Does Marriage Increase Couples' Life Satisfaction?
Evidence Using Panel Data and Fixed-effects Individual Slopes[*]

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Abstract: Many contemporary studies find that married couples are more satisfied with life than unmarried people. However, whether marriage makes people more satisfied with life or whether more satisfied couples are more likely to marry remains a debated question. We reassess this relationship with panel data from the German Family Panel (*pairfam*) and extend previous analyses by adding individual trajectories (slopes) to standard fixed-effects regressions (FEIS). We are thereby able to distinguish – controlling for time-constant unobserved heterogeneity – whether there is in fact an effect of marriage on life satisfaction, whether people who are simply happier in their relationship are more likely to get married, or whether people whose development in life satisfaction is more positive are more likely to get married. We translate these different social mechanisms into different analytical strategies and find that OLS regression – due to its confounding effects between and within persons – overestimates the effect of marriage on life satisfaction. A fixed-effects estimator reveals a much lower effect of marriage on life satisfaction for couples who marry compared to those who continue to live apart together or cohabitate. Additionally, using a FEIS estimator and adjusting for – non-linear – development of individual life satisfaction over time, suggests that this effect is in fact causal.

Keywords: Life satisfaction · Marriage · pairfam · Panel data · FEIS models · Causality

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1 Introduction

A vast body of research has examined the association between marriage and life satisfaction.[1] Most research concludes that there is a clear increase in happiness once people get married (*Clark et al.* 2008; *Musick/Bumpass* 2012; *Tao* 2019). However, despite this extensive research, the question whether marriage is really the cause of increased life satisfaction or if it is simply the case that individuals who are already more satisfied with life are more likely to get married is vigorously debated. Due to the obvious impossibility of assigning marital status randomly, researchers have to rely on so-called observational data to infer the difference in life satisfaction between married and unmarried people. Thus far, researchers have brought forth a variety of empirical strategies in order to disentangle causal effects of marriage from possible selection into marriage. Especially due to the wide availability of panel data covering long time spans for many countries, considerable improvements have been made to disentangle the relationship between marriage and life satisfaction. A recurring finding from the literature, irrespective of cross-sectional or longitudinal estimation techniques, is that happiness increases with marriage (*Di Tella et al.* 2003; *Qari* 2014). However, the question as to whether this association is a "true effect" of marriage and to what extent it may or not be due to various forms of self-selection into marriage is still under discussion.

Thus, the questions that arise are whether the association between marriage and life satisfaction is causal and how such a potential effect could be identified. The main goal of our article is thus twofold: First, we make a substantial contribution estimating the effect of marriage on life satisfaction by using the FEIS estimator, an estimator that has not been previously implemented in this strand of research, and secondly, we make a methodological contribution by discussing the strengths and limits of using different panel techniques for establishing different forms of causal inference in the social sciences. In the following, we add to this debate by employing a new panel estimator, which not only controls for time-constant individual heterogeneity, but also accounts for future individual development in life satisfaction.

We are therefore able to disentangle to what extent this effect of marriage on happiness is a) due to a selection of satisfied people into marriage, b) a selection of people whose life satisfaction evolves more positively over time, or c) a true causal effect of marriage – that is, whether people select into marriage not because they are more satisfied with life than others but whose relationships evolve more positively over time.

In line with previous research, we find an increase in life satisfaction after marriage, or mechanism c) above. However, this effect is largely overestimated

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[1] The sociological and demographic literature on happiness and marriages uses the terms happiness and life satisfaction interchangeably. However, as one of the reviewers pointed out, the psychological literature clearly distinguishes between these two concepts. Our dependent variable is a measure of overall life satisfaction, we therefore use the term "life satisfaction" in our study. However, when we refer to other authors, we use their respective terminology.

when not accounting for selection as in pooled OLS regression. Accounting (partially) for self-selection into marriage, or accounting for mechanism a) above, using a fixed-effects estimator does presumably underestimate this effect since it does not fully control for the possibility that people with steeper trajectories in life satisfaction; people whose relationship evolves more positively over time, are more likely to be selected as marriage partners. This mechanism b) can only be accounted for when estimating fixed effects with individual slopes (FEIS, see *Ludwig/Brüderl* 2018; *Rüttenauer/Ludwig* 2020; *Wooldridge* 2010). Our analysis results in a stronger effect of marriage on life satisfaction, which provides evidence that marriage does indeed make people more satisfied with life, or mechanism c) above. Hence our results corroborate firstly a self-selection of people with higher life satisfaction into marriage and secondly a "true" effect of marriage on life satisfaction, which under specific assumptions can be interpreted as causal.

In the following we will first review the literature and the respective empirical strategies applied to investigate the relation between marriage and happiness. Then we will discuss their respective strengths and weaknesses and introduce our estimator and how it improves on previous research. Further, we will discuss different strategies to identify treatment effects, or casual inference, in the social sciences. Thereafter we will present our data and our results and conclude with a discussion.

2   The link between marriage and life satisfaction

Background

The relationship between subjective well-being and marriage has been vastly debated across different disciplines in the social sciences (cf. *Evans/Kelley* 2004; *Grover/Helliwell* 2019; *Lucas et al.* 2003; *Perelli-Harris et al.* 2019; *Qari* 2014; *Stutzer/ Frey* 2006). Marriage is associated with a variety of beneficial outcomes, both at the individual and the societal level. For example, marriage makes couples happier (*Clark et al.* 2008), increases self-rated health (*Musick/Bumpass* 2012) and makes depression less likely (*Pearlin/Johnson* 1977), to only name a few of the benefits.

There are four links that are commonly stressed when explaining the positive association between marriage and well-being (*Musick/Bumpass* 2012; *Umberson/ Montez* 2010). These can be separated as to whether they provide benefits of marriage over being single, that is whether it is beneficial to live together with someone, or whether it is marriage that accounts for the difference. In the latter case, married couples should not only be more satisfied with life compared to singles but also with respect to cohabiting couples or couples who live apart together (LAT). It is this latter contrast on which we focus in the paper.

The literature clearly states that marriage and a romantic union in more general terms is beneficial for life satisfaction in comparison to being single. These benefits unfold in many shapes and forms within different life domains. Firstly, spouses give each other support; they provide companionship, and give partner's access

to their social support network. As such, spouses will, for example, take care of each other if one of them becomes ill. In case of continued illness and in lack of proper and affordable care facilities, spouses are usually the ones to take over the often necessary (long-term) care (*Ehrlich/Minkus/Hess* 2020; *Ehrlich/Möhring/Drobnič* 2020). Secondly, marriage demands commitment as it legally binds two people together. Those two people then commit each other to long-term financial investments such as housing and sharing their wealth in more general terms (*Lersch/Vidal* 2014; *Waitkus/Minkus* 2021). Thirdly, from a social role perspective it is argued that marriage structures women's and men's lives by establishing the gendered division of household labour between couples (*Abramowski* 2020; *Becker* 1981; *Minkus/Busch-Heizmann* 2020). While in principle these mechanisms also apply to unmarried couples, we argue that their effect on life satisfaction should be stronger for married couples since commitment and (perceived) structure should be more important for the latter. Finally, an institutional perspective emphasizes that there are certain normative structures defining marriage as the appropriate behaviour. Thus, marriage is socially more acceptable and, since people generally prefer to comply with social norms, they get married. This latter benefit can only be reaped by married couples.

In this article we focus on the increases in life satisfaction when transitioning from living apart together or cohabitation into marriage. A few studies have argued that in contemporary societies where cohabitation is becoming more frequent, it might take on the function of marriage (*Musick/Bumpass* 2012; *Perelli-Harris et al.* 2019). In line with our reasoning above, research shows that couples can also reap benefits from their subjective well-being when transitioning into cohabitation (*Blekesaune* 2018; *Chen/van Ours* 2018; *Perelli-Harris et al.* 2019).

However, we argue that there will be an additional benefit when transitioning from cohabitation or LAT to marriage (*Musick/Bumpass* 2012; *Schneider/Rüger* 2007) and that this additional benefit is mainly due to the greater legal embeddedness marriage provides. Weddings legally bind two people to the contract of marriage. Within that contract there are many legally binding rules for couples. Thus, for example, while unmarried couples can also commit to long-term investments, if they split up there are no or only few institutionalized rules as to how their wealth must be distributed among them, whereas there are some legally binding rules as to how wealth is distributed among spouses who divorce. The same is true for other life course events that potentially come along with legal repercussions, such as parenthood (i.e., paternal rights), inheritances or many insurance cases. What's more, as mentioned above, marriage and weddings have a benefit on their own: The fact that two people commit to a life-long union within a religious ceremony is cited as one of the key motives for weddings and the decision to get married – at least in Germany (*Schneider/Rüger* 2007). Thus, the ceremony as such as well as the commitment made to each other before friends, family and, possibly, the church is a desirable life goal. Accordingly, contemporary research indeed finds evidence that there is an additional increase in subjective well-being when transitioning from cohabitation to marriage (*Blekesaune* 2018; *Chen/van Ours* 2018). Hence, in this article we will scrutinize the additional benefits of marriage over cohabitation and

LAT, the other two forms of being in a romantic union, which adds to a theoretical debate and helps us to more precisely understand the mechanisms as to why living with a partner is beneficial.

Selection or causation

As discussed, there is an abundance of studies pointing toward an increase in subjective well-being when married. However, there has also been a long-standing debate on whether this effect is actually causal, or if the increase in life satisfaction can be attributed to self-selection, that is whether individuals who are more satisfied with life select themselves into marriage. Thus, the question whether marriage makes you really more satisfied with life or if simply only satisfied people get married is an ongoing discussion in the literature.

In the following, we will first briefly lay out how large-scale panel data advanced our knowledge on causal inference[2] concerning the link between marriage and life satisfaction. Then, we'll extend this question of causality even further by asking if and which selection effects are present: Is it really only more satisfied people that get married or people with happier future relationships that get married?[3] Lastly, we will provide an overview on causal inference and the different treatment effects and the assumptions under which it can be estimated.

Early studies in particular employed cross-sectional data for testing the association of marriage and life satisfaction. The large majority of them finds evidence that there is a positive association between marriage and subjective well-being (*Di Tella et al*. 2003; *Gove et al.* 1983; *Lee/Ono* 2012; *Simon* 2002; *Stack/ Eshleman* 1998). However, results from these studies can be interpreted as causal effects of marriage on life satisfaction only when making specific and often highly unlikely assumptions. Specifically, these assumptions postulate that in a regression equation the relevant variable – marriage in our example – is uncorrelated with the error term, i.e., with unobserved variables or variables observed but omitted from the equation. This implies that all variables that are jointly correlated with the dependent and the central independent variable have to be added as control variables. This is known as the exogeneity condition in standard regressions.

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[2] "Causal inference" differs slightly from "causal effect." We can infer what the counter-factual outcome would be – either in the population or in the sample – for those who are treated or for those in the control group. This may or may not be the case for causal effects. For example, a statement such as "if those who received treatment hadn't, their behaviour would have changed by x" is a different statement than saying "treatment condition has an effect on behaviour." The former statement involves a number as well as a degree of uncertainty while the latter does not (*Hernán* 2016). Moreover, a statement such as "A is a cause of B" is much broader than "if A changes by x, B changes by y."

[3] As we discuss below, we cannot infer the responsible mechanism with absolute certainty. However, we use relationship duration as a proxy for being in a happy and stable union that will continue to evolve positively in the future. Thus, from an optional vanishing of the marriage effect, in the FEIS model as compared to the FE-model, we would deduce that the marriage effect is due to better future relationship quality.

However, including all potentially relevant variables is notoriously difficult. First, many of them are unobservable by definition or they are observable in principle but simply not included in the survey data at hand. Secondly, many researchers are trained to think "more control is always better" and therefore they include as many control variables in their equation as possible. However, controlling too much can also result in biased estimates (for a discussion see *Elwert/Winship* 2014). To give an example, much of the modern applied discussion on causality draws on the evaluation of labour market programmes. Let us assume that such a programme is designed to improve the labour market chances of unemployed individuals. However, this very participation of individuals in a specific programme might affect their motivation to look for work. Thus, controlling for motivation in a regression framework might underestimate the causal effect of the programme on future employment, since motivation levels rose as a direct consequence of taking part in such a programme.

Thus, the research question of whether people who are more satisfied with life get married or if marriage actually makes you more satisfied could not be resolved by using ordinary, for example, least squares, regression. Consequently, later studies concentrated on filtering out this very selection effect. Since there is an extensive body of studies focusing on the question of association vs. causation, we concentrate on a few works that signify the most prominent empirical strategies employed in this strand of research. In a nutshell, four empirical strategies are used to identify causal relationships.

First, some studies employed a *matching* estimator using cross-sectional data (*Perelli-Harris et al.* 2019). Here, first the probability of entering the treatment, that is marriage, is modelled, thereafter people with identical probabilities for marriage are matched and their happiness is compared. This approach yields proper estimates of causal effects if the selection process into marriage is correctly specified. Thus, it "cures" the bias caused by the omission of control variables. However, this strategy requires, first of all, that all variables that govern this selection process have been measured ("observed"), secondly, that the selection model including these variables is correctly specified, and thirdly, that the matching algorithm is correctly specified as well. In practice, all three assumptions are problematic and hence empirically the estimators from matching procedures often tend to vary greatly (e.g., *Morgan/ Winship* 2015).

Second, some (panel) studies employ a *lagged dependent measure* (LV) of happiness prior to marriage (*Grover/Helliwell* 2019), thereby controlling for prior happiness levels of respondents. Using this strategy, one is indeed able to control for happiness prior to marriage and hence to control for potential self-selection into marriage. This strategy, however, severely violates an additional assumption for regressions using panel data, namely strict exogeneity:[4] Prior life satisfaction

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[4] Strict exogeneity, compared to exogeneity explained above, means that in addition to the regression assumptions, all independent and the dependent variable are uncorrelated with their past and future values. This – stronger – assumption is obviously mainly of relevance when panel data are being used.

levels are very likely to influence current ones (i.e., one rarely moves from being depressed to being very satisfied with one's life within a year) and are likely to be correlated with previous and future values of the independent variables x. There are also many studies that combine the fixed effects estimator (explained below) with a lagged dependent measure of subjective well-being (*Chen/van Ours* 2018). However, it should be noted that these two empirical strategies assume different data-generating processes and hence are suited for different research questions. A lagged dependent variable approach for panel data may be appropriate if one wants to investigate how strongly past outcomes influence current ones. Consider for example the question as to whether stereotypes about foreigners reduce contact with foreigners or whether stereotypes about foreigners are nourished simply because there is no contact with them. Using a (cross-)lagged panel model would reveal how strong the effects of previous states, or attitudes towards foreigners, on future values of this variable are. Fixed effects estimators, by contrast, reveal the effect on y of a change in x within a person. These are substantially different research questions (see *Brüderl/Ludwig* 2015 for an extensive discussion of whether and when the investigator's focus should be on within changes or state dependency). Additionally, research has shown that LV estimators are in danger of being biased, this applies to linear regression as well as fixed effects environments (*Nickell* 1981; *Phillips/Sul* 2007).

Third, another strategy is to include *time dummies* for the time prior to and after marriage when predicting happiness (*Blekesaune* 2018). Again, this can also be done in combination with a fixed effects estimator (*Qari* 2014; *Tao* 2019). Employing this combination, one is able to track the decline and/or increase in life satisfaction prior to and after marriage, or the general trend or development over time, while simultaneously controlling for unobserved factors that are related to time periods. Yet if these time dummies capture unobserved heterogeneity, as they are likely to do, they are most likely correlated with previous and future values of the dependent and independent variables, thereby again violating strict exogeneity. Therefore, just adding time dummies is insufficient as the only solution to identify causal effects but it provides a useful supplementary strategy to control for trends (see below).

Fourth, as has already become obvious from the above, some studies use a *fixed-effects estimator (FE)* in order to estimate the effect of marriage on well-being (*Musick/Bumpass* 2012; *Næss et al.* 2015). These models have arguably become the central tool in the analysis of panel data outcomes. In FE models, outcomes are derived by de-meaned individual changes. Here, each individual has a person-specific mean, from this person-specific mean all individual deviations over time are subtracted and only these changes are used when estimating the FE model. Thus, in the case of marital transition, only those respondents who actually have a change in relationship status and other relevant independent variables, for example from being in cohabitation or LAT to being married, are analysed. This procedure cancels out all time-invariant personal characteristics and between person heterogeneity; presumably stable personal characteristics such as gender, personal ideology, or religiosity, are mathematically eliminated (*Allison* 2009; *Brüderl/Ludwig* 2015;

Wooldridge 2010).[5] Formally, a regression model with dependent variable y, independent time-constant variable x and independent time-varying variable z, as well error components e and u in a panel context can be described as:

$$y_{it} = b_1 z_{it} + b_2 x_i + e_{it} + u_i$$

where the subscripts i and t indicate variation across individuals (i) or time (t). The fixed-effects model then is:

$$y_{it} - y_i = b_1 (z_{it} - \bar{z}_i) + b_2 (x_i - x_i) + (e_{it} - \bar{e}_i) + (u_i - u_i)$$

Here it becomes evident that all stable individual characteristics are cancelled out and hence are being controlled for ($x_i - x_i = 0$, because there is no subscript t; and the time-constant individual error u, $u_i - u_i = 0$). The only coefficient that can be estimated is the time-varying effect $b_1 (z_{it} - \bar{z}_i)$. As can be seen from the theoretical overview above, the fixed-effects model has become the cornerstone of longitudinal data analysis. An FE model therefore can potentially distinguish whether marriage makes people more satisfied with life – the within estimator of marriage would be positive – or whether there is a selection effect of people who are constantly satisfied with life into marriage. This would be the case when an OLS estimator, which combines effects within and between persons, for marriage is positive but an effect within persons is absent. This would indicate that the OLS effect combining within and between effects is solely due to effects between individuals, or self-selection into marriage based on unobserved characteristics.

However, this model needs assumptions, too. First, to arrive at unbiased (within) effects, it is assumed that all errors or unobservable elements within a unit are time-constant. Sometimes this assumption may be highly unlikely, especially in the case of long panel data sets. For example, priorities between work and family life may change over the life course due to specific life events such as the birth of children, thereby making unobservable personal characteristics such as work motivation time-varying. *Bollen* and *Brand* (2010) provide a statistical test for the mainly untested and often heroic assumption of stable unobservable personal characteristics within the realm of structural equation modelling. Yet these tests are rarely acknowledged or carried out within the more econometrically driven fixed-effects literature. Secondly, it assumes that treated, or married, and untreated, or unmarried, people would behave similarly if they were in a different treatment condition. This is the so-called parallel trends assumption (cf. *Brüderl/Ludwig* 2015). In the setting of marriage and life satisfaction this would imply that over time, the development in life satisfaction would evolve parallel for those who are married and

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[5] Fixed-effects models have been extended to random-effects model, and hybrid models (*Allison* 2009). However, the major advantage of these latter models is to jointly estimate the effect of time-varying and time-constant variables. Since our focus is on the effect of marriage on life satisfaction and both variables are varying over time, we omit the discussion of these models here. See *Brüderl/Ludwig* (2015) for such a discussion.

those who are cohabitating or LAT. However, this assumption would be violated if people whose life satisfaction evolves more positively in the course of a relationship are more likely to get married. Yet this effect would be independent from marriage and these people would be more satisfied with life irrespective of marriage because their (future) relationship works well.

In the following, we use a recent extension of FE model, viz. the *fixed-effects models with individual slopes (FEIS)* (*Ludwig/Brüderl* 2018; *Wooldridge* 2010), which accounts for the second shortcoming mentioned above by relaxing the parallel trends assumption. The FEIS is a generalized FE estimator that allows for different slopes among subgroups by de-trending for the individual trajectory in the dependent and independent variable (*Ludwig/Brüderl* 2018; *Rüttenauer/Ludwig* 2020; *Wooldridge* 2010). That (within) effects of an independent variable differ across subgroups is a standard finding in empirical studies and is usually modelled by the inclusion of interaction effects, such as in an FE model. The FEIS model, however, allows for a different form of effect heterogeneity, viz. that the effect of marriage on life satisfaction might differ for those who marry and those who do not. More specifically, married couples are not only more satisfied with life than unmarried ones at the time of marriage, but continue to become even more satisfied in the development of their relationship. Put differently, using an FE estimator allows us to check whether it is simply people who are more satisfied with life that get married and employing the FEIS estimator one can additionally check whether these people are in happier (future) relationships than their unmarried counterparts. For a graphic illustration of this empirical problem see Figure 1.

Fig. 1: Potential effects of marriage on life satisfaction
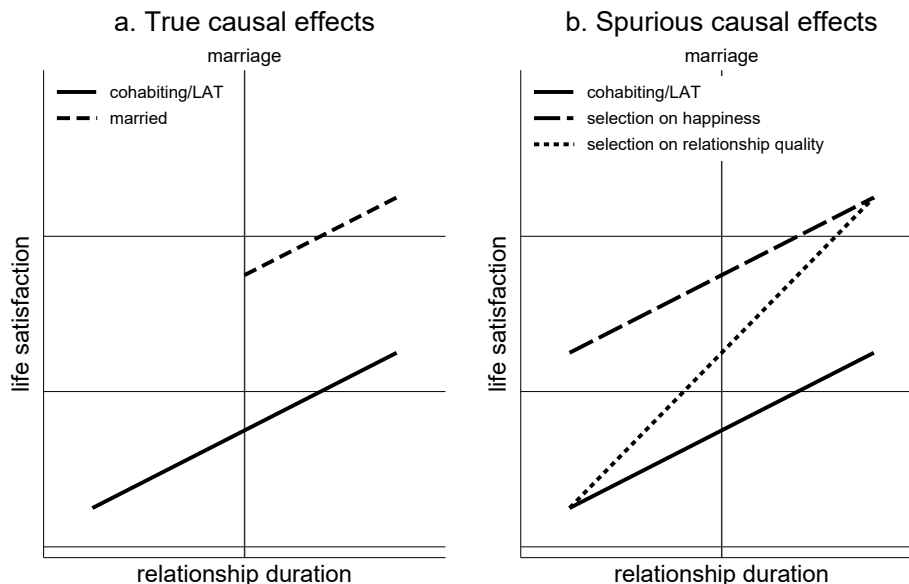
Source: Own illustration, based on *Brüderl/Ludwig* (2015).

Often, such effect heterogeneity across groups is investigated by estimating interaction effects across specific subgroups and the respective treatment. The FEIS model, however, allows for different selection of subgroups or individuals into treatment. Theoretically therefore, if an FEIS model is statistically preferable to a standard FE model, this would lend credibility against a causal interpretation of a marriage effect on life satisfaction. Instead, a non-significant effect of marriage on life satisfaction in an FEIS model would foster the interpretation that happier people are indeed selected into marriage, that is, they are chosen as marriage partners, but not on the basis of being more satisfied in life in general but on the basis of being in happier (future) relationships.

We will test this assumption in the following, but beforehand we will briefly discuss whether there is such a thing as "the causal effect" in the social sciences and which treatment effects can be identified in research, especially when using observational data instead of experimental data.

Causal inference and the different treatment effects

Up to now, we have talked about causal effects or causality rather loosely. In fact, the literature of causal effects and their proper estimation has grown extensively in recent decades and it has identified a variety of causal effects, each with a different interpretation (cf. *Morgan/Winship* 2015 for a thorough and excellent review). Hence, there is no such thing as "the causal effect."

We therefore, in the following, briefly present and discuss the most commonly investigated causal effects. These are the average treatment effect (ATE), the average treatment effect on the treated (ATT or ATET in econometric or STATA terminology), and the average treatment effect on the control group (ATC). For other variants, such as local average treatment effects (LATE) or marginal treatment effects, we refer to *Morgan* and *Winship* (2015). Table 1 illustrates how these treatment effects differ and under which assumptions they can be estimated. Moreover, it demonstrates how the FE estimator and its FEIS generalization improve estimations compared to cross-sectional data.

First one must note that in experiments, the researcher has full control over the assignments of units into the treatment and the control group. The selection process into these two groups therefore is potentially completely randomized and the mean difference between the treatment and the control group tells the researcher how the treated would have behaved if they were in the control group and vice versa. In experiments, therefore, all of the three treatment effects above are identical and their interpretation as "true" causal effects is widely established. However, in real life, experimental manipulation is not possible or feasible and the researcher does not have such full control over treatment assignment. These data are often called observational data: Only the group-mean values for those treated, married, can be observed and only the group-mean value for those who are not married. Yet again, the researcher cannot observe, but has to estimate how those in the treatment group would have behaved if they were in the control groups and the other way

around. In such scenarios, causal inference is much harder to establish and relies on specific assumptions, which may or may not hold true.

The following Table 1 demonstrates how and under what conditions ATC, ATE or ATT will differ – and how a standard OLS regression based on observational data will necessarily result in biased estimates. Note that we cannot observe all cells displayed in the table, which is the core of the problem. We distinguish between those in the treatment group whose expected values are given by E(T) and those in the control group whose expected values are given by E(C). Thus, to arrive at proper treatment effects, we have to subtract the values in the respective columns. However, we only observe the value E(T) for those receiving the treatment, or are in the treatment group, and the value E(C) for those who do not receive the treatment, or are in the control group. The other two cells – "control group" for those in the treatment E(T) and "treatment group" for those in the control group E(C) – have to be estimated.

Tab. 1: Treatment effects for Treatment (T) and Control (C) group with identical and varying starting values as well as equal and different effects for ATC, ATT, and ATE

	Homogeneous effects for T and C, same values for T and C		Homogeneous effects for T and C, different values for T and C		Heterogeneous effects for T and C, different values for T and C	
	E(T)	E(C)	E(T)	E(C)	E(T)	E(C)
Treatment group	10	10	10	7	10	6
Control group	8	8	8	5	8	5

ATC: Average treatment effect for the control group, ATT: Average treatment effect for the treated, ATE: Average treatment effect in the sample. E(T) and E(C) denote the respective (only partially observed) expected values for the treatment and control group, treatment effects can be derived by subtracting values in the rows for each respective group.

Source: Own illustration, based on *Morgan/Winship* (2015).

The first panel ("Homogeneous effects, same values") gives a situation without self-selection into treatment, or treatment is randomized and exogeneity is as in classical experiments: the treated individuals – mean observed value 10 in the row E(T) – would have yielded a mean value of 8 (unobserved) if they had been assigned to the control group. Hence, they would have shown the same behaviour as those in the control group if the latter had received treatment. Only in this case would a regression analysis comparing means across groups give us the correct treatment effect of 2. Moreover, this effect would be the ATT, the ATC, and the ATE. Now consider the next panel ("Homogeneous effects, different starting values"). For both groups (T and C) the treatment effect would be 2, again by subtracting values in the respective columns for treatment, E(T), and control group, E(C). However, a regression analysis would compare the *observed* mean values E(T) for those in the treatment group with the *observed* mean values E(C) in the control group, (erroneously) estimating the causal effect at 5 (10-5 in the diagonal for the observed

values). However, again, ATT, ATC, and ATE are identical if properly estimated by subtracting values in the respective rows. This bias in standard regression results is due to the non-random treatment assignment, in other words, treatment and control group also differ in other respects and not solely in the treatment assignment. In the final panel however, even this is different. Again, those receiving the treatment have higher initial values of y than those in the control group – if those who receive the treatment had not received treatment, we would observe values of 8 instead of 10, compared to those in the control group of 6 and 5 respectively. Hence, treatment is not assigned randomly – apparently there is something unobserved that selects respondents into treatment and exogeneity does not apply. However, to make things more complicated, the treatment effect now differs for both groups: The ATT would be 2, the ATC would be 1, the ATE would be an average depending on the distribution of the treatment across the sample, and the OLS-coefficient would be an obscure 5, far from either relevant effect. As a potential solution for these problems, estimation techniques for panel data have been proposed that focus on the changes within persons, thereby using individuals in a pre-treatment phase as their own control group – whose values have been observed.

Nevertheless, the core problem with observational data of partially unobservable values for groups also arises when panel data and methods such as FE or FEIS are used. Despite providing more information than cross-sectional data, again treatment is not randomly assigned. Therefore, fixed-effects estimators, with or without effect heterogeneity, that is, individual slopes, only give the average treatment effect on the treated (ATT). We can observe how those who receive treatment behave afterwards. That is, we compare the values in the columns for those who are treated before and after treatment. However, we cannot observe how those who do not receive treatment would have behaved if they had received treatment. The ATC and consequently the ATE, which is a weighted average of ATC and ATT, remain unknown. It may be argued that in our case this is exactly what is wanted. "What is the effect of marriage on life satisfaction for those who marry?" may be a more relevant question than "What would be the effect of marriage on those who never get married if they would get married?" However, since for the latter there might be observables and unobservables that prevent those people from being married, if they were to be married "by force" their ATT might differ substantially.

This judgment may differ for other research purposes, but it is an important restriction to keep in mind. For example, we could identify the effect of a divorce on life satisfaction (or earnings, or whatever) with an FE estimator. This would give us the effect of the treatment, that is, the ATT. However, we might want to assess the effect of a programme for preventing divorce. In that case, we would be interested in how life satisfaction or earnings would change for those not yet divorced, or the ATC.

3   Data and Methods

Data

This study uses data from the first 11 waves of the German Family Panel (*Brüderl et al*. 2019). Starting in 2008, the German Family Panel (*pairfam*) provides data on the formation and the development of intimate relationships and families in Germany (*Huinink et al*. 2011). Data are collected annually from a nationwide random sample of four birth cohorts (1971-73, 1981-83, 1991-93, and, since wave 11, 2001-2003). A special feature of the panel is the multi-actor design: In addition to the initial respondent, his/her partner, child(ren) and parents are also interviewed. After the initial attrition between the first and second wave (23 percent), *pairfam's* panel attrition was very low (currently 8 percent, see *Brüderl et al.* 2020).

Sample

We start out with 83,132 person-years. First, we exclude respondents from the *pairfam* demodiff sample,[6] reducing our original sample by about 9 percent. Next, following *Brüderl* and *Ludwig* (2015), we exclude respondents who stated that they were married, divorced, or widowed in pairfam's first wave and thereby lose about 32 percent of the remaining sample. Likewise, we exclude all subsequent person-years for respondents after the year they report having had a divorce or becoming widowed, reducing the remaining sample again by about 1 percent. Thereafter, we dropped all person-years for singles, reducing the remaining sample by about 47 percent. Then we delete all respondent-years with missing values on life satisfaction, marital status, and our independent variables, causing an additional loss of 0.1 percent of the remaining sample. Lastly, because FEIS needs at least three person-years (depending on the number of individual slope parameters), we had to drop everyone who is observed less than three times. Those restrictions reduce the remaining sample again by roughly 18 percent. This leaves us with a sample size of 3,350 persons and 22,007 person-years.

Variables

As the *dependent variable* we employ overall life satisfaction. More specifically, every respondent in all eleven waves is asked "Now I would like to ask about your general satisfaction with life. All in all, how satisfied are you with your life at the moment?" They then have to rate their life satisfaction on a scale from 0 "very unsatisfied" to 10 "very satisfied."

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[6]   Demodiff is a supplement to pairfam for East German respondents only. There are several problems when integrating pairfam and demodiff, thus we decided to drop demodiff entirely from the sample.

Our main variable of interest, *marital status*, is a time-varying measure coded as one, once a respondent gets married. The dummy is coded one if respondents are married and cohabiting (n = 4499) or married and live separately (n = 41).

Furthermore, we employ the continuous variable *relationship duration*. This variable is measured in years and represents the duration of the relationship of married and non-married couples. As explained above, controlling for individual trajectories of relationship duration and its impact on life satisfaction constitutes the major difference between the FEIS model and the FE model. If the marriage effect on life satisfaction is due to steeper trajectories in relationship quality, this would imply that people with greater life satisfaction are more likely to marry, which would run counter to the interpretation of a causal effect of marriage.

We employ several *controls*. First, we employ categorical dummies measuring education retrieved from the CASMIN categories: lower secondary education and below ("low education"), higher education entrance qualification and below ("intermediate education"), tertiary education ("higher education"), and being "currently enrolled." Additionally, we control for age (in years) and the number of biological children.

Descriptive statistics for these variables and the two samples are displayed in Table 2.

Tab. 2:   Descriptive statistics

	Ever-Married		Never-married		Δ
	Mean	SD	Mean	SD	
Life satisfaction	7.90	1.44	7.69	1.53	0.21***
Relationship duration (years)	7.07	5.07	3.71	4.21	3.36***
Education					
Low education	0.12	0.32	0.11	0.31	0.01*
Intermediate education	0.46	0.50	0.35	0.48	0.11***
Higher education	0.31	0.46	0.15	0.36	0.17***
Currently enrolled	0.11	0.31	0.40	0.49	-0.29***
Number of children	0.69	0.89	0.26	0.64	0.43***
Age (years)	31.0	6.34	25.9	7.50	5.14***
Observations (n)	8334		13673		22007
Persons (N)	993		2357		3350

Note: not weighted; SD = standard deviation. Stars indicate the significance of differences in means; $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Source: Based on pairfam 11.0, own calculations

4   Findings

Descriptive findings

Table 2 illustrates that on average, people who get married are more satisfied with life than those who do not. They also have longer relationships, more children, and higher education levels. Additionally, descriptive results suggest that ever-married respondents are on average older and significantly less often currently enrolled. Thus, first descriptive evidence suggests that there are clear observable differences, indicating that people who get married are systematically different from those who do not. Since, as discussed above, such systematic differences can bias results, we follow up with a more detailed analysis to detect a potential causal effect.

Regression analysis including control variables

For instructional purposes we compare our FEIS estimator not only with its FE counterpart but also with the results obtained by an OLS regression for the pooled sample and by an FE regression, where we interact the marriage effect with relationship duration (FEGS). This allows us to separate the ATT of marriage (FE estimator) from an estimator confounding ATT and self-selection into marriage (OLS estimator). In addition, it allows us to properly estimate the ATT due to potential additional selection into marriage based on the identification of individuals whose life satisfaction evolves more favourably over time (FEIS estimator). If this estimator differs from the FE estimator, then there is not only self-selection of more satisfied people into marriage but additional self-selection of people whose life satisfaction evolves more favourably over time. If the effect of marriage turns insignificant when using a FEIS estimator, this would provide strong evidence against a causal effect (ATT) of marriage on life satisfaction (see *Ludwig/Brüderl* 2018 for an example). If the effect of marriage would remain significant, it would provide evidence for an ATT, even after controlling for this additional source of self-selection.[7]

   The main results from these analyses are depicted in Table 3.[8] We can see that the effect of marriage on life satisfaction is overestimated when employing the ordinary least square estimator. The POLS coefficient is three times as large as the coefficient estimated using an FE model. This former effect is clearly biased since it confounds the effect of marriage within those who marry with the selection effect that people who are more satisfied with life are also more likely to get married. Since both of these effects work in the same direction and this estimate is much higher than the estimates obtained from the within estimators, the FE model supports the notion of a causal – albeit weaker – effect (ATT) of marriage on life satisfaction.

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[7]   Indeed, *Brüderl* and *Ludwig* have modelled the association of happiness and marriages within a FEIS framework in their previous research (*Brüderl* and *Ludwig*, April 2019). Assigning singles and cohabiting couples in the control group, they also find that marriage affects happiness positively, even when controlling for individual growth.

[8]   FEIS models are estimated using the STATA command xtfeis provided by *Ludwig* (2015).

Tab. 3: Marital increase in life satisfaction estimated using POLS, FE, FEGS, and FEIS

	POLS		FE		FEGS		FEIS	
Married	0.42***	(0.05)	0.14***	(0.04)	0.15**	(0.05)	0.14**	(0.05)
Relationship duration (years)	0.02**	(0.01)	-0.03***	(0.01)	-0.03***	(0.01)		
Low education (Ref.)								
Intermediate education	0.26**	(0.08)	0.16	(0.10)	0.16	(0.10)	0.17	(0.11)
Higher education	0.47***	(0.09)	0.21*	(0.10)	0.21*	(0.10)	0.16	(0.12)
Currently enrolled	0.37***	(0.08)	0.25**	(0.09)	0.25**	(0.09)	0.24*	(0.10)
Number of children	-0.07*	(0.03)	0.09**	(0.03)	0.09**	(0.03)	0.10*	(0.04)
Age (years)	-0.03***	(0.00)	-0.00	(0.01)	-0.00	(0.01)	-0.01	(0.01)
Ever married x relationship duration	-0.03***	(0.00)	-0.00	(0.01)	-0.00	(0.01)		
Persons (N)	3350		3350		3350		3350	
Observations (n)	22007		22007		22007		22007	
R squared[1]	0.034		0.005		0.005		0.002	

[1] Please note that the reported R^2 for FE, FEGS, and FEIS is the within R^2. Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source: Based on pairfam 11.0, own calculations

Extending this model to a model that allows this effect of marriage to differ according to relationship duration (FEGS), the non-significant interaction effect gives us a first hint that there are no group-specific deviations in slopes. Thus, we clearly have to differentiate between a (non-existent) heterogeneous effect of marriage across groups as illustrated with the non-significant respective FEGS coefficients and a different propensity of becoming married across different groups, as illustrated by the large difference in the POLS to the FE coefficient. The FEIS model displays a similar coefficient to the FE model. The effect of marriage on life satisfaction remains significant and identical in size. Thus, we do not have a spurious effect of marriage on life satisfaction caused by different individual life satisfaction trajectories. To further test whether this suspicion proves correct, we estimated a Hausman test designed to assess the model fit of FEIS vs. FE models. We find that there are no significant differences between FEIS and standard FE (prob $>$ chi^2 = 0.92).

Non-linear dynamics of marriage on life satisfaction

In the previous analysis, we assumed a linear effect of relationship duration and development in life satisfaction. That is, we assumed that for each individual, life satisfaction steadily and linearly increases or decreases with relationship duration. However, contemporary literature examining the link between marriage and life satisfaction found evidence that the association between the two is not linear (cf. *Blekesaune* 2018; *Qari* 2014; *Tao* 2019). To test this assumption, we estimated two additional FEIS models, one adding a squared term of relationship duration and the other adding not only a squared but also a cubic term in addition to the linear term of relationship duration for modelling individual life satisfaction trajectories.[9] Table 4 shows that the effect of marriage on life satisfaction becomes *greater* when including polynomials. However, Hausmann tests again showed that there is no additional gain when modelling squared (prob $>$ chi^2 = 0.54) or squared and cubic terms (prob $>$ chi^2 = 0.26) in addition to the linear term, as opposed to a simple fixed-effects regression.

Table 4 provides tentative evidence that the relationship between marriage and life satisfaction is not linear over time. To test to what extent life satisfaction varies pre- and post-marriage, we ran POLS and FE regression including yearly time dummies. We restricted the sample to ever-married couples, four years prior, the year of the marriage, and four years after marriage. Results are depicted in Table 5. Results suggest that the effect of marriage on life satisfaction varies over the years and is especially strong in the year of marriages as well as one year prior to marriage.

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[9]   Please note that observation numbers are smaller in the models that include polynomials. This is due to the increased degrees of freedom of the respective models, see also *Ludwig* and *Brüderl* (2018).

Tab. 4: Marital increase in life satisfaction; FEIS model; including only linear, squared and cubic term

	FEIS		FEIS (squared relationship duration)		FEIS (squared and cubic relationship duration)	
Married	0.13**	(0.05)	0.15*	(0.06)	0.21**	(0.08)
Low education (Ref.)						
Intermediate education	0.19	(0.12)	0.06	(0.15)	0.00	(0.18)
Higher education	0.19	(0.13)	0.03	(0.16)	-0.04	(0.19)
Currently enrolled	0.24*	(0.12)	0.12	(0.14)	0.07	(0.18)
Number of children	0.09*	(0.04)	0.13*	(0.05)	0.14*	(0.06)
Age (years)	-0.01	(0.01)	-0.00	(0.01)	-0.00	(0.01)
R squared (within)	0.002		0.002		0.003	
Observations (n)	18397		18397		18397	
Persons (N)	2301		2301		2301	

Standard errors in parentheses.

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

Source: Based on pairfam 11.0, own calculations

Tab. 5:   Marital increase in life satisfaction estimated using POLS and FE; sample restricted to four years prior to and after marriage

	POLS		FE	
Married (time)				
Three years to marriage (Ref.)				
Four years to marriage	-0.08	(0.07)	-0.14	(0.10)
Two years to marriage	0.09	(0.06)	0.17	(0.09)
One year to marriage	0.13*	(0.07)	0.32*	(0.15)
Year of marriage	0.22**	(0.07)	0.49*	(0.21)
One year after marriage	0.15	(0.08)	0.47	(0.28)
Two years after marriage	0.12	(0.08)	0.49	(0.35)
Three years after marriage	0.20*	(0.09)	0.60	(0.42)
Four years to marriage	0.07	(0.10)	0.55	(0.48)
Low education (Ref.)				
Intermediate education	0.11	(0.12)	-0.16	(0.21)
Higher education	0.33**	(0.12)	0.03	(0.22)
Currently enrolled	0.05	(0.13)	-0.13	(0.19)
Number of children	-0.05	(0.04)	0.07	(0.04)
Age (years)	-0.01	(0.01)	-0.03*	(0.01)
Constant	8.11***	(0.23)	8.71***	(0.37)
Persons (N)	993		993	
Observations (n)	6194		6194	
R squared[1]	0.01		0.01	

[1] Please note that the reported R^2 for the FE model is the within R^2. Standard errors in parentheses.

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

Source: Based on pairfam 11.0, own calculations

Thus, marriage does make people more satisfied with life, but not so much in the long run. Fixed-effects results in Table 5 instead suggest that it is the anticipation of marriage and the year of marriage during which couples are significantly more satisfied with life. This supports the argument that marriage does have an intrinsic value, making respondents more satisfied. This value is neither necessarily tied to objective (long-term) legal benefits such as additional rights that are only granted to spouses nor to the benefits of living together with a partner. In our opinion, it is related to compliance with social norms and, potentially, to the anticipation of a wedding as a pleasant social event (cf. *Schneider/Rüger* 2007).

Robustness

Finally, we would like to draw attention to the selection of control variables. In a robustness analysis (see Table A1 in the Appendix), we added a control variable for current pregnancy. The table in the appendix illustrates that our main result, i.e. marriage increases life satisafaction, is robust, although the association becomes

slightly weaker once we control for pregnancy. However, pregnancy is in all likelihood closely related to the future development of a relationship, which is exactly what we are trying to model with the FEIS estimator. Moreover, the temporal relationship between marriage and pregnancy is unclear. It is possible that there is a causal effect of marriage on pregnancy; that if people had not married, a pregnancy would not have occurred, as well as the other way around; that people marry because of a pregnancy. To complicate matters further, people may marry because they anticipate becoming pregnant or vice versa. In our specification, these mechanisms cannot be further separated.[10] We therefore decided to refrain from accounting for pregnancy in the main analysis presented in this article.

5 Summary and Discussion

The main goal of our article was twofold: The first was to properly estimate the substantial causal effect of marriage on life satisfaction and the second was to lay out and discuss the strengths and limitations of establishing causal inference using panel techniques.

As to the substantial question, comparing married to unmarried couples, we found that there is indeed an instant and genuine increase in life satisfaction when people get married. This effect is overestimated in POLS models and decreases a great deal when employing a fixed effects estimator (FE estimator). Our analysis revealed that people in happier relationships are more likely to get married, but that marriage among cohabiting/LAT couples nevertheless increases life satisfaction substantially. In addition, we extended the widely employed FE estimator that separates these two effects with the FEIS estimator that controls for different developments of life satisfaction over time. Thereby, we demonstrated that it is not the selection into marriage of individuals who are more satisfied with life in future, but a genuinely positive effect of marriage on life satisfaction. However, we also found that the relationship between life satisfaction and marriage is potentially underestimated when using a linear term for estimating such individual trajectories. Instead, the true coefficient is apparently modelled more correctly when allowing for non-linear trends in the development of relationship quality. Selection into marriage thus occurs not only because of higher current life satisfaction levels but also higher (non-linear) growth of relationship quality, thereby qualifying the "causal effect" (ATT) derived from the FE estimator. In substantial terms, our analysis further showed that one is especially satisfied with life in anticipation of marriage (i.e., one year prior to the wedding), and during the wedding year.

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[10] An excellent discussion on when and how to include such future anticipated treatments can be found in *Elwert* and *Pfeffer* (2019); *Elwert* and *Winship* (2014) provide a more general discussion on the perils of controlling too much. Both papers provide formal representations within a directed acyclical graph (DAG) framework. An extensive discussion of this framework is beyond the scope of this paper; the interested reader is again referred to *Morgan* and *Winship* (2015).

In summary, our evidence shows that marriage indeed makes cohabiting/LAT couples happier, and it does so for reasons additional to being in a romantic relationship. Theoretical arguments laid out in the manuscript suggest that this is possibly the legally binding character of marriage as well as the anticipation of the festive event. However, it should be noted that also in classical experiments the respective mechanisms may or may not be properly identified. To return to our previous example of labour market programmes, it might be that a programme is randomized and thus experimentally established as successful in raising employment rates. However, the experiment may fail to demonstrate whether this is due to sending signals to employers, providing useful skills, raising work ethos, or something else.

Methodologically, our goal was to point out the benefits, but also the limitations of estimating causal effects with panel data. The literature often argues that panel data are able to identify causal relations while cross-sectional data are not. However, this reasoning is imprecise since the literature on causality distinguishes a variety of causal effects for which specific assumptions must apply if estimated properly. Panel data, as any other data, identify particular causal effects (here: the average treatment effect on the treated – ATT) only if specific assumptions apply, but in comparison to cross-sectional data these assumptions are much less restrictive. In our analysis, we demonstrated that employing panel data and techniques allow us to separate selection effects into a "treatment" – in this case, marriage – from the effect the treatment has. We clarified that this effect is the ATT, which is revealed by the FE estimator.

However, as our study demonstrated, often selection effects into treatment occur in two ways. In addition to the selection based on current levels of the outcome – in this case, life satisfaction – there might be selection based on different future levels of the outcome. Using the FEIS estimator is helpful whenever one wishes to control for this subtler latter selection effect. Such treatment effects are, however, erroneously specified when modelling the temporal development of the outcome incorrectly. Our results are therefore in line with a growing body of literature that underlines the necessity to carefully model temporal dependencies and to go beyond the almost standardly employed FE estimator. For example, *Plümper* and *Troeger* (2019) demonstrate that the FE estimator, which is generally considered to robustly estimate the ATT, is suspect to such dynamic misspecification and potentially results in severely biased estimates. In that respect the FEIS estimator can serve as one important tool to more adequately model temporal dynamics.

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Appendix

Tab. A1: Robustness: Marital increase in life satisfaction estimated using POLS, FE, FEGS, and FEIS; including a pregnancy dummy

	POLS		FE		FEGS		FEIS	
Married	0.40***	(0.05)	0.10*	(0.04)	0.11*	(0.04)	0.10*	(0.05)
Relationship duration (years)	0.02**	(0.01)	-0.03***	(0.01)	-0.03***	(0.01)		(0.01)
Low education (Ref.)								
Intermediate education	0.26**	(0.08)	0.17	(0.10)	0.17	(0.10)	0.18	(0.11)
Higher education	0.47***	(0.09)	0.21*	(0.10)	0.21*	(0.10)	0.17	(0.12)
Currently enrolled	0.38***	(0.08)	0.26**	(0.09)	0.26**	(0.09)	0.25*	(0.10)
Number of Children	-0.07*	(0.03)	0.14***	(0.03)	0.14***	(0.03)	0.20***	(0.05)
Age (years)	-0.03***	(0.00)	-0.01	(0.01)	-0.01	(0.01)	-0.01	(0.01)
Pregnant (= 1)	0.27***	(0.05)	0.30***	(0.05)	0.30***	(0.05)	0.29***	(0.05)
Ever married x relationship duration					-0.00	(0.01)		
Persons (N)	22007		22007		22007		22007	
Observations (n)	3350		3350		3350		3350	
R squared[1]	0.04		0.01		0.01		0.01	

[1] Please note that the reported R^2 for FE, FEGS, and FEIS is the within R^2. Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source: Based on pairfam 11.0, own calculations