The distributional effects of marital status and children: Evidence from large administrative panel data

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ABSTRACT. In this paper I study the effects of marital status and children on the income distribution using unique tax panel data. I control for unobserved heterogeneity by including individual fixed effects when estimating the mentioned effects. Using counterfactual analysis I am able to calculate the effects at the unconditional quantiles of income. My main findings are threefold. First, there is considerable heterogeneity in the income effects for women but not for men. High-income women are less negatively affected by a marriage and divorce. Second, marriage and divorce do not only significantly affect labour income but also total income. The heterogeneity of the effects for women is robust to the choice of the income aggregate. Finally, only looking at couples I find that being married and having children increase the income gap between men and women whereas the effect of divorce goes the opposite way.

Keywords: Marital Status, Children, Heterogeneity, Counterfactuals, Quantile Regression, Fixed Effects

JEL Codes: J12, D31, J13

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1 Introduction

Marriage, divorce and having children are important socio-economic indicators because of different reasons. One is that they have large economic consequences for income. There is a broad literature looking at the financial effects of being married, divorced or having children. The effects are different for men and women which makes them relevant since they affect gender inequality. This diversity arising due to gender affiliation is well documented. In addition to gender specific effects it could be that these impacts differ depending on individual income. It is the goal of this paper to show how diverse the effects are conditional on income levels. Either of these inequalities indicates that individuals face varying costs and benefits of marriage, divorce and having children.

Conceptually, the present analysis differs from previous studies in three dimensions. First, this paper applies quantile regression with fixed effects to estimate the income effects which has not been done before. This approach allows to control for unobserved heterogeneity while allowing the effects to vary across the distribution of income. However, some of the heterogeneity of the effects may be coming from differences in the control variables and not exactly from the variables of interest. Thus, it is essential to convert the effects at the conditional quantiles to effects which are independent of any covariates. I will do this by using counterfactuals. Second, the used administrative tax data[1] is unique since individuals can be identified even when they are taxed as part of a couple. Apart from being unique, the large extent of the data is another advantage as it makes it possible to estimate the effects very precisely. Third, the distinction between labour and total income makes it possible to differentiate between how much money people earn and how much rents and transfers they get. This may be important as transfers and rents may affect incentives to provide more or less labour supply. Further, it can be analysed whether rents and transfers reduce the heterogeneity of the effects. This relates to a debate about whether transfers and rent should or should not redistribute among individuals, i.e. whether inequality should be reduced.

In contrast to preceding studies, my results show that marriage and having children have heterogeneous effects for women but not for men. High-income women lose least or benefit most

[1]The data was made available in the context of the project Income and Wealth Inequalities in Switzerland (`www.inequalities.ch`) which is a project of the Swiss National Science Foundation. This project studies income and wealth trends with cantonal tax data and is carried out by the University of Bern and the Bern University of Applied Sciences.

due to marriage and having children. Regarding the direction of the effects, my results are in line with previous analyses. I find that being married is associated with a marriage premium for men and lower wages for women. This holds even when a broader income aggregate is considered. Being divorced does not affect men's labour income but has a positive effect for women. The effect becomes negative for men and largely positive for women when private transfers and rents are added to labour income. Finally, having children is again beneficial for men and negative for women. Additionally, I show that marriage and having children both increase the income gap between man and woman of a couple. Being divorced reduces the income gap but only in terms of total income. In the remaining part of this section I briefly review the relevant literature for my analysis.

Possible explanations for the so-called marriage premium for men are that marriage allows them to specialize and to be more productive (Becker, 1985; Korenman and Neumark, 1991; Chun and Lee, 2001) or that being married is associated with unobserved characteristics which are favourable for employers as well as for women (Hill, 1979; de Linde Leonard and Stanley, 2015). De Linde Leonard and Stanley (2015) conduct a meta-analysis showing that the marriage premium of 9-13% cannot be exclusively due to the specialization nor the selection hypothesis. The authors guess that employers use marriage as a favourable signal of stability. Other studies reject the selection hypothesis too (Antonovics and Town, 2004; Hersch and Stratton, 2000; Chun and Lee, 2001). Furthermore, married men are likely to work more than unmarried ones (Ahituv and Lerman, 2007). However, there are studies showing a substantial decline in the marriage premium over the last years (Blackburn and Korenman, 1994; Gray, 1997). For women, marriage is supposed to lower human capital investment incentives due to specialization (Goldin and Polachek, 1987). Additionally, married women are absent more frequently, have higher turnover rates (Malkiel and Malkiel, 1973) and are less mobile (Loughran and Zissimopoulos, 2009). However, a recent analysis by Juhn and McCue (2016) finds that married but childless women earn more than their single counterparts. Overall, marriage is likely to reduce women's wages.

The effect of divorce on economic circumstances is considered to be mixed for men and negative for women. Previous findings suggest that the impact is more severe for women (Jarvis and Jenkins, 1999; Andress *et al.*, 2006). Poortman (2000) shows that separation reduces total household income by 31% for men and by -46% for women. The main reasons for these negative effects are that a partnership dissolution leads to a loss of efficiency, forgone gains from specialization and to higher costs due to separate households (time and monetary costs). The difference between men and women stems from the facts that women get custody of the children more often, work fewer hours, have less human capital (Poortman, 2000) and depend more on their partner (Andress *et al.*, 2006). Mothers face the highest costs due to separation (Poortman, 2000). Most of these studies focus either on measures of well-being (and not on income) or only on short-term consequences and are therefore not directly comparable to the analysis of this paper. Peterson (1996) provides such a study and estimates the effect on economic well-being to be around -27% for women and +10% for men. Jarvis and Jenkins (1999) show that the effect is highly diverse across individuals for both, men and women.

Having children is shown in most studies to have a negative effect for women's wages (e.g. Waldfogel (1997); Anderson *et al.* (2002); Avellar and Smock (2003); Juhn and McCue (2016)). However, Lundberg and Rose (2000) find that mainly women which leave the labour force are affected. Only married men are known to benefit from a fatherhood premium (Killewald, 2013). Both the income gap and the wage gap within couples is shown to increase when entering parenthood (Angelov *et al.*, 2016).

The rest of the paper proceeds as follows. Section 2 describes the data since its uniqueness is one of the main gains of this analysis. In section 3 I present the theoretical background and the applied econometric method. Next, section 4 provides the estimation results whereas the main insights are summarized in section 5 where possible extensions and possibilities for future research are discussed too.

2 Data

This paper uses regional tax data to apply the regression methods. The data cover all taxable individuals and couples in the Canton of Bern, Switzerland, for the years 2002 to 2012. Two versions of the main dataset[2] are used: A dataset where the unity is an individual and another

[2]Individuals and couples are taxed differently and both types of taxpayers are treated in different ways within tax data. Therefore, the original dataset is a mix of two unities and can hardly be used without transformation. The individual dataset is constructed by splitting the partners where information on separate income is available. Individuals that are once married can be assigned to their partner even for years when they are not married. Hence, the dataset for couples consists of all couples that are at least married in one year between 2002 and

dataset where the unity is a couple. The first is constructed to estimate the effect on individual income whereas the second one is needed to show how the difference between the man's and woman's income of the same couple is affected. Both datasets contain information about individual income, marital status, number of children, age and sex. Individuals as well as couples can be identified with a constant ID number. The dependent variable for the following analysis treating individuals is yearly labour income in Swiss franc (CHF) from all of his or her jobs. This information is available for both persons of a couple as well as for all individually taxed persons. Labour income here is the net income which means that social security contributions have already been subtracted. One should be careful when comparing the results of this analysis to others because labour income depends not only on the wage level (per hour) but also on the employment level (full or part time); since no information about the level of employment of an individual is available, changes in wage level and changes in employment level cannot be separated. To give a more complete analysis of how marital status affects income, an additional outcome variables is analysed: total income. This variable additionally includes pensions from the retirement provision, life annuities, unemployment benefits, accident insurance payments, daily allowances, payments from the compensation fund as well as paid and received private transfers (child and partner alimony). These transfers and rents may be substantial for divorced or separated people and hence affect the "actual" amount of money that is available to the individual. Since individuals over 60 years old are excluded, these rents and transfers consist mainly of paid and received private transfers, widow's or orphan's pensions and early retirement provisions. The reason why total income is included in the analysis is that the listed income sources may affect the decision of how much an individual "has" to earn. For instance divorced people may earn less labour income just because they are (over)compensated by some other incomes. Furthermore, it is worthwhile not only to consider the job market value (labour income) but also some measure closer to the available income since this is more relevant for the individual.[3,4]

2012.

[3]For singles, labour income and total income are clearly correlated (men: 0.61, women: 0.89). The numbers are almost the same for individual income within couples.

[4]The total income variable provides not a complete picture of all incomes since e.g. rental income is not contained.

2.1 Descriptive Statistics

On average, the individual dataset consists of 516'000 individuals per year. The dataset for the couples is smaller with about 141'700 couples yearly. Several groups of people are excluded from the analysis (not contained in the number above) because they can not be compared with normal taxpayers.[5] Overall, the data is unlikely to suffer from substantial sample selection bias because it covers almost all relevant individuals living in the Canton of Bern and the excluded groups are relatively small. Table 1 summarizes the descriptive statistics for both datasets and for men and women separately over all years. Note that widowed individuals are in the reference category here since the analysis focuses on being divorced and not on being alone. This has implications for the rents since widowed women receive much higher payments from the mandatory occupational provision and the retirement provision.

Table 1: Summary Statistics for both Datasets

	Individual Dataset				Couples Dataset			
	Men		Women		Men		Women	
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Labour Income (CHF)	58074	54471	29429	28188	69989	60473	25340	26230
Total Income (CHF)	59626	87629	32701	30343	71512	99197	27148	28010
Number of Children	.66	1.02	.73	1.04	1.18	1.13	-	-
Age	39.56	11.83	39.62	11.72	43.74	9.45	41.25	9.52
Married in %	49.23	49.99	53.48	49.88	88.21	32.25	-	-
Divorced in %	10.36	30.48	13.11	33.75	5.21	22.22	-	-
N		2'794'885		2'881'291				1'555'849

Source: Tax data from the Canton of Bern

In the individual dataset, men earn on average about twice as much as women. This huge differential is surprising at the first glance but arises from the fact that married women often do not have any labour income. This income gap should not be confused with a classical gender wage gap analysis since this is a purely descriptive analysis. It remains unclear whether this differential can be explained by covariates or not. However, it is not the goal of this paper to

[5]The brackets indicate the average number of excluded individuals per year. First, the analysis excludes individuals below 18 (21'500) and above 60 (228'900) years olds as adolescents and retirees may have different income patterns. Second, specially taxed people are excluded. This means people which are only living in the Canton of Berne for one part of a year (10'000) or people that do not hand in their tax declaration (18'900). People that have negative entries for the income variables (90) are excluded too. This leaves the mentioned 516'000 individuals per year for the analysis. With tax data, there are always numerous people with an income of 0 (84'400). About half of them (39'600) never have an income in the years analyzed. If individuals with no income were excluded this would result in a selection bias which is the reason why they remain in the data.

explain this gap.[6] For the other variables, Table 1 shows that men and women have almost identical summary statistics. A person is considered married in years where a person is paying taxes as part of a couple. The percentage of married people can vary between men and women since people may be married with a partner paying taxes outside the Canton of Bern or someone older as individuals over 60 are excluded. Individuals are treated as divorced ones when they were once married and did not remarry again until the relevant year.

The same groups of individuals are excluded for the couples dataset. The raw wage differential between men and women is even higher for couples than for individuals. This could be due to some sort of specialization, selection or the marriage premium as presumed by others. It has to be mentioned that this dataset may suffer from a selection bias since couples that are never married cannot be identified.

2.2 Scope of the Analysis

A requirement for the estimation of QR models is that the outcome variable is continuously distributed. In the present case this is only partially given since labour income has a masspoint at 0. Figure 1 points out that about 16% of the population have a labour income of 0 which violates the strict continuity assumption. Because of this, the coefficients for the quantiles below the first quartile should be treated carefully. As all regression models include individual fixed effects, effects can be estimated as well for the lowest quantiles. The same issue is less problematic for couples. Here, the line shows the difference between husband and wife. Hence, the difference is negative in cases where the woman earns more.[7]

[6] The available tax data does not contain variables such as education and job tenure which explain parts of the income gap.

[7] It is unclear whether the dependent variable should be transformed or used in absolute terms. Different model specifications have been tested with the Box-Cox transformation tests but the results are rather unclear since the dataset is large enough to reject all transformations. Therefore, the linear model specification is used.

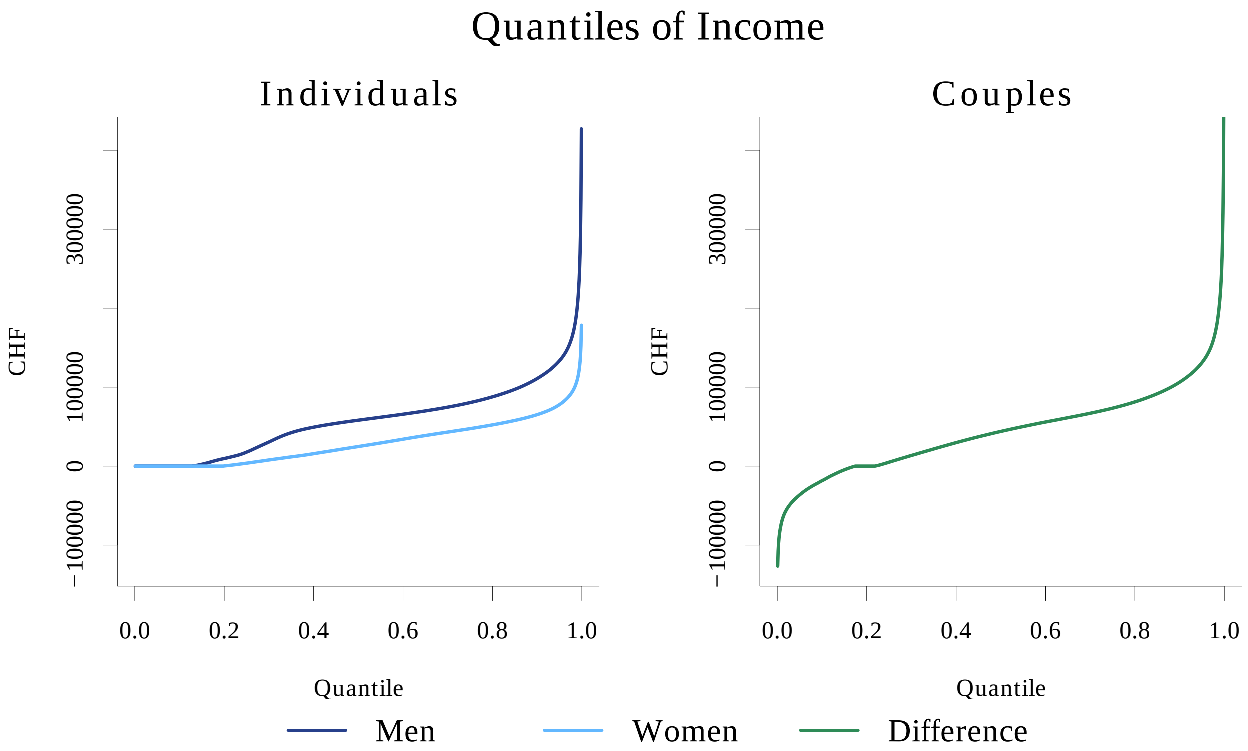

Figure 1: Quantiles of labour income for individuals and quantiles of income difference (income men - income women) for couples. All individuals and couples of all years are included. Source: tax data from the Canton of Bern.

Unobserved and non-constant covariates affecting the outcome would result in a bias since the fixed effects only capture constant characteristics. Experience, job tenure or a change in the industry someone is working in could potentially be such covariates causing an omitted variable bias. A change in the hierarchy level or the level of complexity of a job could influence income as well. As these factors attribute to the income differential between men and women, the estimated effects will most probably overestimate the effect of being married, divorced or having children. Similarly, it could be that working and not working individuals have different non-constant and unobserved characteristics and hence cannot be compared. However, it is likely that such covariates as gender, education, skill and citizenship which cause long-term unemployment are constant. Still, if the effect of those time invariant variables changes over time, this would introduce a bias. Considering that the data captures a relatively short time period, this should not cause large biases. Given that, I do not expect that these issues will affect my estimates.

Finally, there is an issue considering reverse causality. If income affects the decision to get married or divorced, then the models studied here would not identify the true effects (see e.g. Kalmijn *et al.* (2007)). This may be the case because of tax reasons since the sum of taxes could be higher for couples than if they would remain individually taxed. A study of the Swiss federal tax office (Peters, 2014) finds that this disadvantage for married couples compared to singles living together is relatively small. The disadvantage is larger with higher income and when both individuals earn almost the same amount of money. Thus, only a small number of couples are affected by large incentives to remain unmarried. Again, I do not expect that this issue will affect my estimates.

3 Inference

3.1 Introduction and FE-QR

Fixed effect quantile regressions (FE-QR) offer two major advantages compared to standard models as ordinary least squares (OLS). First and foremost, the effects of interest are allowed to vary across the conditional distribution of the outcome variable. This enables the researcher to go beyond average effects analysing the heterogeneity of an impact. Second, including fixed effects removes the dependence from unobserved but constant characteristics. These models are more likely to capture the true effects in settings where unobserved variables are suspected to be influential. That is a common procedure in similar studies. Applying an FE-QR estimator yields conditional effects which depend on the values of the covariates. However, this may not be the effect we are looking for. A part of the heterogeneity of the results will always stem from differences in the control variables which is not of interest here. Imagine an individual which is at the bottom of the (unconditional) income distribution, say at the first quartile. Further assume that this person has a high income compared to others which are similarly old. Once we include age in our model, the individual may be at the top of the conditional distribution as she has a high income *given* the covariates. Consequentially, conditional quantile effects may be difficult to interpret. Thus, I define counterfactuals distributions to get unconditional effects. This last step is particularly important in the context of fixed effects. Beside the obvious intention to analyse the heterogeneity of a particular effect, QR methods offer various other advantages compared to standard procedures as OLS. For instance, QR models are robust to outliers and are equivariant to monotone transformation (Koenker, 2005) which may be a favourable feature as e.g. OLS does not achieve equivariance. A crucial requirement for all FE models and hence for FE-QR models is the availability of panel data to estimate the fixed effects. However, the inclusion of the fixed effects is more complicated than in the linear regression setting since the quantile function is not linear. This makes it impossible to get rid of the fixed effects by first differencing or demeaning. There are different possibilities of how the fixed effects can be included. Using a Kolmogorov-Smirnov version of the Hausman test (Hausman, 1978) I will be able to decide which approach to use. It turns out the be the model following Kato *et al.* (2012). This is the first paper to use FE-QR models and counterfactual theory to estimate the income effects of marriage, divorce and children. This section presents the applied FE-QR model and the way I use counterfactual analysis.

One of the first approaches to quantile regression including fixed effects was the one by Koenker (2004). For individual $i = 1, ..., n$ and time period $t = 1, ..., T$ he suggested the following model specification:

$$Q_{Y_{it}}(\tau|\mathbf{X}_{it}, \alpha_i) = \alpha_i + \mathbf{X}_{it}'\beta(\tau), \tag{1}$$

where Y_{it} is an outcome variable of individual i at time t, $\mathbf{X}_{it}$ is $N \times K$ matrix of covariates including a constant where N is the number of observations and K is the number of different regressors, $\beta(\tau)$ is a coefficent vector and α_i is an individual specific fixed effect. In this representation, the left hand side is the τ^{th} conditional quantile of Y_{it} given $\mathbf{X}_{it}$ and α_i.[8] Throughout the paper this notation will be the same. Note that in equation (1) the fixed effects are pure location shift parameters whereas the effects of the covariates $\mathbf{X}_{it}$ are allowed to depend on the quantile. The inclusion of a potentially large number of fixed effects increases the variability of all estimates and hence shrinkage of the fixed effects towards a common value is needed to reduce this variability. Koenker (2004) and Lamarche (2010) propose different ways of how this can be achieved. Another issue arises from the fact that only a limited number of time periods are available to estimate the fixed effects causing the incidental parameter problem

[8] This paper only treats QR models with additive fixed effects. There is a literature considering non-seperable models see Graham and Powell (2012) or Chernozhukov *et al.* (2013a). It could be that the individual parameters are not only shifting the location but also affecting the scale which would not be captured by these models. In this sense allowing only for additive separable fixed effects is a restriction.

(Neyman and Scott, 1948). Therefore, a bias correction is essential such that the estimator is consistent. Following Dhaene and Jochmans (2015) for all models a split-panel jacknife bias correction is applied.

I will use a slightly more general version of the FE-QR model in equation (1). The applied model will follow the approach by Kato *et al.* (2012). The major difference to equation (1) is that the fixed effects may now depend on the quantile which leads to a more flexible model specification. The model can be represented by equation (2) whereas the estimation of the coefficient vector is done by the minimization problem in equation (3).

$$Q_{Y_{it}}(\tau|\mathbf{X}_{it}, \alpha(\tau)) = \alpha_i(\tau) + \mathbf{X}_{it}'\beta(\tau) \tag{2}$$

$$(\hat{\alpha}(\tau), \hat{\beta}(\tau)) = \underset{\alpha,\beta}{\text{argmin}} \frac{1}{nT} \sum_{i=1}^{n} \sum_{t=1}^{T} \rho_\tau(Y_{it} - \alpha_i(\tau) - \mathbf{X}_{it}'\beta(\tau)), \tag{3}$$

where $\rho_\tau(u) = u\{\tau - \mathrm{I}(u \leq 0)\}$ is the check function of Koenker and Bassett (1978) and $\mathrm{I}(\cdot)$ is the indicator function. Here, $\hat{\alpha}_i$ is vector of all individual specific fixed effects. Note that estimating equation (3) may be computationally demanding in large problems as every fixed effect is a separate parameter to be estimated. For this estimator to be consistent and asymptotically normal it is required that $\frac{n^2(logn)^3}{T} \to 0$ which is a more restrictive condition than comparable estimator require (e.g. Canay (2011)).

For the estimated FE-QR models the covariate matrix $\mathbf{X}_{it}$ includes a constant, two dummy variables for the marital status (being married/divorced), a dummy variable for having children, the interactions of kids with each marital state and a linear as well as a quadratic term for the age. All these covariates are interacted with a dummy variable identifying the gender of the individual to get the separate effects for men and women. The dummy variable for being married remains 1 even if this person gets divorced. Thus, the dummy variable for divorce identifies the difference in income between married and divorced individuals. Note that including year fixed effects into a model according to equation (2) would cause the matrix $\mathbf{X}_{it}$ to be singular since the individual fixed effects together with the linear age term already account for year effects. Thus, no year fixed effects are included. Parts of the literature suggest that the effect of marriage (Juhn and McCue, 2016) and divorce (Andress *et al.*, 2006) is different for parents than for childless couples. I explicitely allow for the fact that the effect of kids may differ between single, married and divorced individuals by including the interaction terms above. All QR models are estimated in R (R Core Team, 2016) with the package 'quantreg' by Koenker (2016). A sparse matrix formulation is chosen due to the considerable number of fixed effects. The models are estimated using the Frisch-Newton algorithm for QR which is described in Portnoy and Koenker (1997).

3.2 Counterfactuals

Having estimated equation (3), one could answer questions like: what is the effect of being married on labour income for a person at the first quartile given that she is 36 years old, has no children and is herself (fixed effect). As already pointed out, this is not the effect we are looking for as we want the results to be independent of the covariates. Removing this dependency is done by calculating counterfactual distributions.

This section follows closely the notation and definition in Chernozhukov *et al.* (2013b). Define $F_{Y|\mathbf{X},M,D}(y|\mathbf{x},m,d)$ to be the conditional distribution function of the outcome Y for individuals given the covariates $\mathbf{X}$, M and D where the latter two are dummy variables for married and divorced. Note that I explicitly write M and D separately to emphasize that I will vary these specific covariates later on whereas X contains all covariates which will not be changed. The estimation of the quantile regression in equation (3) yields the conditional quantile function $Q_{Y|\mathbf{X},M,D}(y|\mathbf{x},m,d)$. To get the conditional distribution function we have to apply equation (4):

$$F_{Y|\mathbf{X},M,D}(y|\mathbf{x},m,d) = \int_0^1 1(Q_{Y|\mathbf{X},M,D}(u|\mathbf{x},m,d) \leq y)du. \tag{4}$$

Let $F_{\langle Y|M=1,D=0\rangle}(y)$ be the counterfactual distribution of income for all individuals if everyone was married and no one was divorced. This distribution cannot be observed and will thus be calculated in following way.

$$F_{\langle Y|M=1,D=0\rangle}(y) = \int_{\mathbf{X}} F_{Y|\mathbf{X},M,D}(y|\mathbf{x},m=1,d=0)dF(\mathbf{x}) \tag{5}$$

Technically, one switches the dummy variable for married to 1 and the one for divorced to 0 for all individuals and computes the potential distribution of income given that all other covariates do not change. It has to hold that $0 < Pr(M = 1, D = 0|X) < 1$ for all $x \in X$ as a condition for the support. Taking the left inverse of the counterfactual distribution one is able to get the counterfactual quantile function $Q_{\langle Y|X,M=1,D=0\rangle}$. Analogously, it can be calculated what the counterfactual quantile function would be if no one would be married $Q_{\langle Y|X,M=0,D=0\rangle}$ implying that nobody is divorced. Finally, let $\Delta_{QE_M}(\tau)$ be the unconditional quantile effect of being married which is defined as the difference of these two quantile functions.

$$\Delta_{QE_M}(\tau) = Q_{\langle Y|M=1,D=0\rangle} - Q_{\langle Y|M=0,D=0\rangle} \tag{6}$$

Here, the effect does no longer depend on the values of X as they are the same for both quantile functions. The effects of divorce and having children are computed very similarly. Comparing the distribution of income in a case where everyone would be divorced with a with a case in which everyone was married yields the quantile effect of divorced. The quantile effect of having children is much simpler as we only have to vary one dummy variable. Consequentially, the effects can be written as follows.

$$\Delta_{QE_D}(\tau) = Q_{\langle Y|M=1,D=1\rangle} - Q_{\langle Y|M=1,D=0\rangle} \tag{7}$$

$$\Delta_{QE_K}(\tau) = Q_{\langle Y|C=1\rangle} - Q_{\langle Y|C=0\rangle} \tag{8}$$

All these effects are estimated for men and women separately. For notational simplicity I dropped the dummy variable for gender F but all effects are computed conditional on either $F = 0$ or $F = 1$ respectively. To get standard errors of these effects, a bootstrap technique with replacement and sub-sampling is applied.[9] From these bootstrap results the uniform confidence bands are computed as outlined in Chernozhukov *et al.* (2016). As these models all yield potentially biased results due to the incidental parameter problem I use a split panel jacknife bias correction after having calculated the quantile effects.

[9]The models are estimated 500 times with a sample of 10% of the main dataset. Individuals are either included or excluded over all years to make sure that the estimates are precise.

3.3 Tests

In this analysis I study the quantile effects at all parts of the distribution of the outcome. Therefore, it is straightforward to test whether these effects actually vary across quantiles or not. One way to do this is applying a Kolmogorov-Smirnov test as outlined in Chernozhukov and Fernndez-Val (2005). In order to apply this test, the following test statistic is used for a single quantile effect to test $H_0 : \hat{\Delta}_{QE}(\tau) = \hat{\Delta}_{QE}(0.5)$ vs. $H_1 : \hat{\Delta}_{QE}(\tau) \neq \hat{\Delta}_{QE}(0.5)$:

$$T^{\star} = \max_{\tau \in (\epsilon, 1-\epsilon)} T(\tau), \text{ where } T(\tau) = \frac{\sqrt{n}|\hat{\Delta}_{QE}(\tau) - \hat{\Delta}_{QE}(0.5)|}{s.e.(\hat{\Delta}_{QE}(\tau) - \hat{\Delta}_{QE}(0.5))}. \tag{9}$$

As for the point estimates, all percentiles are calculated. Further, this test statistic is bootstrapped[10] and recentered to get

$$T_b^{\star} = \max_{\tau \in (\epsilon, 1-\epsilon)} T_b(\tau), \text{ where } T_b(\tau) = \frac{\sqrt{m}|\hat{\Delta}_{QE_b}(\tau) - \hat{\Delta}_{QE_b}(0.5) - \hat{\Delta}_{QE}(\tau) + \hat{\Delta}_{QE}(0.5)|}{s.e.(\hat{\Delta}_{QE}(\tau) - \hat{\Delta}_{QE}(0.5))} \tag{10}$$

and m is the size of the subset used for bootstrapping. In a next step, the p-value is calculated depending on the number of cases in which $T_b^{\star}$ is larger than $T^{\star}$:

$$\text{p-value} = \frac{1}{B} \sum_{b=1}^{B} \mathrm{I}(T^{\star} \leq T_b^{\star}), \tag{11}$$

where B is the number of bootstrap replications. This test gives a good indication whether or not $\hat{\Delta}_{QE}(\tau)$ is constant across quantiles. A low p-value indicates that the estimates differ a lot and hence there is heterogeneity in the quantile effects. Note that $\hat{\Delta}_{QE}$ is a scalar in these equations. Similarly, I test whether the results of differ between the FE-QR model of Kato *et al.* (2012) and the approach by Canay (2011). The null hypothesis for this test is $H_0 : \hat{\Delta}_{QE,kato}(\tau) = \hat{\Delta}_{QE,canay}(\tau)$ against $H_1 : \hat{\Delta}_{QE,kato}(\tau) \neq \hat{\Delta}_{QE,canay}(\tau)$. The exact specification of the test can be found in the Appendix. It turns out that I can reject the null hypothesis implying that the model by Kato *et al.* (2012) should be used as it represents the more general case.

[10] Due to the considerable size of the dataset a bootstrap with subsampling (10%) and 100 replications is used.

4 Results

4.1 Marriage

The results chapter is grouped by the different type of effects. In each subsection I first present the effects for individuals followed by the effect on the difference in annual income between men and women within a couple. All figures will plot the effects on total and labour income at once to make a comparison possible. Starting with the effects of marriage on labour and total income, figure 2 presents the first results. Being married causes a higher income for men and a lower income for women. For men, the effects are rather homogeneous but for women there seems to be considerable heterogeneity regarding how marriage status affects income. To the best of my knowledge this is the first paper which finds that these effects are heterogeneous.

Figure 2: Counterfactuals based on the FE-QR estimation results following the apporach by Kato *et al.* (2012). The dependent variables are annual labour and total income in CHF. Additionally included covariates are age and age^2 (both interacted with gender). Standard erros are computed with an exchangable bootstrap (500 draws with 10% of the sample). Source: Tax data from the Canton of Bern.

The marriage premium for men clearly exists but is smaller than suggested by previous findings (de Linde Leonard and Stanley, 2015) and the corresponding negative effect for women is in line with the literature too. The fact that high-income women face the lowest negative impact due to marriage supports the hypothesis that economic autonomy matters (Andress *et al.*, 2006). These women bear the highest opportunity costs of reducing working time. This may be a reason why they are not as negatively affected as others. At the top, the reduction in income is about one third smaller than at the bottom of the distribution. Note that constant effects in CHF as the one for men implies very different relative effects. Thus, people at the top quantiles are relatively much less affected by the fact that they marry. The results for men suggest that marriage increases e.g. the productivity or the labour supply by some constant amount which is independent of current income. While interpreting the results we have to keep in mind that income from tax data is a product of wage and working time. Thus, it is impossible to identify the separate effect of those factors.

The effects on total income are generally lower than the ones on labour income. A reason for this is that married individuals get the lowest rent payments in all categories, primarily from occupational provision. A detailed table for all rents and transfers of individuals can be found in the Appendix. Including rents and transfers only shifts the results downwards but does not alter the shape of the curves. Thus, I can say that these additional sources of income do not reduce the heterogeneity of the effect. This may be relevant from a policy point of view as transfers and rents are instruments of redistribution. Alike figure 2, some graphs will show kinks and wiggly results around the second centile. This stems from the fact that below this threshold the income distribution is almost flat at a very low level. Thus, within this centile there is quite a high variance of income. This may lead to a rather imprecise estimation.

The following results show the impact of marriage on the difference between the man's and woman's income within a couple. Parts of the literature (Angelov *et al.*, 2016) use this difference to analyse within couple inequality controlling for scale effects. Note that these models use a different dataset which only contains people that were once married. Included covariates are a linear and a quadratic term of the age of the husband, two dummy variables for each marital state, a dummy variable for having children as well as the interaction of having children with each martial state. The interpretation is somehow different than in the preceding models since the outcome variable is now a differential. The lowest quantiles are couples where the woman earns more than the men. At the top quantiles, men earn much more than women which can be seen from right part of figure 1. The results have to be interpreted in the following way: Being married increases the income differential by around 10'000 to 15'000 CHF depending on how much more the man earns.

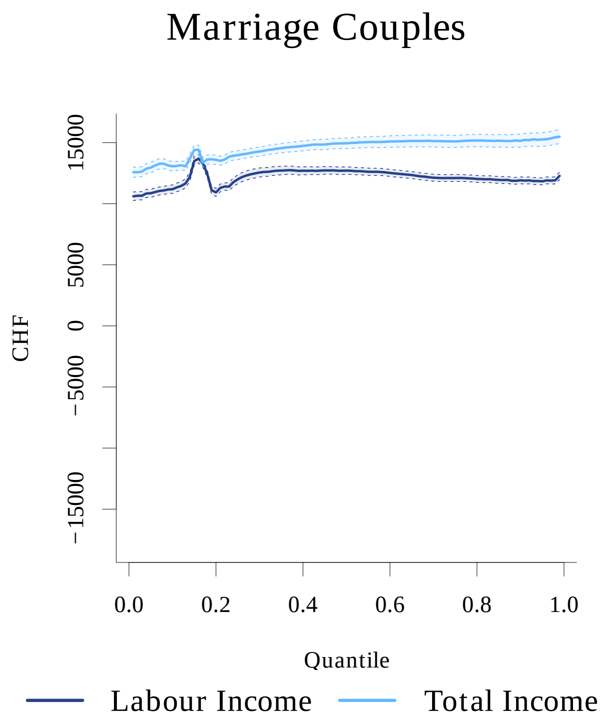

Figure 3: Counterfactuals based on the FE-QR estimation results following the apporach by Kato *et al.* (2012). The dependent variables are annual labour and total income in CHF. Additionally included covariates are the husbands age and age^2. Standard erros are computed with an exchangable bootstrap (500 draws with 10% of the sample). Source: Tax data from the Canton of Bern.

Interpreting the income gap as measure of inequality within a couple, one could say that being married increases this inequality. This is not surprising since married couples are probably affected by some specialization. Further, it could be that couples optimize their effort divison into housework and labour supply. This would imply that men increase their working time as they have higher wages on average. Basically, the same argument would hold for a household in which the woman earns more. My results suggest that in these households no comparable decision is taken. One could interpret this as a sign of traditional role concepts. The moderate heterogeneity of the effect matches with the results in figure 2 as low-income women face larger negative effects. Overall, there is only little heterogeneity. This implies that specialization due to marriage is about the same across the distribution of income. Married men get more rents and transfers than their female counterparts. This is why marriage increases the gap between men and women even more when total income is considered. Apart from that, the interpretation of the result remains exactly the same.

4.2 Divorce

Turning to the impact of divorce, note that these graphs plot the counterfactual effect from being married to being divorced. Thus, the reference category are no longer single individuals. The impact on income is much larger compared to marriage, this is why the scale of the graphs is different. Figure 4 shows that men's labour income is unaffacted by getting divorced whereas women earn more through labour supply. The latter effect is constant and around 4'000 to 6'000 CHF. I offer a possible explanation for this positive impact, namely that there is a necessity to earn more due to lost economies of scale of marriage and higher costs. Splitting up a common household may be an example of that. Previous studies have suggested that the effect of divorce is negative and more severe for women than for men (e.g. Andress *et al.* (2006)). However, most of these studies focus on some measure of well-being or household income. My results are new as they show that divorce potentially has large positive effects for women. This indicates that women adjust their labour supply or get higher wages when they are divorced. The latter could be a signalling effect. It remains an open question whether this additional income is enough to cover the rising costs and hence I cannot infer something about the welfare effect of divorce. The issue gets even more pronounced when we consider the effects on total income. Here, divorced women benefit largely from private transfers paid by men. These transfers are partner and child alimonies to cover costs due to divorce or arising from child custody. Important to mention is that received private transfers are a function of the ex-partners income but as well of what is needed, especially when there are children. It is thus not possible to interpret this income as total available income since the transfers may be high to cover additional costs due to separation. Nevertheless, my results are different than earlier findings as they show a positive effect for women. In contrast to labour income, men's total income is negatively affected by divorce. This is in line with what others have found (Poortman, 2000).

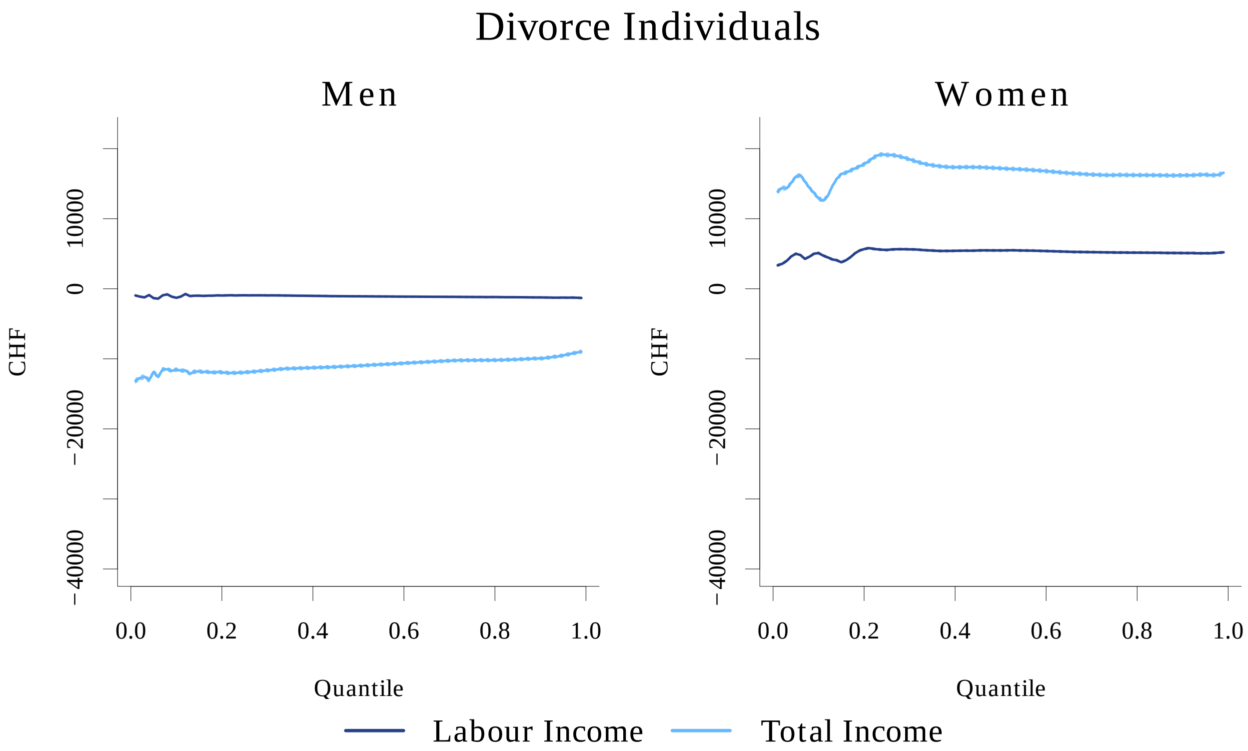

Figure 4: Counterfactuals based on the FE-QR estimation results following the apporach by Kato *et al.* (2012). The dependent variables are annual labour and total income in CHF. Additionally included covariates are age and age^2 (both interacted with gender). Standard erros are computed with an exchangable bootstrap (500 draws with 10% of the sample). Source: Tax data from the Canton of Bern.

At the lowest quantiles, the effect is rather volatile. This may come from the fact that private transfers depend on the ex-partners income which may be low as income between partners is generally positive correlated (0.32 before marriage). The effect is declining after the third centile as from there on women do not need these transfers as urgently as before. Because of the same reason high-income men pay slightly less transfers. Considering the magnitude of these effects, it should be said that they seem fairly homogeneous which is partly due to the large scale of the y-axis. The effect on total income varies between 13'000 and 19'000 CHF for women and between -10'000 and -8'000 CHF for men. Especially for women, this is still quite a large range compared to their average total income.

Looking at the effect for couples, they logically follow from what we have seen in figure 4. Remember that this is not necessarily the case as the datasets are different and the included fixed effects may capture not exactly the same. The difference in labour income is reduced by around 10'000 CHF which is slightly lower than by how much marriage increases this differential. Women may not be able to increase their labour supply flexibly after getting divorced since they miss experience and tenure. This could be why divorce does not reduce the difference in income by the same amount as marriage did increase it. Adding the effects for men and women in 4 would result in a lower total impact. This may be due to the fact that in the second class of models where I only consider couples I am able to control explicitly for within couple effects. Overall, the reduction of the income gap is mainly due to rents and benefits (~ 72 % of the total effect) and only a small part comes from an adjustment in labour income (~ 28 %). This fact underlines the importance of additional income sources when studying the effects of divorce.

Divorce reduces the difference in total income more at the bottom of the distribution. This is where women earn a lot compared to their male counterparts. It seems to be the case that these women get even larger rents and transfers. This suggests that high-income women benefit most from divorce which does not directly follow from the results in figure 4.

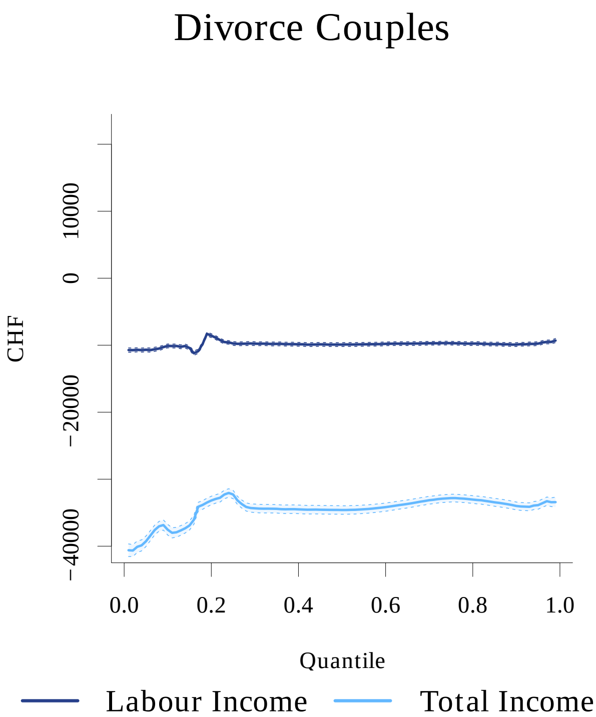

Figure 5: Counterfactuals based on the FE-QR estimation results following the apporach by Kato *et al.* (2012). The dependent variables are annual labour and total income in CHF. Additionally included covariates are the husbands age and age^2 . Standard erros are computed with an exchangable bootstrap (500 draws with 10% of the sample). Source: Tax data from the Canton of Bern.

4.3 Having Children

The last part of this section treats the impact of having children on income. Having children reduces women's labour income by up to 5'000 CHF. Again, this result is close to what others find (e.g. Anderson *et al.* (2002)). This reduction in income most probably stems from a reduction in working time rather than from a lower wage. For men, having children causes a higher income which is likely associated with a necessity to earn more due to higher costs. The magnitude of the effects is far lower than with the effects of marriage and divorce which suggests that marital status is more important for income. To some extent this result is new as it shows that once you control for marital status, having children has a minor impact on income. Note that being married and having children is correlated. However, as these models identify the change in one of the dummies we do not have to worry about multicollinearity because the changes of these are much less correlated. In contrast to the effect of marriage, women do not seem to reduce working time less at the top of the income distribution.

Individuals having children benefit from child alimonies which implies that they have a higher total income. The difference is around 2'000 CHF for men and between 0 and almost 5'000 for women. Figure 8 points out that women at the top of the distribution get far more transfers and rents. However, the reason for that is more subtle. Comparing women with and without children throughout the distribution of labour income, one realizes that at the bottom of the distribution the former get much lower rents. The largest part of that difference comes from the retirement provision and the mandatory occupational provision. Thus, it is not that having kids increases some rent income but rather that at the bottom of the distribution there are many women with high rent income and no kids.

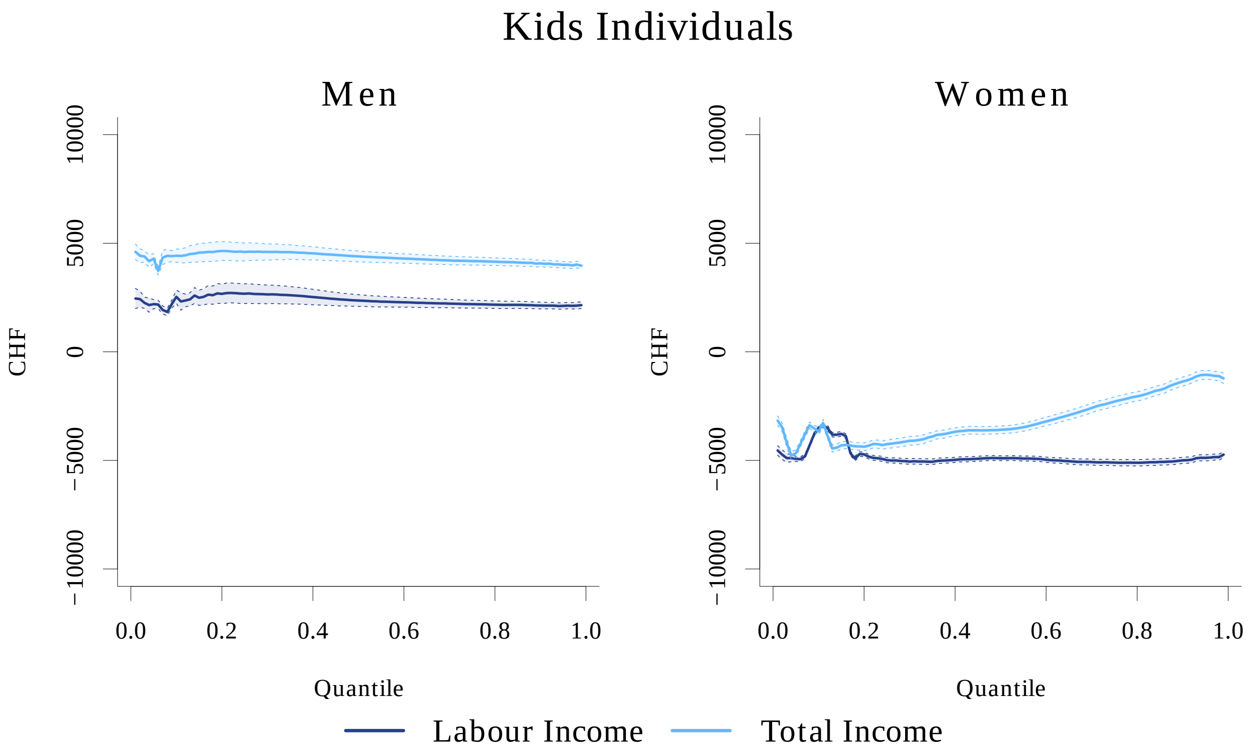

Figure 6: Counterfactuals based on the FE-QR estimation results following the apporach by Kato *et al.* (2012). The dependent variables are annual labour and total income in CHF. Additionally included covariates are age and age^2 (both interacted with gender). Standard erros are computed with an exchangable bootstrap (500 draws with 10% of the sample). Source: Tax data from the Canton of Bern.

The effect of having children increases the income gap between men and women by around 3'000 to 10'000 CHF which is in line with what others find (Angelov *et al.*, 2016). For labour income the model for individuals and the one for couples yield exactly the same result. One can see this by adding the two effects in figure 8 which gives the effect in figure 7. The same is true for total income. However, there is some benefit from plotting the impact on the total income gap as it becomes clear that the increase in the gap is larger where the difference in income is already large. This finding provides evidence for the fact that rents and transfers increase the inequality between couples. As already pointed out, this mainly is due to the higher rents of childless women at the bottom of women's the distribution. Similarly to the effect of marriage, we see no increase of high-income women's income due to children. It seems that specialization of the couple only goes in one direction.

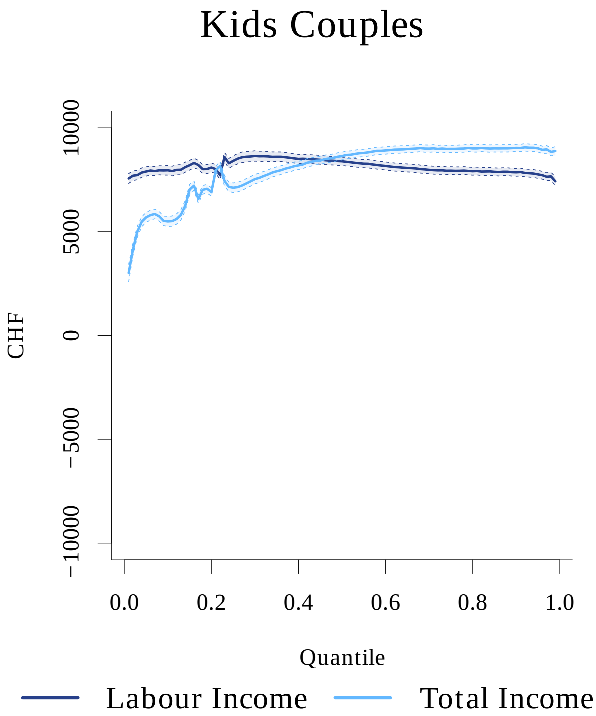

Figure 7: Counterfactuals based on the FE-QR estimation results following the apporach by Kato *et al.* (2012). The dependent variables are annual labour and total income in CHF. Additionally included covariates are the husbands age and age^2. Standard erros are computed with an exchangable bootstrap (500 draws with 10% of the sample). Source: Tax data from the Canton of Bern.

All tests outlined in section 3 yield a p-value of 0. One explanation for the low p-values is the large size of the datasets used which allows a quite precise estimation. Consequently, the bootstrapped results differ little from the point estimation results. I conclude that all effects vary across quantiles.

So far, the literature focused on household income (Poortman, 2000) or some sort of economic well-being (Peterson, 1996) but not explicitly on the difference between labour income and other aggregates of individual income.[11] The estimation results indicate that the effect of divorce and having children heavily depend on which measure of income is considered. Especially in the case of divorce the effects are much larger for total income. This clearly suggests that only looking at labour income does not reveal the whole issue. Similarly, the effect of having children for women depends on rents and transfers which underlines the importance the income aggregate looked at. These results imply that rents and private transfers may largely affect the incentive or necessity to earn money through labour supply. Thus, it is crucial to study the amount

[11] Jarvis and Jenkins (1999) distinguish between different measures of income. However, their analysis is more descriptively orientated.

of rents and transfers across the distribution of labour income. A descriptive analysis shows that rents in total are a decreasing function of labour income. Similarly, paid private transfers are higher for high-income people. A graph plotting the mean values of those variables for each quantile can be found in the Appendix. Although the rents and transfers seem to have a redistributive effect, including them does not reduce the heterogeneity of the analysed impacts. The reason for that is that there are large differences in rent payments depending on marital status and gender. Married and single men are almost equally well off while divorced men have to pay a lot of transfers. Divorced women receive by far the highest payments followed by single and widowed women. Thus, the effects remain heterogeneous even though rents and transfers are higher for people with a low level of labour income. Put differently, I can say that the variation in rent and transfer income is larger across marital status and gender than across labour income. For women, being married and being divorced has even more diverse effects when total and not labour income is considered. The change in the results from labour income to total income may be interesting from a policy perspective too. Since private transfers and rents depend on civil law, policy makers directly influence these income aggregates. Depending on whether income inequality is desirable or not, these results may contribute to a better understanding on how private transfers and rents affect income.

Overall, high-income women benefit the most (or lose least). In the case of marriage, it could be that not all women are equally affected by some sort of specialization within the couple. In particular, it may be that high-income women face higher costs of reducing working time and are hence more likely keep on working. In principle this argument applies to men too, but since more men work and most men work full time[12] it is less relevant. Apart from the effect of working time, it could be that wages are lower too. However, the effects of working time and wage cannot be identified separately in this paper. There are numerous studies e.g. Loughran and Zissimopoulos (2009) which find negative wage effects for women caused by marriage and hence it is likely that the negative effects found here are due to both lower working time and lower wages.

[12] Two things have to be considered: How many men and women actually work and how much they work. Data for Switzerland suggests that 88% of all men and 75% of all women do work (average for 2002-2012). 57% of working women work below 90% of a full time equivalent which is much more than the part-time working group of men (12%). The data can be downloaded from the Federal Statistical Office BFS (2017b) and BFS (2017a).

5 Conclusion

The existing literature suggests that being married or divorced as well as having children tend to decrease the income of women. For men, there is a well documented marriage premium but it is rather unclear how divorce and children affect income. Being in line with the previous findings for the effects of marriage and children and partly with those of divorce, this paper contributes in three ways. First, I show that marriage and divorce have heterogenous effects for women but not for men. Women's income is reduced least or increased most at the top conditional quantiles of income. In couples, the income gap between man and women is reduced most or increased least in relationships where the women earns more than their male counterparts. This provides evidence for the fact that economic autonomy matters as suggested by Andress *et al.* (2006). Divorce increases women's income which is a new finding compared to similar studies. Second, the results change when additional income sources such as rents and private transfers are included. Being married then reduces women's income even more. It looks different in the case of divorce: Men now face a large negative impact whereas women do benefit much more due to private transfers. Last, only considering the difference in incomes within couples the results show that being married and having children increase the income gap. This holds for all parts of the distribution. Being divorced reduces the same gap as women need to work more to cover the additional costs arising from separation.

Further, the results contribute by showing that rents and transfers do not reduce the heterogeneity of the effects although low-income people get more of them. This is important to realize in the context of redistribution. Policy makers may want to increase or decrease income inequality which could be done by changing the rents and transfer schemes. Thus, the results are important from a policy perspective too.

In a more technical perspective, this paper applies a new econometric method to estimate the quantile effects at the unconditional distribution of the outcome. Including fixed effects into such a model is promising as potential omitted variable biases through constant covariates are avoided. This is a crucial advantage of this paper since e.g. education or nationality are known to affect income but are taken care of through the fixed effects. In this perspective, this paper uses the known fixed effects methods (e.g. by Korenman and Neumark (1991), Hersch and Stratton (2000)) and combines them with QR methods which makes a more sophisticated analysis possible.

Using unique regional tax data, the presented estimates can give insights in how individual earnings are affected. However, it is impossible to decompose income in wage and hours worked which makes a classical wage study infeasible. A possible task for future research would be to apply the FE-QR models and counterfactual theory to cases where wage and not income is the dependent variable. Another track for possible research could be the extension to wealth since marriage, divorce and children may affect individual welfare through this channel too. Finally, the analysis of the allocation of incomes within couples could be extended. For instance, it would be possible to apply distribution regression methods (Chernozhukov *et al.*, 2013b) to model the bivariate density of a couple's income.

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6 Appendix

6.1 Descriptive Statistics

Table 2: Rents and Transfers, Individuals (Means in CHF)

	Single/Widowed		Married		Divorced	
Income Source	Men	Women	Men	Women	Men	Women
Public retirement provision (AHV/IV)	1039	1711[13]	662	388	1276	1697
Mandatory occupational provision	202	703	427	139	717	478
Life annuities	18	23	36	12	59	38
Accident insurance payments	77	140	157	23	254	64
Unemployment benefits	470	422	569	277	1008	713
Disability and military insurance payments	164	126	223	66	343	202
Income compensation payments	233	12	22	15	19	16
Received private transfers	4	311	9	155	86	8612
Paid private transfers	-244	-3	-338	0[14]	-10031	-87
N	1'139'042	1'005'182	1'403'200	1'533'153	252'644	342'957

Source: Tax data from the Canton of Bern.

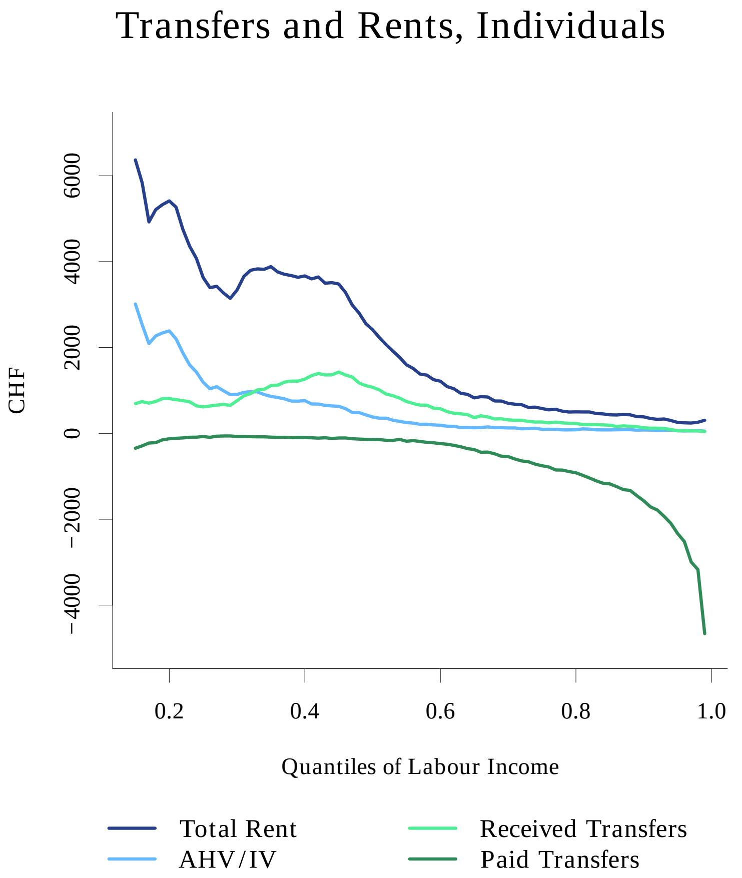

Figure 8: Means of transfers and rents per quantile. Source: Tax data from the Canton of Bern.

[14]Women more often decide to take the money earlier and accept a reduction in total payments (Mėry, 2014).

[14]Paid transfers cannot be assigned within couples. It is assumed that the men pay these transfers as this is most probably the typical case. In Switzerland, the better earning part of the couple has to pay the alimonies which will be the man in most cases, see figure 1B.

6.2 Testing two FE-QR models

To decide whether Canay's two-step estimator or the estimator following Kato et al. is more appropriate, I test whether the results differ substantially between the two estimators. One way to do this is to apply a Kolmogorov-Smirnov version of the Hausman test (Hausman, 1978) as outlined in Chernozhukov and Fernndez-Val (2005). In order to apply this test, the following test statistic[15] is used:

$$G^{\star} = \max_{\tau \in (\epsilon, 1-\epsilon)} G(\tau), \text{ where } G(\tau) = \frac{\sqrt{n} |\hat{\Delta}_{QE,canay}(\tau) - \hat{\Delta}_{QE,kato}(\tau)|}{s.e.(\hat{\Delta}_{QE,canay}(\tau) - \hat{\Delta}_{QE,kato}(\tau))} \tag{12}$$

and $\hat{\Delta}_{QE,canay}(\tau)$ and $\hat{\Delta}_{QE,kato}(\tau)$ are the estimates of the quantile effect followed by a FE-QR estimation according to Canay (2011) and Kato *et al.* (2012) respectively and n is the size of the dataset. This test statistic is bootstrapped[16] and recentered to get

$$G_b^{\star} = \max_{\tau \in (\epsilon, 1-\epsilon)} G_b(\tau), \tag{13}$$

$$\text{where } G_b(\tau) = \frac{\sqrt{m} |\hat{\Delta}_{QE,canay,b}(\tau) - \hat{\Delta}_{QE,kato,b}(\tau) - \hat{\Delta}_{QE,canay}(\tau) + \hat{\Delta}_{QE,kato}|}{s.e.(\hat{\Delta}_{QE,canay}(\tau) - \hat{\Delta}_{QE,kato}(\tau))} \tag{14}$$

and m is the size of the subset used for bootstrapping. In a next step, the p-value is calculated depending on the number of cases in which $G_b^{\star}$ is larger than $G^{\star}$:

$$\text{p-value} = \frac{1}{B} \sum_{b=1}^{B} \mathrm{I}(G^{\star} \leq G_b^{\star}), \tag{15}$$

where B is the number of bootstrap replications. Note that $\hat{\Delta}_{QE}$ is a scalar in these equations. A low p-value indicates that the estimates differ a lot and hence the more restricted model should be rejected. In the present case, we then would reject the model according to Canay's approach. This test yields a p-value of 0, we thus reject the FE-QR by Canay (2011) and go with the model of Kato *et al.* (2012).

[15]Note that I use the variance of the estimators and not the difference of each variance separately. This is more conservative since it could be that the difference of the variances is not positive semi-definite.

[16]Due to the considerable size of the dataset a bootstrap with subsampling (10%) and 100 replications is used.