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Nico Pestel

September 2014

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Discussion Paper No. 8482  
September 2014

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## ABSTRACT

### **Beyond Inequality Accounting: Marital Sorting and Couple Labor Supply<sup>\*</sup>**

This paper examines to what extent non-random sorting of spouses affects earnings inequality while explicitly disentangling effects from increasing assortativeness in couple formation from changing patterns of couples' labor supply behavior. Using German micro data, earnings distributions of observed and randomly matched couples are compared to each other. Earnings of hypothetical couples are adjusted for changes in hours worked given the differences in the household context using predictions based on a structural model of labor supply. The main finding is that the impact of marital sorting on earnings inequality has been underestimated in previous approaches. Predicting hours worked for hypothetical couples reveals a strong disequalizing impact of nonrandom sorting on inequality which is stable since the 1980s. Taking labor supply choices as given would suggest a smaller effect. This suggests that increasing earnings correlation among couples is to a considerable extent driven by changing patterns of labor market behavior rather than changes in the assortativeness in couple formation.

JEL Classification: D31, D63, J12, J22

Keywords: earnings inequality, sorting, labor supply, Germany

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# 1 Introduction

Increasing correlation of spouses' earnings is typically interpreted as increasing similarity of spouses in terms of earnings-related characteristics (assortative mating, see Mare and Schwartz, 2005). Marital sorting has an amplifying effect on inequality across households since it reduces the potential for income equalization within families (Burtless, 2009; Schwartz, 2010). When the share of couples with both partners being either high or low wage earners increases, 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 resources. The trend towards more positive sorting in earnings is also related to increasing female labor force participation (Bredemeier and Juessen, 2013; Greenwood et al., 2014). More generally, changes in household context affecting "who lives with whom" (Jenkins and Micklewright, 2007, p. 19) have been found to contribute to growing income inequality (see, e.g., Jenkins, 1995; Daly and Valletta, 2006; Martin, 2006; Peichl et al., 2012). Hence, with regard to economic inequality, trends of widening earnings gaps cannot be assessed independently of changes in the socio-demographic composition of the population of interest.

Previous studies on the effect of an increasing association of female and male earnings on inequality can largely be classified as accounting approaches. The observed distribution of income or earnings is typically compared to a number of counterfactual distributions by manipulating female earnings or the correlation between spouses' earnings (e.g., Karoly and Burtless, 1995; Burtless, 1999; Aaberge et al., 2005). Cancian and Reed (1998, 1999) emphasize that the question of 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 explicitly 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 is related to 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 marital sorting on earnings inequality should adjust for labor supply behavior in order to explicitly distinguish two different determinants, which are observed simultaneously: First, assortativeness in couple formation is related to partners matching according to their preferences or productivities and is indicated by similar age, education or ethnicity within couples. Second, correlation of spouses' earnings is related to labor supply choices *given* the observed match. These two related but still different determinants should be disentangled in order to identify the socio-demographic trends of growing inequality.

This paper quantifies to what extent non-random sorting among spouses affects earnings inequality explicitly taking into account labor supply behavior of couples. Using German micro data, earnings distributions of observed and randomly matched couples are compared to each other. Earnings of hypothetical couples are not taken as given, but are adjusted for changes in hours worked given the differences in the household context using predictions based on a structural model of labor supply. This provides estimates on preferences for disposable income, leisure as well as various interactions with household characteristics, which constitute a key part of the household context and affect individual labor supply decisions. In order to capture hypothetical labor supply adjustments, I use the estimated coefficients, predict labor supply behavior of the hypothetical couples and calculate the respective earnings of randomly matched individuals and, hence, total household earnings. Differences in earnings inequality between the distributions of observed and hypothetical couples after labor supply adjustment allow to disentangle the effects of sorting in couple formation and labor supply behavior. For this, an index measuring the effect of the association between spouses' earnings on inequality (the "flocking index", see Aaberge et al., 2005) is extended to account for hypothetical labor supply choices.

The main finding is that the impact of marital sorting on earnings inequality has been underestimated in previous accounting approaches. Predicting hours worked for hypothetical couples reveals a strong disequalizing impact of non-random

sorting on inequality which is stable since the 1980s. Taking labor supply choices as given would suggest a smaller effect. This result is driven by two factors: First, women with high (low) earnings potential tend to couple with high (low) earning men. Second, labor force participation and working hours of women living in couples with high earning men were rather low in the 1980s, but increased disproportionately over the period under consideration. Taken together, this indicates that increasing earnings correlation between females and males results to a large extent from increasing labor force attachment of women rather than from changes in couple formation. From a policy maker's perspective, this result implies a trade-off between policy measures promoting female labor force participation and redistributive policies. Achieving the objective of higher female employment apparently comes at the price of higher inequality. The policy implications are ambiguous. On the one hand, one could argue that government intervention is not justified, since the observed trend of increasing female labor force participation is the result of couples' choices. On the other hand, the growing share of dual earner couples implies a declining importance of intra-family redistribution, which could potentially be substituted by government redistribution.

The paper is organized as follows. Section 2 gives an overview of previous literature. Section 3 introduces the methodology and describes the empirical application and the data. Results are presented in section 4. Section 5 concludes.

## **2 Background and Literature**

Previous studies have addressed the interrelationship between earnings correlation of couples and household income inequality in various ways. They have in common that observed individual earnings are taken as given when constructing counterfactuals. Schwartz (2010) estimates the contribution of the association between spouses' earnings to growing earnings inequality among married couples in the US. She finds that earnings inequality would have been 25–30% lower than actually observed when the trend correlation between male and female earnings in couples would have remained at its level in the 1960s (particularly at the top of the distribution). Karoly and

Burtless (1995) apply the Lerman and Yitzhaki (1985) decomposition technique to examine how demographic trends in the US have affected income inequality across families and conclude that female earnings had a key influence on family income inequality due to increasing correlation with total family income since 1980. Burtless (1999) attributes 13% of overall inequality to the growing correlation of husbands' and wives' earnings. However, Cancian and Reed (1998, 1999) conclude that female earnings were not the main driving force towards increasing inequality and find the role of husbands' earnings to be much more important. Reed and Cancian (2009) find that changes in *income* sorting account for more than half of the increase in income inequality. They discuss several trends that have contributed to increasing correlation of male and female earnings in couple households, among others increases in assortative mating, the increasing propensity to work for women married to highly educated men and the rise in returns to education.

Based on a decomposition of the Gini coefficient Aaberge et al. (2005) introduce an index for the association of spouses' labor incomes and find that this has increased in Norway over the period 1973–1997. In their application, they compare the observed distribution of couple earnings to a reference distribution of randomly matched couples holding individual earnings fixed. However, they write that “the correct way to derive the hypothetical [...] income distribution would consist in, first, randomly matching the partners' productivities, i.e. potential wages, and second, simulating their income-producing choices, given the random match” (Aaberge et al., 2005, p. 507).

### 3 Methodology

In order to measure the extent of marital sorting on couple earnings inequality, an index derived from a decomposition of the Gini coefficient is used (Aaberge et al., 2005). The “flocking index” quantifies both the extent and the sign of the effect of the association of female and male labor earnings (“flocking together”<sup>1</sup>) on inequality

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<sup>1</sup> The earliest citation of this proverb dates back to Minsheu (1599): “*Birdes of a feather will flocke together*”. 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).



across couples. It is calculated based on the observed as well as a hypothetical distribution of couple earnings. The hypothetical distribution is constructed by matching spouses' individual earnings randomly to each other. However, it has to be noted that a shortcoming of previous applications of this index is that the difference between the observed and the counterfactual distribution does not reflect changes due to labor supply behavior. Hence, taking into account labor supply coordination requires a simulation of counterfactual choices given the randomly matched household context. In the following, an extended version of the “flocking index” that adjusts for labor supply choices is suggested.

### 3.1 The flocking index

Consider a population of  $n$  couple households indexed  $i \in \{1, \dots, n\}$  and a distribution of household earnings  $Y = (y^1, \dots, y^n)$ , where household  $i$ 's total earnings are simply the sum of both the female and the male spouse's individual earnings:  $y^i = y_f^i + y_m^i$ . The distribution of total earnings  $Y$  is determined by the gender-specific marginal earnings distributions  $Y_f$  and  $Y_m$  as well as the correlation of spouses' earnings,  $Corr[Y_f, Y_m]$ , and, hence, their positions in the respective earnings distribution.<sup>2</sup> Taking  $Y_f$  and  $Y_m$  as given, the level of inequality in total household earnings, represented by the Gini coefficient  $G(Y)$ , is bounded between an upper and a lower extreme value respectively:  $G(Y) \in [G^{min}(Y), G^{max}(Y)]$ . These depend on the spouses' earnings distributions and are defined as

$$G(Y) = \begin{cases} G^{max}(Y) & \text{if } F(y_f^i) = F(y_m^i) \\ G^{min}(Y) & \text{if } F(y_f^i) = 1 - F(y_m^i) \end{cases} \quad (1)$$

This means that the level of total couple earnings inequality is highest (lowest) if the highest earning woman forms a couple with the highest (lowest) earning man, the second highest earning woman with the second highest (lowest) man and so on. Hence, the pattern of marital sorting with respect to earnings has the most (dis)equalizing effect on earnings inequality across couple households in a situation

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<sup>2</sup> See Decancq et al. (2012) for a copula-based decomposition of couple earnings inequality.

where sorting in earnings is perfectly negative (positive).

A way to assess to what extent the observed inequality in the distribution of couple earnings is affected by non-random sorting in earnings is to compare the observed distribution with a hypothetical one where spouses' earnings are randomly matched to each other. Consider a counterfactual distribution of randomly matched couples indexed  $\tilde{i} = \pi(i) \in \{1, \dots, n\}$  with couple  $\tilde{i}$ 's total earnings  $y^{\tilde{i}} = y_f^{\tilde{i}} + y_m^{\tilde{i}}$ . Note that, without any further adjustments, the inequality levels in the gender-specific marginal distributions do not change, i.e.,  $G(\tilde{Y}_s) = G(Y_s)$  for  $s \in \{f, m\}$ . However, inequality of total earnings  $\tilde{Y}$  is affected, since the random matching of couples changes the correlation of spouses' earnings. This implies that in general  $G(\tilde{Y}) \neq G(Y)$ . Normalizing the difference between the observed and the hypothetical Gini coefficients by the distance between the hypothetical Gini and the upper and lower bounds respectively yields an index of the extent of "flocking together" (Aaberge et al., 2005):

$$V(Y, \tilde{Y}) = \begin{cases} \frac{G(Y) - G(\tilde{Y})}{G^{max}(Y) - G(\tilde{Y})} & \text{if } G(Y) \geq G(\tilde{Y}), \\ \frac{G(Y) - G(\tilde{Y})}{G(\tilde{Y}) - G^{min}(Y)} & \text{if } G(Y) < G(\tilde{Y}), \end{cases} \quad (2)$$

where  $V \in [-1, 1]$ . Positive values of  $V$  imply that  $G(Y) > G(\tilde{Y})$ , i.e., observed inequality of couple earnings is greater than inequality of the distribution of random matches. This reflects a disequalizing pattern of sorting in earnings, while negative values of  $V$  indicate a sorting pattern that is equalizing compared to random matching. 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 coincide.<sup>3</sup>

**Adjusting for labor supply behavior.** Sorting of couples with respect to earnings, i.e., non-zero earnings correlation, does not necessarily only reflect changes in the assortativeness in couple formation but is also affected by changes in the coordi-

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<sup>3</sup> Note that the interpretation of the flocking index is similar to a measure of correlation between two stochastic variables. Aaberge 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.

nation of couples' labor market behavior. Consider, for example, a perfectly negative sorting pattern where the highest 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, since resources are typically assumed to be equally shared within the household. However, since earnings are a function of earnings *potential* (the wage rate) and the supply of working time on the labor market (hours), it is not clear whether earnings correlation rather 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*). This example describes a situation where the number of hours worked is negatively associated with spouse's income. This implies that the extent of "flocking together" with respect to earnings can be assumed to be affected by patterns of couples' labor supply choices.

Formally, household  $i$ 's observed earnings  $y^i$  depend on the spouses' wages, hours worked as well as household characteristics  $X^i$ :

$$y_s^i = \bar{w}_s^i \cdot h_s^i = \bar{w}_s^i \cdot h_s(\bar{w}_f^i, \bar{w}_m^i, X^i) \quad (3)$$

for  $s \in \{f, m\}$  and where  $\bar{w}$  and  $h$  denote individual hourly wage rates and hours worked respectively. Hence, taking the thought experiment of a hypothetical random matching of couples seriously, necessarily implies that individual hours worked would adjust given the hypothetical household context, i.e.,  $y_s^i \neq \hat{y}_s^i$  since  $(\bar{w}_f^i, \bar{w}_m^i, X^i) \neq (\hat{\bar{w}}_f^i, \hat{\bar{w}}_m^i, X^i)$ . In order to adjust for labor supply behavior, one has to impute the hypothetical labor supply choice and, consequently, the earnings for randomly matched couples based on a prediction, which is denoted by a hat:

$$\hat{y}_s^i = \hat{\bar{w}}_s^i \cdot \hat{h}_s(\hat{\bar{w}}_f^i, \hat{\bar{w}}_m^i, X^i), \quad (4)$$

In the empirical application, the prediction of hypothetical labor supply choices will be based on estimates for a structural model of household labor supply. The predictions can then be used to calculate the level of inequality in the counterfactual couple earnings distribution,  $G(\hat{Y})$ , and finally the flocking index after labor supply

adjustment:

$$\widehat{V} = \widehat{V}(Y, \widehat{Y}). \quad (5)$$

The interpretation of the adjusted flocking index is the same as before: Positive values indicate a disequalizing and negative values an equalizing pattern. The main difference is that labor supply coordination given the household context is explicitly taken into account. Comparing the unadjusted and the adjusted flocking indexes,  $V$  and  $\widehat{V}$ , indicates whether taking into account randomly matched couples' labor supply behavior changes the impact of earnings correlation on inequality across couple households. This is summarized in the following cross-tabulation of potential outcomes.

	$\widehat{V} > V$	$\widehat{V} < V$
$V < 0 \rightarrow$ equalizing effect	overestimated	underestimated
$V > 0 \rightarrow$ disequalizing effect	underestimated	overestimated

The case of  $V < 0$  implies an equalizing effect of spouses' earnings correlation on inequality when not taking into account labor supply adjustments. This is in absolute terms overestimated (underestimated) when adjusting for labor supply yields a larger (smaller) value for  $\widehat{V}$ . On the other hand, in the case of  $V > 0$ , the implied disequalizing pattern is underestimated (overestimated) when adjusting for labor supply yields a larger (smaller) value for  $\widehat{V}$ . This means that observed patterns of labor supply coordination among couple households may either cushion or exacerbate the extent to which the assortativeness in spouses' characteristics affects earnings inequality across couple households.

**Structural model of household labor supply.** In order to predict counterfactual labor supply decisions for randomly matched couples, I 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). Assume that a couple  $i$ 's spouses jointly maximize utility  $U$  by optimally choosing from a discrete choice set of  $J$  combinations of working time categories  $(h_f^{ij}, h_m^{ij})$ . Utility of couple  $i$  in

category  $j \in \{1, \dots, J\}$  is given by

$$U^{ij} = W(D^{ij}, h_f^{ij}, h_m^{ij} | X^i) + \epsilon^{ij}, \quad (6)$$

where  $W(\cdot)$  captures the systematic part of the utility function with the main arguments being the household's disposable income  $D^{ij}$  and working time of both spouses (assuming disutility from labor) given a set of household characteristics  $X^i$ . Disposable income is given by  $D^{ij} = d(\bar{w}_f^i h_f^{ij}, \bar{w}_m^i h_m^{ij}, I^i | X^i)$ , where  $\bar{w}$  denotes hourly wage rates, which are assumed to be fix across choices, and  $I^i$  denotes non-labor income. The tax-benefit function  $d(\cdot)$  transforms labor earnings and other gross income into disposable income given household characteristics. Unobserved heterogeneity in preferences is captured by adding the stochastic term, which is assumed to be *iid* following a Gumbel (extreme value type I) distribution. These assumptions allow the empirical estimation of a conditional logit model following McFadden (1974), where the probability that household  $i$  chooses working time category  $k$  over all other available categories  $l \in \{1, \dots, J\} \setminus k$  is

$$P(U^{ik} > U^{il}) = P(W^{ik} - W^{il} > \epsilon^{il} - \epsilon^{ik}) = \frac{\exp(W^{ik})}{\sum_{l=1}^J \exp(W^{il})}. \quad (7)$$

The resulting set of estimated coefficients from the systematic part of the utility function  $W(\cdot)$  based on observed couples' behavior can be interpreted as population averages of preferences for disposable income and leisure given observed heterogeneity in household characteristics. The estimates obtained can be used to predict counterfactual labor supply choices for randomly matched couples given hypothetical wages  $(\bar{w}_f^i, \bar{w}_m^i)$  and household characteristics  $X^i$ .

## 3.2 Empirical Application

**Labor supply estimation.** The structural model of household labor supply and the estimation procedure described in (6) and (7) are standard tools frequently applied in microsimulation studies.<sup>4</sup> The systematic part  $W(\cdot)$  of the utility function

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<sup>4</sup> For detailed overviews of microsimulation models and the empirical estimation of structural labor supply models, see Creedy and Kalb (2006); Bargain et al. (2014).

in (6) is represented by a quadratic specification, i.e., the main arguments – disposable income as well as female and male working time – enter both in linear as well as in quadratic form. In addition, several interactions of income and leisure with household characteristics  $X^i$  capture observed heterogeneity in labor supply decisions (“taste shifters”). These comprise individual spouses’ characteristics (age, age squared, indicators for high and low skill, indicator for handicap status) as well as household characteristics (indicators for the presence of children aged 0–2, 3–6 and 7–16, marital status and an indicator for the presence of a person needing care). In addition, indicators for fixed cost of work as well as for working time categories are included (Van Soest, 1995).

The conditional logit estimation of (7) is based on a discrete choice set of 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  $7 * 7 = 49$  categories.<sup>5</sup> This requires an imputation of disposable income for working time categories which are not observed. While it is straightforward to impute *gross* labor earnings for counterfactual categories by multiplying the individual hourly wage rates with the number of working hours assuming that wage rates are determined independently from working time, one of the labor supply model’s main arguments is the households’ disposable income  $D^{ij}$ .<sup>6</sup> This is imputed based on a reduced-form regression approach (see Frenette et al., 2007; Biewen and Juhasz, 2012; Peichl, 2012; Bargain et al., 2013), where for each year  $t$  observed disposable income of household  $i$  is the left-hand side variable:

$$D_t^i = X_t^i \alpha_t^x + Z_t^i \alpha_t^z + X Z_t^i \alpha_t^{xz} + u_t^i, \quad (8)$$

where  $D_t^i$  is observed disposable income,  $Z_{it}$  is a vector of gross incomes (from labor, assets, private pensions and other sources) including third-order polynomials

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<sup>5</sup> The labor supply model is estimated separately for couples with a choice set restricted to only seven working time categories, where one spouse can adjust hours worked in the market flexibly and the other spouse is in education, in military/civilian service, on parental leave, pensioner, civil servant, self-employed or has capital income exceeding half the level of labor income.

<sup>6</sup> 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). Wages are predicted for the entire sample.

and  $X_t^i$  is a set of household characteristics which are relevant for tax-benefit policies in Germany (marital status, age, age squared and hours worked of both spouses, indicators for the presence of children of different ages as well as indicators for civil servants and self-employed). The vector  $XZ_t^i$  comprises various interactions of gross incomes and household characteristics. The error term is denoted by  $u_t^i$ . 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, has sufficient predictive power to impute disposable incomes in both observed and counterfactual choice categories. Regression results for both the conditional logit estimations as well as the reduced-form tax-benefit model are presented in tables 1–8 in the appendix.

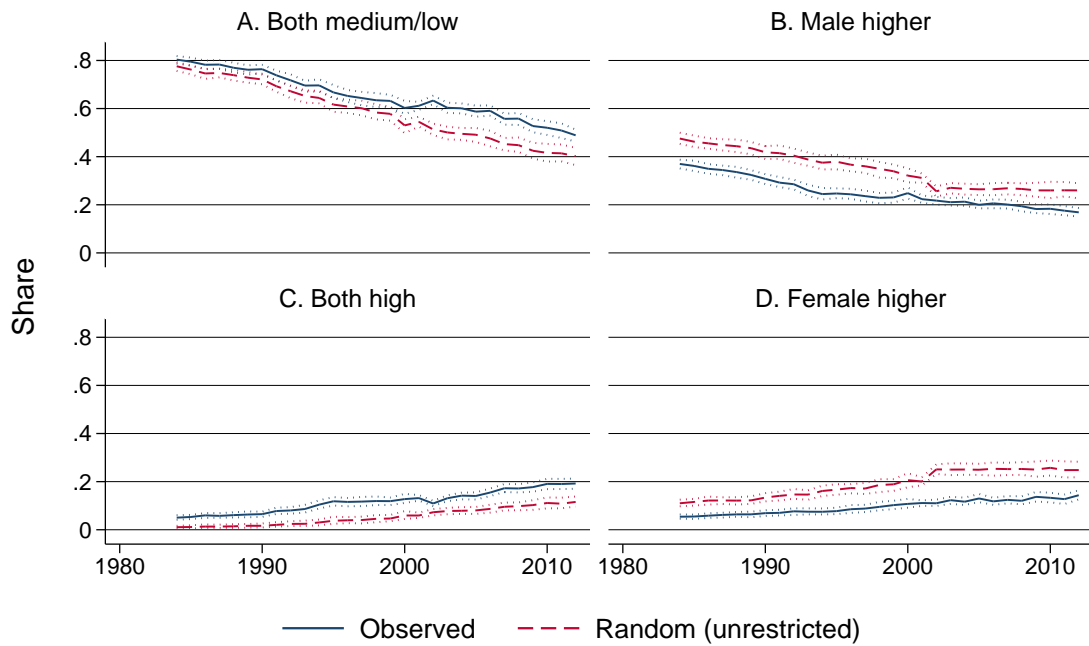
**Data, sample selection and randomization.** The simulation model is based on micro data from the German Socio-Economic Panel Study (SOEP), which is a panel survey of households and individuals that has been conducted annually since 1984 and currently comprises 29 waves (Wagner et al., 2007; SOEP, 2013). Population weights make the respondents’ information representative for the German population. The sample is restricted to West Germany, since especially shortly after the reunification of Germany in 1990, labor supply behavior of East Germans differs substantially from that of West Germans. Moreover, income levels are still substantially different between East and West. The sample is further restricted to couples (both married and cohabiting) where both spouses are of prime working age (30–59).

Couples observed in the sample are matched randomly to each other separately for each data year. In a baseline scenario, there are no restrictions in the randomization procedure at all. This means that any woman and any man from the sample can potentially be matched to form a hypothetical couple. In order to make sure that predictions of hypothetical labor supply choices are not entirely driven by certain couple characteristics, three additional randomization procedures are performed that restrict the potential hypothetical couples. Hence, the following four different algorithms are applied:

- (1) *unrestricted*: No restrictions on potential hypothetical spouses.
- (2) *restricted by marital status*: Randomization is done separately by marital status, which implies that married (unmarried) individuals can only be randomly matched with a married (unmarried) individual of the opposite sex.
- (3) *restricted by the presence of children*: Similar to the restriction by marital status, only individuals with and without dependent children in the household respectively can be matched to each other.
- (4) *restricted by age*: Finally, randomization is done separately for individuals who are below or above the gender-specific median age.

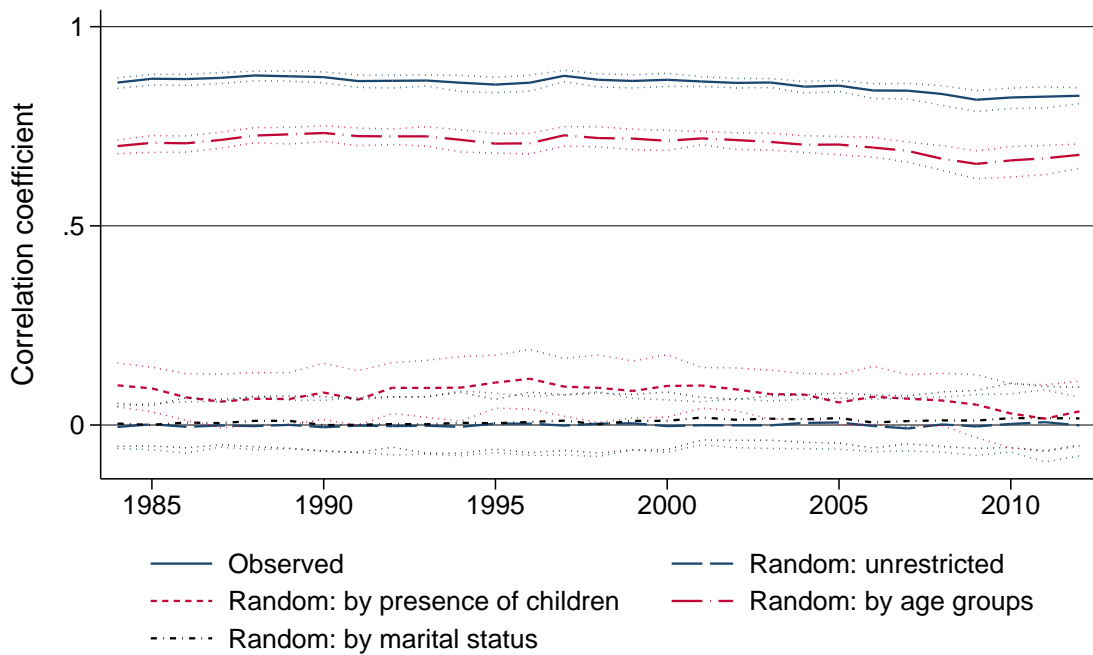
Figure 1 shows how the different randomization algorithm perform. Figure 1a shows the educational composition of couples both observed in the data as well as after randomization. Here, results are shown for the unrestricted randomization algorithm only. Panels A and C in the left column show the share of couples where both spouses have the same level of education, while panels B and D on the right show the shares where educational levels within the couple are different. It becomes apparent that there is substantial sorting with respect to education since random same-education shares are lower than observed. At the same time, couples with different educational attainment should be observed more often when couple formation was purely random with respect to education. Figure 1b shows the correlation coefficient of spouses' ages. Observed age correlation is unsurprisingly very high and steady over time with a coefficient above 0.8. People tend to couple with individuals of similar age. Randomization eliminates age correlation and is close to zero for hypothetical couples. The main exception is the algorithm restricting random matching to younger and older couples respectively. That is why the age correlation coefficient for this algorithm is by construction still quite high at around 0.7, but significantly lower than observed. Another minor exception is the random matching within the groups with and without dependent children. Here, the coefficient is around 0.1, which is not surprising given that parents with children in the house are on average younger than parents whose children have left the house already.





Source: SOEPv29, own calculations.  
 Note: Dotted lines indicate 95% confidence interval based on 250 bootstrap replications.

a. Educational composition



Source: SOEPv29, own calculations.  
 Note: Dotted lines indicate 95% confidence interval based on 250 bootstrap replications.

b. Age correlation

Figure 1: Educational and age composition of couples by randomization

## 4 Results

### 4.1 Descriptives

The trends in observed earnings inequality across couple households in West Germany over the period 1984–2012 is displayed in figure 2a. The Gini coefficient (left panel) of total labor earnings has increased from around 0.3 by about 10% since the early 2000s. This trend is paralleled by an increase in disposable income inequality from a Gini coefficient below 0.25 in the 1980s and 1990s to above that level in the 2000s.

At the same time, the correlation (right panel) of female and male earnings and wage quintiles have also increased.<sup>7</sup> The correlation in earnings trended upward throughout the period under consideration from slightly negative to slightly positive. Whether this is due to increasing labor force participation or increasing assortativeness in couple formation is a priori unclear.

The fact that the level of the correlation in hourly wage quintiles is positive and more pronounced, particularly in the 1980s and 1990s, indicates that changing labor supply behavior of couples might have played an important role.

This is also in line with the observation that increases in female labor force participation, hours worked in particular, has not been uniformly distributed across the distribution of male earnings (Juhn and Murphy, 1997; Bredemeier and Juessen, 2013). Figure 2b shows the mean change in female hours worked by *male* earnings quintile. There is a clear U-shaped pattern indicating that women in couples with men at the bottom and the top of the male earnings distribution have expanded their labor supply disproportionately. Comparing the 1980s with the 2000s, the most pronounced increase is observed at the top: Women with a male partner in the top quintile nowadays work about seven hours more per week than in the 1980s, up from about 14–15 hours.

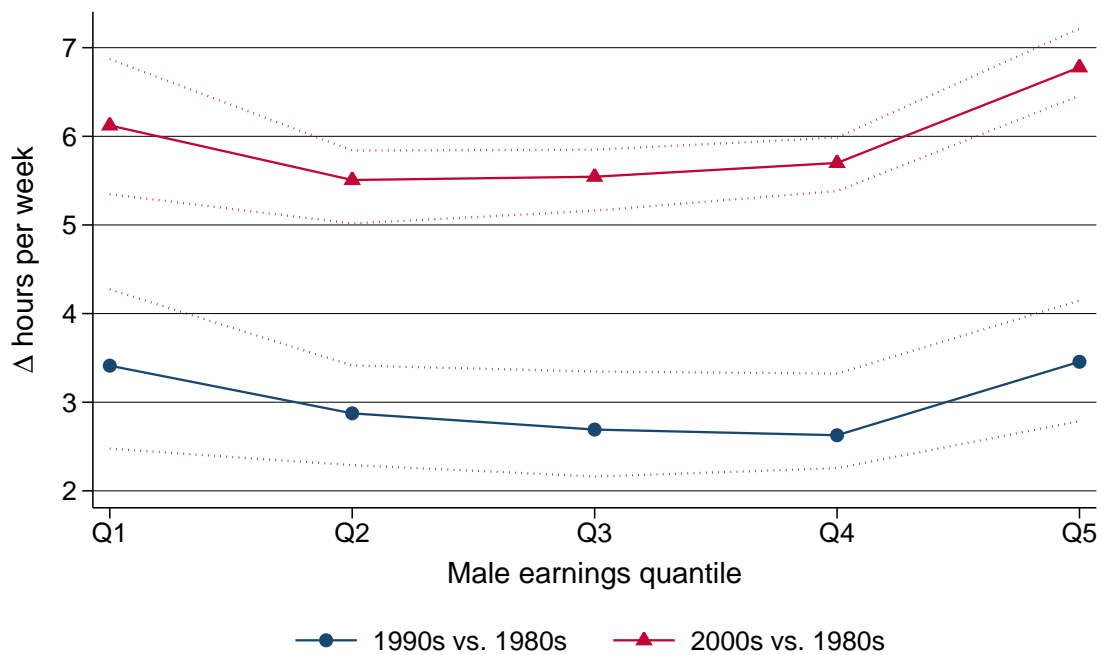
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<sup>7</sup> The correlation in gender-specific quintiles is not affected by changes in marginal distributions and therefore is a preferable measure for the assortativeness in earnings and wages.



Source: SOEPv29, own calculations.

a. Inequality and correlation among couple households in West Germany



Source: SOEPv29, own calculations.

Note: Dotted lines indicate 95% confidence interval based on 250 bootstrap replications.

b. Changes in female hours worked by male earnings quintile

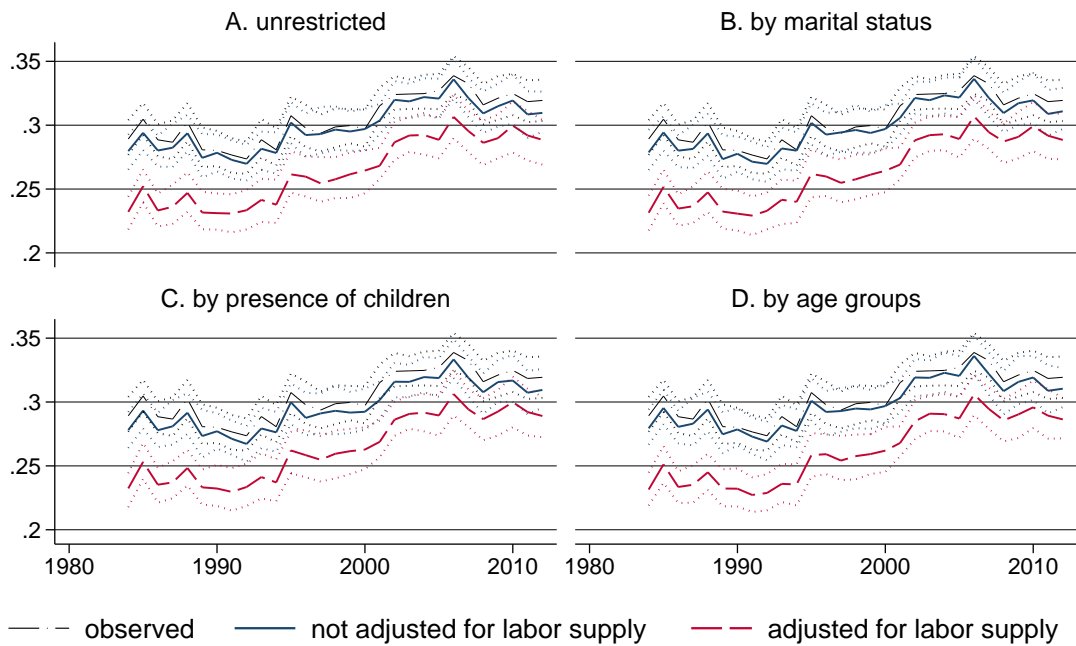
Figure 2: Inequality, correlation and female labor supply of couple households

## 4.2 Flocking index

In order to disentangle the effects of assortativeness in couple formation from the effects of changes in couples' labor supply behavior on earnings inequality the flocking indexes, with and without adjustment for labor supply choices, are compared to each other. The flocking index is a function of Gini coefficients, see equation (2). Results for the Gini coefficients as well as the resulting flocking indexes are displayed in figure 3 separately for all four types of randomization procedures.

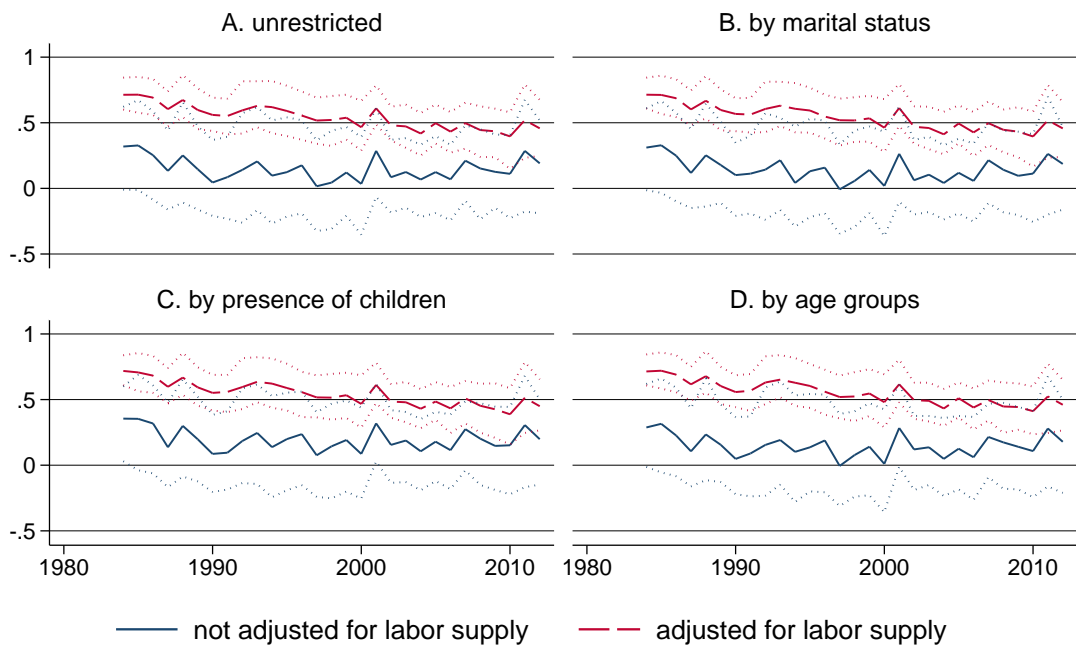
The solid-dot lines in figure 3a indicate the observed trends of the Gini coefficient of couple labor earnings, while the solid lines show the trend of the hypothetical Gini coefficients that result from randomly matching couples to each other, but not adjusting for labor supply choices. There is no significant difference between the two lines, which results in an unadjusted flocking index not significantly different from zero, which is shown by the solid lines in figure 3b. Recall that the flocking index can vary between  $-1$  (extremely equalizing) and  $1$  (extremely disequalizing), while a value of zero indicates neutrality. According to this, the pattern of sorting in earnings was rather inequality neutral, at most marginally disequalizing throughout the period under consideration. This reflects the descriptive result of close to zero correlation in earnings in figure 2a. However, it remains unclear whether this result is rather driven by changes in couple formation or by changes in labor supply behavior.

The dashed lines in figure 3a show the Gini coefficients that result from adjusting for labor supply behavior. Randomly matching couples to each other and adjusting for labor supply choices clearly makes the earnings distribution across couples more equal. The line indicating the Gini after labor supply adjustment is significantly below the observed trend in inequality. However, over the period under consideration, the gap has become smaller. The resulting flocking indexes adjusted for labor supply choices are shown in figure 3b (dashed lines). The levels are clearly positive over the entire period and also considerably larger than the unadjusted flocking index. The difference between the unadjusted and the adjusted flocking indexes is particularly large in the 1980s and has decreased since then.



Source: SOEPv29, own calculations.  
 Note: Dotted lines indicate 95% confidence interval based on 250 bootstrap replications.

a. Gini coefficients

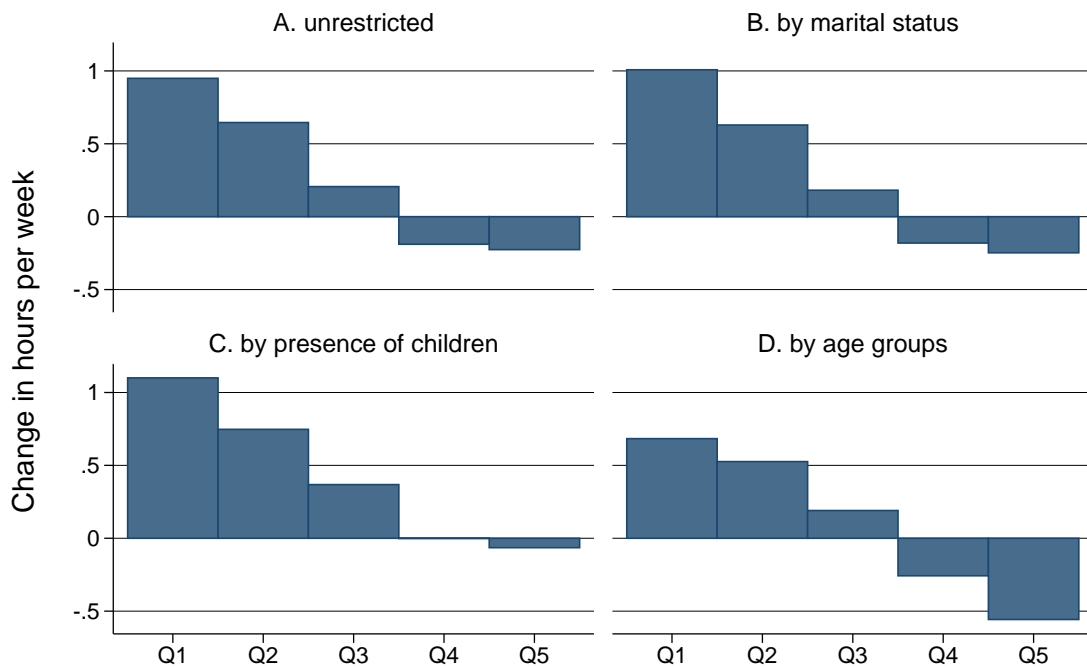


Source: SOEPv29, own calculations.  
 Note: Dotted lines indicate 95% confidence interval based on 250 bootstrap replications.

b. Flocking indexes

Figure 3: Gini coefficients and flocking indexes by randomization

The interpretation of this result is that, while the pattern of sorting in earnings has a rather limited impact on couple earnings inequality, the pattern of sorting in earnings *potential* does have a strong disequalizing impact and is veiled by patterns of labor market behavior of women with high earnings potential in couples with high earning men who were less attached to the labor market in earlier periods. This is consistent with the pattern of hypothetical labor supply adjustments of women across the distribution of male earnings. Figure 4 shows the mean adjustment of female hours worked by male earnings quintiles. Clearly, women randomly matched to a men at the bottom of the distribution would expand their labor supply, while women matched with high earning men slightly reduce their hours worked. This result is in line with the interpretation of male earnings having an “income effect” on labor supply of women (Reed and Cancian, 2009; Bargain et al., 2014).



Source: SOEPv29, own calculations.

Figure 4: Adjustment of female labor supply by male earnings quintile

## 5 Conclusions

This paper examines to what extent non-random sorting among spouses affects earnings inequality while explicitly taking into account labor supply behavior of couples in order to disentangle effects from increasing assortativeness in couple formation from changing patterns of couples' labor supply behavior. Constructing counterfactual distributions based on observed earnings is misleading since labor supply choices are affected by both earnings potential as well as labor supply coordination in couple households. Using German micro data, earnings distributions of observed and randomly matched couples are compared to each other. Earnings of hypothetical couples are not taken as given, but are adjusted for changes in hours worked given the differences in the household context using predictions from a structural model of labor supply. Based on this, an extended version of the "flocking index" (Aaberge et al., 2005), measuring the effect of the association between spouses' earnings on inequality, is calculated to account for hypothetical labor supply choices.

The main finding is that the impact of marital sorting on earnings inequality has been underestimated in previous accounting approaches. Imputing predicted hours worked for hypothetical couples reveals a strong disequalizing impact of non-random sorting on inequality which is stable since the 1980s. Taking labor supply choices as given would suggest a smaller effect. This suggests that the observation of increasing correlation of spouses' earnings is to a large extent driven by changing patterns of labor market behavior of couples rather than changes in the assortativeness in couple formation. However, the strongly disequalizing effect of sorting in earnings potential has been cushioned by patterns of labor supply behavior of women in couples with high earning men in the 1980s. Over time, this equalizing effect has been diminishing, since overall increases in female labor force participation were most pronounced at the top of the earnings distribution. This suggests that increasing earnings correlation between females and males in couples results to a considerable extent from advances in labor force attachment of women (especially with high wages) rather than from changes in couple formation.

From a policy perspective, this implies 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 share of the total population. Apparently, increasing female labor market participation comes, to some extent, at the price of higher inequality. However, based on these results, there are no unambiguous policy implications. On the one hand, government intervention is not justified, since the observed trend of increasing female labor force participation is the result of couples' choices. On the other hand, a growing share of dual earner couples implies a declining importance of intra-family redistribution, which might be substituted by government redistribution. Future research should address the normative implications based on a theoretical framework of optimal taxation of couples.



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## Appendix





Table 3: Conditional logit regression results: (flex. couples, 1984-1998)

	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998
choice															
disp. inc.	0.005***	0.008***	0.001***	0.005***	0.000	0.002***	-0.001***	0.003***	0.005***	0.001***	0.002***	0.004***	0.003***	0.001***	0.002***
disp. inc. <sup>2</sup> /100	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
disp. inc. x age (male)/100	-0.008***	-0.019***	-0.003***	-0.006***	-0.007***	-0.012***	0.007***	-0.007***	0.005***	0.010***	-0.010***	-0.023***	-0.006***	-0.003***	-0.023***
disp. inc. x age <sup>2</sup> (male)/100	0.009***	0.020***	0.004***	0.006***	0.007***	0.010***	-0.011***	0.007***	-0.005***	-0.010***	0.012***	0.025***	0.007***	0.004***	0.026***
disp. inc. x age (female)/100	-0.012***	-0.011***	-0.002***	-0.009***	0.010***	0.011***	0.006***	0.006***	-0.023***	-0.006***	0.003***	0.010***	-0.003***	0.012***	0.028***
disp. inc. x age <sup>2</sup> (female)/100	0.015***	0.012***	0.001***	0.009***	-0.012***	-0.008***	-0.003***	-0.007***	0.026***	0.005***	-0.004***	-0.010***	0.005***	-0.014***	-0.031***
disp. inc. x high-skilled (male)/100	-0.058***	-0.032***	-0.017***	-0.029***	-0.028***	-0.022***	-0.017***	-0.040***	-0.033***	-0.044***	-0.030***	-0.017***	-0.021***	-0.031***	0.004***
disp. inc. x unskilled (male)/100	0.034***	0.019***	0.015***	-0.004***	0.018***	0.014***	0.015***	0.022***	-0.015***	0.022***	0.020***	0.005***	0.024***	0.003***	0.005***
disp. inc. x high-skilled (female)/100	-0.005***	0.038***	0.031***	0.040***	0.004***	-0.016***	-0.020***	0.043***	-0.042***	-0.061***	-0.041***	-0.020***	0.019***	-0.007***	-0.008***
disp. inc. x unskilled (female)/100	-0.048***	-0.004***	-0.009***	-0.020***	-0.018***	-0.044***	-0.014***	-0.019***	-0.003***	-0.035***	-0.021***	-0.030***	-0.023***	-0.027***	-0.025***
disp. inc. x kids 0-2/100	-0.002***	-0.003***	-0.028***	-0.007***	0.021***	-0.057***	-0.031***	-0.034***	-0.038***	0.041***	-0.024***	-0.046***	0.050***	-0.019***	0.057***
disp. inc. x kids 3-6/100	0.033***	-0.031***	-0.007***	-0.022***	-0.023***	0.023***	0.015***	-0.032***	-0.024***	-0.008***	0.005***	-0.008***	-0.023***	-0.020***	-0.017***
disp. inc. x kids 7-16/100	0.024***	-0.006***	0.004***	-0.000***	-0.003***	0.011***	0.011***	0.001***	0.008***	-0.003***	-0.008***	-0.004***	-0.006***	-0.009***	-0.021***
disp. inc. x married/100	0.015***	0.017***	0.201***	0.052***	0.076***	-0.013***	-0.056***	-0.044***	-0.023***	-0.013***	-0.020***	-0.045***	-0.042***	-0.065***	-0.097***
disp. inc. x care/100	0.008***	0.022***	-0.036***	-0.063***	0.080***	-0.064***	-0.008***	-0.008***	0.010***	0.051***	-0.007***	0.032***	0.049***	-0.017***	0.042***
leisure (male)	0.448***	0.285***	0.186***	0.629***	0.227***	0.675***	0.485***	0.267***	0.521***	0.654***	0.381***	0.373***	0.488***	0.587***	0.540***
leisure (female)	0.217***	0.374***	0.182***	0.215***	0.044***	0.148***	0.170***	0.111***	0.287***	0.324***	0.137***	0.199***	0.311***	0.290***	0.326***
leisure (male) <sup>2</sup> /100	-0.381***	-0.227***	-0.241***	-0.664***	-0.279***	-0.761***	-0.688***	-0.568***	-0.797***	-0.664***	-0.595***	-0.324***	-0.430***	-0.680***	-0.384***
leisure (female) <sup>2</sup> /100	-0.189***	-0.288***	-0.241***	-0.261***	-0.222***	-0.224***	-0.221***	-0.224***	-0.225***	-0.215***	-0.208***	-0.118***	-0.191***	-0.217***	-0.241***
leisure (male) x age (male)/100	-0.820***	-0.592***	-0.364***	-0.695***	-0.129***	-0.625***	0.055***	0.665***	0.193***	-0.874***	-0.172***	-0.843***	-1.017***	-0.733***	-1.376***
leisure (male) x age <sup>2</sup> (male)/100	0.973***	0.723***	0.513***	0.781***	0.257***	0.751***	0.058***	-0.604***	-0.162***	1.037***	0.282***	1.109***	1.319***	0.964***	1.755***
leisure (male) x high-skilled (male)/100	-4.025***	-2.779***	-1.295***	-3.369***	-4.622***	-3.197***	-3.568***	-2.943***	-4.545***	-3.488***	-2.573***	-1.432***	-2.405***	-2.687***	-1.689***
leisure (male) x unskilled (male)/100	3.908***	2.417***	1.972***	1.454***	2.180***	1.390***	2.958***	2.394***	2.425***	3.184***	3.631***	2.915***	2.455***	2.750***	2.081***
leisure (male) x married/100	-2.446***	-1.359***	3.949***	-1.488***	-1.641***	-2.563***	-6.002***	-5.669***	-3.297***	-3.976***	-0.216***	-0.935***	-1.241***	-0.034	-1.170***
leisure (male) x handicap (male)/100	1.550***	1.937***		2.136***	3.591***	4.591***		4.064***	4.945***		4.008***	3.398***	4.506***	3.598***	5.442***
leisure (female) x age (female)/100	-0.411***	-0.563***	-0.136***	-0.079***	0.479***	-0.021***	-0.022***	0.355***	-0.380***	-0.564***	0.218***	-0.553***	-0.789***	-0.276***	-0.568***
leisure (female) x age <sup>2</sup> (female)/100	0.778***	0.936***	0.397***	0.375***	-0.226***	0.382***	0.385***	-0.121***	0.689***	0.889***	0.061***	0.967***	1.209***	0.459***	0.957***
leisure (female) x high-skilled (female)/100	-1.232***	1.368***	1.217***	0.704***	-1.086***	-0.821***	-0.831***	-0.296***	-4.126***	-6.736***	-4.497***	-3.396***	-2.354***	-2.695***	-2.173***
leisure (female) x unskilled (female)/100	-0.874***	-0.437***	-0.771***	-1.481***	-1.270***	-1.809***	-0.609***	-0.895***	-0.364***	-1.223***	-0.885***	-0.330***	-0.293***	-1.639***	-0.041***
leisure (female) x kids 0-2/100	1.070***	4.878***	3.280***	5.779***	6.274***	2.323***	3.341***	5.677***	5.617***	7.440***	6.548***	7.274***	9.376***	3.952***	6.456***
leisure (female) x kids 3-6/100	4.788***	3.924***	4.683***	3.695***	4.040***	5.243***	4.881***	4.766***	4.028***	4.446***	4.482***	4.390***	3.869***	3.411***	4.080***
leisure (female) x kids 7-16/100	2.544***	2.423***	2.327***	2.355***	2.166***	2.832***	2.537***	2.028***	2.118***	2.205***	2.035***	2.073***	1.876***	1.892***	1.949***
leisure (female) x married/100	3.251***	0.311***	7.326***	5.307***	6.374***	5.595***	1.742***	2.202***	0.419***	-0.076***	-0.415***	0.040	3.304***	0.120***	0.548***
leisure (female) x handicap (female)/100	2.369***	-0.895***		-2.026***	-2.155***	1.492***		0.184***	-0.904***		0.517***	-0.835***	-0.982***	2.020***	2.511***
leisure (female) x care/100	2.492***	-2.175***	-0.555***	-0.014	3.571***	0.768***	-0.079***	2.154***	1.022***	5.627***	4.469***	3.242***	2.417***	2.526***	3.456***
fixed costs (male)	-7.283***	-4.089***	-4.616***	-12.513***	-4.516***	-15.105***	-13.644***	-11.309***	-15.329***	-13.635***	-13.376***	-6.651***	-8.437***	-13.892***	-6.982***
part-time 20h (male)	0.010	-1.290***	-2.125***	0.513***	-2.341***	1.052***	0.798***	0.790***	1.759***	2.109***	1.033***	-0.185***	-0.256***	1.795***	-1.336***
part-time 40h (male)	1.803***	1.509***	1.617***	1.262***	1.545***	1.309***	1.452***	1.554***	1.252***	1.718***	1.977***	1.600***	1.717***	1.376***	1.355***
fixed costs (female)	-2.869***	-3.498***	-3.110***	-3.210***	-2.741***	-2.657***	-2.651***	-2.585***	-2.340***	-2.384***	-2.354***	-1.872***	-1.970***	-2.436***	-2.516***
part-time 20h (female)	0.816***	0.787***	0.770***	0.821***	0.956***	0.795***	0.709***	0.879***	0.671***	0.658***	0.525***	0.616***	0.765***	0.678***	0.408***
part-time 40h (female)	1.533***	1.261***	1.333***	1.493***	1.611***	1.393***	1.255***	1.364***	1.328***	1.326***	1.383***	1.228***	1.529***	1.422***	1.081***
Pseudo R <sup>2</sup>	0.391	0.350	0.358	0.390	0.367	0.372	0.369	0.368	0.354	0.373	0.376	0.323	0.368	0.351	0.327
Observations	289566235	285269964	287435764	286261087	289158310	293102173	301247345	291533291	288807225	294499114	300542529	305974762	310367421	303087834	307254451

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







Table 8: Conditional logit regression results: (semi-flex. couples, female, 1999-2012)

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
choice														
disp. inc.	-0.016***	0.012***	-0.006***	-0.006***	-0.001***	0.006***	-0.013***	-0.001***	0.003***	0.010***	0.041***	0.012***	0.021***	0.001***
disp. inc. <sup>2</sup> /100	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	0.000***	-0.000***	-0.000***	-0.000***
disp. inc. x age (male)/100	0.052***	-0.017***	-0.000	-0.003***	-0.017***	-0.023***	0.016***	0.017***	0.026***	-0.014***	0.008***	-0.017***	0.038***	-0.017***
disp. inc. x age <sup>2</sup> (male)/100	-0.056***	0.019***	-0.003***	0.000	0.015***	0.023***	-0.014***	-0.015***	-0.026***	0.014***	-0.007***	0.018***	-0.035***	0.012***
disp. inc. x age (female)/100	0.031***	-0.039***	0.031***	0.027***	0.024***	-0.005***	0.048***	-0.019***	-0.045***	-0.002	-0.189***	-0.008***	-0.129***	0.037***
disp. inc. x age <sup>2</sup> (female)/100	-0.028***	0.049***	-0.028***	-0.024***	-0.021***	0.012***	-0.054***	0.028***	0.055***	-0.006***	0.220***	0.004***	0.145***	-0.035***
disp. inc. x high-skilled (male)/100	-0.046***	-0.058***	-0.048***	-0.006***	0.007***	-0.007***	-0.036***	-0.048***	-0.069***	-0.013***	-0.058***	-0.022***	0.037***	0.041***
disp. inc. x unskilled (male)/100	0.076***	0.004***	-0.089***	-0.019***	-0.060***	0.007***	-0.002*	0.131***	0.178***	-0.047***	0.095***	-0.051***	-0.012***	0.070***
disp. inc. x high-skilled (female)/100	-0.212***	0.112***	-0.035***	-0.020***	-0.035***	0.011***	0.115***	-0.011***	0.014***	-0.059***	-0.152***	0.040***	-0.122***	-0.105***
disp. inc. x unskilled (female)/100	-0.389***	0.194***	-0.023***	-0.009***	0.030***	0.081***	0.077***	-0.061***	0.107***	-0.150***	0.006***	-0.206***	0.272***	0.135***
disp. inc. x kids 0-2/100	0.161***	0.087***	-0.025***	0.042***	0.142***	0.050***	0.098***	0.074***	-0.020***	0.114***	0.350***	0.782***	0.513***	0.205***
disp. inc. x kids 3-6/100	0.149***	-0.010***	0.008***	0.035***	0.063***	-0.017***	-0.055***	0.056***	0.112***	-0.068***	0.005***	-0.228***	0.116***	-0.063***
disp. inc. x kids 7-16/100	0.021***	0.093***	-0.007***	0.004***	0.025***	-0.002***	-0.011***	0.018***	0.003***	-0.063***	0.040***	-0.150***	-0.012***	0.059***
disp. inc. x married/100	-0.176***	-0.081***	-0.088***	0.025***	-0.082***	-0.039***	-0.027***	0.003***	0.012***	-0.269***	-0.365***	-0.281***	-0.235***	-0.367***
disp. inc. x care/100	-4.392***	-0.221***	-0.367***	0.135***	-0.053***	0.489***	-0.094***	-0.047***	0.028***	0.237***	0.028***	-0.095***	0.384***	0.601***
leisure (female)	-0.251***	0.323***	-0.022***	-0.258***	-0.012***	0.303***	-0.195***	0.152***	0.463***	0.695***	1.042***	0.286***	0.947***	-0.011*
leisure (female) <sup>2</sup> /100	-0.271***	-0.173***	-0.188***	-0.156***	-0.139***	-0.192***	-0.198***	-0.157***	-0.172***	-0.220***	-0.134***	-0.195***	-0.140***	-0.202***
leisure (female) x age (female)/100	2.316***	-0.770***	0.896***	1.597***	0.654***	-0.717***	1.729***	-0.248***	-1.477***	-1.510***	-4.112***	0.266***	-3.588***	1.201***
leisure (female) x age <sup>2</sup> (female)/100	-2.228***	1.206***	-0.688***	-1.421***	-0.431***	1.211***	-1.648***	0.819***	1.997***	1.592***	5.143***	-0.306***	4.276***	-0.996***
leisure (female) x high-skilled (female)/100	-7.698***	-1.118***	-5.413***	-3.359***	-3.850***	-2.018***	2.666***	-2.458***	-2.599***	-5.380***	-7.635***	-2.268***	-5.946***	-3.715***
leisure (female) x unskilled (female)/100	-5.312***	5.361***	-3.605***	-0.172***	2.777***	5.108***	7.622***	1.992***	4.383***	-3.051***	0.417***	-6.180***	6.691***	1.021***
leisure (female) x kids 0-2/100	13.763***	12.499***	3.849***	9.152***	7.659***	6.696***	5.991***	11.760***	3.050***	9.307***	8.654***	28.626***	22.421***	7.553***
leisure (female) x kids 3-6/100	6.841***	4.073***	4.675***	5.642***	5.471***	2.402***	2.347***	5.376***	8.133***	1.206***	6.217***	-1.006***	7.417***	3.258***
leisure (female) x kids 7-16/100	3.329***	5.308***	1.737***	2.572***	2.751***	1.891***	1.649***	2.696***	2.428***	0.135***	2.549***	-2.348***	0.234***	5.110***
leisure (female) x married/100	-2.163***	-3.836***	-1.748***	1.922***	-4.106***	-2.995***	-1.451***	-1.649***	0.057	-7.800***	-9.774***	-7.816***	-2.956***	-8.443***
leisure (female) x handicap (female)/100	-6.990***	-3.285***	1.461***	-2.351***	-5.976***	-4.234***	1.113***	-4.334***	-3.061***	-2.057***	6.099***	2.746***	11.983***	6.620***
leisure (female) x care/100	-121.977***	-8.098***	-13.124***	4.194***	1.350***	16.379***	-5.885***	3.969***	0.423***	12.591***	-1.296***	-2.559***	7.005***	7.565***
fixed costs (female)	-2.321***	-1.606***	-1.887***	-1.309***	-1.485***	-1.955***	-1.229***	-0.810***	-0.955***	-1.432***	-1.057***	-1.326***	-0.897***	-1.588***
part-time 20h (female)	0.651***	0.820***	0.675***	0.543***	0.595***	0.552***	-0.171***	0.299***	0.069***	-0.118***	0.602***	0.467***	-0.068***	0.372***
part-time 40h (female)	0.758***	0.770***	0.766***	0.896***	0.971***	0.970***	0.639***	1.117***	0.760***	0.589***	0.739***	0.860***	0.611***	0.533***
Pseudo R <sup>2</sup>	0.221	0.206	0.173	0.179	0.163	0.173	0.179	0.185	0.178	0.185	0.171	0.199	0.151	0.178
Observations	11437503	11257855	11345187	10355898	10159471	10198664	10112403	9455250	9225580	9128826	8308972	9065280	8622271	9574397

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