# Beyond Inequality Accounting: Couple Sorting and Labor Supply in West Germany

*Preliminary work in progress – Please do not quote!*

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## Abstract

In this paper, we measure the effect of the association of female and earnings on inequality across couple households in West Germany from 1986 to 2010 by matching spouses randomly to each other and predicting labor supply choices of hypothetical couples. This allows quantifying the extent of sorting in earnings potential rather than observed earnings which result from both productivity and labor supply coordination within couples. Constructing counterfactuals based on observed earnings might be misleading since labor supply is affected by the household context. Using German microdata as well as a behavioral microsimulation model we find that the impact of observed sorting on earnings inequality among couples turned from equalizing to disequalizing in recent years, but is rather weak. However, after correcting for the effect of labor supply choices, we find that sorting in productivity has a much larger impact on observed earnings inequality.

# 1 Introduction

Increasing correlation of spouses' earnings in couple households has contributed to growing income inequality (Burtless, 1999, 2009; Schwartz, 2010) and has been widely interpreted as increasing similarity of spouses in terms of earnings-related characteristics (assortative mating, see Mare and Schwartz, 2005). This has an amplifying effect on inequality since it reduces the level of redistribution within couple households. When the share of couples with both partners being either high or low wage earners grows, inequality across couple households will be higher compared to a situation where couples with one high and one low wage earner dominate. Since the population living in couple households makes up a large part of the total population, this affects the overall distribution of economic well-being. The trend towards more positive sorting is also related to increasing female labor force participation, since the number of single-earner families has been decreasing in many countries (Blau and Kahn, 2007; Heim, 2007; Blundell et al., 2011a,b). A number of studies have found that changes in household demographics affecting "who lives with whom" (Jenkins and Micklewright, 2007, p. 19) have amplified increases in income inequality (Jenkins, 1995; Daly and Valletta, 2006; Martin, 2006; Peichl et al., 2012). Hence, with regard to economic inequality, trends of widening (labor) market income gaps cannot be assessed independently of changes in the socio-demographic composition of the population of interest.

Income inequality has strongly increased in many Western countries over the past decades (OECD, 2008, 2011) and the economic literature has identified numerous factors that have contributed to this trend. Especially the distribution of labor earnings, which make up the largest share of total household income, has become much more dispersed.[1] Previous studies on the effect of an increasing association of female and male earnings on inequality can largely be classified as accounting approaches since the observed distribution of income or earnings is compared to a

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[1] See Katz and Autor (1999) for an overview. Numerous studies analyze issues related to increases in inequality of hourly wages: skill-biased technological change and globalization (Juhn et al., 1993; Autor et al., 1998, 2008), changes in labor market institutions (DiNardo et al., 1996; Card and DiNardo, 2002; Lemieux, 2006) and the gender wage gap (Blau and Kahn, 2006; Arulampalam et al., 2007).

number of counterfactual distributions manipulating female earnings or the correlation between spouses' earnings (Karoly and Burtless, 1995; Burtless, 1999; Aslaksen et al., 2005). Cancian and Reed (1998, 1999) emphasize that the the question whether female earnings contribute to income inequality can only be meaningfully assessed when the observed distribution of household income is compared to an appropriate reference distribution. However, when constructing such a counterfactual the role of behavioral effects (labor supply) has so far not been taken into account. This is important, since earnings do not only reflect a worker's productivity (the wage rate) but also depend on the number of hours worked, which is determined by the allocation of partners' time on paid work, household production and leisure (Juhn and Murphy, 1997; Devereux, 2004; Gottschalk and Danziger, 2005). This depends on the household context and therefore changes in household characteristics are reflected in changing labor supply behavior. That is why the assessment of the effect of partner sorting on income inequality should explicitly adjust for labor supply behavior in order to disentangle the pure effect of sorting compared to the observed (non-random) sorting of spouses' earnings.

In this paper, we measure the effect of the association of female and male earnings on total earnings inequality across couple households in West Germany over a 25-year period from 1986 to 2010 and explicitly take into account labor supply behavior of couples. Using data from the German Socio-Economic Panel Study (SOEP) and a behavioral microsimulation model for Germany (IZAΨMOD, see Peichl et al., 2010) we estimate a discrete choice model of labor supply for couples for each year separately. This provides estimates on preference parameters for income, leisure as well as various interactions with household characteristics. Then, we create a sample of hypothetical couples by randomly matching individual earnings and characteristics of females and males from couple households. This sample serves as a counterfactual benchmark to assess the effect of non-random sorting on inequality. Spousal characteristics, which constitute an integral part of the household context, affect individual labor supply decisions and therefore individuals would respond to a counterfactual environment. In order to capture labor supply adjustments, we use the estimated preference coefficients and predict labor supply behavior of the

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hypothetical couples. This allows us to calculate the respective earnings of randomly matched individuals and hence total household earnings. Differences in levels of earnings inequality between the distributions of observed and hypothetical couples after labor supply adjustment allow quantifying the pure effect of partner sorting on inequality by applying an index measuring the effect of the association between spouses' earnings on inequality (Aslaksen et al., 2005).

We find that the observed pattern of sorting in earnings had a fairly weak impact on earnings inequality among couple households and the trend suggests that it has turned from slightly equalizing to slightly disequalizing in recent years. After correcting for the effect of labor supply choices based on the hypothetical household context, however, we find that sorting in productivity has a large impact on earnings inequality. This result is driven by two factors: First, women with high (low) earnings potential generally tend to couple with high (low) earning men. Second, female participation and hours in couples with high earning men were low in the 1980s, but increased disproportionally over the period under consideration. Taken together, this indicates that increasing earnings correlation between females and males results from increasing labor force attachment of women rather than from changes in couple formation. From a policy-maker's perspective, this suggests a trade-off between enhancing female labor force participation and reducing inequality.

The paper is organized as follows: Section 2 introduces the methodology before the empirical application and the data are described in section 3. Results are presented in section 4. Section 5 concludes.

## 2 Methodology

In order to quantify the extent of sorting on couple earnings inequality, we use an index introduced by Aslaksen et al. (2005), which is derived from a decomposition of the Gini coefficient. The index quantifies both the extent and the sign of the effect of the association of female and male labor earnings ("flocking together"[2]) on

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[2] The earliest citation of this proverb dates back to Minsheu (1599): "*Birdes of a feather will flocke togither*". This means that those with similar taste tend to congregate in groups. A modern version refers to "*doctors marrying doctors rather than nurses*" (OECD, 2011).

earnings inequality across couples. It is calculated based on the observed distribution and a hypothetical one, where spouses' individual earnings are randomly matched. However, it has to be noted that a correct way of constructing the hypothetical distribution requires a simulation of the labor supply decisions given the random match. In the following, we will first introduce the unadjusted "flocking index" (Aslaksen et al., 2005) and then suggest an extension that adjusts for labor supply choices given the randomly matched household context.

**The flocking index.** Consider a population of $n$ couple households indexed $i \in \{1, \ldots, n\}$ and a distribution of household earnings $Y = (Y_1, \ldots, Y_n)$, where household $i$'s total earnings are simply the sum of both the female and the male spouse's individual earnings: $Y_i = Y_i^f + Y_i^m$. The cumulative distribution of total earnings, $F_Y$, is a function of the gender-specific marginal earnings distributions $F_Y = F_Y(F_Y^m, F_Y^f)$.[3] Each distribution is associated with mean earnings ($\mu_Y$, $\mu_Y^f$ and $\mu_Y^m$) and a level of earnings inequality, represented by the Gini coefficient $G(\cdot)$. The Gini coefficient of the distribution of total couple earnings $Y$ reads

$$G(Y) = \frac{2}{\mu_Y} \cdot Cov[Y, F_Y] = \frac{\mu_Y^f}{\mu_Y} \cdot \gamma^f + \frac{\mu_Y^m}{\mu_Y} \cdot \gamma^m, \tag{1}$$

where $\gamma^s = 2/\mu_Y^s \cdot Cov[Y^s, F_Y]$ for $s \in \{m, f\}$, which is a measure of the association between female or male earnings respectively and total earnings (see Aslaksen et al., 2005, p. 503). It depends on the covariance of gender-specific earnings $Y^s$ and the couple's position in the total earnings distribution $F_Y$, which does not necessarily coincide with spouses' individual positions in the gender-specific distributions $F_Y^s$.

Taken the distributions of $Y^f$, $Y^m$ and hence $Y$ as given, the level of inequality in total household earnings $G(Y)$ is bounded between an upper and a lower level, i.e. $G(Y) \in [G^{min}(Y), G^{max}(Y)]$. These bounds depend on the spouses' positions in the gender-specific earnings distributions relative to the household's position in the

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[3] See Decancq et al. (2012) for a copula-based decomposition of couple earnings inequality.

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total distribution. With $s, -s \in \{m, f\}$ and $s \neq -s$ these are defined as follows:

$$
G(Y) = \begin{cases} G^{max}(Y) & if \ F_Y^s(Y_i^s) = F_Y^{-s}(Y_i^{-s}) \\ G^{min}(Y) & if \ F_Y^s(Y_i^s) = 1 - F_Y^{-s}(Y_i^{-s}) \end{cases} \tag{2}
$$

This means, the level of total couple earnings inequality is highest (lowest) if the highest-earning woman is married to the man with the highest (lowest) earnings within the male distribution, the second highest-earning woman with the second highest (lowest) man and so on. Hence, the pattern of sorting has the most (dis)equalizing effect on earnings inequality across couple households in a situation where sorting of spouses is perfectly negative (positive) with respect to individual earnings.

A way to assess to what extent the observed inequality in the distribution of couple earnings is affected by non-random sorting of spouses is to compare the observed distribution with a hypothetical one where partners' earnings and characteristics are randomly matched to each other. Consider as a counterfactual a distribution of randomly matched couples indexed $\tilde{i} \in \{1, \ldots, n\}$ with total earnings $Y_{\tilde{i}} = Y_{\tilde{i}}^f + Y_{\tilde{i}}^m$. Note that without any adjustments the levels of inequality in the gender-specific marginal distributions do not change, $G(\widetilde{Y}^s) = G(Y^s)$ for $s \in \{m, f\}$, whereas the inequality of total earnings is affected, i.e., in general $G(\widetilde{Y}) \neq G(Y)$. Normalizing the difference between observed and hypothetical inequality by the distance between random inequality and the upper or lower bound yields an index of the extent of "flocking together" (Aslaksen et al., 2005):

$$
V(Y, \widetilde{Y}, Y^f, Y^m) = \begin{cases} \frac{G(Y)-G(\widetilde{Y})}{G^{max}(Y)-G(\widetilde{Y})} & if \ G(Y) > G(\widetilde{Y}), \\ \frac{G(Y)-G(\widetilde{Y})}{G(\widetilde{Y})-G^{min}(Y)} & if \ G(Y) < G(\widetilde{Y}), \end{cases} \tag{3}
$$

where $V \in [-1, 1]$. Positive values of $V$ imply that $G(Y) > G(\widetilde{Y})$, i.e., observed inequality of couple earnings is greater than inequality of the distribution of random matches. This reflects a disequalizing pattern of "flocking together", while negative values of $V$ indicate a sorting pattern that is equalizing compared to random sorting. Note that the extreme cases of either perfect positive, i.e., $G(Y) = G^{max}(Y)$ (negative sorting, i.e., $G(Y) = G^{min}(Y)$) imply the maximum (minimum) values of

$V = 1$ ($V = -1$). Finally, the case of $V = 0$ represents a situation where observed and random sorting pattern happen to coincide.[4]

**Household context and the adjusted flocking index.** Previous studies assessing the effect of female earnings or the correlation of spouses' earnings on total inequality have constructed various counterfactuals from income distributions observed in the data. What has so far been neglected in the applications is the fact that observed household earnings and incomes and their distribution across the population do not only reflect couple formation but are also determined by income-producing choices, in particular spouses' (joint) decisions on labor supply.[5] Hence, the observation of increasing correlation of spouses' earnings does not necessarily only reflect changes in the assortativeness in couple formation but is also affected by changes in the coordination of labor market behavior within existing couple households. Consider for example a perfectly negative sorting pattern where the best earning woman and the least earning man form a couple and vice versa. This would indicate that sorting with respect to earnings is most equalizing. However, since earnings are a function of earnings *potential* (the wage rate) and supply of paid working time on the labor market (hours) it is not clear whether this sorting pattern reflects assortative mating in traits like ability or education (doctors marry nurses) rather than patterns of labor market behavior of couples (female doctors work less when married to a male doctor). The latter example reflects a situation where the number of hours supplied on the labor market is negatively associated with partner income, e.g., the higher the male earnings the lower the number of hours worked by the female spouse (and vice versa). This implies that the extent of "flocking together" with respect to earnings is influenced by labor supply choices of couples. Hence, when constructing a proper counterfactual distribution of couple earnings, we have to take into account the dependency of individual earnings, in particular both the extensive and the intensive margin of labor supply, on the

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[4] Note that the interpretation of the flocking index is similar to a measure of correlation between two stochastic variables. Aslaksen et al. (2005) show that the flocking index is equal to the correlation coefficient when the Gini coefficient is replaced by the squared coefficient of variation.

[5] See Bargain et al. (2012) for a comprehensive documentation of significant cross-wage elasticities.

household context which comprises the earnings potential and other characteristics of the partner.

When we randomly match individual earnings, instead of using the observed earnings $Y_i^s$, which is a function of observed couple characteristics $X_i$, we have to impute hypothetical earnings $Y_{\tilde{i}}^s$ based on the hypothetical setting $X_{\tilde{i}}$ which is to a large part determined by the hypothetical spouse. Then we can define an adjusted flocking index $\widehat{V}$ using predicted counterfactual distributions for both female and male earnings. In order to do so, we make explicit that hypothetical individual earnings will adjust given the counterfactual couple characteristics, that is $\widehat{Y}_{\tilde{i}}^s = \widehat{Y}_{\tilde{i}}^s(X_{\tilde{i}})$, where a hat indicates a random match and labor supply adjustment. The nature of this relationship can be predicted based on the relationship of observed earnings and household characteristics $Y_i^s = Y_i^s(X_i)$ (see below). We can construct the adjusted flocking index similar to equation (3) using the adjusted distributions of female and male as well as total earnings:

$$\widehat{V} = \widehat{V}(Y, \widehat{Y}, \widehat{Y}^f, \widehat{Y}^m). \tag{4}$$

The interpretation of the adjusted flocking index is the same as for the unadjusted flocking index: Positive values indicate a disequalizing sorting pattern, while negative values imply an equalizing sorting pattern. The main difference is that labor supply coordination given the household context, which affects individual earnings, is explicitly taken into account and hence the adjusted index gives an indication of the effect of partner sorting on earnings inequality across couple households adjusted for labor supply behavior.

**Modeling household labor supply.** In order to predict the relationship between household and partner characteristics and individual labor supply decision we make use of microsimulation techniques and apply a structural model of household labor supply (Aaberge et al., 1995; Van Soest, 1995; Blundell et al., 2000). We assume that couple households have a utility function $U_i = U_i(D_i, h_i^f, h_i^m; X_i)$, where the arguments are household disposable income $D_i$ and leisure time of the female and male partner respectively ($h_i^f$ and $h_i^m$) given household characteristics $X_i$. We assume

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that utility is maximized by jointly deciding on $(h_i^f, h_i^m)$, since disposable income is given by $D_i = d(w_i^f h_i^f, w_i^m h_i^m, I_i; X_i)$, where $w_i^f$ and $w_i^m$ are the fixed individual wage rates and $I_i$ is non-labor income. The tax benefit function $d(\cdot)$ transforms labor earnings and other gross income into disposable income given household characteristics. Furthermore it is assumed that couple households can choose among a fixed choice set of combinations of net income and leisure time. This is reflected by a finite set of $m$ working time categories for each individual, which gives a total of $m^2 = J$ choices of $(h_{ij}^f, h_{ij}^m)$ per couple.

Household utility $U_{ij}$ of household $i$ in choice $j$ comprises the systematic influence of the arguments as well as observable heterogeneity captured by characteristics $X_i$ and its interactions with the arguments. Unobserved heterogeneity in preferences is captured by adding a stochastic term (random utility maximization, see McFadden, 1974). Hence, total household utility is $V_{ij} = U_{ij} + \epsilon_{ij}$. Assuming that the error terms follow a Gumbel (extreme value) distribution and are independently and identically distributed across choices $j \in \{1, ..., J\}$ and the assumption of utility maximizing behavior imply that the probability of household $i$ choosing category $k$ over all other available categories $l \in \{1, ..., J\} \backslash k$ is

$$P_{ik} = P(V_{ik} > V_{il}) = P(U_{ik} - U_{il} > \epsilon_{il} - \epsilon_{ik}) = \frac{\exp(U_{ik})}{\sum_{l=1}^{J} \exp(U_{il})}. \qquad (5)$$

The set of coefficients $\beta$ of the systematic part of the utility function $U_i(D_i, h_i^f, h_i^m; X_i)$ can be estimated empirically on the sample of observed couple households (see Creedy and Kalb, 2006, for a detailed overview of microsimulation models of labor supply). The vector of estimates $\hat{\beta}$ can be interpreted as population averages of preferences for consumption and leisure given observed heterogeneity in household characteristics. Hence, after having estimated the labor supply model we can use the vector $\hat{\beta}$ to predict the probability distribution across choices $\widehat{P}_{ij}$ for each hypothetical couple household. This is the basis for calculating labor supply choices $\hat{h}_i^s$, which gives hypothetical individual earnings $\widehat{Y}_i^s$ for $s \in \{m, f\}$ and total earnings $\widehat{Y}_i$ as well as the resulting levels of inequality which are required for calculating the adjusted flocking index according to equations (3) and (4).

# 3 Empirical Application

**Microsimulation model.** We use the microsimulation model IZAΨMOD of the Institute for the Study of Labor (IZA), which comprises a static tax-benefit calculator for Germany as well as a random utility model of labor supply as described in the previous section (see Peichl et al., 2010, for a documentation of the model). In order to predict labor supply choices we have to impute income levels for counterfactual choices of working time.[6] It is straightforward to calculate gross labor earnings for categories that are not actually chosen by multiplying the individual hourly wage rates with the number of hours of work.[7] However, since labor supply decisions are based on the trade-off between leisure time and disposable income (see above) it is necessary to calculate income and payroll taxes as well as benefit payments. Since the model's tax-benefit calculator is currently only available for recent years (since 2005) and not yet fully extended to the period from the mid-1980s onwards we do not make use of IZAΨMOD's standard tax-benefit calculator. Instead we apply a reduced-form regression methodology to calculate disposable income from gross incomes (see Frenette et al., 2007; Biewen and Juhasz, 2012; Peichl, 2012; Bargain et al., 2012, for recent applications). We run the following ordinary least squares (OLS) regression model for each year $t = 1986, ..., 2010$ separately:

$$D_{it} = \alpha_t^0 + X_{it}\alpha_t^x + Z_{it}\alpha_t^z + (X'Z)_{it}\alpha_t^{xz} + u_{it}, \tag{6}$$

where $D_{it}$ is observed disposable income, $X_{it}$ is a vector of gross incomes (from labor, assets, private pensions and other gross income) including the squared values and $Z_{it}$ is a set of household characteristics that are relevant for various tax-benefit policies (marital status, age, age squared and hours worked of both spouses, number of children and number of working-age adults as well as dummies for civil servants and self-employed). The vector $(X'Z)_{it}$ comprises interactions of gross incomes and

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[6] The model comprises seven working time categories for each individual with 10, 20,...,60 hours of work per week as well as the non-work category of zero hours. Therefore, couple households have a choice set of 7x7=49 categories.

[7] Wage rates are not observed for individuals currently not in employment and are estimated on observed wages using a Heckman correction for sample selection (Heckman, 1976, 1979). We use predicted wages for the entire sample.

household characteristics. The regression results yield values for $R^2$ very close to one (0.97–0.99), which means that this fairly simple regression model captures almost the entire observed variation in disposable household incomes and therefore can be assumed to have sufficient predictive power to calculate tax liabilities and benefit payments in both observed and counterfactual choice categories.[8]

Using this input, we estimate the conditional logit model (see Bargain et al., 2012, for an overview) as described in equation (5). For the systematic part of the household utility function $U_{ij}$ we use a translog specification, i.e., the main arguments consumption and leisure as well as the interactions of consumption with female and male leisure enter the utility function in natural logarithms. In the conditional logit estimation, we use the squared arguments as well as several interactions with household characteristics as additional explanatory variables of labor supply decisions. The interaction variables are age and age squared of both partners as well as dummy variables for skill levels (university and low education), the presence of children in various age groups and for working part-time (10–30 hours per week) following Van Soest (1995).[9]

**Data and sample selection.** The simulation model is based on microdata from the German Socio-Economic Panel Study, which is a panel survey of households and individuals that has been conducted annually since 1984 and currently comprises 27 waves (Socio-Economic Panel, 2011). Population weights make the respondents' information representative for the German population. Issues concerning sampling and weighting methods or the imputation of information in case of item or unit non-response are well documented by the SOEP Service Group (see Haisken-DeNew and Frick, 2005; **?**).

We restrict our sample to West Germany, since especially shortly after the reunification of Germany in 1990 labor supply behavior of East Germans can be assumed to differ from West Germans. Moreover, income levels are still substantially different between East and West Germany. The sample is further restricted to couples (both married and cohabiting) where both spouses are of prime working

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[8] Regression output tables are not presented here but available from the author upon request.

[9] Estimation results are not presented here but available from the author upon request.

age (25–55) and at least one spouse can adjust labor supply flexibly. This means, we exclude couples where both spouses are in education, in military or community service, pensioners, on parental leave, civil servants, self-employed or have gross household income from capital that exceeds half of income from labor. Individual earnings comprise gross income from dependent work as well as self-employment in the month prior to the survey interview. Household labor earnings are the sum of both partners' earnings.

## 3.1  Descriptives

**Earnings inequality.**  Our results of the development of observed earnings inequality across couple households in West Germany over the period 1986–2010 are displayed in figures A.1 and A.2. The Gini coefficient of total couple labor earnings (figure A.1) has increased quite strongly from around 0.23 in the mid-1980s to around 0.3 at the end of the period under consideration. At the same time, the correlation coefficient of female and male earnings in the sample of couples has also increased from around $-0.13$ in 1986/87 to 0.03 in 2009/10 and turned from a negative to a positive correlation in the mid-2000s. The co-movement of inequality and correlation indicates a relationship between the association of couple earnings and inequality between couples. The trends of female and male earnings inequality are displayed in figure A.2. While the Gini coefficient of male earnings displays both a similar level and upward trend as couple earnings inequality, female earnings inequality has substantially decreased over the past 25 years. Starting from a very high level (around 0.64 in 1986) it has constantly fallen to around 0.5 in 2010, which is still quite high compared to male earnings inequality.

**Employment rates and hours worked.**  The observation of decreasing earnings inequality among women is for a large part driven by advances in female labor force participation. In the mid-1980s about 50% of women in couples were employed, while the employment rate has increased to more than 70% at the end of the last decade (see figure A.3). This development has particularly dampened female earnings inequality since the share of women with zero earnings has been constantly

shrinking. At the same time the employment rate of prime-aged men has remained fairly constant at a high level of 90–95%. In addition, men work on average full-time with at least 40 hours per week over the entire period, while the average number of hours worked by women is much lower due to lower participation rates and part-time work (see figure A.4). Previous research (e.g., Juhn and Murphy, 1997) has documented that changes in both female labor force participation and hours worked by women are not uniformly distributed across the distribution of male earnings. Figures A.5 and A.6 show the changes in employment rates and hours by male earnings quintile and within 5-year subperiods.[10] We find that female labor force participation was below average especially for women living with men in the upper tail of the earnings distribution in the 1980s. For example, only 40% of women with men in the top 10% of the male earnings distribution were employed and worked about 13 hours per week on average, while 50–60% of non-working or low-earning men (bottom decile) were employed and worked 20–23 hours. This pattern has changed over time. Employment growth among women has been largest at the upper tail of the male distribution. In the recent period 2006-2010 there are almost no differences in employment rates and hours across the male distribution.

# 4 Results

## 4.1 Flocking together

**Unadjusted flocking index.** The descriptive results suggest that earnings inequality both among couples and among men has increased, while earnings inequality among women has decreased. At the same time, earnings correlation between females and males in couples has turned from negative to slightly positive over the period 1986 to 2010. In order to analyze whether increasing association of female and male earnings has contributed to overall inequality we calculate the unadjusted flocking index following Aslaksen et al. (2005) as defined in equation (3) for each year separately. Therefore we match spouses from observed couples randomly to

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[10] We assign individuals to one of six groups. Individuals with zero earnings are assigned to the group "not in work" and individuals with positive earnings are assigned to their earnings quintile (based on positive earnings).

each other. For calculating the index at this stage we do not adjust the earnings levels, but take them as given, i.e., for each individual it holds that $Y_{\tilde{i}}^s = Y_i^s$.[11]

The resulting trend over time is presented in figure A.7. The extent of "flocking together" remains fairly constant from the mid-1980s until the early 1990s. The resulting negative values ranging from around $-0.08$ to $-0.11$ suggest that the pattern of sorting during this period has slightly dampened earnings inequality across couple households. However, the effect was not particularly strong.[12] From the mid-1990s until the mid-2000s the index remains mostly negative but values are closer to zero, which implies that the pattern of earnings sorting is rather neutral with respect to couple earnings inequality. We find positive values of the flocking index only for the period 2006–2010. Ranging from 0.01 to 0.07 they indicate a disequalizing pattern of sorting, which is however not very strong. Nevertheless, we find an upward trend of the extent of association between spouses' earnings on inequality over the period 1986–2010. In particular, this effect has switched signs in the 2000s turning from an equalizing to a disequalizing pattern of earnings sorting among couples.

**Adjusted flocking index.** As discussed in section 2, when measuring the effect of the association of spouses' earnings on inequality across couples using observed earnings, results might be biased when earnings reflect both assortativeness of earnings potential in couple formation as well as labor supply behavior of households. Therefore, we propose an adjusted flocking index where labor supply behavior is explicitly taken into account. We use the estimated coefficients on preferences for consumption and leisure as well as for several interactions with household and partner characteristics (see section 3) and predict labor supply behavior of the randomly assigned hypothetical couples. This gives us predicted earnings levels after labor supply adjustment, which allows calculating the adjusted flocking index as defined in equation (4).

The results are presented in figure A.7. We find that the level of the adjusted flocking index is considerably larger than the static flocking index. From the

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[11] Note that the upper and lower bounds are the same as in equation (3) since the counterfactual distribution taking into account labor supply is compared to the observed distribution of couple earnings.

[12] Recall that the flocking index is bounded between $-1$ and 1.

mid-1980s until the mid-1990s the level ranges between 0.3 and 0.4 and decreases somewhat afterwards, ranging from around 0.25 to 0.3 during the past 15 years. This means, the level of couple earnings inequality based on random sorting and accounting for labor supply behavior is much lower compared to inequality of the observed pattern of sorting. Our interpretation of this result is that, while the pattern of observed earnings sorting does not have a large impact on earnings inequality, the pattern of sorting in earnings *potential* did have a strong disequalizing impact if it was not veiled by a particular pattern of labor market behavior of (potentially high-wage) women in couples with high-earning men who tend not to participate in the labor force in early years (see above). Therefore, the difference between unadjusted and adjusted flocking index is particularly large at the beginning of the period under consideration in the 1980s but has decreased considerably since then due to increasing labor market attachment of women. Therefore, we take a closer look at which parts of the female and male earnings distributions labor supply adjustments take place when couples are matched randomly.

**Labor supply adjustments.** The resulting labor market outcomes of employment and hours worked are presented in figures A.3 and A.4. Overall, employment rates and average hours slightly decrease compared to the observed numbers, the trends are very similar. We find that changes in male labor force participation are very small (see figures A.8 and A.9). Reductions in participation are concentrated among men from lower deciles of the observed earnings distribution, while hours are slightly reduced in upper deciles. Both participation and consequently hours increase for men not in work. However, note that this group makes up only about 5–10% of males due to the very high observed employment rates (see above). The small difference in overall employment rates between the observed and randomly assigned sorting pattern masks considerable differences across the earnings distribution of women, which is shown in figures A.10 and A.11. Women who are observed to be not in employment would increase their participation considerably in the case of random assignment by up to 40 percentage points and more than ten hours in the 1980s. Recall that not employed women tend to be in couples with high-earning men in earlier years. Hence, being assigned to a man with lower earnings (poten-

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tial) apparently creates incentives to participate in the labor force and/or work more hours, which is in line with negative cross-wage and income elasticities documented in the literature (Aaberge et al., 1995, 1999; Devereux, 2004; Blau and Kahn, 2007; Bargain et al., 2012), which is even reinforced by incentives stemming from joint taxation of married couples.

At the same time, women in employment would on average reduce their labor supply both at the extensive and the intensive margin. This pattern remains fairly similar over time, however the extent of the adjustments decrease between the 1980s and the 2000s. The responsiveness of women to other income has generally decreased over time (see Blau and Kahn, 2007; Heim, 2007) and is generally lower for women in upper deciles of the female earnings distribution. Finally, figures A.12 and A.13 show the predicted labor supply adjustments of women across the earnings distribution of randomly assigned men. We find that women who are assigned to a non-working or low-earning man tend to respond with an increase in labor supply while women assigned to men in upper deciles reduce participation and hours worked. This is another piece of evidence for the "income effect" of male earnings on labor supply of women (Reed and Cancian, 2009).

# 5   Conclusions

In this paper, we measure the effect of the association of female and earnings on total earnings inequality across couple households in West Germany over a 25-year period from 1986 to 2010. We assign couples randomly to each other and predict labor supply choices of hypothetical couples, which yields a counterfactual distribution of earnings and allows quantifying the extent of sorting in earnings potential as opposed to observed earnings which are the result of both earnings potential and labor supply coordination in couple households. Constructing counterfactuals based on observed earnings might be misleading since labor supply choices are affected by the household context.

Using data from the German Socio-Economic Panel Study (SOEP) and a behavioral microsimulation model for Germany we find that the observed pattern of

sorting in earnings had a fairly weak impact on earnings inequality among couple households. However, the trend suggests that the pattern of sorting has turned from slightly equalizing to slightly disequalizing in recent years. After correcting for the effect of labor supply choices based on the household context, we find that sorting in productivity has a large impact on observed earnings inequality. This result is driven by two factors: First, women with high (low) earnings potential generally tend to couple with high (low) earning men. Second, women in couples with high earning men are more often not employed and work less in the 1980s, but increased labor supply above average over the period under consideration. Taken together this suggests that increasing earnings correlation between females and males in couples results from increasing labor force attachment of women (especially with high earnings potential) rather than from changes in couple formation.

These results suggest that advances in the attachment of women to the labor market affect the distribution of earnings across couple households. For policy makers, this might imply a trade-off, since measures supporting further increases in female labor force participation potentially amplify economic inequality across couple households, which make up a large, though diminishing share of the total population.

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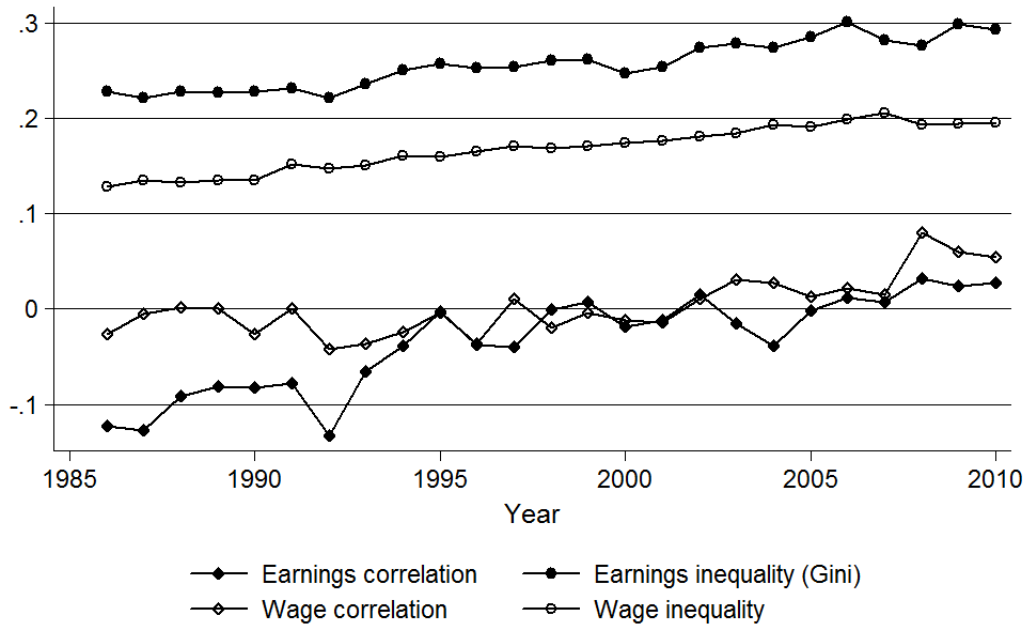
# A   Graphs



Figure A.1: Correlation and inequality of couple earnings
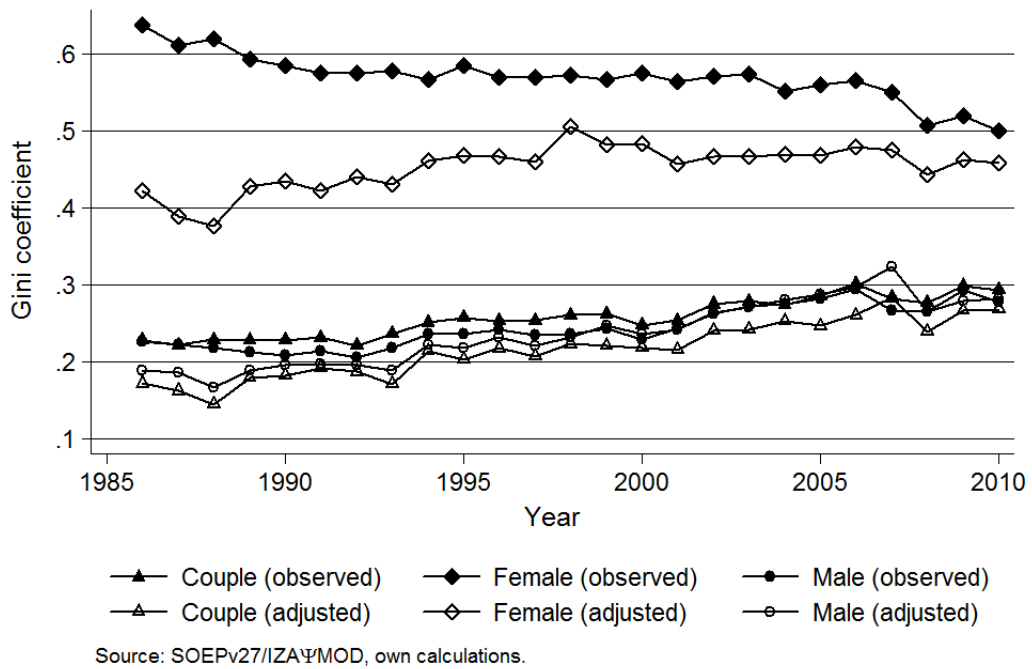
Figure A.2: Earnings inequality in couple households
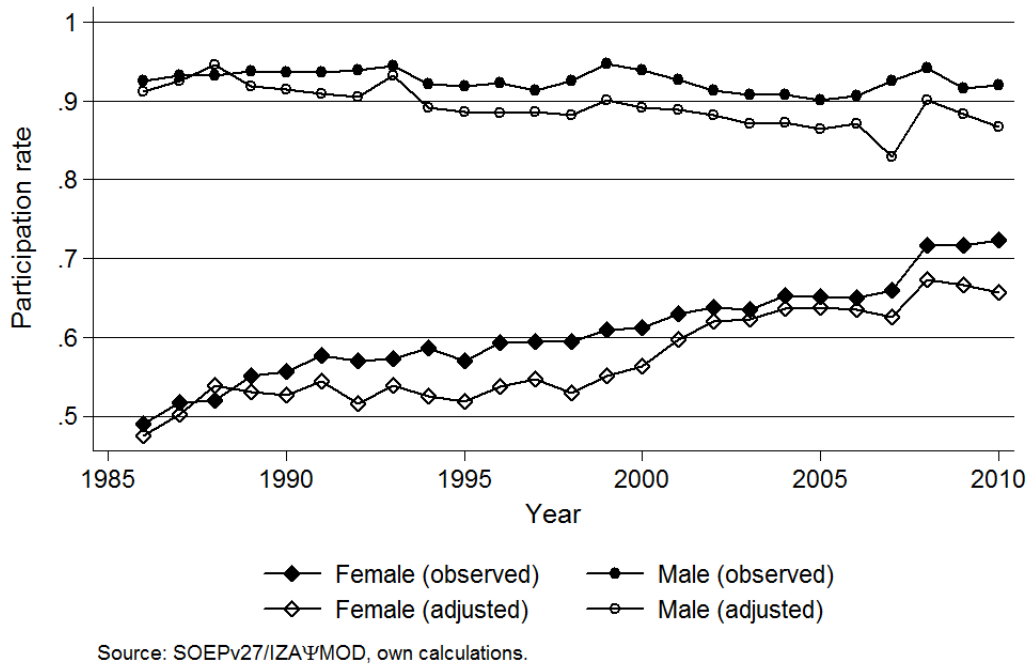


Figure A.3: Female and male employment rates

Source: SOEPv27/IZAΨMOD, own calculations.
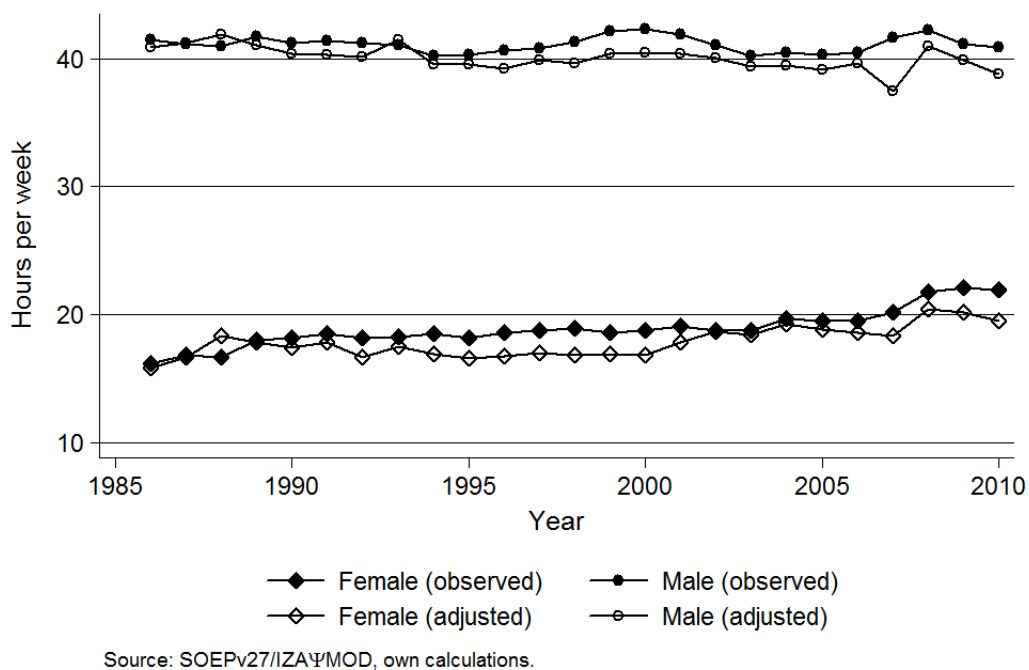
Figure A.4: Female and male hours of work (overall)



Source: SOEPv27/IZAΨMOD, own calculations.
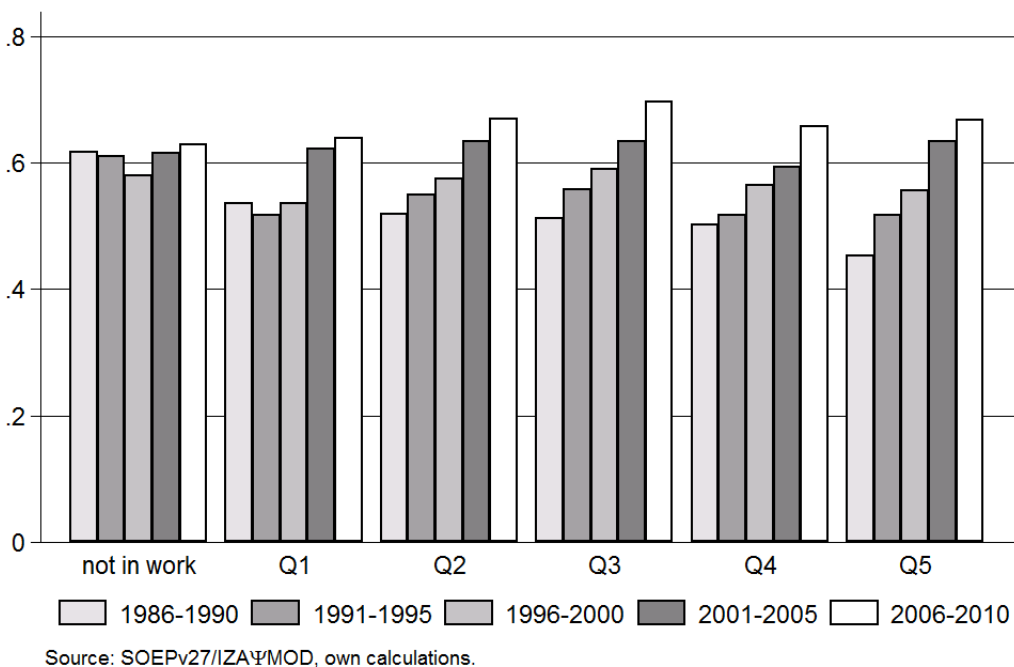
Figure A.5: Observed female employment rates by earnings quantile
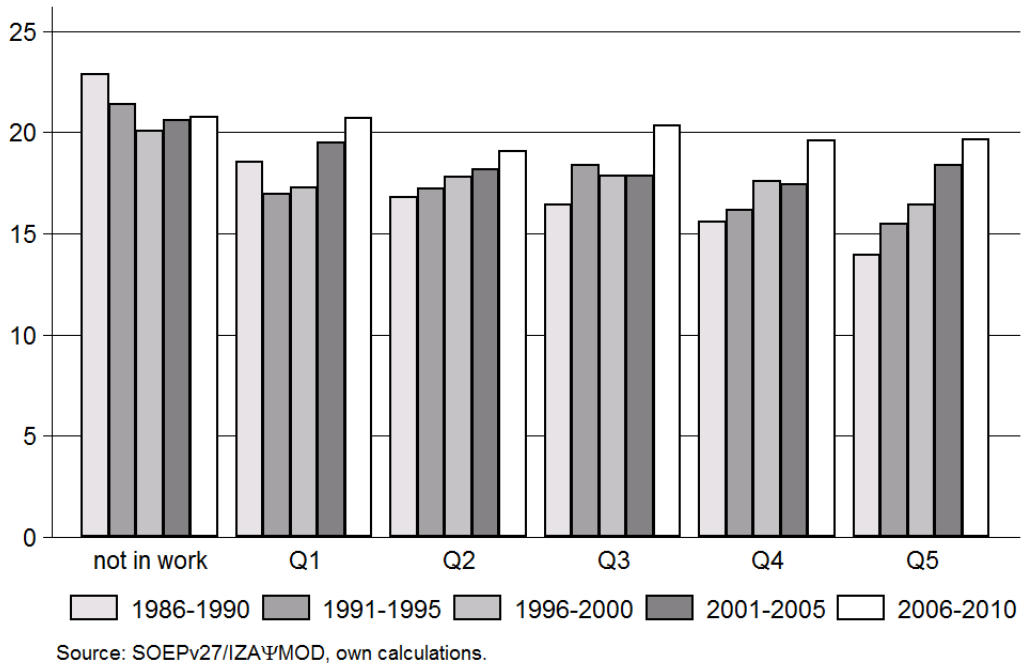
Figure A.6: Observed female hours of work by earnings quantile
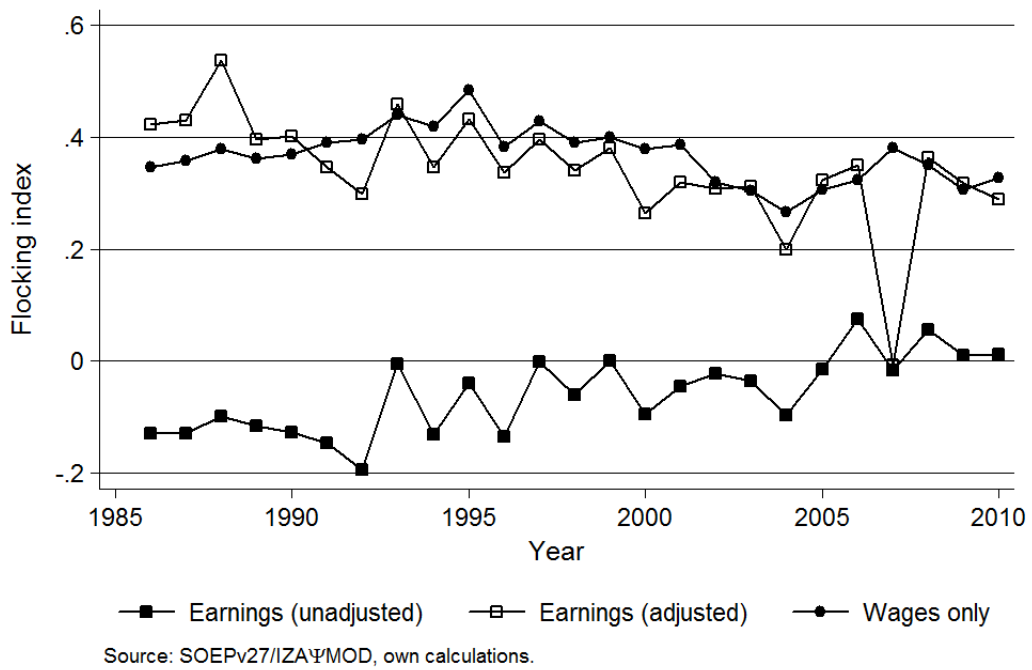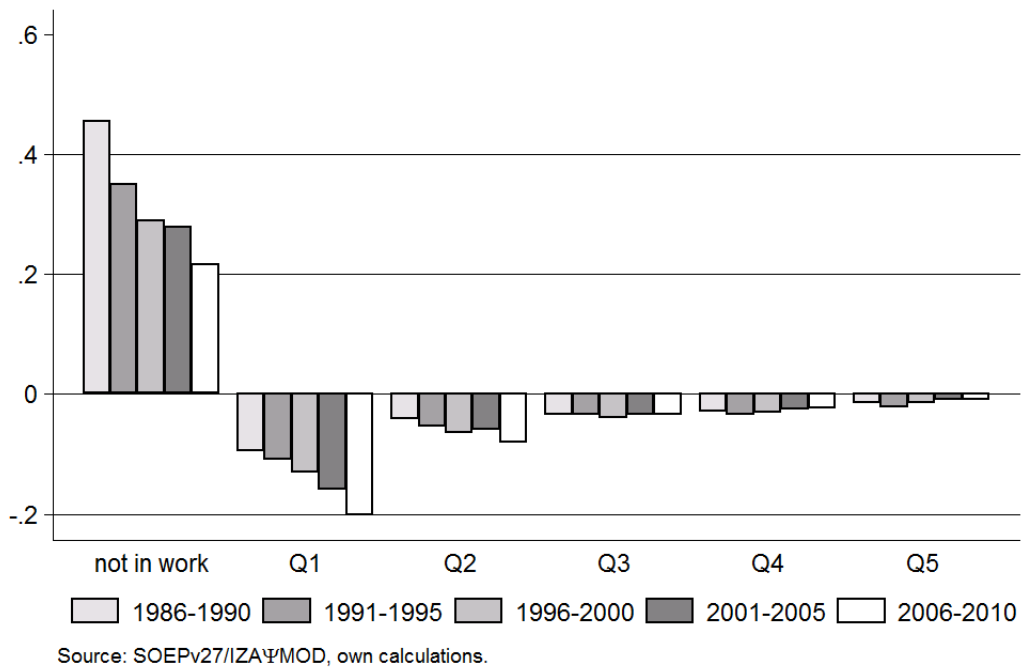


Figure A.7: Flocking index

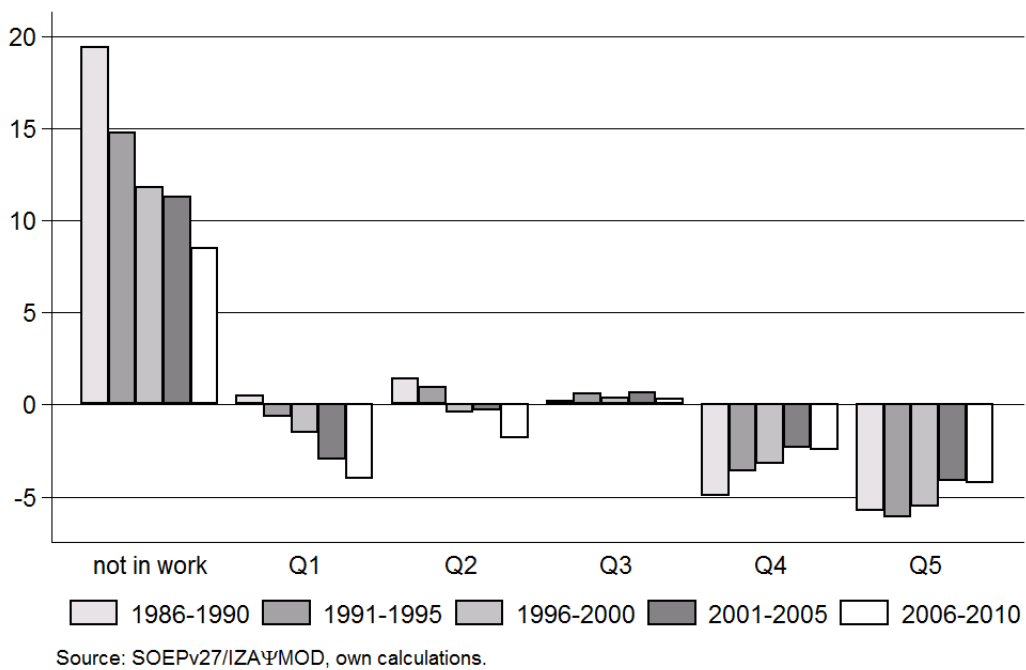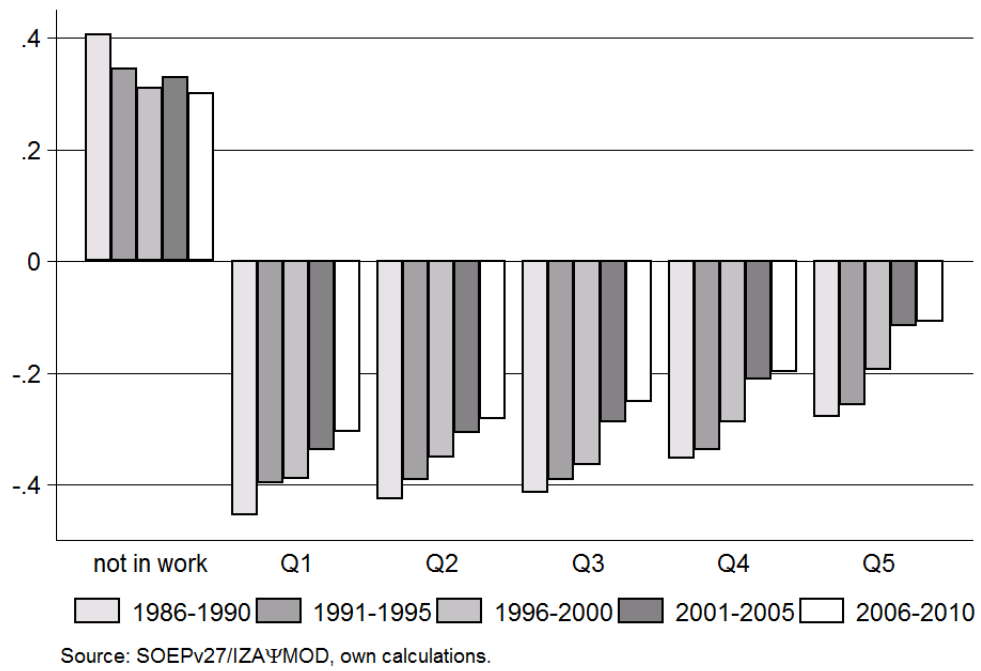Figure A.8: Change in male hours of work by earnings quantile



Figure A.9: Change in male hours of work by earnings quantile

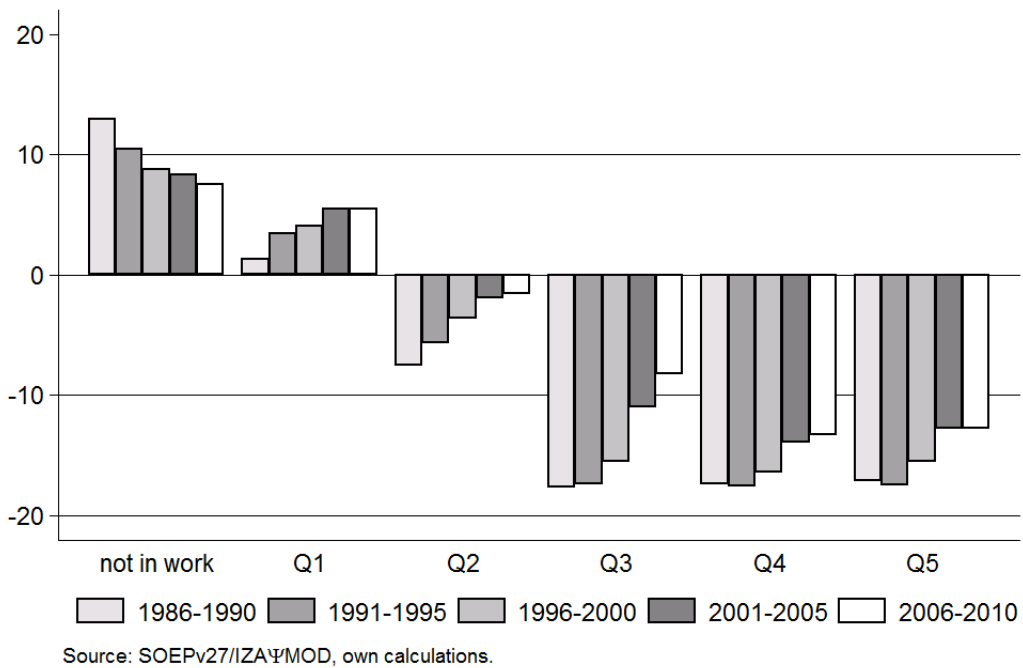Figure A.10: Change in female employment rates by earnings quantile



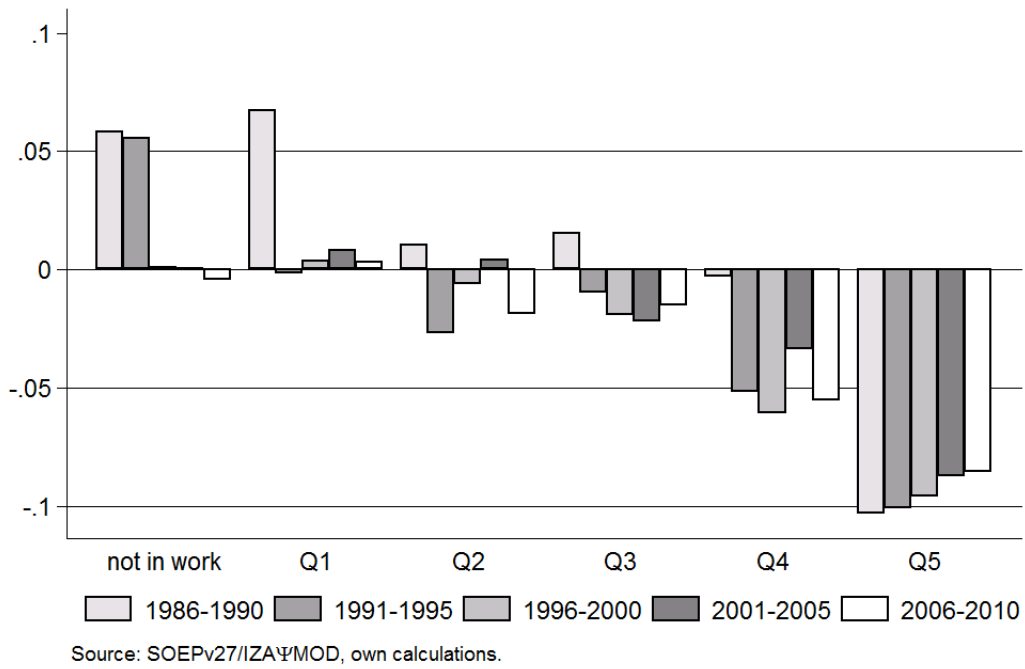Figure A.11: Change in female hours of work by earnings quantile

Figure A.12: Change in female employment rates by earnings quantile of the hypothetical males
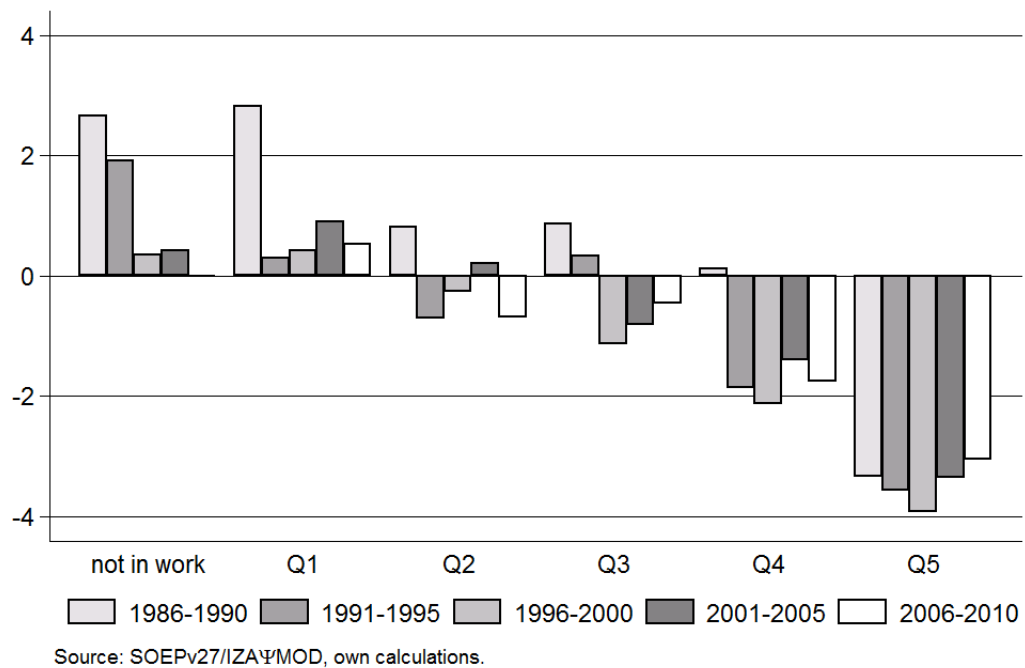


Figure A.13: Change in female hours of work by earnings quantile of the hypothetical males