How Marriage, Divorce and Kids Affect Income
A Quantil Regression Approach with Panel Data

Master Thesis at the Department of Economics, University of Bern

Supervisor:

Prof. Dr. Blaise Melly

To obtain the diploma of "Master of Science in Economics"

Author:	Jonas Meier
Student ID:	12-108-577
Adress:	Schaufelweg 15
	3098 Schliern
E-Mail:	jonasmeierbern@bluewin.ch
Date:	21.11.2016

Abstract

Marriage, divorce and childbearing may have large economic consequences for income. Most of the literature focuses on mean effects of these events on income. However, people are affected differently by these major stepping stones of life. To fill this gap, this paper applies quantile regression with fixed effects to explain the impact of these events on labor income. To do so, a panel data set containing individual-level tax data from the Swiss canton of Bern is used. As there are different possibilities to treat the fixed effects, two theoretical approaches are implemented. The first method by Canay (2011) considers the fixed effects as pure location shifts whereas the second one allows them to depend on the quantile (Kato et al., 2012). The main results of the analysis show that (i) being married or divorced increases the income of men and decreases the one of women, (ii) the immediate effects of getting married or divorced are large and heterogenous for women but small and homogenous for men and (iii) childbearing substantially lowers the income of women. Hence, this paper contributes to the existing literature in showing that the effects differ for men and women and are heterogenous across the income distribution. In addition, the two different approaches of fixed effect quantile regression are shown to differ with respect to their results.

Table of Contents

1 Introduction

Marriage, divorce and childbearing[1] are major happenings for an individual because they have large social and economic consequences. It is well known that the economic effects are different for men and women. In fact, married men benefit from a *marriage premium* and that mothers suffer from a *motherhood penalty.* However, there is relatively little research on how these effects vary for different income groups. This paper tries to fill this gap, applying a quantile regression to a large panel data set.

The present analysis has a huge potential because of four reasons. Firstly, the applied quantile regressions can show how to what degree the economic effects of marriage, divorce and childbearing are heterogenous. Secondly, the panel dataset created is very large and contains new information on individual income before and after marriage which was not available until now. Thirdly, this paper makes a clear-cut distinction between the effect of *being married* and the one of *getting married/divorced* whereas in most of the literature this is not explicitly done. This difference is small but crucial: *being married* refers to the effect of all married years whereas *getting married/divorced* estimates the effect in years directly after the marriage/divorce. Fourthly, the results point out that the two different approaches of fixed effect quantile regression differ substantially.

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.

The rest of the paper proceeds as follows. The next section gives an overview of the relevant literature. Section 3 presents the theoretical background and the applied econometric method. In section 4 the data is described and section 5 provides the estimation results. The main insights are summarized in section 6 where possible extensions and possibilities for future research are discussed too.

[1] Throughout the paper, childbearing refers to having a baby and not pregnancy.

2 Short Overview of the Existing Literature

There is a wide and established range of literature which deals with income differences between men and women, married and unmarried people, parents and childless people and with income variation between different levels of education.[2] Most of the research has been done on the marriage premium for men and on the motherhood penalty for women. The present paper takes a somehow broader perspective in estimating the effects of marriage, divorce and childbearing for both sexes simultaneously. This section briefly reviews the relevant literature.

2.1 Marriage Premiums and Penalties

For men, marriage is assumed to increase wages because of at least four reasons:

(i) being married allows the man to specialize (Korenman and Neumark, 1991)
(ii) married men work harder (Becker, 1981)
(iii) employers favor married men over unmarried ones (Hill, 1979)
(iv) married men have some unobserved characteristics which are favorable for women and employers (de Linde Leonard and Stanley, 2015).

Related to (i), Kenny (1983) suggests that married men are more productive as they invest more in human capital than single men. Hypothesis (ii) may seem old fashioned but builds on the idea that married men are forced to work more because they must take care of a family.[3] A reason in favor of the selection hypothesis (iii) to be true is that married men may be already more productive before they marry (Nakosteen and Zimmer, 1987). More recently, Dougherty (2006) claimed that the marriage premium is due to an unobserved time-distributed fixed effect. In their meta-analysis, De Linde Leonard and Stanley (2015) give an updated overview of the different aspects. They conclude that neither the specialization (i) nor the selection hypothesis (iii) can fully explain the observed marriage premium of 9-13% for US men.[4] Instead the authors

---

[2] There would be much more subfields that could be named here, but the focus of this paper lies on the effect of marriage, divorce and childbearing on income.

[3] The definition of a family depends on the context. For Becker, the family covers all members living in one household but there are different sociological definitions. Here, children are considered to belong to a family when they show up in the tax data which means that they do not have to live in the same household.

[4] The meta-analysis of De Linde Leonard and Stanley (de Linde Leonard and Stanley, 2015) estimates the marriage premium for US men over 59 published studies.

suggest another explanation, namely that employers use marriage as a signal of stability. If the specialization hypothesis was true, then the increased labor supply of women of the past years would have reduced the marriage premium. As this is not what the authors observe, they deduce that the specialization hypothesis can be rejected. The results of Killewald and Gough (2013) do not support the specialization hypothesis for women but confirm that there is a marriage premium for childless men and women. Another analysis by Cornwell and Rupert (1997) gives lower estimates effects of the marriage premium: They claim that the effect is not more than 5-7% and that most of it is due to unobservable individual effects which are correlated with marital status and wages. Dougherty (2006) finds that the marriage premium increases with the years of marriage.

On the other hand, women should earn less due to marriage because of the following reasons. According to Goldin and Polachek (1987) the specialization within a couple should reduce (v) the human capital investment incentives for women and hence lower wages. Korenman and Neumark (1991) argue that these reduced incentives lower (vi) work tenure and work intensity. Finally married women could be discriminated by employers because they may have (vii) higher labor turnover and absenteeism rates (Malkiel and Malkiel, 1973). Marriage could also decrease wage because of reduced mobility (Loughran and Zissimopoulos, 2009). This could be the case for both men and women. The same authors find that marriage lowers the wages of women by 2-4% in the year of marriage. Rarely considered by the literature are effects on income coming from a reduction in working time. Following the specialization hypothesis, it could be the case marriage leads to an increase in working hours for men and a decrease for women. In a nutshell, it can be concluded that married men are expected to earn more due to marriage premium between 5 to 13% whereas married women's income is lower compared to unmarried women.

2.2 Divorce

The research on the effects of divorce is not as broad as the one dealing with the consequences of marriage. Weitzman (1985) calculates the change in the standard of living[5] caused by a divorce. He finds that women are negatively affected with a reduction of their standard by 73% while men benefit from a divorce by a 42% increase of their standard of living. These estimates

[5] Both, Weitzman (Weitzman, 1985) and Peterson (Peterson, 1996) use the ratio of income to needs as a measure for the standard of living.

are clearly higher than the ones from other studies. Peterson (1996) replicates the study by Weitzman and concludes that with -27% and +10% respectively, the same point estimates are much lower. More recently, Tach and Eads (2015) find that the negative effect of divorce has weakened since 1980 but that cohabitation dissolutions affect mothers more severely than earlier. Hence it remains unclear if women are better off today when separating from their partner. As shown by Uunk (2004) the negative effect of divorce for women varies substantially across European countries. Considering direct effects on income the following studies are relevant for this paper. Day and Bahr (1986) find that divorce lowers the family per capita income of women. That there is a difference between men and women is supported by the study of Poortman (2000) which estimates the effect of separation on total household income. For men, total household income is decreased by -31% where the same estimate is -46% for women. Andress et al. (2006) analyze the effect in different institutional settings and conclude among other facts that women are more strongly affected by a partnership dissolution. However, the effect is negative for men too. Lastly, Jenkins (2008) shows that the direct effect on income declined for women with children from -30% to -12% whereas it stayed constant for men at around +30%. Hence, the effect for women should be clearly negative but the literature provides varying but mostly positive estimates for men.

2.3 Children

Childbearing is generally supposed to reduce wages for women, documented for example in Anderson et al. (2003) or Gough and Noonan (2013). Loughran and Zissimopoulos (2009) split the effects into a direct and an indirect one. The direct reduction in wages arises from the lower productivity (at least temporarily) due to the absence from the labor market. The indirect effect is the wage penalty that results from mothers being less experienced and missing promotion opportunities because of this absence. Childbearing essentially reduces the probability that women work and lowers the wages of working women. The authors conclude that the negative effect of childbearing (as well as the one of marriage) has worsened over time. It should be added that the age at the first child birth and age when getting married are correlated. Thus, it could be that marriage and childbearing are strongly correlated and this could lead to biased estimates depending on the model specification.[6] The mentioned paper claims that this

[6] In fact, the age at marriage and at first child birth are almost perfectly correlated (0.96) in the present dataset. Nevertheless, marriage and child birth itself are loosely related (correlation of 0.12). Therefore, this problem should not be of great importance for this analysis.

correlation has weakened over the last decades. The study by Angrist and Evans (1998) estimates the effect of a third child to lower female labor force participation by 12 percentage points and female labor earnings by 21-27%. Ellwood et al. (2004) report that the effect of childbearing is more severe for well educated women hence these women are more likely to delay or avoid childbearing.

2.4 Gender Wage Gap

After having reviewed the closely related literature, it is important to mention the general income differential between men and women. This is probably the most prominent topic in the field of wage differences. This paper is not a classic gender wage study as the focus lies on the effect of marital status and childbearing on income.[7] However, the existence of the gender wage gap is important for the analysis because of two reasons. Firstly, the absolute effects on income are affecting men and women differently. Secondly, the gender wage gap may vary across the distribution which is a first sign that a quantile regression approach is needed. Thus, a short summary of relevant studies is provided.

International meta-analysis and comparisons as the ones by Weichselbaumer and Winter-Ebmer (2005) and Simón (2012) show that the gender wage gap is still substantial and differs across countries. The former paper finds that the raw wage differential has fallen worldwide from the 1960s to the 1990s from 65% to about 30%. This decrease is mostly due to better labor endowment of women which means better education, training and work attachement. Nevertheless, Grund (2015) recently showed that the gender wage gap, even among very well educated people, is still substantial. Furthermore, the wage differentials are more pronounced for bonus payments than for fixed salaries (Cornwell and Rupert, 1997). It is of high interest if the gender wage gap is constant or varies across the wage distribution. The quantile regression approach by Christofides et al. (2013) points out that for European countries the wage differentials depend on the income quantiles. Additionally, the authors find evidence for sticky floors[8], large gaps in the wage distribution at the median and glass ceilings[9] in various countries. Another study for European countries (Arulampalam et al., 2006) finds as well both, sticky floors

[7] The tax data used in this analysis does not include sufficient covariates to analyze the gender wage gap which is the reason why the econometric studies are restricted to the effect of marital status on income.

[8] Sticky floor refers to the inability of a low-income people to get jobs above a certain level of income due to specific personal characteristics (e.g. gender). Hence, these people remain in low-income and low-mobility jobs.

[9] Glass ceilings are barriers to career progress for qualified people also due to personal factors.

and glass ceilings for different countries but argues that the gap is typically larger at the top of the distribution.

2.5 Summary

From the empirical literature, we expect (i) positive effects of marriage and divorce for men and negative effects of these two events for women and (ii) negative effects of childbearing for women. The effect of childbearing for men is rather unclear. The direct effect of marriage depends on which hypothesis is more relevant. If men would specialize and work harder due to marriage (hypothesis (i) and (ii)), then marriage is expected to directly increase a man's income. Contrary to this, the hypothesis (iii) and (iv) about the signaling effect of marriage probably affect the income with a time lag. For women, it is rather unclear if there are any direct effects of marriage. Divorce should positively influence the income of men and negatively the one of women in the long and in the short run. There is much more evidence for the negative impact on women. On the other hand, childbearing will affect a woman's income very directly since mothers may reduce their working time after having a baby. This is the case because some women may be longer absent than their paid maternity leave. As there are no other studies applying quantile regression with fixed effects to estimate in this field it is rather unclear how much of the effects is captured by the fixed effects.

This paper tests whether these effects are constant across the income distribution or not using a quantile regression approach. As stated above, wage differentials between men and women are not econometrically analyzed in this paper because the study focuses on the effect of marriage, divorce and childbearing. The analysis takes advantage of a unique dataset available for this study which makes it possible to estimate the effects from a new and broad perspective.

3 Method and Estimation

3.1 Fixed Effect Quantile Regression

This section presents the econometric literature which is necessary to derive the procedure used in the later sections. Standard ordinary least squares estimation (OLS) does not address the heterogeneity of an effect. With OLS, only the effect on the conditional mean is calculated. There are cases, in which the analyzed effect varies in different parts of the distribution. In such a case, OLS is no longer an adequate econometric approach because it neglects possible heterogeneity. Quantile regression may be a solution to this problem (Mosteller and Tukey, 1977). To be precise, the method applied here estimates the effect at different quantiles of the conditional distribution of the outcome variable. In addition, quantile regression has two favorable features. On one side, it is more robust to outliers (Koenker, 2005) than OLS and on the other hand there is no need for an assumption about the parametric form of the error term (Hao and Naiman, 2007).

Panel data offer a great opportunity to the researcher. Observing the same individuals over time allows for estimation methods such as fixed effect regression. This is particularly important when individuals have unobserved characteristics which are constant over time. De-meaning or differencing the regression equation eliminates these fixed characteristics and makes it possible to avoid a potential omitted variable bias.

The focus of the present paper is to shed light on the heterogeneity of the effect of marriage, divorce and childbearing on income. Therefore, quantile regression with fixed effect is applied. This allows to account for the heterogeneity of an effect while controlling for unobserved individual effects. This is a relatively recent field of research with several different estimation methods.

In the following Y_{it} will denote an output variable (income) for individual $i \in \{1, \dots, n\}$ and time period $t \in \{1, \dots, T\}$. The vector of covariates is written as X_{it} and includes a constant. One of the first approaches was the one by Koenker (2004) which uses the following model for the conditional quantile function[10]:

$$Q_{Y_{it}}(\tau | X_{i1}, \dots, X_{iT}, \alpha) = X_{it}'\beta(\tau) + \alpha_i \tag{1}$$

In this specification, $Q_Y(\tau|X)$ is the τ^{th} conditional quantile of Y given X. Koenker introduced the fixed effects α_i as a pure location shift (independent of τ) and suggests a penalized quantile regression estimator that simultaneously estimates quantile regression coefficients for a set of quantiles and fixed effects. It is Important to mention that in contrast to OLS, quantile regression does not allow to get rid of the fixed effects by demeaning or first differencing. The reason for this is that the quantile function is not linear while the expectation operator is. Lamarche (2010) applies a similar method as Koenker (2004) while Canay (2011) uses a different approach. Still assuming that α_i is a pure location shift, Canay (2011) derives a two-

[10] In the following only models for conditional quantiles are considered as these are the objects of interest. Powell's analysis (Powell, 2016) for example treats unconditional quantile functions.

step estimator which first runs a demeaned fixed effect regression and generates a new outcome variable by subtracting the residuals from the former outcome variable. The second step applies a quantile regression of the new outcome variable on the same covariates used for the first step. The intuition for this procedure is as follows. The residuals of the demeaned fixed effect regression are an estimate for the individual fixed effect. Subtracting these residuals from the outcome variable generates a response variable that accounts for individual heterogeneity. Hence, the quantile regression of the new outcome variable yields the effects already controlled for individual fixed effects. The setup used by Canay is the following:

$$Y_{it} = X_{it}'\beta(U_{it}) + \alpha_i \tag{2}$$

Where U_{it} and α_i are unobserved and assumed to be independent conditional on X. Next Canay defines $S_{it} = X_{it}'\beta(U_{it})$ such that $Y_{it} = S_{it} + \alpha_i$ is a convolution of S_{it} and α_i conditional on X.[11] Using a deconvolution argument like the one in Neumann (2007) he argues that the conditional distributions of S_{it} and α_i can be identified from the conditional distribution of Y_{it}. Adding some regularity conditions and assuming that $U_{it} \sim \mathrm{U}[0,1]$ this results in the identification of $\beta(\tau)$. For the regression in the first step, Canay defines $u_{it} = X_{it}[\beta(U_{it}) - \beta_\mu]$ such that the the conditional mean equation (2) can be written as:

$$Y_{it} = X_{it}'\beta_\mu + \alpha_i + u_{it} \tag{3}$$

Where $\mathrm{E}[u_{it}|X_i, \alpha_i] = 0$. The first step of Canay's estimation method is the demeaned fixed effect regression which results in a $\sqrt{T}$-consistent estimator of α_i, given a $\sqrt{nT}$-consistent estimator of β_μ. $\widehat{\alpha}_i$ then can be used to calculate $\hat{Y}_{it} = Y_{it} - \widehat{\alpha}_i$ which he uses in the second step to estimate $\beta(\tau)$ by a quantile regression in the following version of (2):

$$\hat{Y}_{it} = X_{it}'\beta(\tau) + e_{it}(\tau) \tag{4}$$

Where $e_{it} = X_{it}[\beta(U_{it}) - \beta(\tau)]$. To be precise, the estimator for $\beta(\tau)$ is defined as:

$$\hat{\beta}(\tau) = \arg\min_{\beta \in B} \frac{1}{nT} \sum_{i=1}^{n} \sum_{t=1}^{T} \rho_\tau\left(\hat{Y}_{it} - X_{it}'\beta\right) \tag{5}$$

Where $\rho_\tau(u) = \{\tau - 1(u \leq u)\}$ is the check function of Koenker and Bassett (Koenker and Bassett Jr, 1978) and $1(\cdot)$ is the indicator function. Canay argues that this new outcome variable weakly converges to Y_{it} as $T \to \infty$. For the estimator to be consistent $n \to \infty$ is needed as

[11] To identify the vector of interest $\beta(\tau)$, it is important to know the distribution of this convolution. However, without the deconvolution method nothing can be deduced for the conditional distributions of S_{it} and α_i.

well. Assuming that n and T both go to infinity is frequent in the context of fixed effect quantile regression, see for example Koenker (2004), Lamarche (2010), Galvao (2011) or Kato et al. (2012). For Canay's two-step estimator n and T going to infinity is necessary because otherwise the fixed effects may not be consistently estimated. However, this problem which is called the incidental parameter problem is not discussed by Canay. If the fixed effects are not consistent then obviously the coefficients of the covariates are neither. Other approaches like the one by Kato et al. (2012) deal with this problem. They introduce sufficient conditions such that their fixed effect estimator is consistent and asymptotically normal. The model specification of Kato et al. (2012) differs from the one used by Canay with respect to the fixed effect as these depend on the quantile. The resulting model can be written as:

$$Q_{Y_{it}}\left(\tau \middle| X_{i1}, \dots, X_{iT}, \alpha(\tau)\right) = X_{it}'\beta(\tau) + \alpha_i(\tau) \tag{6}$$

For Koenker (2004), the individual specific intercepts are constant across quantiles contrary to specification (6) where the intercept term depends on the quantile. In addition, Kato et al. (2012) treat every fixed effects as a separate parameter which is not what Canay does. They use the following estimator to get the coefficients of the quantile regression:

$$(\hat{\alpha}, \hat{\beta}) = arg \min_{\alpha,\beta} \frac{1}{nT} \sum_{i=1}^{n} \sum_{t=1}^{T} \rho_\tau \left(Y_{it} - \alpha_i(\tau) - X'_{it}\beta\right) \tag{7}$$

where $\alpha = (\alpha_1, \dots, \alpha_n)'$. As every individual fixed effect is estimated as a parameter, the solution may be computationally demanding. Koenker (2004) argues that in most applications the design matrix is often sparse which makes it possible to solve the problem. The two approaches described so far differ with respect to the model specification and the assumptions used for the estimator to be consistent. The data used for this study covers 11 time periods, which is obviously far from infinity. Due to this data limitation and the different specification of the panel data models, it is unclear how the estimators of Canay (2011) and Kato et al. (2012) perform in this case. Therefore, both will be estimated and compared with respect to their results.

There will be two types of models, both estimated once with the two-step estimator of Canay (2011) and once with the procedure of Kato et al. (2012). With respect to the exact model specification, the two types capture different sorts of effects. The first one estimates the effect of being married and being divorced whereas the second one gives an answer to the question how large the effect of getting married or divorced is. Therefore, the first model only includes two variables for the marital status, namely dummy variables for being married or divorced.[12] The effect of the number of children is estimated with one variable which is just the raw number of children. On the other hand, the second model contains dummy variables for getting married or divorced in a specific year and lags of these variables. Similarly, for the number of children the second model includes dummy variables for having one kid more/less in a year and the lags of these variables. Three lags are included for all the lagged variables in the second model.[13] In addition to the mentioned variables, the matrix X_{it} includes a constant and the covariates age and age^2 as well as year fixed effects for both models. To get the effects separately for men and women all covariates are interacted with a dummy variable identifying men and women. This is the case for both models. It is important to mention that an individual is considered to be married in years in she is taxed as one part of a couple and single in other years.[14] Depending on how immediate the effect of marriage is, this dummy variable may catch the effect only from the second year on. This is the case for people that marry late in one year because they earn a large part of their income in this year as single but are treated as married.

It should be highlighted that the two models differ substantially with respect to their estimated effects. While first one estimates the effect of *being married* and *being divorced* over all available time periods, the second one gives the immediate effects for *getting married* or *getting divorced*. In the context of the reviewed literature, the first model is probably more interesting. The first model may answer the question about how different married and unmarried people are. However, the second model gives direct impacts which are important from another perspective. In the following, the models are referred to as model type 1 and model type 2.

---

[12] One could think that these two dummies are highly correlated and should therefore not be in the same model. Although the correlation is moderate (-0.38), it is theoretically justified that the two variables remain in the model. Otherwise, estimating separate models would mean that e.g. divorced and single individuals are treated the same when only a dummy for being married is included.

[13] From this it follows that 4 years of observations are lost since the third lag of the first year is still missing for all individuals.

[14] Of course, people get married and divorced throughout the year but for tax administration one can only be married or not in one year. The martial status on the 31th of December defines how a person is taxed. (https://www.fin.be.ch/fin/de/index/steuern/ratgeber/besondere_lebenssituationen/heirat.html, accessed on the 19.11.2016)

3.2 Estimation Technique

The programs R[15] and Stata are used to estimate the desired objects. For all models the Frisch-Newton algorithm for quantile regressions is used. This approach is documented in Portnoy and Koenker (1997). For the quantile regressions according to Canay, the standard errors are computed using a kernel estimate as proposed by Newey and Powell (1990). In the case of the the models following the specification of Kato et al., a sparse matrix formulation is applied. To get standard errors and t-statistics for these models, a bootstrap method is implemented. The coefficients of the quantile regressions are estimated 100 times using a subsample of 20% of the initial dataset which is used for estimating the coefficients.[16] These subsamples are randomly selected with replacement. Then, the standard errors and t-statistics are computed over these 100 values for the same coefficients. The goodness of fit is measured with the standard AIC criterion for the models according to Canay. As it is difficult to get the AIC for bootstrapped results, for all models the pseudo R^2 defined in Koenker and Machado (1999) is used. The same restricted model only including an intercept is estimated for both applied methods[17] to ensure that the statistics are comparable.

3.3 Remarks

For these models, unbiased estimators can only be calculated when there are no unobserved variables which are non-constant over time. Otherwise these variables would result in an omitted variable bias. Constant covariates affecting income do not cause a bias because they are filtered out by the fixed effects. For non-constant covariates as experience it can be argued that age covers a large part of these effects. Job tenure or a change of the industry someone is working in could potentially cause an omitted variable bias. A change in the hierarchy level or the level of complexity of a job could influence the income as well. As these factors attribute to the income differential between men and women, the effects estimated will most probably overestimate the effect of marriage, divorce and childbearing.

Another issue arises considering reverse causality. If income affects the decision to marry or get divorced, then the models studied here would not identify the true effects. This may be the

[15] All quantile regressions are estimated with the package `quantreg' (Koenker et al., 2016).

[16] This will be a subsample itself (30% of the whole dataset).

[17] For the models following the specification of Canay, the original outcome variable is used and not the one corrected for the individual fixed effects.

case because of tax reasons since the sum of taxes could be higher for couples than if they would remain individually taxed.[18] A study of the federal tax office (ESTV) (Peters, 2014) finds that this disadvantage for married couples compared to singles living together is relatively small. However, the disadvantage is larger with higher income and when both individuals earn almost the same amount of money. Other costs like the wedding party are most probably neglectable. As the effect of divorce is not too clear there probably are no strong monetary incentives to get divorced with respect to the labor income. Of course, there are other economic motives for instance the splitting of the collective wealth or the retirement funds. However, for labor income[19] reverse causality seems to be unlikely.

A remark should be made regarding the second model. The lagged variables identify the effect for all individuals that get married or divorced once. Future changes in marital status are not taken into account. From this follows that there are people which influence the effect of marriage *and* divorce when they change their marital situation more than once. However, restricting the model only to those who are still married or divorced would result in a sample bias. The reason therefore is that it is unclear if these individuals differ from the ones remaining married or divorced. It has to be kept in mind that the model estimates the effect for all individuals that change their marital status once irrespective of what their future marital situations are.

4 Data

This paper uses tax data to apply the quantile regression methods outlined in section 3. The tax data covers all taxable individuals and couples[20] in the Canton of Bern for the years 2002 to 2012. Individuals and couples are taxed differently and hence both types of taxpayers are treated in different ways within the dataset.[21] The dependent variable for the following analysis

[18] The federal as well as the cantonal tax administration tried to eliminate these negative incentives with tax reforms.

[19] Private transfers such as child allowances are not contained in labor income.

[20] Civil unions ("eingetragene Partnerschaften") are taxed as couples as well.

[21] A lot of characteristics are only available for a couple, meaning that they cannot be separated on individual level.

is yearly labor income[22] which is the sum of the income from a person's main job and the side jobs. This information is available for both persons of a couple as well as for all individually taxed persons. Labor income in this context is the net income which means that social security contributions are already subtracted.[23] One should be careful when comparing the results of this analysis to others because labor income how it is defined here depends not only on 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 study the effect of marriage and divorce the couples are split such that the new dataset contains individuals only.[24] In addition to the labor income, information about marital status, number of children, age, sex and the community of residence is available. Every individual has an identification number which stays the same across time. Consequently, every change in marital status taking place within the observed time periods can be identified. On average the dataset consists of 593'000 normally taxed individuals per year. Several groups of people are excluded from the analysis (not contained in the number above) because they can hardly be compared with normal taxpayers. In the following, the brackets indicate the average number of these individuals per year. Firstly, the analysis excludes individuals below 18 (21'500) and above 66 (150'900) years old persons as adolescents and retirees may have a different income patterns. Secondly, specially taxed people are excluded. This means people which are only living in the Canton of Bern for one part of a year (10'000) or people that do not hand in their tax declaration (22'200).[25] This leaves the mentioned 593'000 individuals per year for the analysis. With tax data, there are always numerous people with an income of 0 (122'400). About half of them (60'300) never have an income in the years analyzed.[26] If individuals with no income were

[22] Other specifications were tested as well for example models where the dependent variable is logarithmized. However, these seemed to be miss specified. This could be since the fixed effects are additive in levels but not in logs. Box-Cox transformation tests reveal that the level specification is best fitting.

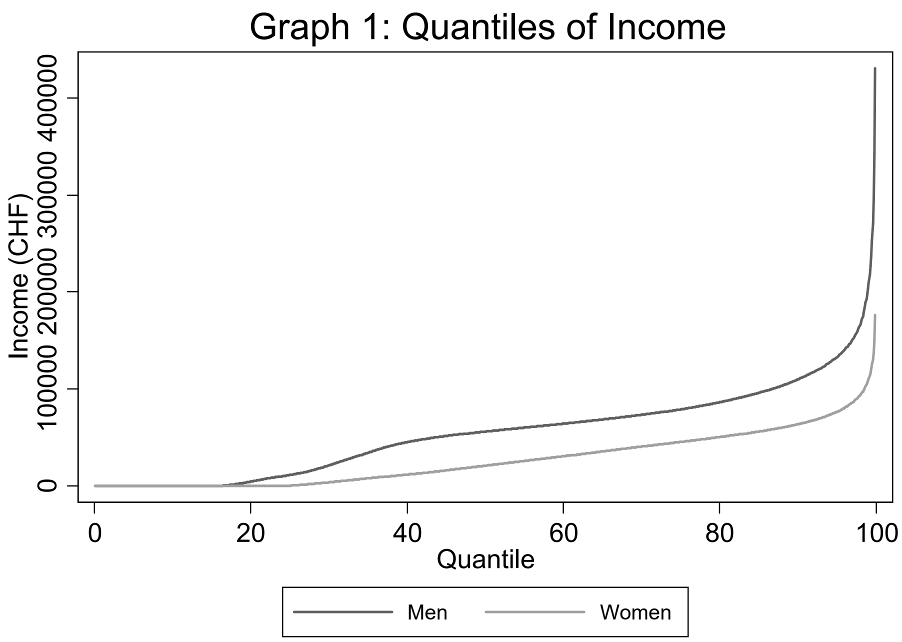
[23] The difference between total and net income is about 6 to 7 percent. (http://www.bsv.admin.ch/vollzug/documents/view/809/lang:deu/category:22, accessed on the 19.11.2016)

[24] To the best of my knowledge, this was never done before.

[25] This is a special case of the Swiss tax system. If no tax declaration is handed in, the tax office will make an estimation of the person's ("Ermessensbesteuerte").

[26] In the case of this study these are people which are self-employed or only living from their investment income, people living only from pensions (retirees but also accident, unemployment or disability benefits) or private transfers such as child alimony. These forms of income are observed for every individual (also the ones paying tax

excluded this would result in a selection bias which is the reason why they remain in the data. Graph 1 shows one important problem with the present data that arises when quantile regression is applied.



All individuals of all years included.
Data source: tax data from the Canton of Bern 2002-2012.

Quantile regression methods rely on the assumption that the dependent variable strictly increases. However, from this plot it becomes clear that about 25% of the population has an income of 0 which violates this 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. There may be a selection bias due to different labor market behavior of men and women. This is that e.g. working and not working women may have different characteristics and hence cannot be compared. The fixed effect method applied here will eliminate such characteristics when they are constant, but the possibility remains that there are non-constant factors influencing labor market behavior. There are no missing values for labor income, sex, age or number of children therefore no data had to be dropped from the sample because of missing values.[27] The data

as couples) but are not treated in this analysis because the focus is on the labor income which is probably more strongly affected by a change in marital status. In addition, changes in income would be difficult to interpret if all sorts of income would be summed up.

[27] There are individuals with an income as man and as women (overall years: 129), these cases were excluded.

used 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 men and women over all years.[28]

Table 1: Summary Statistics by Sex

	Men n = 3'207'694		Women n = 3'315'939	
Variable	Mean	St. d.	Mean	St. d.
Labor Income (CHF)	55469	54968	27094	28231
Age	43	14	43	13
Number of Children	0,58	0,98	0,64	1,00
Married	54%	50%	55%	50%
Divorced	10%	29%	12%	33%
Marriage	1%	11%	1%	11%
Divorce	1%	8%	1%	8%

Data source: tax data from the Canton of Bern, 2002-2012.

The values reported are calculated over the whole sample.

Men earn on average more than 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 labor income. For the other variables, table 1 shows that men and women have almost identical summary statistics. As already mentioned, the variable *married* is 0 in years where a person is taxed as single person and 1 in years where a person is paying taxes as part of a couple. Technically the percentage values for married men and women should be the same[29] but due to the exclusion of individuals older than 66 years it may happen that only one person of the couple remains in the data. *Divorced* is defined as 0 for singles, widowed[30] or married and 1 if a person was married once and did not marry again until the relevant year. Finally, *marriage* and *divorce* are dummy variables equal to 1 if a person's marital status changes accordingly in a specific year.

From table 2 it is not apriori clear whether married people have a higher income than singles. The reason for this is that age certainly increases income and hence the higher average income of married people could be due to this age effect. In addition, the descriptive statistics by marital status show that there is a considerable amount of heterogeneity. These statistics

[28] Table 1 calculates the mean of all years meaning that individuals are contained several times

[29] When civil unions ("eingetragene Partnerschaften") are not considered.

[30] There are only 1100 widowed individuals per year in the analyzed dataset.

cannot answer the question whether this heterogeneity is due to the observed covariates or unobserved ones. The standard deviation for income reported in both tables is generally very high since there are a lot of individuals with a labor income of 0.

Table 2: Summary Statistics by Marital Status

	Single[1]		Married		Divorced	
	n = 2'264'987		n = 3'542'647		n = 715'999	
Variable	Mean	St. d.	Mean	St. d.	Mean	St. d.
Labor Income (CHF)	37605	33800	42618	52163	44158	43867
Age	33	13	47	11	49	9
Number of Children	0,06	0,28	1,01	1,12	0,42	0,78

[1] This category also includes widowed people.
Data source: tax data from the Canton of Bern, 2002-2012.
The values reported are calculated over the whole sample.

The standard deviation is highest for married individuals. Thus, the group of married people is the most heterogenous one regarding income. To address the question of heterogeneity between men and women, Table 3 shows the mean values of all covariates calculated for every decile[31] of labor income. The values reflect the average of the yearly distributions.[32] It becomes clear that the raw wage differential increases throughout the distribution and is highest at the top. For most studies the object of interest is the gender wage gap which cannot be explained by observable factors. However, only considering this gap descriptively one cannot say which factors are causing this differential. For instance, it could be the case that the best earning men are just better educated and hence earn more. Nevertheless, the fact that the raw gender wage gap increases with income shows that men and women are different with respect to their income patterns. Purely descriptive one can observe that for men, all covariates monotonically increase with income. As already mentioned this is not surprising for age, but the fact that more men are married in higher deciles could be a first sign for the marriage premium. The first decile seems to be an exception for both men and women. This group of people with no income seems

[31] Generally, the x^{th} decile consists of people with an income higher than the decile x-1 but lower than x^{th} decile. Assigning people with no income into deciles is arbitrary when this group is larger than a decile which is the case for all yearly distributions. Here, all individuals with no income are treated as a homogenous group and left in the first decile. When the size of this group is even bigger than two deciles, then the first two deciles are treated as a quintile and assigned the same mean values of the covariates.

[32] Technically this means that the income distribution of every year is calculated. Table 3 then reports the (unweighted) average of these yearly distributions.

to be heterogenous consisting of rather old and married individuals. For women, income does not increase with the covariates. There is no clear pattern about the relationship of income and age but income seems to be connected to the number of children and the percentage of married women in a special way. As income increases, both variables increase in the beginning but start to fall after some point.

Table 3: Summary Statistics by Sex and Decil of Income

		Decile									
Sex	Variable	1	2	3	4	5	6	7	8	9	10
Men	Labor Income (CHF)	0	4262	21100	45091	56131	64147	73152	86196	109624	>109624
	Age	49	40	33	36	37	41	43	45	46	48
	Number of Children	0,43	0,44	0,22	0,29	0,34	0,52	0,73	0,82	0,93	1,12
	Married	56%	43%	27%	34%	37%	51%	62%	67%	71%	79%
	Divorced	13%	7%	5%	7%	7%	9%	10%	11%	11%	10%
Women	Labor Income (CHF)	0	0	3684	11764	20840	30467	40551	50107	63355	>63355
	Age	49	49	41	38	40	42	41	39	39	43
	Number of Children	0,68	0,68	0,84	0,75	0,82	0,83	0,69	0,46	0,36	0,36
	Married	71%	71%	60%	56%	62%	64%	55%	39%	33%	34%
	Divorced	11%	11%	8%	7%	8%	11%	15%	16%	17%	18%

Data source: tax data from the Canton of Bern, 2002-2012.

The reported values are the unweighted average over all yearly distributions.

Note: the standard errors are left out to enusre a better readability. The full table with standard errors can be found in the Appendix.

.

The percentage of married women increases only a tiny bit from the 3rd to the 6th decile and decreases rapidly afterwards. On the other hand, we have a completely different pattern for men where the percentage of married person increases throughout the distribution. An interpretation of this would be that being married is associated with different patterns of income for men and women. This would be in favor of the classical role model where the woman stays at home and looks after the children when they marry. Or in other words: A woman with a high income is less likely to be married or to have children. After all, this descriptive analysis shows that men and women do differ substantially in their distribution of income. The mean values of the covariates depend on income and sex which provides evidence for the heterogeneity that will be analyzed in the next section.

5 Results

This section presents the results of all quantile regressions. The two types of models are once estimated with the two-step estimator of Canay (2011) and once with the procedure of Kato et al. (2012). All estimation tables with standard errors and t-statistics are reported in the Appendix B. As the dataset is large and the models are computationally demanding, for most analysis only a part of the initial dataset is used. All observations are used for the estimation of model type 1 in the Canay setting whereas for three remaining regressions roughly one third of the dataset is used.[33]

5.1 Canay's Two-Step Estimator

5.1.1 Model Type 1

The first model includes three variables of interest: A dummy variable which is equal to 1 if the individual is married, another dummy which is 1 when someone is divorced and the raw number of children. All three are interacted with a variable that identifies men and women. Therefore, the effects for men and women can be calculated separately. The following table provides the estimation results of the quantile regression, the second step by Canay. The results of the first step as well as all forthcoming estimation results can be found in the Appendix B. From table 4, one can see that the impact of age differs for men and women as well as for the quantiles. The linear and the quadratic term change in such a way that the shape of the function stays almost the same. Apparently, the effect of one additional year is larger for men than for women. For women as well as for men, age has a lower total impact towards the top of the distribution. It could be argued that for top earning individuals age is not as important because income depends to a larger part on qualifications such as education.[34] Regarding the

[33] First, individuals are randomly assigned an identification number. Then, all observations of one individual are either included or excluded based on the random identification number. People only appearing once in the dataset are excluded because in these cases, the fixed effects cannot be consistently estimated. This procedure ensures that for the fixed effects, the loss of precision is minimized. As the model of type 2 three lags, roughly 35% of the data is excluded. Hence, for the two models of type 2 the same randomly selected third of the initial dataset is taken but only 60% of it is used, resulting in about 20% of the initial dataset.

[34] Although the fixed effect procedure eliminates constant characteristics, it could be that they influence individuals differently. Thus, the results give the effects controlled for individual qualification but still, qualification

coefficients of the number of children and the marital status, two facts can be seen from table 4[35]. Firstly, all effects are positive for men and largely negative for women. Secondly, this gap stays almost constant for the number of children and being married but decreases towards the top of the distribution for the effect of being divorced. Relating to the hypotheses in section 2, a marriage premium for men clearly exists. However, the effect seems to be smaller than suggested by others (De Linde Leonard and Stanley, 2015). Table 4 points out that being divorced in fact increases income of men and decreases the one of women as found by Jenkins (2008), Andress et al. (2006) and Poortman (2000). Finally, the hypothesis that having children lowers the income of women is confirmed too. This is in line with the findings of Anderson et al. (2003) and Gough and Noonan (2013).

Table 4: Quantile regression Results Model Type 1, Canay

Quantile	5		25		50		75		95	
Variable	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Age	10032	6036	9435	5600	8944	5198	8570	4872	9218	5699
	10	10	3	3	2	2	3	3	12	11
	972	591	2738	1772	4813	2926	2867	1791	780	539
Age^2	-112	-63	-100	-58	-94	-54	-89	-51	-94	-62
	0	0	0	0	0	0	0	0	0	0
	-894	-527	-2213	-1541	-4041	-2654	-2514	-1728	-623	-500
Number of Children	1347	-5998	981	-5621	705	-5446	502	-5346	590	-6636
	50	26	9	7	5	5	10	7	47	19
	27	-234	114	-755	130	-1089	51	-770	13	-348
Being married	-47	-6102	1750	-9014	2071	-8890	2250	-9054	3943	-9331
	113	61	22	15	13	10	23	16	103	47
	0	-101	78	-587	163	-877	97	-564	38	-200
Being divorced	1845	-6019	1967	-5430	1716	-4280	1410	-3149	1295	-1566
	151	89	29	22	16	14	30	24	133	71
	12	-68	68	-244	107	-307	48	-133	10	-22
AIC	$1{,}504{*}e^{8}$		$1{,}428{*}e^{8}$		$1{,}408{*}e^{8}$		$1{,}424{*}e^{8}$		$1{,}499{*}e^{8}$	
Pseudo R^2	0,14		0,62		0,72		0,72		0,70	
Number of Observations	6523633		6523633		6523633		6523633		6523633	

The dependent variable is yearly labor income in CHF. All quantile regressions include a constant and year fixed effects.
The first row gives the coefficient, the second row the standard errors and the third row the t-statistic.
Data source: tax data from the Canton of Bern, 2002-2012.

could have a different effect for individuals. In the models considered here, this is captured by different fixed effects.

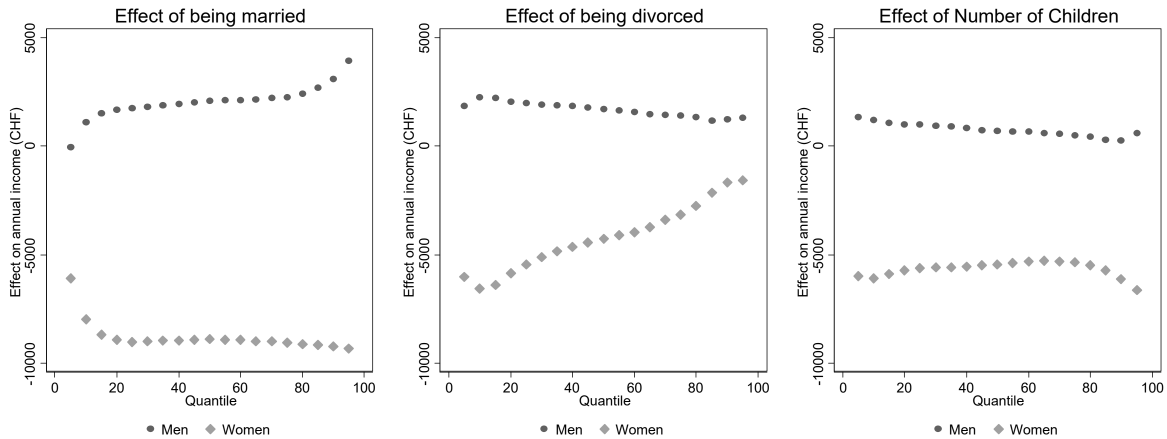
[35] It may be surprising that negative effects for the lowest quantiles appear in this table and afterwards since these people do not have any income. The reason for this is the inclusion of the fixed effects which may be larger than the negative impact of some variable.

The coefficients in table 4 should be interpreted as follows: Married women earn 8890 CHF less than others at the median of labor income controlled for the included covariates. Following this logic, one more child increases the income of men in the first quartile ceteris paribus by 981 CHF compared to others in this quantile. Astonishingly, the effect of being divorced is negative for low-income women. This is not intuitive as these women are expected to work much more after a divorce since they must cover larger costs now. One possible explanation could be that for low-income women, private transfers and child allowances extend the increased costs and instead they reduce working to look after their child. Regarding the measures for the goodness of fit, the standard AIC is lower for the regressions at the quartiles and the median. This indicates that the model fits better in the middle of the distribution which is supported by the fact that the pseudo R^2 is very low for the regression at the 5^{th} quantile. The reason for this may be the low variation of income at the bottom of the distribution. Hence, the estimates of the 5^{th} quantile should be interpreted carefully.

These quantile regressions consider absolute effects on income. However, it could be argued that relative effects matter for the individuals. Obviously, these depend strongly on how much a person already earns. The available data covers a large group of people with no income for which relative effects are difficult to estimate and even more difficult to interpret. In addition, absolute effects are easily comparable between the two applied methods. Therefore, the analysis focuses on absolute effects. However, from the distribution of income in table 3 it can be inferred that impacts on income are far more severe for low-income individuals than for others. It is important to remind the fact the effects on income can be related to changes in employment level or in wage level (or both), but most probably, most of the effects are due to changes in employment level after marriage, divorce and especially childbearing. The welfare effect of changing leisure time is not considered here.

Visualizing the results of table 4, graph 2 shows the absolute effects on income by plotting the coefficients of all three variables of interest against 19 quantiles. Being married has a slightly positive effect for most men but decreases income for all women. This effect seems to be almost constant for the quantiles. On the other hand, being divorced is again negative for women and positive for men but the effect clearly depends on the quantile. The decreasing gap towards the top of the distribution points out that well earning women are less affected than others. The effect of the number of children is almost constant for both men and women. The magnitude of this effect may be substantial because more than half the families having children (62%) have more than one child. Having three children reduces the income of women at the median by roughly 16500 CHF.[36] Table 4 as well as graph 2 indicate that the being married or divorced and the number of children have very different effects on men and women. All effects are negative for women and most men are only slightly affected by them. There seems to be a small marriage premium for men but at the same time there is a far more important marriage penalty for women. From the perspective of quantile regression, the effect of being divorced is most interesting since the (absolute) magnitude of it varies with the quantiles.

Graph 2: Model Type 1, Canay



Data source: tax data from the Canton of Bern 2002-2012.

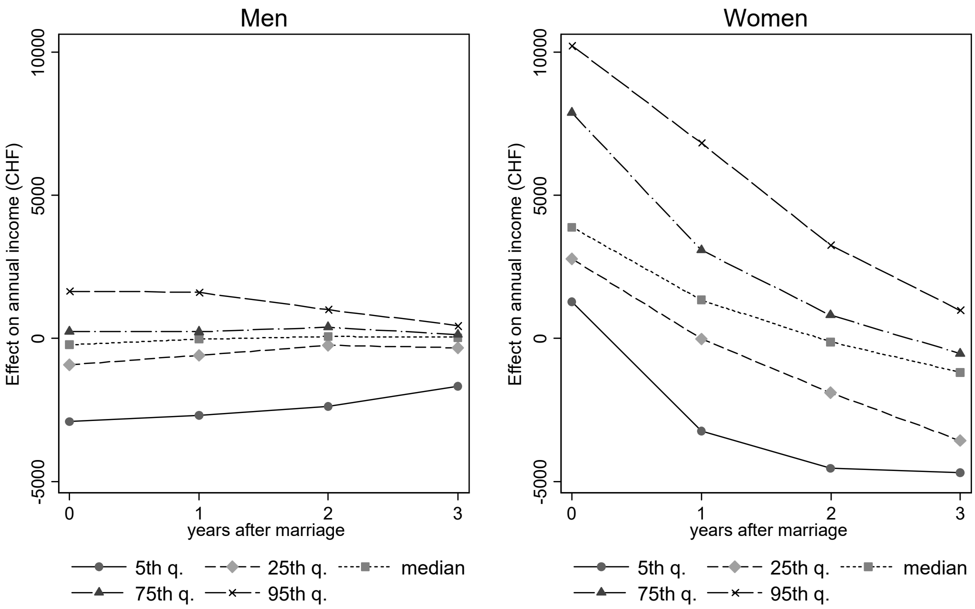
5.1.2 Model Type 2

The next part of the analysis turns to immediate effects of marriage, divorce and childbearing. Until now, the model estimated differences in income between people in different marital states. But what happens to someone changing his marital status or getting a baby right in the years afterwards? The following models of type 2 estimate exactly this effect. To do so, dummy variables of the corresponding changes and the lags of them are introduced. The direct impacts of marriage, divorce and childbearing can hardly be related to signaling effects as these mostly arise when people start a new job. More important are changes in working time as they immediately affect income. Some sort of specialization within a married couple could also lead

[36] The model specification assumes that the number of children has a linear effect. Other specifications (log, quadratic, cubic) have been tested but none of them did fit better.

to an increase or decrease of income.[37] An issue arises from the fact that only the year of such a change is known and not the exact date. Hence, the labor income in this specific year may not be directly affected if someone e.g. marries in December. Because of this, the effects in this initial time period should be interpreted carefully. The following graphs plot the same absolute effect on income against the quantile as before. For each quantile, a separate regression is estimated and the coefficients of all time lags are reported. The effect of marriage itself (year 0) is computed as the impact on annual income compared to years in which there was no marriage. The same holds for the lags.

Graph 3: Effect of Marriage, Canay



Data source: tax data from the Canton of Bern 2002-2012, one third of the dataset is used.

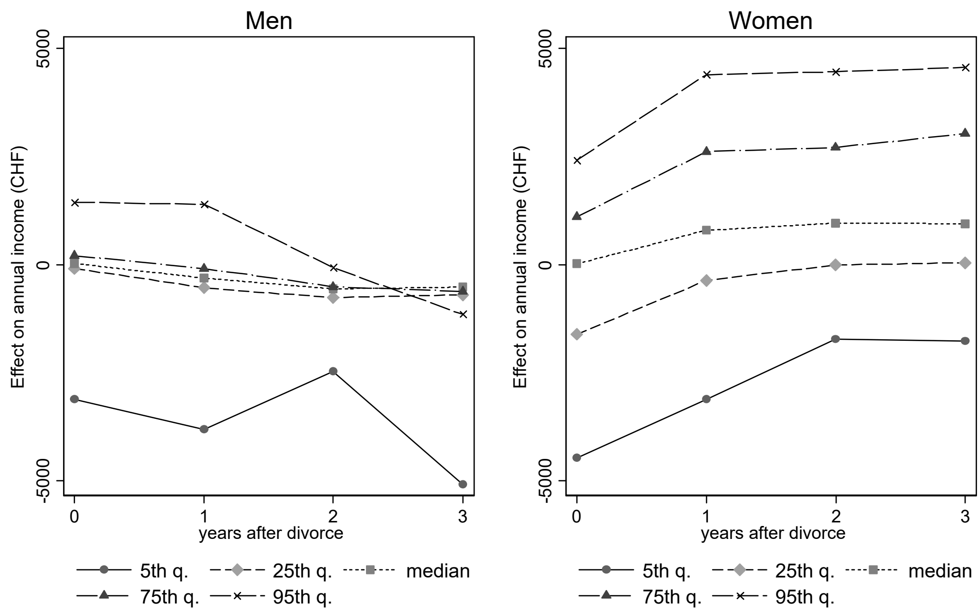
Marriage itself has large monetary consequences for women but not for men, this is what graph 3 suggests. For both sexes, it seems to be the case that low-income people reduce income after marriage whereas better earning individuals increase their wages and/or employment levels. Before considering the magnitude of the effects, it should be noted that the impact on yearly income is highest in the year of marriage but gets smaller in absolute terms afterwards. Low-

[37] With models of type 2, only a part of the hypothesis outlined in section 2.5 can be tested as some of these have effects only in the long run.

income women could be an exception of this as their coefficients seem to have a negative trend which may continue in the years followed by marriage. Only looking at 3 time periods after the year of marriage it cannot be concluded what the long run effects are. However, this is not what models of type 2 are about. On the first glance, the high positive coefficients for women may be surprising. All women earn more, at least in the year of marriage. One possible interpretation could be that women anticipate the moment of marriage and expand their time worked such that they can afford working less in the years thereafter. This would explain why best earning women increase their income more in absolute terms. Assuming that the coefficients continue to fall for women, the results of graph 2 are consistent with the marriage penalty reported in graph 1. Regarding the immediate impacts, the mixed results for men and the positive effect for women do not correspond to what would be expected in the long run. However, hypotheses claiming that marriage should reduce the income of women are rather applicable to long-run effects. For men, it seems that the signaling effects of marriage are stronger than short-run impacts of specialization and a potential increase in working effort. This would explain why there is a marriage premium overall (table 4 and graph 2) but moderate effects in the years following marriage. It should be noted that table 7 in Appendix C indicates that the standard errors are much higher at the bottom and the top than in the middle of the distribution. This is the case for all coefficients of model type 2 when estimated following Canay's approach. The AIC as well as the pseudo R^2 give further evidence for the fact that the model fits best at the quartiles. Compared to the model type 1, this specification fits the data generally better. This means that the covariates included in model type 2 have more explanatory power which is not surprising as these models contain more regressors. As the models are not nested it is difficult to judge whether one of them is better, they may explain different effects.

Turning to the effect of divorce, graph 4 shows how income is affected by this change in marital status. Again, low-income individuals earn less whereas a part of better earning people have a higher income in years after divorce. For women, the effect is smaller in the year they get divorced and higher as well as constant afterwards. This may come from the fact that on average, people are divorced only for 6 months in the first period considered. The loss of low-income people could arise from a reduction of economies of scale within a household. Living on their own now would result in less available time to work which reduces labor income. However, this may only be true for women which do have to spend more time looking after their children. On the other hand, it looks different for well earning women. If these individuals would be better qualified, it may be easier for them to find a new job. Thus, they can (or: the have to) expand their working time and earn more. The negative effects for women and the increase of income for men suggested by the literature (Jenkins, 2008; Poortman, 2000; Andress et al., 2006) can hardly be seen only looking at the first years after getting divorced. Here, it seems that the long-run impacts reported in table 4 do not translate in the direct effects of divorce.

Graph 4: Effect of Divorce, Canay

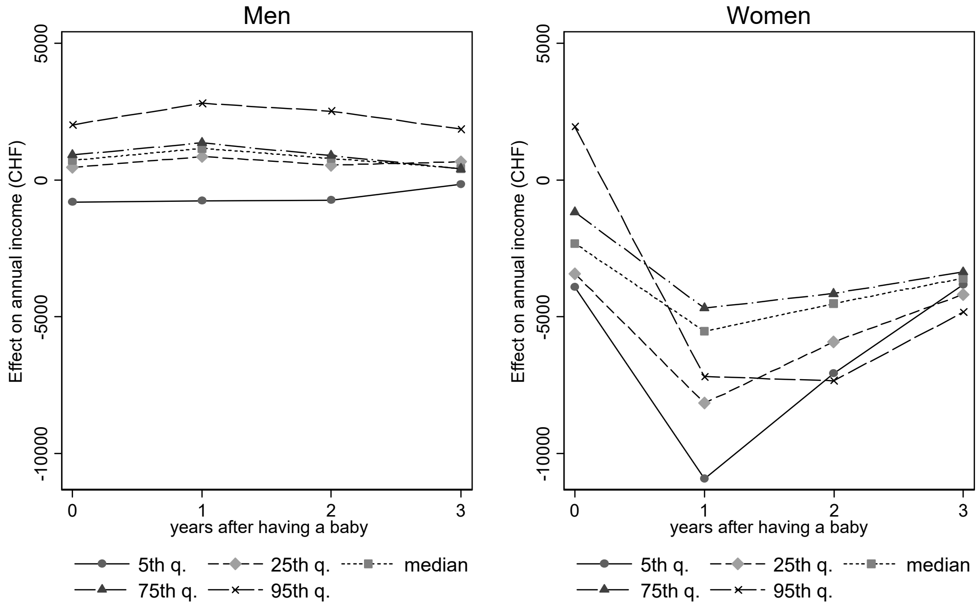


Data source: tax data from the Canton of Bern 2002-2012, one third of the dataset is used.

The same argument as for low-income women could apply for low-income men. In contrast to the clear trend for women, it is unclear what happens to at the bottom of the men's distribution because for the 5th quantile it is difficult to see a trend. The standard errors show that the estimate for this quantile are imprecise which makes it more difficult to interpret these coefficients. The rest of the men are only little affected by divorce. The slightly negative coefficients for the two quartiles and the median show that most men reduce their employment rates and/or wages only marginally after getting divorced. Reconsidering the relative meaning of these coefficients, it is obvious that the low-income people are most strongly affected by getting divorced.

Regarding the last variable of interest the expectation is clear: Having a baby[38] should reduce a woman's income since a mother lowers her working time. This sharp decrease of income is reported in the graph below. The results are in line with previous studies like the ones of Anderson et al. (2003), Gough and Noonan (2013) or Loughran and Zissimopoulos (2009). Contrary to the effects of getting married or divorced, the impact of having a baby seems to be similar in the short and in the long run.

Graph 5: Effect of having a baby, Canay



Data source: tax data from the Canton of Bern 2002-2012, one third of the dataset is used.

At the median, having a baby reduces the labor income of women by 5000 CHF in the first year afterwards. For low-income women, the effect is more than twice as large which points out the substantial heterogeneity of this effect. The effect of best earning women attracts attention since the reduction of income is higher than for women at the median or the third quartile. A reason for this could be that these women can afford to work less, even in the second and third year after having a baby. There is a common trend for all women and for all periods but the heterogeneity of the effect is largest at the beginning and shrinks then. In the third year, all women are almost affected with a similar reduction of income which means that low income

[38] The available data contain the number of biological children for both parents, even when they are not married.

groups are relatively affected much more. Most men increase their income after becoming a father, which is probably due to the increased costs. However, men at the 5th quantile earn less. These men maybe spend more time with their newborn as an increase in working time would not lead to much more income. This would hold if there is a relation between low-income and low-wage individuals, which is most probably the case. However, the coefficients for this quantile are not statistically different from zero at the 5% level which makes an interpretation meaningless.

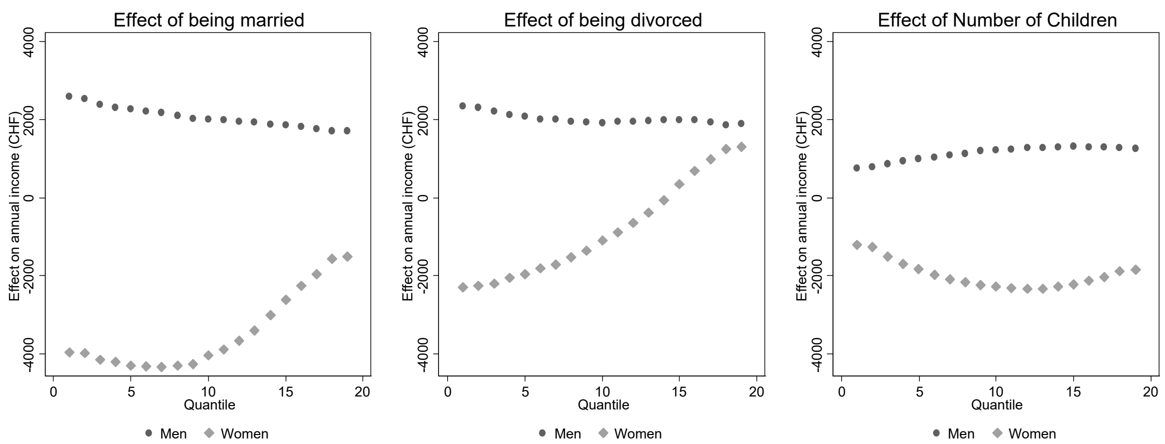
5.2 Kato et al. Fixed Effects Estimator

This section presents the results of the same regressions as in 5.1 but estimated with individual fixed effects that depend on the quantiles. Only the graphs will be reported, the regression tables can be found in the Appendix B. A small change of the included covariates is necessary, namely that X_{it} does not contain any year fixed effects. This has to be the case since otherwise, X_{it} would not be singular as the variable age and the person fixed effect already control for the effect of different years. Because of a similar reason no general intercept is used: As for every person a parameter is estimated, this already accounts for an intercept.

5.2.1 Model Type 1

Starting with the same model of type 1, the following graph gives the results for the coefficients of being married or divorced and the number of children. It looks similar than graph 2 but two key aspects are different: Firstly, all effects for women are generally shifted upwards whereas for men almost nothing has changed. Secondly, now there seems to be considerable heterogeneity for married women.

Graph 6: Model Type 1, Kato et al.



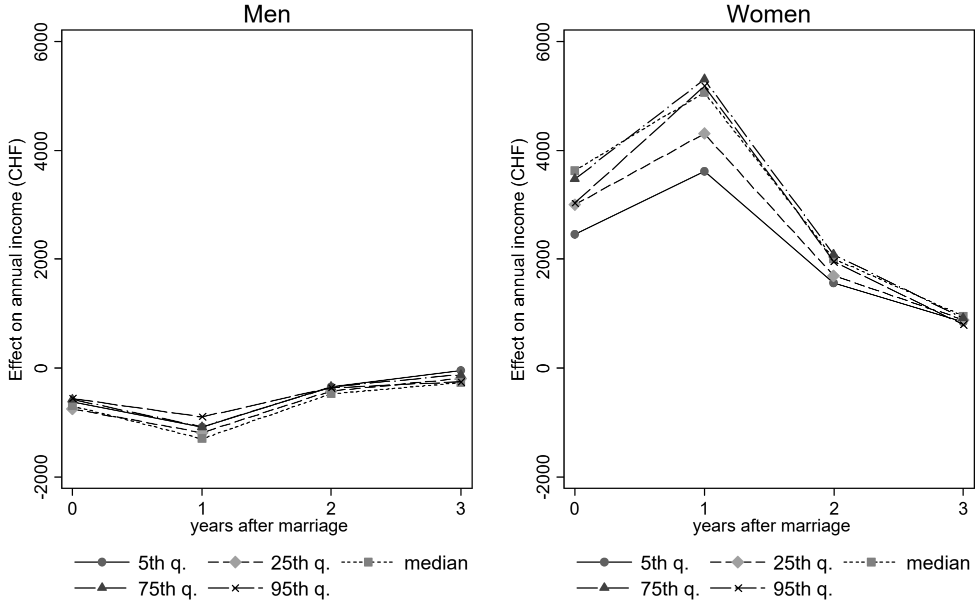
Data source: tax data from the Canton of Bern 2002-2012.

Compared to the results reported in graph 2, the absolute gap between men and women is smaller for all variables. As before, all three coefficients are almost constant for men. However, being divorced or married matters much more for women at the bottom of the income distribution. For both, the absolute difference between a woman at the 5th quantile and one at the 95th is about 2'000 CHF. Although the effects are smaller with the method of Kato et al., the results of graph 6 confirm the ones of graph 2 with respect to the shape of the curves. The fact that even in absolute terms the effects are larger for low-income people shows that in relative terms, these individuals are even more affected than people at the top. Again, these results match with the ones of other studies and confirm the hypothesis of section 2.5. The pseudo R^2 is higher for the estimation with Kato et al. than with the former but this may be since the fixed effects account better for individual income variation. Overall, the standard errors are much higher which follows logically from the fact that only a third of the observations are used.

5.2.2 Model Type 2

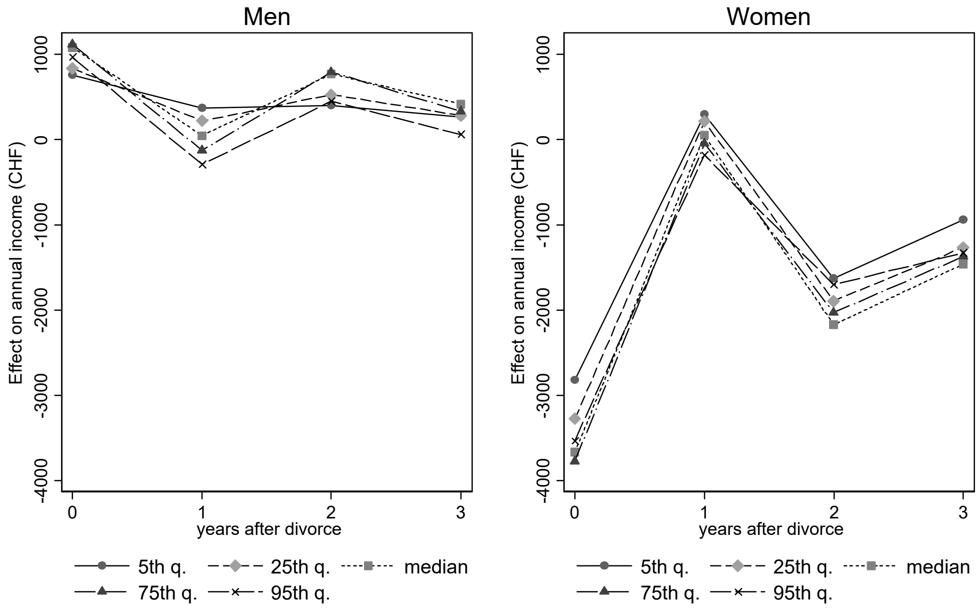
The next graph gives further evidence for the fact that marriage has different implications for men and women. Men are only slightly affected with coefficients around -1'000 to -200 CHF. There seems to be a positive trend meaning that these negative effects vanish over time. Furthermore, it can be said that all men are affected almost equally in absolute terms which means that the relative effect is much stronger for low income groups. The heterogeneity is lower than in graph 3 for both men and women. The positive effect of marriage for women seems more pronounced since it is strictly positive for all women and for all considered time periods. Nevertheless, the same negative trend as in the results of graph 3 can be seen in graph 7. Generally, the interpretations for the estimation following Canay's method hold for these results too. Regarding the goodness of fit, model type 2 fits similarly well for both estimation procedures. Whereas the standard errors were higher at the ends of the distribution when estimated with Canay's procedure, this is not the case for the results here. Furthermore, the standard errors are generally larger which should be kept in mind when interpreting the results.

Graph 7: Effect of Marriage, Kato et al.



Data source: tax data from the Canton of Bern 2002-2012, one third of the dataset is used.

Graph 8: Effect of Divorce, Kato et al.

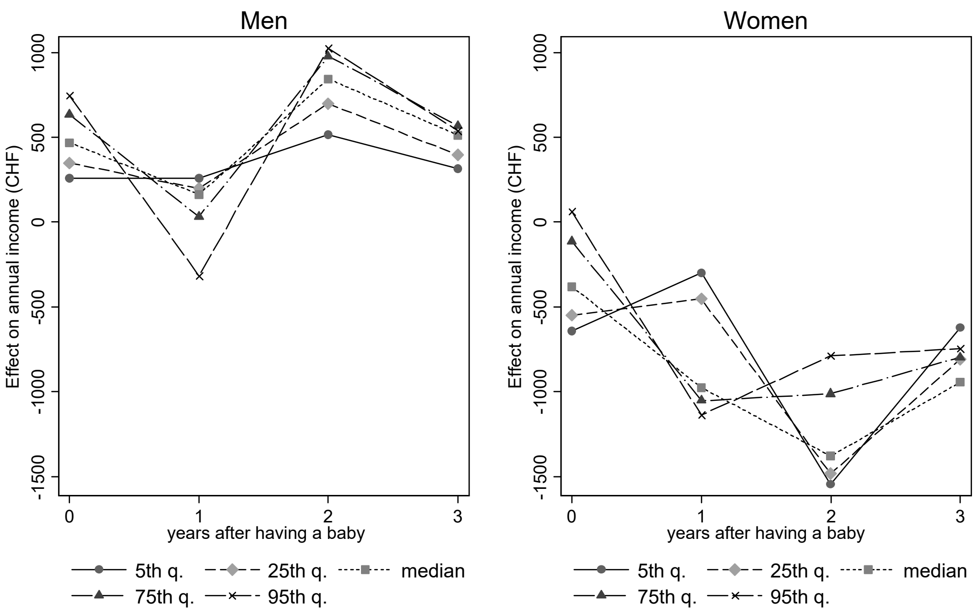


Data source: tax data from the Canton of Bern 2002-2012, one third of the dataset is used.

Reconsidering the effect of divorce, graph 8 points out that women's income is lower after separating from their partner. The shape of the effect over time is surprising since there seems to be no straightforward reason why divorce should have such heterogenous effects in different years. As already mentioned, women may have to earn less after a divorce since they receive private transfers. On average, the effect is negative for all quantiles which stays in contrast to the results obtained by the models according to Canay. Further, the results indicate that low-income women are less affected than others (with a difference of about 1’000 CHF). The effect on men is mostly positive but small and almost the same for all quantiles. These results correspond to the effects estimated by other studies (Jenkins, 2008; Andress et al., 2006 and Poortman, 2000).

Finally, turning to the effect of becoming a father or mother the results of the graph 9 are less clear-cut than the one of the analogue graph 5. An increase in income of about 300 to 1’000 CHF for men almost exactly replicates the results seen so far. There is no clear picture which men are more affected and the differences are small. For women, having a baby still corresponds to a decrease of income but the impact is about ten times smaller than in graph 5. The explanation for that is that the fixed effects included here more explicitly estimate the individual’s level of income. Low-income women’s income is again lower in the second year after having a baby. A possible explanation for this could be that some of them get one more baby since the probability of having a child is clearly higher for people which already became parents two years ago (16%), than for others (4%).

Graph 9: Effect of having a baby, Kato et al.



Data source: tax data from the Canton of Bern 2002-2012, one third of the dataset is used.

5.3 Testing

The reason to apply quantile regression is that the analyzed effect can vary across the conditional distribution of the outcome variable. Hence, it should be tested whether the effects for different parts of the distribution are statistically different from each other. Precisely this can be done with an ANOVA test procedure. For all models, the coefficients of five quantiles (5^{th}, 25^{th}, median, 75^{th}, 95^{th}) will be jointly tested to have the same slope coefficients. For the results of the regressions by Canay's method, a Wald test is used according the general class of tests in Koenker and Bassett (1982). The coefficients of the regressions by Kato et al. are tested separately to be the same across the five quantiles using a multivariate test of means.[39] The results of the tests indicate that the null hypothesis of equal coefficients across quantiles can be rejected in all cases. All tables are reported in the Appendix C.

5.4 Summary

Summing up the results, it can be said that being married and being divorced definitively have negative impacts on the income of women but positive ones for men. Being divorced has a larger effect at the bottom of the distribution but for marriage it depends which estimation method is applied. In numbers, the effect of marriage varies between -2'000 and -10'000 CHF for women and between 0 and +2'000 CHF for men depending on the estimation method and the quantiles. The effect of being divorced ranges from -5'000 to +1'000 CHF for women and from +1'000 to +2'000 CHF for men. Both applied methods show further that the raw number of children lowers the income of women but slightly increases the one of men. A first or one more child reduces the income of women by about -1'500 to -6'000 CHF and increases the income of men by +500 to 1'500 CHF.

Regarding the immediate impacts of marriage, divorce and childbearing the results are mixed. Marriage itself has small negative consequences for men and hugely positive effects for women whereas the latter decrease sharply in the years afterwards. In the year of marriage and the first year afterwards the income of women increases by about +3'000 to +10'000 CHF while for men the effect is between -2'000 and +1'000 CHF. So far, the two approaches predict about

[39] This test assumes multivariate normality according to (Mardia et al., 1979). Hence, the bootstrapped vectors of coefficients are tested to be normal. In the case of model type 1, for 49 of 50 coefficients the null hypothesis of normality cannot be rejected on the 5% level. For the model of type 2, 138 of 140 coefficients (5 quantiles times 28 regressors) are considered to be normal following the same test.

the same. However, the effect of divorce is once very heterogenous (Canay) and once clearly negative for women (Kato et al.). As the range of the effects is very large (-4’000 to +5’000) it cannot be said with certainty how women are affected by divorce in the short run. For most men, getting divorced affects income only by -500 to +1’000 CHF but for low-income individuals, the effect can be about -5’000 CHF. Similarly, for women the effect of having a baby is strongly negative and heterogenous when estimated with the method of Canay but much less clear when the estimation procedure of Kato et al. is applied. The effect ranges from -1’500 to -10’000 CHF. Becoming a father has an effect between -500 to +2’000 CHF. Concluding, it can be said that all effects are larger for women than for men. Additionally, the magnitude of the effects is far higher when the method of Canay is applied.

With respect to the hypothesis outlined in section 2 the following conclusions can be drawn. The results of the present paper confirm that there is a marriage premium for men even though it is smaller than found in previous studies. Since this premium is almost equal for all quantiles, the relative impact of being married varies a lot from about 2 to 10%. For most men, marriage itself leads to a small decrease in income which casts doubt on hypothesis that married men work harder and specialize. Hence, the signaling effects of marriage seem to dominate. Getting married increases women’s income in the short run but being married decreases the income substantially in the long run. As the theoretical explanations for women’s reduction in income due to marriage may be more relevant in the long run, this finding does not contradict the results of previous studies. Nevertheless, the fact that marriage first increases income for women is not documented in the literature so far. Apparently, being divorced lowers income of women which is line with other studies. However, the direct impact of getting divorced depends on which quantile regression method is applied. The results of the approach by Kato et al. confirm existing findings whereas the ones following the method of Canay support mixed interpretations. For men, getting divorced slightly increases income in most cases which corresponds to the expected long-run effects. Regarding the effect of childbearing, the main hypothesis that having a baby reduces women’s income is confirmed.

It may surprise that the two methods applied differ with respect to their results. However, considering the different inclusion of fixed effects, a large part of this difference can be explained. Explicitly controlling for individual effects lowers the magnitude of all effects and reduces the heterogeneity within the results. This is intuitive as the method by Kato et al. is more precise with respect to eliminating individual effects and thus more of the changes in income are removed. This is the case since only a few covariates are used for all models, the residuals computed in the first stage of Canay's procedure may be an imprecise estimate for the true individual fixed effects. In addition, the fixed effects of Kato et al. are more flexible by definition because they vary with the quantiles. In other words, fixed effects that depend on quantiles can explain more of an individual's variance in income since more parameters are estimated. From this it follows that covariates may only catch the remaining variance in income which is smaller than in the Canay setting. Hence, all studied effects are lower with fixed effects that depend on quantiles. This leads to the conclusion that the results of Kato et al. are more reliable if as much as possible of individual fixed effects should be removed.

To what extent the results presented here generalize is unclear. The Canton of Bern is large and represents about 10% of all Swiss residents.[40] However, it could be the case other regions have different income distributions or differ regarding their structure of employment levels. In addition, different institutional settings such as the regulation of the paid maternity leave or the private transfers after a divorce may influence the results.

6 Conclusion

Most prominently, this paper shows that the effect of marriage, divorce and childbearing on labor income may be different for high or low-income people. This supports the use of quantile regression when tackling these subjects. Furthermore, it is pointed out that the effects depend on how fixed effects are included into quantile regression models. Individual fixed effects which are allowed to vary with quantiles of the outcome variable account for more income variation which reduces the effect of other covariates. In contrast to this, the method according to Canay considers the part of variation which cannot be explained by the other covariates as fixed effects. These fixed effects are imprecise when the covariates only explain little of the outcome variable or when the fixed effects depend strongly on the quantile which may be the case in this study.

The results confirm the findings of the existing literature, namely that there is a marriage premium for men, a marriage penalty as well as a motherhood penalty for women. With respect

[40] From the department of statistics. (https://www.bfs.admin.ch/bfs/de/home/statistiken/bevoelkerung/stand-entwicklung.assetdetail.159578.html, accessed on the 19.11.2016)

to the effect of divorce too, the present paper verifies previous results in showing that being divorced has a positive impact on income for men but a negative one for most women. However, this effect is largely heterogenous for women since high-income are much less affected. In addition, the direct effects of marriage, divorce and childbearing are estimated. For women, getting married explicitly increases labor income which was not found in the literature so far. Getting divorced affects women differently and having a baby has a negative impact. The latter is again consistent with previous studies. There is considerable heterogeneity within all effects for women but almost none for men. The latter are much less affected by all those events.

Contrary to most of the previous research, the effects on income should be interpreted as changes in (hourly) wage *and* changes in working time. The long-run effects may be related to both whereas the immediate impacts probably come from changes of the employment level. Hence, earning more is not necessarily related to "benefitting" from getting married, divorced or having a baby. It is likely that these people must cover higher costs due to a corresponding change which reduces their standard of living even when they earn more in absolute terms.

Considering reverse causality, it could be the case that well earning people are more likely to have children. High-income men may be more attractive for marriage and it could be that for women, income influences the decision to marry or not since they can or cannot afford to stay independent. The inclusion of individual fixed effects prevents this potential sample bias to affect the results which is a crucial advantage of the present paper.

Several aspects of the studied effects open gates for further research. Additional information on individual employment level would enable the analysis to distinguish between effects on wage and working time. Similarly, with data on private transfers, child alimonies and child care expenditures the effects on available income could be estimated more precisely. Furthermore, the effects could be separately estimated for people with and without children as parts of the literature suggests that these differ. Finally, including the effects on wealth may reveal that individual welfare is affected through other channels too.

7 Literature

Anderson, D.J., Binder, M., Krause, K., 2003. The Motherhood Wage Penalty Revisited: Experience, Heterogeneity, Work Effort, and Work-Schedule Flexibility. Ind. Labor Relat. Rev. 56, 273.

Andress, H.-J., Borgloh, B., Brockel, M., Giesselmann, M., Hummelsheim, D., 2006. The Economic Consequences of Partnership Dissolution--A Comparative Analysis of Panel Studies from Belgium, Germany, Great Britain, Italy, and Sweden. ResearchGate 22, 533–560.

Angrist, J.D., Evans, W.N., 1998. Children and Their Parents' Labor Supply: Evidence from Exogenous Variation in Family Size. Am. Econ. Rev. 88, 450–477.

Arulampalam, W., Booth, A.L., Bryan, M., Australian National University, Centre for Economic Policy Research, 2006. Is there a glass ceiling over Europe?: exploring the gender pay gap across the wages distribution. Centre for Economic Policy Research, Canberra.

Becker, G.S., 1981. Altruism in the Family and Selfishness in the Market Place. Economica 48, 1.

Canay, I.A., 2011. A simple approach to quantile regression for panel data: A simple approach to quantile regression for panel data. Econom. J. 14, 368–386.

Christofides, L.N., Polycarpou, A., Vrachimis, K., 2013. Gender wage gaps,"sticky floors" and "glass ceilings" in Europe. Labour Econ. 21, 86–102.

Cornwell, C., Rupert, P., 1997. Unobservable Individual Effects, Marriage and the Earnings of Young Men. Econ. Inq. 35, 285–294.

Day, R.D., Bahr, S.J., 1986. Income Changes Following Divorce and Remarriage. J. Divorce 9, 75–88.

de Linde Leonard, M., Stanley, T.D., 2015. Married with children: What remains when observable biases are removed from the reported male marriage wage premium. Labour Econ. 33, 72–80.

Dougherty, C., 2006. The Marriage Earnings Premium as a Distributed Fixed Effect. J. Hum. Resour. XLI, 433–443.

Ellwood, D., Wilde, T., Batchelder, L., 2004. The mommy track divides: The impact of childbearing on wages of women of differing skill levels. Harv. Univ. March 152.

Galvao Jr., A.F., 2011. Quantile regression for dynamic panel data with fixed effects. J. Econom., Annals Issue on Forecasting 164, 142–157.

Goldin, C., Polachek, S., 1987. Residual differences by sex: Perspectives on the gender gap in earnings. Am. Econ. Rev. 77, 143–151.

Gough, M., Noonan, M., 2013. A Review of the Motherhood Wage Penalty in the United States. Sociol. Compass 7, 328–342.

Grund, C., 2015. Gender pay gaps among highly educated professionals—Compensation components do matter. Labour Econ. 34, 118–126.

Hao, L., Naiman, D.Q., 2007. Quantile regression, Quantitative applications in the social sciences. Sage Publications, Thousand Oaks, Calif.

Hill, M.S., 1979. The Wage Effects of Marital Status and Children. J. Hum. Resour. 14, 579.

Jenkins, S.P., 2008. Marital Splits and Income Changes over the Longer Term, in: Changing Relationships. p. 217.

Kato, K., Galvao, A., Montes-Rojas, G.V., 2012. Asymptotics for panel quantile regression models with individual effects. J. Econom. 170, 76–91.

Kenny, L.W., 1983. The Accumulation of Human Capital During Marriage by Males. Econ. Inq. 21, 223–232.

Killewald, A., Gough, M., 2013. Does Specialization Explain Marriage Penalties and Premiums? Am. Sociol. Rev. 78, 477–502.

Koenker, R., 2005. Quantile Regression. Cambridge University Press.

Koenker, R., 2004. Quantile regression for longitudinal data. J. Multivar. Anal. 91, 74–89.

Koenker, R., Bassett, G., 1982. Robust Tests for Heteroscedasticity Based on Regression Quantiles. Econometrica 50, 43–61.

Koenker, R., Bassett, G., 1978. Regression quantiles. Econom. J. Econom. Soc. 33–50.

Koenker, R., Machado, J.A.F., 1999. Goodness of Fit and Related Inference Processes for Quantile Regression. J. Am. Stat. Assoc. 94, 1296–1310.

Koenker, R., Portnoy, S., Ng, P.T., Zeileis, A., Grosjean, P., Ripley, B.D., 2016. Package “quantreg.”

Korenman, S., Neumark, D., 1991. Does marriage really make men more productive? J. Hum. Resour. 282–307.

Lamarche, C., 2010. Robust penalized quantile regression estimation for panel data. J. Econom. 157, 396–408.

Loughran, D.S., Zissimopoulos, J.M., 2009. Why wait? The effect of marriage and childbearing on the wages of men and women. J. Hum. Resour. 44, 326–349.

Malkiel, B.G., Malkiel, J.A., 1973. Male-Female Pay Differentials in Professional Employment. Am. Econ. Rev. 63, 693–705.

Mardia, K.V., Kent, J.T., Bibby, J.M., 1979. Multivariate Analysis. Lond. Acad. Press 61, 206–206.

Mosteller, F., Tukey, J.W., 1977. Data analysis and regression. Addison-Wesley Ser. Behav. Sci. Quant. Methods.

Nakosteen, R.A., Zimmer, M.A., 1987. Marital Status and Earnings of Young Men: A Model with Endogenous Selection. J. Hum. Resour. 22, 248–268.

Neumann, M.H., 2007. Deconvolution from panel data with unknown error distribution. J. Multivar. Anal. 98, 1955–1968.

Newey, W.K., Powell, J.L., 1990. Efficient Estimation of Linear and Type I Censored Regression Models Under Conditional Quantile Restrictions. Econom. Theory 6, 295–317.

Peters, R., 2014. Steuerliche Ungleichbehandlung von verheirateten und unverheirateten Paaren in den Kantonen und beim Bund. ESTV.

Peterson, R.R., 1996. A Re-Evaluation of the Economic Consequences of Divorce. Am. Sociol. Rev. 61, 528–536.

Poortman, A.-R., 2000. Sex Differences in the Economic Consequences of Separation. A Panel Study of the Netherlands. Eur. Sociol. Rev. 16, 367–383.

Portnoy, S., Koenker, R., 1997. The Gaussian hare and the Laplacian tortoise: computability of squared-error versus absolute-error estimators. Stat. Sci. 12, 279–300.

Powell, D., 2016. Quantile regression with nonadditive fixed effects.

Simón, H., 2012. The gender gap in earnings: an international comparison with European matched employer–employee data. Appl. Econ. 44, 1985–1999.

Tach, L.M., Eads, A., 2015. Trends in the Economic Consequences of Marital and Cohabitation Dissolution in the United States. Demography 52, 401–432.

Uunk, W., 2004. The Economic Consequences of Divorce for Women in the European Union: The Impact of Welfare State Arrangements. Eur. J. Popul. Rev. Eur. Démographie 20, 251–285.

Weichselbaumer, D., Winter-Ebmer, R., 2005. A Meta-Analysis of the International Gender Wage Gap. J. Econ. Surv. 19, 479–511.

Weitzman, L.J., 1985. divorce revolution. Collier Macmillan.

8 Appendix

8.1 Appendix A: Descriptive Statistics

Table 3A: Summary Statistics by Sex and Decil of Income

Sex	Variable	Decile 1	2	3	4	5	6	7	8	9	10
Men	Labor Income (CHF)	0	4262	21100	45091	56131	64147	73152	86196	109624	>109624
	Age	49	40	33	36	37	41	43	45	46	48
		14	16	16	14	13	12	11	10	9	8
	Number of Children	0,43	0,44	0,22	0,29	0,34	0,52	0,73	0,82	0,93	1,12
		0,91	0,94	0,69	0,74	0,75	0,89	1,03	1,07	1,10	1,15
	Married	56%	43%	27%	34%	37%	51%	62%	67%	71%	79%
		50%	49%	44%	47%	48%	50%	48%	47%	45%	41%
	Divorced	13%	7%	5%	7%	7%	9%	10%	11%	11%	10%
		33%	26%	22%	26%	26%	29%	30%	31%	31%	31%
Women	Labor Income (CHF)	0	0	3684	11764	20840	30467	40551	50107	63355	>63355
	Age	49	49	41	38	40	42	41	39	39	43
		13	13	15	15	14	12	12	12	12	10
	Number of Children	0,68	0,68	0,84	0,75	0,82	0,83	0,69	0,46	0,36	0,36
		1,08	1,08	1,13	1,06	1,06	1,03	0,97	0,83	0,75	0,76
	Married	71%	71%	60%	56%	62%	64%	55%	39%	33%	34%
		45%	45%	49%	49%	49%	48%	50%	49%	47%	47%
	Divorced	11%	11%	8%	7%	8%	11%	15%	16%	17%	18%
		31%	31%	28%	25%	27%	31%	36%	37%	37%	39%

Data source: tax data from the Canton of Bern, 2002-2012.

The reported values are the unweighted average over all yearly distributions.

8.2 Appendix B: Regression Results

Table 5: Fixed effect Regression Model Type 1

Variable	Coefficient	Standard Error	T-Statistic
Age	9248***	14.899	620.733
Age*Woman	-3757***	20.810	-180.517
Age^2	-98***	0.163	-600.343
Age^2*Woman	40***	0.231	173.381
Number of Children	794***	28.140	28.212
Number of Children*Woman	-6655***	39.486	-168.541
Being married	2022***	83.174	24.305
Being married*Woman	-10655***	115.979	-91.870
Being divorced	1712***	118.640	14.428
Being divorced*Woman	-5941***	166.071	-35.775
Year 2003	-731***	34.368	-21.275
Year 2004	-1289***	33.098	-38.934
Year 2005	-1489***	32.123	-46.360
Year 2006	-1413***	31.492	-44.877
Year 2007	-871***	31.240	-27.877
Year 2008	-343***	31.362	-10.942
Year 2009	-343***	31.866	-10.769
Year 2010	-496***	32.716	-15.174
Year 2011	-129***	33.877	-3.813
Constant	-112576***	246.912	-455.937
R^2 overall	0.1273		
Number of Observations	4101419		

Data source: tax data from the Canton of Bern, 2002-2012.

The dependent variable is yearly labor income in CHF.

The sign * indicates an interaction between two variables.

The stars of the coefficients report their significance level: * for significant at the 5% level, ** at the 1% level and *** at the 0.1% level.

Table 6: Fixed effect Regression Model Type 2

Variable	Coefficient	Standard Error	T-Statistic
Age	10481***	24.414	429.292
Age*Woman	-6318***	33.948	-186.119
Age^2	-110***	0.260	-424.355
Age^2*Woman	69***	0.365	188.150
Marriage	-225	120.280	-1.870
Marriage*Woman	5777***	173.638	33.271
L1_Marriage	-69	120.690	-0.576
L1_Marriage*Woman	1896***	173.619	10.918
L2_Marriage	-317**	119.404	-2.656
L2_Marriage*Woman	194	171.410	1.133
L3_Marriage	-276*	127.400	-2.164
L3_Marriage*Woman	-1596***	182.769	-8.735
Divorce	-542**	168.784	-3.212
Divorce*Woman	-29	235.109	-0.122
L1_Divorce	-594***	170.611	-3.480
L1_Divorce*Woman	1338***	236.675	5.655
L2_Divorce	-599***	170.869	-3.504
L2_Divorce*Woman	1629***	235.957	6.902
L3_Divorce	-802***	183.824	-4.365
L3_Divorce*Woman	2339***	253.333	9.234
Child	863***	78.045	11.060
Child*Woman	-2654***	111.473	-23.805
L1_Child	1097***	79.864	13.742
L1_Child*Woman	-8670***	113.949	-76.090
L2_Child	788***	78.382	10.048
L2_Child*Woman	-6958***	111.355	-62.482
L3_Child	676***	75.817	8.915
L3_Child*Woman	-4956***	107.508	-46.103
Year 2006	-64	33.686	-1.913
Year 2007	293***	32.224	9.092
Year 2008	586***	31.429	18.651
Year 2009	404***	31.362	12.890
Year 2010	21	32.036	0.668
Year 2011	139***	33.394	4.156
Constant	-117756***	417.094	-282.324
R^2 overall	0.1273		
Number of Observations	4101419		

Data source: tax data from the Canton of Bern, 2002-2012.

The dependent variable is yearly labor income in CHF.

The sign * indicates an interaction between two variables and LX refers to the xth lag of the variable.

The stars of the coefficients report their significance level: * for significant at the 5% level,

** at the 1% level and *** at the 0.1% level.

Table 7: Quantile regression Results Model Type 2, Canay

Quantile	5		25		50		75		95	
Variable	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Age	12286	5719	10724	4331	10209	3908	9808	3575	9658	3551
	23	21	7	6	4	3	6	5	27	24
	543	274	1532	706	2800	1229	1642	691	365	149
Age2	-135	-58	-113	-42	-107	-39	-102	-36	-97	-36
	0	0	0	0	0	0	0	0	0	0
	-496	-238	-1326	-649	-2357	-1171	-1425	-674	-297	-130
Marriage	-2910	1290	-927	2777	-225	3888	242	7880	1639	10225
	578	428	115	116	78	116	132	238	435	357
	-5	3	-8	24	-3	34	2	33	4	29
L1_Marriage	-2697	-3232	-589	-14	-29	1336	234	3085	1606	6825
	549	481	115	199	80	103	120	167	571	426
	-5	-7	-5	0	0	13	2	19	3	16
L2_Marriage	-2387	-4529	-244	-1900	62	-121	388	807	1004	3254
	731	351	116	225	74	96	129	122	685	376
	-3	-13	-2	-8	1	-1	3	7	2	9
L3_Marriage	-1664	-4683	-327	-3570	34	-1184	134	-525	443	980
	648	369	111	223	72	113	120	102	433	369
	-3	-13	-3	-16	1	-11	1	-5	1	3
Divorce	-3116	-4472	-87	-1612	28	18	206	1106	1442	2415
	978	391	130	184	99	86	193	169	1029	540
	-3	-12	-1	-9	0	0	1	7	1	5
L1_Divorce	-3818	-3114	-537	-366	-313	793	-89	2610	1396	4391
	919	559	173	168	105	98	178	199	1162	410
	-4	-6	-3	-2	-3	8	-1	13	1	11
L2_Divorce	-2478	-1725	-766	-7	-559	963	-513	2706	-75	4458
	1320	421	145	138	90	86	168	207	1010	401
	-2	-4	-5	0	-6	11	-3	13	0	11
L3_Divorce	-5082	-1773	-702	43	-519	944	-618	3025	-1150	4555
	990	399	164	141	98	99	169	199	787	378
	-5	-4	-4	0	-5	10	-4	15	-2	12
Child	-793	-3921	456	-3424	724	-2319	919	-1167	2016	1942
	388	224	76	89	46	51	79	93	404	232
	-2	-18	6	-38	16	-46	12	-13	5	8
L1_Child	-765	-10914	862	-8158	1159	-5520	1351	-4675	2801	-7189
	473	243	75	135	47	65	79	51	383	191
	-2	-45	12	-60	25	-85	17	-92	7	-38
L2_Child	-732	-7062	541	-5918	788	-4515	901	-4154	2518	-7336
	371	234	68	95	43	54	71	45	388	167
	-2	-30	8	-62	18	-83	13	-92	7	-44
L3_Child	-150	-3832	663	-4182	419	-3583	404	-3355	1858	-4827
	371	199	65	71	35	41	68	43	385	176
	0	-19	10	-59	12	-88	6	-78	5	-27
AIC		31278784		29571514		29080584		29457882		31196435
Pseudo R^2		0,51		0,79		0,85		0,85		0,83
Number of Observations		1368723		1368723		1368723		1368723		1368723

The dependent variable is yearly labor income in CHF. All quantile regressions include a constant and year fixed effects.

The first row gives the coefficient, the second row the standard errors and the third row the t-statistic.

Data source: tax data from the Canton of Bern, 2002-2012. One third of the dataset is used.

Table 8: Quantile regression Results Model Type 1, Kato et al.

Quantile	5		25		50		75		95	
Variable	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Age	5662	2490	5518	2740	5145	2815	4666	2652	4426	2456
	103	117	80	114	73	92	59	80	65	81
	547	-268	692	-245	706	-251	798	-254	682	-241
Age^2	-53	-22	-50	-25	-45	-25	-40	-23	-38	-21
	1	1	1	1	1	1	1	1	1	1
	-472	245	-596	228	-611	220	-699	223	-597	201
Number of Children	763	-1211	999	-1828	1232	-2280	1323	-2224	1276	-1838
	69	100	65	122	64	114	57	110	73	133
	113	-199	152	-233	192	-306	229	-318	174	-234
Being married	2593	-3948	2277	-4295	2012	-4027	1863	-2608	1726	-1495
	384	628	281	521	307	492	282	386	313	383
	66	-104	81	-125	66	-123	69	-120	55	-85
Being divorced	2364	-2288	2091	-1956	1917	-1091	2006	349	1897	1312
	446	697	357	600	331	596	373	597	374	530
	51	-66	58	-66	59	-51	55	-29	51	-11
Pseudo R^2		0,62		0,70		0,75		0,78		0,87
Number of Observations		2157514		2157514		2157514		2157514		2157514

The dependent variable is yearly labor income in CHF.

The first row gives the coefficient, the second row the standard errors and the third row the t-statistic.

Data source: tax data from the Canton of Bern, 2002-2012.

Table 9: Quantile regression Results Model Type 2, Kato et al.

Quantile	5		25		50		75		95	
Variable	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Age	5150	1801	5012	1928	4695	1902	4349	1802	4252	1736
	95	114	89	109	70	95	67	97	79	87
	541	-293	564	-284	674	-294	648	-266	540	-290
Age2	-46	-15	-44	-16	-40	-16	-37	-15	-36	-14
	1	1	1	1	1	1	1	1	1	1
	-469	273	-513	272	-613	286	-552	243	-454	264
Marriage	-618	2456	-750	3000	-697	3632	-575	3474	-559	3033
	210	314	194	320	207	353	208	384	221	401
	-29	99	-37	116	-33	121	-26	105	-26	91
L1_Marriage	-1084	3609	-1187	4304	-1298	5061	-1081	5305	-896	5180
	337	615	328	608	304	578	340	653	355	689
	-31	80	-37	92	-43	110	-32	99	-25	90
L2_Marriage	-346	1569	-420	1695	-471	2009	-345	2087	-362	1957
	214	314	217	347	218	341	238	387	192	341
	-17	62	-17	60	-20	71	-13	62	-18	68
L3_Marriage	-43	854	-191	888	-269	956	-125	913	-253	797
	227	334	198	290	192	283	205	294	203	325
	-3	28	-7	35	-13	42	-7	34	-12	31
Divorce	759	-2822	836	-3275	1084	-3668	1120	-3773	967	-3532
	352	633	324	585	325	527	325	617	371	636
	21	-59	27	-71	34	-91	36	-81	26	-73
L1_Divorce	371	296	220	212	48	50	-127	-45	-290	-180
	180	290	180	263	180	271	186	258	161	258
	20	-2	14	-3	5	-2	-7	2	-17	2
L2_Divorce	402	-1632	528	-1893	770	-2172	795	-2031	452	-1700
	333	535	299	510	307	504	332	507	364	591
	12	-41	18	-48	25	-59	24	-57	14	-41
L3_Divorce	268	-937	285	-1266	418	-1460	335	-1369	62	-1329
	295	438	266	466	237	431	259	401	326	515
	8	-28	10	-33	17	-46	12	-44	4	-30
Child	258	-643	347	-549	468	-380	634	-114	746	60
	104	146	106	142	111	157	108	160	130	156
	26	-63	32	-64	42	-53	60	-48	57	-44
L1_Child	256	-301	197	-453	162	-976	31	-1053	-318	-1138
	217	318	215	344	183	375	194	315	253	433
	11	-18	10	-19	9	-31	0	-35	-12	-21
L2_Child	515	-1546	698	-1484	843	-1379	978	-1013	1025	-789
	98	212	116	173	124	203	117	170	125	156
	54	-99	59	-127	68	-109	85	-119	81	-117
L3_Child	314	-623	395	-811	512	-945	566	-797	537	-747
	83	140	101	142	106	160	110	145	114	156
	38	-69	39	-86	48	-91	52	-95	48	-84
Pseudo R^2		0,72		0,76		0,80		0,82		0,90
Number of Observations		1368723		1368723		1368723		1368723		1368723

The dependent variable is yearly labor income in CHF.

The first row gives the coefficient, the second row the standard errors and the third row the t-statistic.

Data source: tax data from the Canton of Bern, 2002-2012.

8.3 Appendix C: Test Results

Table 10: Joint Test of Equality of Slopes, Canay

Model Type	DF	Resid Df	F-Statistic	Prob > F
1	80	32618085	6795.5	$< 2.2e^{-16}$ ***
2	148	6843467	1393.5	$< 2.2e^{-16}$ ***

Data source: tax data from the Canton of Bern, 2002-2012.

Df refers to degrees of freedom.

The stars of the coefficients report their significance level: *** indicates that the probability is essentially 0.

Table 11: Joint Test of Equality of Slopes, Model Type 1, Kato et al.

Variable	Hotellings T^2	Critical F-Value	Prob > F
Age	19060.78	4620.80	0
Age*Woman	10586.45	2566.41	0
Age^2	22656.58	5492.50	0
Age^2*Woman	12801.83	3103.47	0
Number of Children	4782.64	1159.43	0
Number of Children*Woman	15386.95	3730.17	0
Being Married	408.24	98.97	0
Being Married*Woman	4152.08	1006.57	0
Being Divorced	46.74	11.33	0
Being Divorced*Woman	2635.14	638.82	0

Data source: tax data from the Canton of Bern, 2002-2012.

The sign * indicates an interaction between two variables.

All coefficients are seperately tested to be the same across the 5th, 25th, 50th, 75th and 95th quantile.

Table 12: Joint Test of Equality of Slopes, Model Type 2, Kato et al.

Variable	Hotellings T^2	Critical F-Value	Prob > F
Age	10344.20	2507.69	0
Age*Woman	5508.41	1335.37	0
Age^2	12182.53	2953.34	0
Age^2*Woman	6753.09	1637.11	0
Marriage	61.02	14.79	0
Marriage*Woman	823.31	199.59	0
L1_Marriage	84.26	20.43	0
L1_Marriage*Woman	449.61	109.00	0
L2_Marriage	14.77	3.58	0
L2_Marriage*Woman	164.30	39.83	0
L3_Marriage	50.27	12.19	0
L3_Marriage*Woman	44.92	10.89	0
Divorce	127.93	31.01	0
Divorce*Woman	270.94	65.68	0
L1_Divorce	868.40	210.52	0
L1_Divorce*Woman	17.32	4.20	0
L2_Divorce	131.94	31.99	0
L2_Divorce*Woman	178.46	43.26	0
L3_Divorce	70.48	17.09	0
L3_Divorce*Woman	158.54	38.43	0
Child	1007.07	244.14	0
Child*Woman	140.70	34.11	0
L1_Child	407.36	98.75	0
L1_Child*Woman	272.04	65.95	0
L2_Child	1246.97	302.29	0
L2_Child*Woman	367.57	89.11	0
L3_Child	472.83	114.62	0
L3_Child*Woman	599.30	145.28	0

Data source: tax data from the Canton of Bern, 2002-2012.

The sign * indicates an interaction between two variables and LX refers to the x^{th} lag of the variable. All coefficients are seperately tested to be the same across the 5th, 25th, 50th, 75th and 95th quantile.

9 Statement of Authorship

I hereby declare that I have written this thesis without the use of documents and aids other than those stated above. We have mentioned all used sources and cited them correctly according to established academic citation rules. We are aware that otherwise the Senat is entitled to revoke the degree awarded on the basis of this thesis, according to article 36 paragraph 1 letter o of the University Act from 5 September 1996.

Bern, 22.11.2016