consequences of the gap are internalized within the household and the smaller (bigger) the burden faced by the women. In other words, to the degree that households pool resources, the risk of wage discrimination is also shared and mitigated within the household.

4.4. Net gender pay gap with labor supply adjustments

The estimation of a structural model of labor supply enables us to take the analysis a step further and to present results on net gender pay gaps that take into account changes in labor supply. These are results that allow for adjustments in terms of labor supply of households deriving from the existence of the unexplained gap. Table A6 in the Appendix reports the estimates from the conditional logit model underlying our results, and Table A7 reports the associated labor supply elasticities.

Panel B of Table 6 replicates the results of the previous section allowing for labor supply adjustments.¹⁵ In terms of household net income, the gaps with adjustments are slightly higher than without – suggesting that behavioral reactions on the working hours margin may raise the net financial consequences of the unexplained gap. In terms of female net income, the more individualistic the sharing rule is, the higher the difference when we allow for labor supply effects. Furthermore, the effects are considerably bigger for women in couple households than in single households (consistently with the smaller elasticities of the latter, see Table A7 in the Appendix). Thus, the upper bound for females in couple households goes up to 14% when allowing for labor supply effects to take place, a four percentage points difference with respect to the static scenario.

Additionally, Table 7 reports the aggregate labor supply effects deriving from our counterfactual female wage distribution. According to our results, the existence of the unexplained component of the gender wage gap corresponds to an increase of labor market participation of about 109,000 people (most of them women). In terms of working hours supplied, the existence of the unexplained gap accounts for a reduced labor supply of ca 251,100 full-time equivalents (taken to be 40 hours per week). However, most of the change would happen with individuals that have already taken up employment.

¹⁵For the sake of presentation, results on net pay gaps with behavioral adjustments by income quintiles can be found in Table A8 in the Appendix.

Table 7: Labor Supply Effects

	People (in 1000)	Working Hours (Full-time Equivalents, in 1000)		
		Total Change	Additional Hours	Newly Employed
Couple Households				
w/o children				
Women	36.5	101.5	77.4	24.1
Men	1.7	2.6	3.9	-1.3
with children				
Women	42.7	63.5	42.8	20.7
Men	1.9	2.9	1.2	1.7
Single Households				
w/o children	18.8	62.0	47.6	14.4
with children	7.5	18.6	13.9	4.7
Total	109.1	251.1	186.6	64.4

Source: SOEP.v29.1, own calculations.

5. Conclusion

The aim of this paper was to provide a net measure of the raw gender wage gap as well as its explained and unexplained components. 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. It is important to quantify the distributional impact of the gender wage gap in terms of disposable income because of its nature as an inequality measure as well as potential behavioral responses deriving from it. From a policy perspective, this is highly relevant for female labor supply, gender-specific distribution of income within couple households as well as the economic independence of women.

The point of departure for our framework was a quantile regression-based decomposition with which we obtain an estimate of the raw gender wage gap as well as its explained and unexplained components across the whole wage distribution. The construction of individual counterfactual wages enables us to derive the gender gap both in terms of gross monthly earnings and in terms of net household income. This step of the analysis requires two important assumptions: We assume the prices of labor market skills paid to male individuals to be the reference prices of labor market skills. Whereas the literature has explored some alternatives in the context of mean decompositions, such a technique is missing for quantile-based decompositions. The main consequence for our analysis was

that it takes a partial equilibrium perspective. The second assumption is that we need to impose rank invariance in either the conditional or the unconditional wage distribution. In our application we choose the latter, although our methodological framework would be compatible with both of them.

Once we assign a counterfactual hourly wage to each individual, we proceed to compute the resulting household net income via microsimulation. By comparing household net income with counterfactual and observed wages, we can derive the net financial consequences of the gender pay gap at household level. Whereas for single households the net financial consequences at household level equal those at individual level, for couple households we require further information on how the income is distributed within the household. Given that we do not observe the true sharing rule in the our sample, we suggest to use two opposite concepts of sharing rules: (1) perfect income pooling within the household and (2) proportional sharing of household net income. While none of these two extreme sharing rules are (expected to be) realistic, we have chosen them so as to obtain a lower and upper bound of the net gender pay gap at individual level.

In a last step, we estimate a structural labor supply model to estimate net pay gaps with labor supply adjustments. This relaxes the assumption that working hours are not modified by the existence of the gender wage gap. Additionally, we can also estimate aggregate labor supply effects from the gender wage gap.

We exemplify our procedure with an application about the unexplained gap in West Germany. In particular, we derive the effects in terms of disposable income of the unexplained component of the gender wage gap in West Germany. The quantile-based decomposition exercise shows that, in terms of hourly wages, the overall gender wage gap is highest at the lower end of the distribution and decreases with wages. The unexplained component of the gender wage gap follows an inverted u-shape and is similarly distributed for different household types. As expected, both female gross monthly earnings and households' equivalised net income rise in the absence of the unexplained gap. We find that on average the household unexplained net gap lies around 5.2% of household's equivalised net income and is higher for women living in single households (with or without children) than in couple households. Furthermore, within each of these two groups, the net financial consequences of the unexplained gap are higher for households without children. This pattern can be explained by larger earnings inequality of households with children. In particular, the share and level of female earnings in couple households with children are smaller than in households without children. At individual level, we can only identify bounds for the net pay gap. These range, on average, from 5.2% to 9.7%. The more (less) the actual sharing rule approaches perfect income pooling,

the lower (higher) the net unexplained gap at individual level. The gender wage gap also has negative labor supply effects. When we allow for labor supply adjustments, we find a higher impact for women living in couple households than in single households, which is consistent with the higher labor supply elasticities of the first group. On the aggregate, we find the unexplained gap to be associated with the labor market non-participation of around 105,500 women and with a reduction of working hours of about 247,600 full-time equivalents.

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A. Tables

Table A1: Descriptives of the wage estimation sample

Sample Means	Men	Women	Total
Age	44.214	43.700	43.958
Experience	21.196	17.306	19.261
Tenure	13.742	10.772	12.265
Public Sector	0.241	0.325	0.282
Education:			
Primary School	0.100	0.107	0.104
Sec./Midd Vocational	0.470	0.503	0.486
Upper Sec./High Voc.	0.163	0.170	0.167
University Degree	0.267	0.219	0.243
Occupation:			
Untrained Worker	0.132	0.143	0.138
Trained Worker	0.187	0.028	0.108
Foreman	0.062	0.006	0.034
Untrained Employee	0.020	0.082	0.051
Trained Employee	0.039	0.147	0.093
Qualified Professional	0.186	0.396	0.290
Highly Qualified Prof.	0.264	0.115	0.190
Lower Civil Servant	0.031	0.015	0.023
Upper Civil Servant	0.080	0.069	0.074
Industrial Branch:			
Electronics	0.192	0.075	0.134
Mining. Energy	0.018	0.007	0.013
Chemical Industry	0.069	0.042	0.055
Construction Sector	0.082	0.016	0.049
Heavy Industry	0.073	0.016	0.045
Textile Sector	0.004	0.006	0.005
Trade and Retail	0.088	0.156	0.122
Transports. Post	0.068	0.033	0.050
Public Services	0.238	0.422	0.330
Private Services	0.102	0.153	0.127
Others	0.057	0.069	0.063
Agriculture	0.010	0.005	0.007
Size of Firm:			
Up to 5 Employees	0.040	0.096	0.067
5-200 Employees	0.404	0.478	0.441
200-2000 Employees	0.247	0.203	0.225
2000+ Employees	0.309	0.223	0.266
Number of Observations	15,713	15,556	31,269

Notes: Pooled waves for years 2008 through 2012.

Source: SOEP.v29.1, own calculations.

Table A2: Sample means by quartiles of the hourly wage distribution

Sample means	Men				Women			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Hourly Wage	9.95	15.28	19.96	32.00	7.24	11.56	15.47	25.50
Age	38.46	42.92	45.47	48.27	42.66	42.09	43.49	46.13
Experience	16.19	21.14	23.09	23.91	14.90	16.47	17.88	20.01
Tenure	6.95	13.16	16.08	17.26	6.59	8.87	11.87	15.27
Public Sector	0.14	0.23	0.32	0.26	0.13	0.23	0.43	0.48
Education:								
Primary School	0.17	0.12	0.11	0.03	0.19	0.13	0.08	0.04
Sec./Midd Vocational	0.65	0.62	0.48	0.22	0.61	0.61	0.51	0.31
Upper Sec./High Voc.	0.11	0.17	0.20	0.17	0.11	0.17	0.22	0.18
University Degree	0.07	0.10	0.22	0.57	0.09	0.09	0.19	0.47
Occupation:								
Untrained Worker	0.33	0.15	0.08	0.01	0.34	0.16	0.06	0.02
Trained Worker	0.26	0.29	0.18	0.05	0.04	0.03	0.02	0.01
Foreman	0.04	0.09	0.09	0.04	0.01	0.01	0.01	0.00
Untrained Employee	0.06	0.02	0.01	0.00	0.19	0.09	0.04	0.01
Trained Employee	0.09	0.05	0.03	0.01	0.20	0.24	0.12	0.04
Qualified Professional	0.13	0.21	0.26	0.14	0.19	0.40	0.57	0.42
Highly Qualified Prof.	0.05	0.10	0.20	0.59	0.02	0.05	0.11	0.27
Lower Civil Servant	0.03	0.05	0.04	0.01	0.00	0.01	0.02	0.02
Upper Civil Servant	0.02	0.03	0.11	0.15	0.01	0.01	0.05	0.19
Industrial Branch:								
Electronics	0.14	0.15	0.20	0.25	0.07	0.07	0.07	0.09
Mining. Energy	0.01	0.01	0.02	0.03	0.00	0.00	0.01	0.01
Chemical Industry	0.06	0.07	0.07	0.07	0.04	0.04	0.04	0.05
Construction Sector	0.11	0.13	0.07	0.03	0.02	0.02	0.02	0.01
Heavy Industry	0.07	0.08	0.08	0.06	0.01	0.02	0.02	0.02
Textile Sector	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.00
Trade and Retail	0.16	0.11	0.06	0.04	0.23	0.24	0.12	0.05
Transports. Post	0.10	0.08	0.05	0.04	0.03	0.04	0.03	0.03
Public Services	0.14	0.21	0.29	0.29	0.26	0.38	0.51	0.52
Private Services	0.11	0.07	0.09	0.14	0.21	0.12	0.12	0.16
Others	0.07	0.06	0.06	0.05	0.11	0.06	0.05	0.05
Agriculture	0.02	0.01	0.01	0.00	0.01	0.01	0.00	0.00
Size of Firm:								
Up to 5 Employees	0.10	0.04	0.03	0.01	0.21	0.11	0.05	0.02
5-200 Employees	0.60	0.46	0.34	0.26	0.56	0.53	0.45	0.38
200-2000 Employees	0.16	0.26	0.30	0.26	0.11	0.19	0.27	0.24
2000+ Employees	0.14	0.24	0.33	0.47	0.11	0.18	0.22	0.36

Notes: Quartiles of the male and female distributions were calculated separately. Pooled waves for years 2008 through 2012.

Source: SOEP.v29.1, own calculations.

Table A3: Wage Regression Coefficients, Males

	OLS	q10	q25	q50	q75	q90
Constant	1.651***	0.747***	1.509***	1.899***	2.023***	2.449***
Age	0.0153***	0.0316***	0.0111**	0.00695*	0.0159***	0.00428
Age sq	-0.0143***	-0.0378***	-0.0108**	-0.00436	-0.0132***	0.00392
Experience	0.0185***	0.0221***	0.0220***	0.0197***	0.0143***	0.0125***
Experience sq	-0.0353***	-0.0361***	-0.0427***	-0.0395***	-0.0285***	-0.0307***
Tenure	0.0162***	0.0222***	0.0168***	0.0132***	0.0114***	0.0117***
Tenure sq	-0.0248***	-0.0354***	-0.0253***	-0.0188***	-0.0160***	-0.0188***
Public Sector	-0.0376***	0.0111	-0.00854	-0.0217**	-0.0722***	-0.114***
Education:						
Primary School	omitted	omitted	omitted	omitted	omitted	omitted
Sec./Middle Vocational	0.0239**	0.00426	-0.00976	0.0234**	0.0266***	0.0274
Upper Sec./High Voc.	0.0839***	0.0948***	0.0647***	0.0880***	0.0892***	0.0844***
University Degree	0.229***	0.244***	0.203***	0.226***	0.223***	0.211***
Occupation:						
Untrained Worker	omitted	omitted	omitted	omitted	omitted	omitted
Trained Worker	0.199***	0.269***	0.223***	0.169***	0.135***	0.113***
Foreman	0.288***	0.372***	0.324***	0.268***	0.211***	0.198***
Untrained Employee	-0.0149	-0.0308	-0.0787***	-0.0671***	-0.0467**	0.0158
Trained Employee	0.145***	0.139***	0.161***	0.129***	0.0901***	0.0822***
Qualified Professional	0.341***	0.405***	0.369***	0.314***	0.277***	0.262***
Highly Qualified Prof.	0.603***	0.624***	0.599***	0.554***	0.547***	0.567***
Lower Civil Servant	0.204***	0.302***	0.209***	0.161***	0.124***	0.122***
Upper Civil Servant	0.422***	0.413***	0.404***	0.394***	0.395***	0.368***
Industrial Branch:						
Electronics	omitted	omitted	omitted	omitted	omitted	omitted
Mining, Energy	0.00861	0.0104	-0.00174	-0.0206	-0.0183	0.0240
Chemical Industry	0.0216**	0.0189	0.00686	0.0220*	0.0279***	0.0123
Construction Sector	-0.0528***	-0.0237	-0.0555***	-0.0706***	-0.0818***	-0.117***
Heavy Industry	0.0268**	0.0143	0.0134	0.0215*	0.0297***	0.0190
Textile Sector	0.000559	-0.126*	-0.163***	-0.175***	-0.0460	0.447
Trade and Retail	-0.143***	-0.188***	-0.176***	-0.149***	-0.145***	-0.139***
Transports, Post	-0.105***	-0.179***	-0.158***	-0.128***	-0.0585***	-0.0368*
Public Services	-0.0796***	-0.0951***	-0.114***	-0.109***	-0.0677***	-0.0184
Private Services	-0.0467***	-0.0933***	-0.101***	-0.0563***	-0.00186	0.0310
Others	-0.0777***	-0.123***	-0.113***	-0.0729***	-0.0504***	-0.0401*
Agriculture	-0.270***	-0.374***	-0.318***	-0.237***	-0.202***	-0.215***
Size of Firm:						
Up to 5 Employees	omitted	omitted	omitted	omitted	omitted	omitted
5-200 Employees	0.147***	0.305***	0.221***	0.136***	0.0626***	0.0242
200-2000 Employees	0.250***	0.447***	0.340***	0.232***	0.146***	0.0799***
2000+ Employees	0.303***	0.493***	0.390***	0.284***	0.206***	0.148***
Year Dummies:						
2008	-0.0438***	-0.0623***	-0.0487***	-0.0524***	-0.0544***	-0.0327**
2009	-0.0365***	-0.0669***	-0.0357***	-0.0351***	-0.0386***	-0.0314**
2010	-0.0278***	-0.0464***	-0.0259**	-0.0314***	-0.0360***	-0.0265*
2011	-0.0244***	-0.0337**	-0.0224**	-0.0260***	-0.0279***	-0.0197
2012	omitted	omitted	omitted	omitted	omitted	omitted
Observations				15,713		

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: SOEP.v29.1, own calculations.

Table A4: Wage Regression Coefficients, Females

	OLS	q10	q25	q50	q75	q90
Constant	1.570***	0.992***	1.388***	1.634***	1.861***	1.909***
Age	0.0157***	0.0191***	0.0124***	0.0133***	0.0134***	0.0228***
Age sq	-0.0194***	-0.0302***	-0.0187***	-0.0159***	-0.0151***	-0.0236***
Experience	0.0113***	0.0143***	0.0150***	0.00972***	0.00951***	0.00560*
Experience sq	-0.0145***	-0.0122	-0.0202***	-0.0132***	-0.0130***	-0.00502
Tenure	0.0150***	0.0220***	0.0160***	0.0177***	0.0144***	0.0103***
Tenure sq	-0.0248***	-0.0386***	-0.0273***	-0.0328***	-0.0250***	-0.0156***
Public Sector	0.0548***	0.0916***	0.0804***	0.0490***	0.0437***	0.0254*
Education:						
Primary School	omitted	omitted	omitted	omitted	omitted	omitted
Sec./Middle Vocational	0.0164	0.0270	0.0160	0.00589	0.0346***	0.0627***
Upper Sec./High Voc.	0.0914***	0.122***	0.117***	0.0811***	0.0889***	0.100***
University Degree	0.206***	0.175***	0.194***	0.197***	0.249***	0.293***
Occupation:						
Untrained Worker	omitted	omitted	omitted	omitted	omitted	omitted
Trained Worker	0.244***	0.241***	0.239***	0.238***	0.254***	0.278***
Foreman	0.248***	0.259***	0.258***	0.233***	0.275***	0.201***
Untrained Employee	0.0455***	0.0151	0.0356*	0.0647***	0.0811***	0.0836***
Trained Employee	0.220***	0.265***	0.244***	0.250***	0.222***	0.183***
Qualified Professional	0.406***	0.456***	0.445***	0.429***	0.388***	0.346***
Highly Qualified Prof.	0.644***	0.650***	0.640***	0.645***	0.646***	0.615***
Lower Civil Servant	0.415***	0.436***	0.405***	0.382***	0.380***	0.443***
Upper Civil Servant	0.593***	0.559***	0.564***	0.607***	0.628***	0.640***
Industrial Branch:						
Electronics	omitted	omitted	omitted	omitted	omitted	omitted
Mining, Energy	0.105***	0.153**	0.0863***	0.0293	0.0559	0.0890
Chemical Industry	-0.0616***	-0.211***	-0.0899***	-0.0362**	0.00226	0.00340
Construction Sector	-0.117***	-0.0190	-0.0776***	-0.134***	-0.159***	-0.219***
Heavy Industry	0.0470*	0.0677	0.110***	0.0322	0.0196	0.0297
Textile Sector	-0.180***	-0.115	-0.162***	-0.203***	-0.200***	-0.201**
Trade and Retail	-0.196***	-0.197***	-0.186***	-0.207***	-0.239***	-0.239***
Transports, Post	-0.0825***	-0.0904**	-0.0735***	-0.117***	-0.0907***	-0.0888***
Public Services	-0.111***	-0.0675***	-0.0898***	-0.136***	-0.168***	-0.156***
Private Services	-0.0890***	-0.111***	-0.107***	-0.115***	-0.0919***	-0.0444**
Others	-0.164***	-0.238***	-0.184***	-0.179***	-0.164***	-0.122***
Agriculture	-0.227***	-0.278**	-0.230***	-0.233***	-0.274***	-0.223**
Size of Firm:						
Up to 5 Employees	omitted	omitted	omitted	omitted	omitted	omitted
5-200 Employees	0.159***	0.225***	0.207***	0.175***	0.147***	0.0851***
200-2000 Employees	0.259***	0.377***	0.318***	0.270***	0.217***	0.134***
2000+ Employees	0.309***	0.386***	0.354***	0.326***	0.287***	0.228***
Year Dummies:						
2008	-0.0346***	-0.0486***	-0.0463***	-0.0410***	-0.0316***	-0.0158
2009	-0.00958	-0.0200	-0.0290**	-0.0178**	-0.00693	0.0202
2010	-0.00593	-0.00503	-0.0147	-0.0165*	-0.00427	-0.00148
2011	-0.00720	-0.0378**	-0.0218**	-0.00304	-0.00486	0.0238*
2012	omitted	omitted	omitted	omitted	omitted	omitted
Observations	15,556					

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: SOEP.v29.1, own calculations.

Table A5: Decomposition Results

Quantiles	Overall Gap				Explained Gap				Unexplained Gap			
	Coeff.	pointwise std error	confidence bands		Coeff.	pointwise std error	confidence bands		Coeff.	pointwise std error	confidence bands	
			lower	upper			lower	upper			lower	upper
0.05	.3148	.0232	.2730	.3565	.1810	.0179	.1501	.2119	.1338	.0243	.0855	.1820
0.10	.3132	.0171	.2801	.3462	.1715	.0146	.1471	.1960	.1416	.0183	.1050	.1783
0.15	.3113	.0141	.2820	.3406	.1621	.0130	.1385	.1857	.1492	.0153	.1198	.1786
0.20	.3072	.0125	.2805	.3339	.1555	.0119	.1323	.1787	.1517	.0135	.1257	.1777
0.25	.3022	.0113	.2776	.3268	.1500	.0111	.1289	.1711	.1522	.0120	.1306	.1738
0.30	.2948	.0103	.2729	.3167	.1452	.0102	.1256	.1648	.1496	.0108	.1295	.1697
0.35	.2865	.0096	.2648	.3082	.1405	.0096	.1222	.1589	.1460	.0098	.1269	.1650
0.40	.2780	.0089	.2592	.2969	.1370	.0090	.1199	.1540	.1411	.0090	.1233	.1589
0.45	.2706	.0084	.2532	.2881	.1334	.0086	.1177	.1491	.1372	.0083	.1207	.1537
0.50	.2636	.0080	.2487	.2785	.1305	.0081	.1157	.1454	.1331	.0079	.1174	.1488
0.55	.2578	.0078	.2439	.2717	.1285	.0078	.1138	.1432	.1293	.0076	.1155	.1432
0.60	.2533	.0077	.2395	.2672	.1267	.0077	.1122	.1411	.1267	.0074	.1131	.1403
0.65	.2507	.0079	.2360	.2654	.1264	.0076	.1115	.1414	.1243	.0073	.1105	.1381
0.70	.2486	.0083	.2336	.2635	.1280	.0075	.1137	.1423	.1206	.0074	.1061	.1351
0.75	.2463	.0088	.2299	.2628	.1300	.0075	.1165	.1434	.1164	.0076	.1004	.1323
0.80	.2437	.0094	.2275	.2599	.1326	.0076	.1186	.1465	.1111	.0081	.0949	.1273
0.85	.2396	.0105	.2198	.2595	.1358	.0079	.1216	.1500	.1038	.0089	.0871	.1206
0.90	.2318	.0125	.2066	.2569	.1400	.0087	.1244	.1556	.0952	.0099	.0754	.1151
0.95	.2107	.0165	.1793	.2420	.1440	.0103	.1255	.1626	.0666	.0139	.0398	.0934

Notes: Statistical inference based on bootstrap with 200 replications.

Source: SOEP.v29.1, own calculations.

Table A6: Conditional logit coefficients

	Couples (both flex)	Singles	Couples (woman flex)
net income	23.50	-5.372 *	-22.47 **
net income ²	-0.78	.5060 ***	1.93 ***
income*leisure _m	-1.36 ***		
income*leisure _f	-0.93 **	.186	-.672
leisure _m	61.99 ***		
leisure _m ²	-7.46 ***		
leisure _f	25.15 **	22.612 **	24.10 **
leisure _f ²	-4.23 ***	-3.012 ***	-2.47 **
leisure _{m,f}	2.56		
dlzm dtm	14.45 *		
dlzf dtf	12.52	-.963	0.84
dlzmf dt	-3.17		
eknp dt	-19.58		
eknp2 dt	1.44		
leisure _m × age	-.28 **		
leisure _m × age ²	.38 ***		
leisure _f × age	.24 **	.04793	.0479
leisure _f × age ²	-.18	.02376	.0237
leisure _m × health	1.85 **		
leisure _f × health	2.57 **	-1.243	.94
leisure _f × child age 3	8.01 ***	10.44 ***	4.87 ***
leisure _f × child age 6	4.02 ***	3.076 ***	3.69 ***
leisure _f × child age 16	2.46 ***		

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: SOEP.v29.1, STSM, own calculations.

Table A7: Female labor supply elasticities by household type

	Change in Hours	Change in Participation
Couples (both spouses flexible)		
without children	0.289	0.063
with children	0.357	0.110
Couples (only woman flexible)		
without children	0.479	0.120
with children	0.457	0.133
Single Households		
without children	0.229	0.049
with children	0.266	0.065

Notes: Elasticities computed for a one percent increase of gross earnings.

Source: SOEP.v29.1, own calculations.

Table A8: Dynamic net gender pay gap by income quintiles and household type

Quintiles	Married		Single		All
	without children	with children	without children	with children	
% of household disposable income, $\tilde{\Omega}_j$					
1	8.3	3.4	9.5	5.4	6.9
2	6.6	3.4	11.0	7.3	7.3
3	5.7	3.7	10.8	8.1	6.7
4	5.1	3.6	9.6	8.1	5.9
5	4.2	2.0	7.4	5.8	4.3
Average	5.5	3.3	9.9	6.3	6.2
absolute difference (in Euro)					
1	124	110	111	89	110
2	140	95	146	159	129
3	145	107	176	184	144
4	181	138	197	191	176
5	183	111	208	179	171
Average	162	111	164	126	146

Notes: Gaps presented as % of net household income. Quintiles of overall equivalized net household income. $\tilde{\Omega}_j$ allows for labor supply adjustment, as described in Section 3.5. Weighted observations.

Source: SOEP.v29.1, own calculations.

B. Imputation of Wages for the Non-Working

In order to estimate employment effects from the unexplained gender wage gap, we need to obtain potential wages for individuals that do not take up paid employment in the time period of our interest. Table B1 below shows for how many observations by year and gender we need to impute wages. Note that the wording “missing wage observation” in this section exclusively refers to individuals who do not work (instead of item non-response or attrition issues) for whom we need to impute a wage.

Table B1: Missing and Non-Missing Wage Observations, by Gender and Year

	Women			Men		
	Non-Missing	Missing	Missing (in%)	Non-Missing	Missing	Missing (in%)
2008	3,087	1,129	36.57	3,277	303	9.25
2009	3,028	966	31.90	3,070	311	10.13
2010	2,433	808	33.21	2,449	247	10.09
2011	3,506	1,126	32.12	3,429	364	10.62
2012	2,895	882	30.47	2,801	278	9.93
Total	14,949	4,911	32.85	15,026	1,503	10.00

Source: SOEP.v29.1, own calculations.

We exploit the longitudinal dimension of the SOEP to impute wages for the non-working. The literature suggests different methods thereto. We cannot use our conditional quantile wage model to predict wages for the non-working because we lack workplace related information for them. For this reason, we preserve the rank they had in the unconditional distribution of the hourly wage when they last worked or when they take up paid employment again. We choose the time period that is closest to the missing wage information, under the rationale that the labor market relevant characteristics of the individual should be the closest to his or her labor market characteristics at the time of the wage missing observation. This procedure allows us to impute wages for a significant chunk of the non-working (see Table B2 below).

Table B2 above indicates that we achieve to impute the most observations in year 2010. For this reason, we use data for 2010 to proceed with the analysis of the unexplained wage gap in terms of net income.

Table B2: Number of successful imputations by gender and year

	Women			Men		
	Missing	Imputed	Imputed (in%)	Missing	Imputed	Imputed (in%)
2008	1,129	732	64.84	303	246	81.19
2009	966	648	67.08	311	251	80.71
2010	808	563	69.68	247	211	85.43
2011	1,126	562	49.91	364	205	56.32
2012	882	456	51.70	278	169	60.79
Total	4,911	2,961	60.29	1,503	1,082	71.99

Source: SOEP.v29.1, own calculations.

C. Simulating labor supply reactions

A general description of the microsimulation model is provided by [Steiner et al. \(2012\)](#). The model consists of a discrete choice labor supply model and a tax and transfer simulation model.

Labor supply estimation Following [Van Soest \(1995\)](#) and [Aaberge et al. \(1995\)](#) we estimate a labor supply model using a static structural discrete choice model. The discrete choice approach allows to account for non-linearities in the budget constraint in a transparent and flexible way. Furthermore we can derive the model from random utility model in which decision makers are assumed to maximize utility. We assume that a household can choose among J working hours categories (in case of couple households, J comprises combinations of working hour categories for both spouses including zero hours). Thresholds between hours categories are derived from the actual distribution of working hours in the sample. The actual distribution of working hours shows well known spikes. In our model, women can chose between six categories (0,8.5,15.5,25.5,38,45.5) and men between four categories (0,12.5,36.5,47) – for couple households this results in 24 possible combinations of working hours. The values are median values of different domains of the hours distribution. The estimation results are robust to variation of thresholds of hours categories or if we choose the mean instead of the median.

Each combination of working hours, given the hourly wage, corresponds to a certain net household income. The different combinations of working hours and leisure j result in different utility levels U_{ij} of household i . The decision maker chooses alternative κ over j if and only if $U_{i\kappa} > U_{ij}$, $\forall \kappa \neq j$. Household utility U_{ij} depends on a systematic function V_{ij} that relates household characteristics to the level of utility and a random

component ϵ_{ij} . For couple households, the utility function includes the logarithm of household net income and its square, the logarithm of leisure of the man, the logarithm of leisure of the woman, the logarithm of the joint leisure of the spouses, the interactions of log leisure of each spouse with German nationality, age, age squared, work incapacity, the interaction of joint log leisure with German nationality, and the interaction of the woman's log leisure with children in the household under 3, 6 and 16 years of age.

The errors are assumed to be iid extreme value. Then we can model the probability that alternative κ is chosen by household i using a multinomial Logit model (McFadden, 1974):

$$P_{i\kappa} = Pr(U_{i\kappa} \geq U_{ij}, \forall j = 0, \dots, J) = \frac{\exp(V_{i\kappa})}{\sum_{j=0}^J \exp(V_{ij})} \quad (9)$$

Based on the observed choices we can estimate the parameter of the utility function using Maximum Likelihood. We specify different models for different households: (1) both spouses can adjust their labor supply flexibly, (2) only one spouse has flexible labor supply (3) single households.

Tax and transfer simulation The households labor supply model described in the previous paragraph requires the simulation of net household income for different combinations of working hours. In brief, the tax and transfer calculation takes into account the whole German tax and welfare system.