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Relationship Stability: Evidence from Labor and Marriage Markets

Abstract

Based on a sample of elderly individuals from the Survey of Health, Ageing, and Retirement in Europe, we investigate the relationship between job and marital stability over the life cycle. We argue that an unobserved, time-varying social skill affects stability in both markets. Using a grouped fixed-effects estimator, we show that unobserved relationship stability in both markets is significantly and positively associated. Instability in both markets is associated with lower levels of trust and conscientiousness and higher levels of extraversion and neuroticism. The absence of the father during childhood perpetuates higher instability later in life. Higher instability is also costly since it is associated with lower levels of late-life well-being.

JEL-Codes: J120, J240, J630, I310, C330.

Keywords: relationship stability, marriage dissolution, job turnover, social skills, non-cognitive skills, grouped fixed-effect estimator, survey of health, ageing and retirement in Europe.

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1 Introduction

The ability to maintain stable relationships is an essential prerequisite for individual success in life. It is particularly important in two primary domains of life, spousal and work relationships. Instability comes at high direct and indirect costs. Divorces and separations in relationships are associated with high monetary and psychological costs (Bartfeld, 2000; Leopold, 2018). Frequent job changes can lead to lower investments in firm-specific human capital (Borjas, 1981; Dustmann and Meghir, 2005) and low job quality (Farber, 2010).

The theoretical literature on matching and (home) production has long recognized that relationships in marriage and labor markets follow similar patterns.[1] Empirically, relationship stability in both markets has mainly been analyzed in isolation, even in completely different strands of the literature (Becker et al., 1977; Farber, 2010). Most studies that consider both markets analyze whether instability in one domain impacts the other domain as well. For example, Eliason (2012) and Killewald (2016) show that job displacement or lack of full-time employment of husbands increases divorce risks.

In this study, we analyze the relationship between job stability and marital stability over the life cycle. We use self-reports of job changes and relationship breakups as measures of instability to investigate the role of observed determinants and unobserved or latent determinants of maintaining stable relationships in these two markets. Kambourov et al. (2015) call the latent ability to maintain stable relationships a relationship (or teamwork) skill and argue that this social skill increases returns to cooperation in contrast to human capital, which affects individual returns. We hypothesize that individuals strongly differ in this unobserved relationship skill. Individuals with a high level of relationship skills are more likely to maintain stable relationships in different areas of life.

It is very likely that relationship skills vary over age. Most studies on the stability of personality traits show a relatively high consistency starting with the college period and a high consistency in later life (Roberts and DelVecchio, 2000). However, employment-

[1]Burdett and Coles (1999) argue that the formation of long-term partnerships in labor and marriage markets follows similar structures and can be modeled on the basis of a matching game, while Becker et al. (1977) argue that, after forming a couple, spouses engage in joint production, similar to employers and employees. Both in labor and marriage markets, relationships split up when the utility of the outside option is larger than the utility of staying together.

related events have been shown to alter personality traits (Cobb-Clark and Schurer, 2012). Moreover, relationship skills may develop more towards (in)stability through (un)favorable experiences as individuals age. A large literature in psychology shows that relationship stability can be changed, for instance, through psychological interventions (Dunn and Schwebel, 1995; Nathan D. Wood and Law, 2005; Spengler and Wittenborn, 2022). Thus, we hypothesize that relationship stability is driven by an unobserved time-varying relationship skill that determines the ability to maintain stable relationships in both marriage and labor markets.

Given the importance of stability for success in both job and marriage markets, it is crucial to identify individuals who are at risk of instability. Knowing who is at risk matters since policies that aim to improve welfare by protecting marriage or reducing divorce may overlook that causality could run in the other direction, namely that those who are worse off face a greater risk of divorce (Stevenson and Wolfers, 2007). Thus, one goal of our empirical analysis is to group individuals according to their relationship skills into latent stable and unstable relationship types in labor and marriage markets. Using this classification, we then explore how these stability types are related to personality traits and social preferences. Finally, we investigate whether instability is associated with costs later in life. We analyze life satisfaction as a proxy of experienced utility (see Frey and Stutzer, 2002; Clark et al., 2008) and household wealth as an additional indicator of well-being.

Analyzing the relationship between job and marital stability is challenging for a number of reasons. Potential endogeneity problems arise from non-random selection into stable relationships, reverse causality, and unobservables determining both job and marital stability. When unobservables are time-constant and longitudinal data is at hand, such endogeneity issues can be partly addressed by a model with individual-specific fixed-effects. When the latent relationship skill develops with age, such a fixed-effects estimator fails to identify causal effects (see Stillman and Velamuri, 2020).

To address the issue that the unobserved relationship skill could vary over age, we apply a grouped fixed-effects (GFE) estimator proposed by Bonhomme and Manresa (2015). The idea is that individuals with similar unobserved characteristics can be grouped together and within each of these groups (or types), unobserved heterogeneity is allowed to arbitrarily vary across age. The GFE estimator then jointly estimates the main parameters of interest, the group assignment, and the group-specific profiles of unobserved heterogeneity. In our application, the GFE estimator groups individuals with similar unobserved relationship skills into stability types and then estimates the relationship between the observed job and marital stability along with the group assignment and the group-specific profiles of age-varying unobserved relationship skills. This allows us to not only estimate and interpret the direct effects between observed job and marital stability (that could be caused, for example, by the psychological distress of separation) but also to investigate the unobserved component of stability, i.e., latent relationship skills, in more detail.

We use a sample based on seven waves and six Western European countries (Austria, Germany, Netherlands, France, Switzerland, Belgium) from the Survey of Health, Ageing and Retirement in Europe (SHARE).[2] SHARE provides a rich set of information on socio-demographics, childhood circumstances, preferences, and personality traits. Importantly, SHARE collects individuals' employment and relationship histories throughout the life cycle. We construct a pseudo-panel covering ages 18 to 60 for each individual. As a measure of relationship instability, we use the cumulative number of job changes and relationship breakups an individual experiences until each age, between ages 18 and 60. To take account of gender differences in labor and marriage market behavior, we analyze men and women separately.

Our first result is that we find significant and positive direct effects of job stability on marital stability and vice versa regardless of whether we use OLS, OLS with standard time-constant individual fixed-effects, or the GFE estimator. The estimated effects are largest with OLS, somewhat smaller when allowing for individual fixed-effects, and by far smallest with the GFE estimator with individual fixed-effects and grouped time-varying fixed-effects. For instance, an additional breakup among men leads to 0.39 additional jobs in OLS models but reduces to about 0.10 in the GFE model. Overall, the GFE effect sizes for the estimated cross-market instability coefficients are between 60 and 90 percent smaller than OLS with individual fixed-effects, depending on the specification. This shows that there exists time-varying unobserved heterogeneity — an unobserved relationship skill in our interpretation — that determines the relationship

[2] We focus on these countries in order to keep our sample homogeneous regarding cultural and economic circumstances.

between the labor and the marriage market to a large extent. Our main finding is robust to alternative specifications, including varying the number of groups, considering outcome dynamics to address reverse causality, or excluding job changes that are career-boosting or are caused by plant closures.

We next analyze the latent stability types and the unobserved heterogeneity profiles obtained from the GFE estimator in more detail. In the labor market, about 60 percent of men and 63 percent of women are classified as being high or very high job stability types. Only 17–18 percent of men and women are classified as low or very low job stability types. High stability types are even more common in the marriage market: about 87 percent of men and 84 percent of women are of the high or very high relationship stability types. Only about 4 percent of men and women are classified as being unstable types. Our analysis reveals that being an unstable type in marriage and labor markets is strongly positively correlated for both men and women, with 1.0-1.5 percent of individuals being very unstable or unstable in jobs and unstable in relationships in both markets. The analysis of the estimated type-specific age profiles of the unobserved relationship skill reveals considerable differences across stability types. Stable types exhibit profiles that are rather flat, with only little variation over time. By contrast, the age profiles of unstable relationship types are characterized by a steady increase in the unobserved heterogeneity over the life cycle. Most profiles are similar for men and women. The correlation between the latent instability types in marriage and labor markets is significant and positive (26 percent for men and 29 percent for women). Thus, individuals who have problems maintaining stable relationships in one market are also likely to face instability in the other market.

Our analysis is based on the hypothesis that the relationship skill is a social skill that increases returns to cooperation. Kambourov et al. (2015) proxy the relationship skill with personality traits, but it may also be related to other social preferences or attractiveness. To shed more light on what explains the relationship skill, we relate the relationship skill to risk aversion, trust, and personality traits. For both men and women, being an unstable type is associated with higher levels of extraversion and lower levels of conscientiousness. Unstable types are also less trusting than stable types. For women, higher levels of openness are a predictor of instability.

Finally, we link being an unstable type to well-being measures at age 55–65. Compared to being a stable type in both markets, unstable types have significantly lower levels of life satisfaction and household wealth at age 55–65, regardless of the market we consider. Moreover, for women, the association between household wealth and being an unstable type is always stronger than for men. This finding is in line with the literature showing that women face a stronger loss in income and have considerably less wealth after a divorce than men (see, for instance, Leopold, 2018; Kapelle, 2021).

Closest to our study are Ahituv and Lerman (2011) and Kambourov et al. (2015), which consider decisions in marriage and labor markets jointly using US data. Ahituv and Lerman (2011) find that job changes reduce the probability of getting or remaining married. At the same time, being married raises job stability. In their analysis, Ahituv and Lerman (2011) only consider men up to their early 30s, thus missing women and a long-term perspective. By contrast, we analyze men and women over the entire life cycle. Kambourov et al. (2015) formulate an equilibrium model of labor and marriage markets in which individuals are endowed with an innate relationship skill that is unobserved to the researcher. This relationship skill reflects a broad measure of a multidimensional and time-constant social skill, including personality traits such as cooperation, persistence, independence, or adaptability. Compared to their analysis, our empirical approach (i) does not use proxies to measure latent relationship skills but leaves it unspecified, (ii) allows the latent relationship skill to arbitrarily change over the life cycle within groups of individuals, and (iii) provides us with an estimate of these grouped time-patterns of the unobserved relationship skill. Our paper extends previous work by considering both a direct connection between labor and marriage markets and an indirect one via relationship types. These two different components are not identified separately in this literature but are likely relevant for policy implications.

We also contribute to the literature on the importance of cognitive and non-cognitive skills for labor and marriage markets (see Heckman et al., 2006). Our interest in personality traits is grounded in a large literature that investigates how personality traits (sometimes also referred to as non-cognitive or socio-emotional skills) are formed and how they influence late-life outcomes, in particular success in labor (e.g., Fletcher (2013)) and marriage markets (e.g., Dupuy and Galichon (2014)) and inequality (e.g., Gensowski et al. (2021)). Personality plays a central role in the psychological and sociological literature on relationship stability (Karney and Bradbury, 1995). It shapes how couples communicate with each other and how well they adapt to stressful experiences (Donnellan et al., 2004). Also, a literature in economics has demonstrated that personality traits play an important role in both labor and marriage markets (Dupuy and Galichon, 2014; Fletcher, 2013; Heckman et al., 2006).

Lastly, our paper is also related to a growing literature that is interested in studying patterns of grouped heterogeneity. This includes applications of the GFE estimator in different settings (for instance, Guner et al., 2018; Janys and Siflinger, 2024; Oberlander et al., 2017; Johar et al., 2022; Bonhomme et al., 2023) but also developments of alternative estimators to study such patterns, such as Ando and Bai (2016), Kim and Wang (2019) or Lewis et al. (2022). The recent interest in these approaches is emphasized in Sarafidis and Wansbeek (2021).

Our study shows that marital and job instability are not only directly associated with each other but also have a strong indirect relationship through a latent relationship skill. To design policies that can fully accommodate all cross-market effects, one needs to understand which individuals are at risk of instability and which factors are associated with being an unstable type.

The remainder of this paper is organized as follows. Section 2 describes the data. In Section 3, we present our empirical strategy. Section 4 presents results that relate instability in both markets. Section 5 relates the stability types to personality traits and late-life outcomes. Section 6 concludes.

2 Data and Descriptive Statistics

We use data from the first seven waves of the Survey of Health, Ageing and Retirement in Europe (SHARE), a large multi-disciplinary cross-national longitudinal panel survey on individuals aged 50 or older which was established in 2004. SHARE contains nationally representative samples from 27 European countries and Israel, collecting data on health, socio-demographics, and family networks. Waves 3 and 7 of SHARE (SHARELIFE) consist of retrospective modules to collect the histories of respondents' working lives, relationships, and marriages using a life history calendar method. This method has been shown to provide reliable information about individuals' past experiences, such as labor market status (Bingley and Martinello, 2014), marital status (Peters, 1988), and childhood circumstances (Havari and Mazzonna, 2015).

Our main measures of relationship instability are the number of job changes and the number of breakups of cohabiting relationships over the life cycle of respondents. SHARELIFE asks for all jobs of a respondent that lasted at least six months. For each job, respondents are asked to indicate the start and end date, which we use to identify job changes.[3] To obtain a measure of instability in the marriage market, we use the reported number of breakups of all cohabiting relationships.[4] As for the job history, SHARELIFE collects the start and end dates of each cohabiting relationship.[5] Due to the relatively high age of the respondents, most cohabiting relationships are marital relationships (about 90 percent). The wording of the questions on the job and relationship history in SHARELIFE can be found in Table A.1 in Online Appendix A.

Using the information on job and relationship histories, we create a pseudo panel of individuals with complete job and relationship information from ages 18–60.[6] We focus on individuals born between 1940 and 1953 who had at least one relationship and one job. Accordingly, the data spans from 1958 to 2013. To keep the sample relatively homogeneous regarding labor and marriage market conditions, we restrict the sample to six Western European countries: Austria, Belgium, France, Germany, Netherlands, and Switzerland. Our sample consists of a balanced panel of 5,493 individuals for whom we have observed job and relationship histories for 43 years.

Figure 1 shows the distribution of the number of job changes and relationship breakups for men and women. Figure 1(a) presents the job change distribution for men and women separately. The number of job changes varies considerably for both genders, ranging from zero to a maximum of 12 jobs over the life cycle. Most men (about 28.6 percent) experience one job change, while most women (30.5 percent) do

[3] We do not consider retirement as a job change. We only use job spells with valid start and end dates and with consistent consecutive dates, excluding, e.g., jobs that ended before they started. For overlapping job reports, we use the more recent job, assuming that start and end dates are more reliable for the more recent job.

[4] While there is no rule for the duration of relationships similar to the one for jobs (only counting jobs lasting at least 6 months), we argue that cohabitation is a sign of the relationship being "significant".

[5] We do not consider the death of a partner as a breakup. We also remove inconsistencies in the start and end dates.

[6] A pseudo-panel is typically the only way to use life-cycle information on both these markets since few surveys exist that cover such a long period. One exception is the US Panel Study of Income Dynamics, which, however, only covers marriage histories and not histories of cohabiting relationships.

not change jobs. About 14 percent of men and 13 percent of women have 4 job changes or more over the life cycle. On average, men have 1.75 job changes between ages 18–60. Women change jobs about 1.62 times during this age. As shown in Figure 1(b), there is much less variation over the number of spousal relationship changes compared to the number of job changes. Men have up to 7 breakups, and women have up to 4. About 75 percent of men and 72 percent of women have no relationship breakup in their lives. A lower share of individuals (19 percent of men and 23 percent of women) report one breakup. A minority of individuals (1.3 percent of men and 0.9 percent of women) had two or more relationship breakups between ages 18–60. The average number of breakups is 0.33 for men and 0.34 for women, which are mostly driven by divorces.[7]

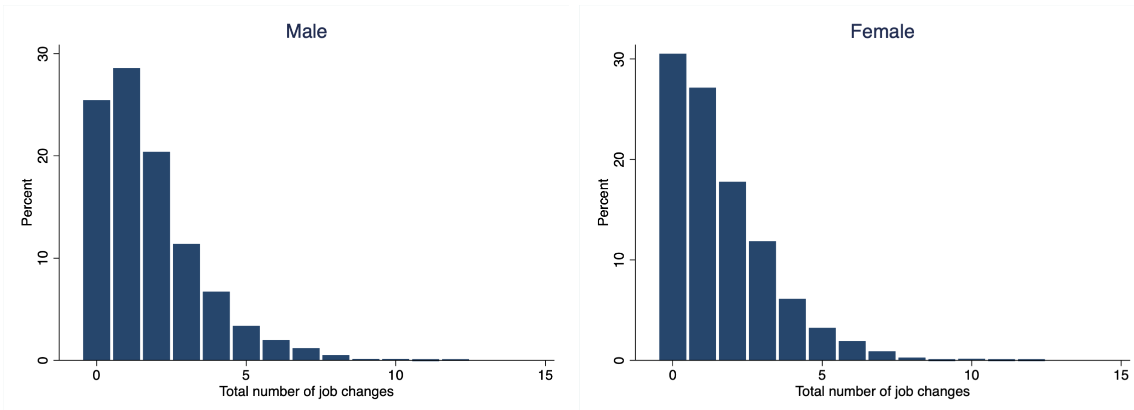
The number of job changes in our sample may seem relatively low. To assess their validity, we compare the number of jobs in SHARE to the number of jobs reported in the Eurobarometer survey in 2005, 2006, and 2008 for individuals older than 60. Table A.4 in Online Appendix A shows that the average number of jobs by country is very similar in both surveys, with the highest number of jobs reported by individuals from the Netherlands and the lowest number of jobs reported by Belgians. Similarly, the number of relationship changes may seem low. To assess the validity of our numbers, we compare divorce rates reported in our SHARE sample with those obtained from Eurostat (Eurostat, 1997).[8] Table A.5 in the Online Appendix compares country-specific divorce rates for the marriage cohorts 1960-1980 from Eurostat to the divorce rates obtained from our SHARE sample. Overall, our sample divorce rates lie well in the range of divorce rates of individuals who married between 1960 and 1980. We thus conclude that the number of relationship breakups reported in SHARE is reasonable.

We next assess the relationship between the number of job changes and the number of breakups. The raw correlation between those two measures is 0.21 for women and 0.15 for men, both significant at the 1 percent level. Figure 2 shows the accumulated average number of job changes by respondents with zero or with at least one relationship breakup over the entire life cycle. Figure 2(a) shows that men in both groups are

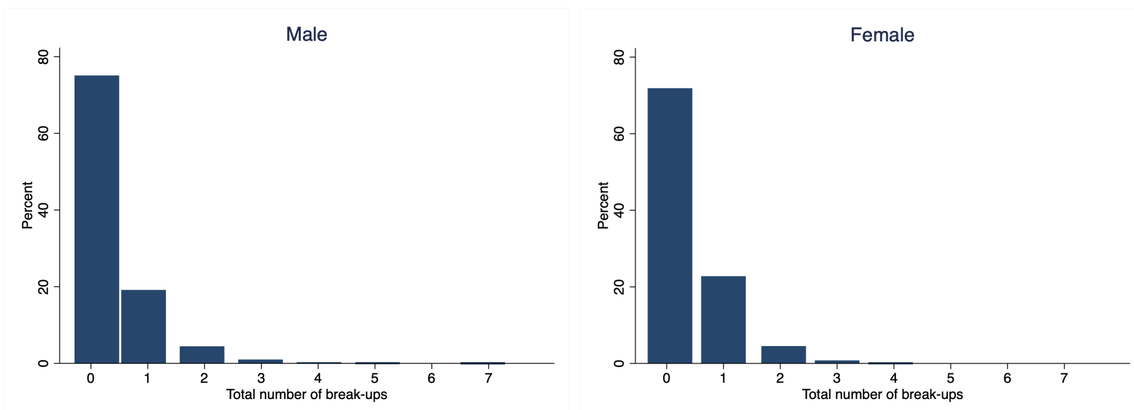
[7]The sample average for job changes and relationship breakups and by type of break-up and by country can be found in Tables A.2 and A.3 in Online Appendix A.

[8]The Eurostat statistics on divorce rates are available by marriage cohort but not by birth cohort. To nevertheless benchmark our sample average in divorce rates against official statistics, we provide the lowest and highest divorce rates by marriage cohort.

Figure 1: Number of job changes and spousal relationship changes by gender.



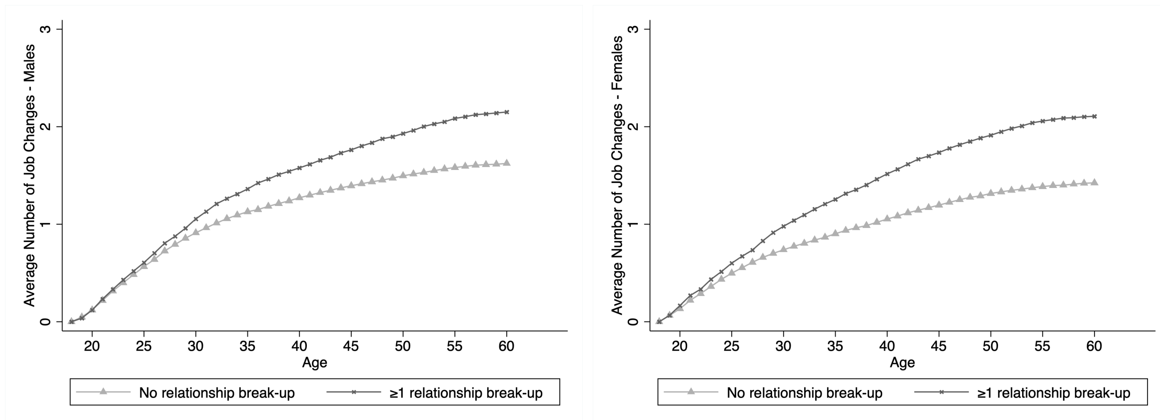
(a) Number of job changes



(b) Number of relationship breakups

on a similar job trajectory at young ages. From around age 25, men with relationship breakups are on a steeper job-accumulation profile than men with no breakups. The difference increases over age such that men without breakups have, on average, experienced about 0.5 fewer job changes than men with breakups (1.62 vs. 2.15 job changes). Figure 2(b) displays the corresponding trajectories for women. Profiles start to diverge at a somewhat younger age than those of men, and the difference in job changes between women without and with breakups is somewhat larger than for men. Women without breakups have, on average, experienced about 0.7 fewer job changes than women with breakups (1.42 vs. 2.11). Otherwise, the patterns found are very similar for men and

Figure 2: Accumulated number of job changes by relationship type and gender.



(a) Men (b) Women

women, revealing a positive association between the number of job changes and the number of breakups over the life cycle. This provides us with first descriptive evidence that higher instability in the marriage market is related to higher instability in the labor market.

To understand the role of non-cognitive skills and preferences for instability, we augment our pseudo panel with personality traits measured with the Big-Five inventory. The dimensions of personality traits included in the Big-Five are conscientiousness, agreeableness, neuroticism, openness, and extraversion. To measure preferences, we utilize questions on risk aversion and trust. We standardize all measures.[9]

We also investigate whether early life conditions and cognitive skills are predictive of being a stable or unstable type. Childhood indicators have been shown to be good proxies for early life conditions of individuals, see, for example, Havari and Mazzonna (2015) and Smith (2009). Measures of childhood endowment are obtained from SHARE-LIFE, which has collected data about the socioeconomic status (SES) and the presence of the father at the age of 10 as well as health during childhood (up to the age of 15). Cognitive skills are obtained from information about self-assessed math and language skills during childhood as well as respondents' educational attainment.[10]

[9]The exact wording of questions can be found in Table A.6 and Table A.7 of Online Appendix A. Descriptive statistics by gender can be found in Table A.8.

[10]The exact question wording and descriptive statistics can be found in Tables A.9 and A.10 of Online

To analyze the impact of being a low relationship skill type on lifetime well-being, we add information on life satisfaction and the log of net household wealth measured at ages 55–65.[11] Life satisfaction is measured on a scale from 0 to 10, with higher values indicating higher levels of life satisfaction. Net household wealth is the sum of a household's net financial assets and real estate.[12]

3 Empirical Strategy

In this section, we present the empirical strategy to estimate the relationship between unstable relationships in labor and marriage markets.

We relate job instability to marital instability and vice versa by specifying the following two linear equations for $i = 1, ..., N$ individuals observed for $t = 1, ..., T$ ages,

$$jobch_{it} = \beta relch_{it} + \boldsymbol{x}'_{it}\boldsymbol{\gamma} + \epsilon_{it}, \quad i = 1, ..., N, \ t = 1, ..., T \tag{1}$$

$$relch_{it} = \delta jobch_{it} + \boldsymbol{x}'_{it}\boldsymbol{\theta} + \nu_{it}, \quad i = 1, ..., N, \ t = 1, ..., T. \tag{2}$$

Equation (1) links the cumulative number of job changes, $jobch_{it}$, to the cumulative number of relationship breakups, $relch_{it}$, a number of covariates $\boldsymbol{x}_{it}$ and an error term ϵ_{it}. Similarly, Equation (2) links the number of relationship breakups, $relch_{it}$ to the number of job changes $jobch_{it}$, the same set of covariates as in Equation (1), and an error term ν_{it}. The main parameters of interest are β and δ, representing the relationship between job and marriage markets.

Under the assumption that job changes (relationship changes) are exogenous, i.e., unrelated to systematic unobserved heterogeneity, one can obtain causal estimates of β and δ using OLS. However, there is reason to believe that $relch_{it}$ and $jobch_{it}$ are endogenous in Equations (1) and (2), respectively, leading to biased estimates of the

Appendix A.

[11]Since SHARE surveys respondents only every two years, we would lose too many observations if we only used answers at the age of 60. We thus use the answer that is closest to the age of 60 within the age range of 55-65. We give priority to answers past the age of 60.

[12]The exact wording of the questions can be found in Table A.11 in Online Appendix A; the corresponding descriptive statistics are provided in Table A.12. In the regressions, we take the log of household net wealth plus the absolute value of the largest negative household wealth footnote to deal with negative household wealth.

main parameters of interest. An individual's unobserved ability to maintain stable relationships may be an important potential omitted variable. According to Kambourov et al. (2015) this unobserved relationship skill denotes a factor that affects the returns to outputs in teams, such as spouses in marriage or employees at work. If we assumed that the unobserved relationship skill is age-invariant, the error term in Equation (1) could be defined as $\epsilon_{it} = \alpha_i + e_{it}$ (or $\nu_{it} = \eta_i + u_{it}$ in Equation (2)) and we could obtain a causal interpretation of $\hat{\beta}$ and $\hat{\delta}$ by estimating OLS with individual-specific fixed-effects.

The literature has shown that personality traits and soft skills may develop over time, for instance, as a consequence of employment shocks, (un)favorable experiences, or through psychological interventions (Borghans et al., 2008; Heckman and Kautz, 2012; Cobb-Clark and Schurer, 2012). This means that the unobserved relationship skill may also change over the course of a person's life. An empirical specification that considers only individual-specific fixed-effects would fail to identify causal cross-market effects of stability. To address this potential endogeneity concern, we apply a grouped fixed-effects (GFE) estimator proposed by Bonhomme and Manresa (2015) and Bonhomme et al. (2022). The main idea of this approach is that individuals who share similar unobserved characteristics can be grouped together. Within groups, unobserved heterogeneity is allowed to vary arbitrarily over age. It implies that individuals who belong to the same group follow the same age profile of unobserved heterogeneity.[13] Allowing for grouped age-varying unobserved heterogeneity along with individual-specific fixed-effects leads to the following modification of Equations (1) and (2),

$$jobch_{it} = \beta relch_{it} + \boldsymbol{x}'_{it}\boldsymbol{\gamma} + \alpha_i + \alpha_{g_i t} + \xi_{it} \tag{3}$$

$$relch_{it} = \delta jobch_{it} + \boldsymbol{x}'_{it}\boldsymbol{\theta} + \eta_i + \eta_{g_i t} + \vartheta_{it}. \tag{4}$$

It can be seen from Equations (3) and (4) that the unobserved part consists of three terms. The parameters α_i and η_i denote age-invariant, individual-specific unobserved heterogeneity, i.e., individual-specific fixed-effects. The parameters $\alpha_{g_i t}$ and $\eta_{g_i t}$ repre-

[13]If individual-specific unobserved heterogeneity were allowed to vary over time, i.e., α_{it}, without imposing any restrictions, either on i or on t, one could not be separate it from idiosyncratic unobserved heterogeneity. We are not aware of any econometric method that can deal with time-varying unobserved heterogeneity in an unrestricted way.

sent age-varying unobserved heterogeneity which is clustered into $g \in \{1, \ldots, G\}$ finite groups. The subscript g_i denotes the group membership of individual i. Each individual i is assigned to one particular group g. Within this group g, unobserved heterogeneity can vary across ages t. Finally, ξ_{it} and ϑ_{it} are idiosyncratic error terms with mean zero.

The GFE estimator for Equations (3) and (4) is defined as the solution of a least squares minimization problem, providing us with estimates of the following unknown parameters: the coefficients β and δ, the coefficients on covariates, $\boldsymbol{\gamma}$ and $\boldsymbol{\theta}$, the group membership g which maps individuals into groups, and the grouped age profiles $\alpha_{g_i t}$ and $\eta_{g_i t}$.[14] Before we apply the GFE estimator, we time-demean Equations (3) and (4) to account for individual-specific, age-invariant unobserved heterogeneity α_i and η_i.

The GFE parameter estimates are obtained through an iterative two-step least squares procedure. In the assignment step, each individual is assigned to the group g_i where the Euclidean norms of its vector of residuals from Equations (3) and (4), respectively, is minimum. This step provides us with an initial group assignment, $\widehat{g}_i(\beta, \boldsymbol{\gamma}, \alpha)$ for Equation (3) and $\widehat{g}_i(\delta, \boldsymbol{\theta}, \eta)$ for Equation (4). In the update step, the parameters β (δ) and $\boldsymbol{\gamma}$ ($\boldsymbol{\theta}$) along with the group-specific unobserved heterogeneity profiles $\alpha_{g_i t}$ ($\eta_{g_i t}$) are estimated using the group assignment from the first step. The procedure is repeated until numerical convergence has been achieved.[15]

The main assumption of the GFE estimator is that there are, at most, G distinct time patterns of unobserved heterogeneity in the population, where G has to be relatively small (Bonhomme and Manresa, 2015). In our application, this implies that

[14] The minimization problem for Equation (3) is,

$$(\widehat{\boldsymbol{\mu}}, \widehat{\alpha}) = \underset{(\boldsymbol{\mu}, \alpha) \in \Theta \times \mathcal{A}^{GT}}{\operatorname{argmin}} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(\widetilde{jobch}_{it} - \tilde{\boldsymbol{z}}'_{it} \boldsymbol{\mu} - \alpha_{\widehat{g}_i(\boldsymbol{\mu}, \alpha) t} \right)^2,$$

where $\boldsymbol{\mu} = (\beta, \boldsymbol{\gamma})$, and $\boldsymbol{z}_{it} = (relch_{it}, \boldsymbol{x}_{it})$. The terms $\widetilde{jobch}_{it} = jobch_{it} - \overline{jobch}_i$ and $\tilde{\boldsymbol{z}}_{it} = \boldsymbol{z}_{it} - \bar{\boldsymbol{z}}_i$ are all time-demeaned quantities. The minimization problem for Equation (4) is analogous.

[15] As argued by Bonhomme and Manresa (2015), the objective is monotonic so that for given starting values, the iteration always converges. However, a known issue with the GFE estimator (and k-means type of clustering in general) is its sensitivity to chosen starting values. To address this, Bonhomme and Manresa (2015) suggest choosing many random starting values and selecting the solution that yields the lowest objective. We follow this advice by choosing $s = 1,000$ randomly drawn starting values from a standard normal distribution and keeping the run with the lowest objective value. A detailed description of the algorithm can be found in the Online Appendix of Bonhomme and Manresa (2015).

the true number of relationship skill types is bounded from above by G. While this assumption restricts the support of unobserved heterogeneity, other features of the relationship with observables are left unrestricted, like in the standard framework with individual-specific, time-constant fixed-effects (Bonhomme and Manresa, 2015). In applications, the true number of groups G is unknown in advance and has to be chosen by the researcher. To select the optimal number of groups G, we follow Bonhomme and Manresa (2015) and apply a Bayesian information criterion (BIC).[16] Assuming that the unobserved relationship skill appears in groups in the population and that BIC has selected the optimal number of groups G, the grouped fixed-effects (along with the individual-specific fixed-effects) sufficiently represent the unobserved (systematic) age-varying relationship skill and the parameters $\beta, \boldsymbol{\gamma}$ and $\delta, \boldsymbol{\theta}$ in Equations (3) and (4), respectively, can be consistently estimated. Consistent estimation of the group assignment g_i and of grouped time-varying heterogeneity, $\alpha_{g_i t}$ and $\eta_{g_i t}$, additionally requires large T.[17] In our data, we observe $N = 5,493$ individuals over $T = 43$ years. We thus assume that the time dimension of our panel is sufficiently large.

The static GFE estimator outlined above can address issues with endogeneity related to omitted age-varying relationship skills. Another source of endogeneity in our application could be reverse causality, i.e., that a job change at age $t-1$ affects the relationship stability at age t, which in turn affects job stability at the same age. A number of studies have shown that job changes lead to changes in spousal relationships in the next period, which in turn affect the likelihood of future job changes (see, for instance, Charles and Stephens, 2004; Ahituv and Lerman, 2011; Eliason, 2012). While we cannot

[16] The BIC for the time-demeaned version of Equation (3) (and analogously for Equation (4)) is

$$BIC(G) = \sum_{i=1}^{N} \sum_{t=1}^{T} \left(\widetilde{jobch}_{it} - \tilde{\boldsymbol{z}}_{it}' \hat{\boldsymbol{\mu}}^{(G)} - \hat{\alpha}_{\hat{g}_i t}^{(G)} \right) + \widehat{\sigma}^2 \frac{G(T+N-G+K)}{NT} \ln(NT),$$

where the second part is the penalty term. The error variance $\widehat{\sigma}^2$ is calculated for a maximum number of groups, G^{max}. In our application, we set $G^{max} = 10$. Janys and Siflinger (2024) show in simulations that the GFE estimator provides consistent estimates for the coefficients on regressors once the chosen number of groups corresponds at least to the optimal one. Thus, selecting too many groups does not bias the estimated coefficients $(\beta, \boldsymbol{\gamma})$ and $(\delta, \boldsymbol{\theta})$.

[17] The problem is the same as with estimating individual-specific fixed-effects. For fixed T and large N g_i is inconsistent because the information in g_i only accumulates over T. Bonhomme and Manresa (2015) show that the incidental parameter problem in the group assignment vanishes rapidly as T increases. The GFE estimator thus can be applied to panels of moderate length.

address general forms of reverse causality, we can account for potential feedback effects as a specific type of reverse causality by estimating dynamic versions of Equations (3) and (4) (Arellano and Bond, 1991). This requires two modifications to Equations (3) and (4) (see also Bonhomme and Manresa, 2015). First, we add lags of the dependent variable as regressors on the right-hand side to control for outcome changes at earlier ages that may affect our main regressors of interest, $relch_{it}$ and $jobch_{it}$, at age t. Second, we assume that these main regressors are predetermined (partially endogenous), thus allowing feedback of past outcomes to future regressors.[18] To instrument the lagged outcomes and the predetermined regressors, we follow the literature and use deeper lags of the lagged dependent variable and the predetermined regressors as instruments (Anderson and Hsiao, 1982; Arellano and Bond, 1991; Roodman, 2009). Under the standard instrumental variable assumptions and given that the feedback mechanism is correctly specified, the coefficients β and δ are consistently estimated. Note that the dynamic specification cannot accommodate simultaneity. To address such endogeneity, one would need a valid (external) instrument which is not available for our application.

4 Results

In this section, we present our main results. We first discuss the estimated effects of instability in labor and marriage markets ($\hat{\beta}$ and $\hat{\delta}$) in Section 4.1. They reflect the direct relationship between both markets. Section 4.2 presents the results from the dynamic GFE specification. In Section 4.3, we discuss the estimated group assignments, $\hat{g}_i$, as well as the group-specific age profiles of unobserved relationship skills ($\hat{\alpha}_{gt}$ and $\hat{\eta}_{gt}$).

[18] Predeterminedness implies that $relch_{it}$ ($jobch_{it}$) at age t are correlated with past shocks $\xi_{i,0}, ..., \xi_{i,t-1}$ ($\vartheta_{i,0}, ..., \vartheta_{i,t-1}$) but uncorrelated with present and future shocks $\xi_{it}, ..., \xi_{iT}$ ($\vartheta, ..., \vartheta_{iT}$). This relaxes the assumption of strict exogeneity to sequential exogeneity, i.e., only current and lagged values for our main regressor of interest are uncorrelated with the respective error term at age t. Note that, in a standard dynamic panel model, sequential exogeneity must hold for the unobserved additive term $\alpha_{g_i t} + \xi_{it}$ ($\eta_{g_i t} + \vartheta_{it}$) in first differences. By controlling for grouped patterns of time-varying unobserved heterogeneity, sequential exogeneity must hold with respect to ξ_{it} (ϑ_{it}).

4.1 Stability in job and marriage markets

Tables 1 and 2 present the results for the associations of stability in job and marriage markets. In all specifications, we include a number of time-varying controls: the number of children at age 0–5, 6–15, and 16 or older; the accumulated number of current health conditions; and the log GDP to capture the country-specific economic performance.[19] All specifications include country-fixed-effects, birth cohort-fixed-effects, and linear country-specific calendar year trends. In specifications without individual fixed-effects, we also control for a set of childhood endowments and cognitive skills. With the exception of the GFE specification, controls also include age-fixed-effects. We present the results from the GFE estimator for four groups of latent relationship types and five groups of latent job types, as suggested by the BIC (see Table A.15).

Columns (1)–(3) of Table 1 show the estimated impact of the number of breakups on the number of job changes for men obtained from OLS, FE, and GFE estimators. OLS estimates a significant increase in the number of job changes of 0.39 for one additional relationship breakup. This estimated coefficient reduces to 0.29 when controlling for individual fixed-effects (Column (2)). Column (3) shows that additionally allowing for grouped fixed-effects further reduces the relationship between breakups and job changes. An additional breakup leads to a 0.10 increase in the number of job changes, which corresponds to a 5.6 percent increase at the sample mean. The results indicate that there is a considerable amount of time-varying unobserved heterogeneity in addition to individual-specific time-constant heterogeneity. Ignoring this would lead to an overestimation of the direct effect of relationship instability on job instability.

Columns (4)–(6) in Table 1 present the estimated impact of job changes on relationship breakups. The OLS and fixed-effect estimates (Columns (4) and (5)) have similar magnitudes and are highly significant. An additional job change increases the number of breakups by 0.05. By contrast, when using the GFE estimator, the estimated impact reduces by a factor of 10 to 0.005 or 1.5 percent at the sample mean. While the estimated coefficient is still significant at the 10 percent level, the impact of job changes on relationship breakups seems to be mostly absorbed by unobserved stability types.[20]

[19] A description of these variables and the descriptive statistics are provided in Tables A.13 and A.14 in Online Appendix A.

[20] We assess the behavior of the estimated GFE coefficients of instability for $G = 2, ..., 6$ groups. Tables A.16 and A.17 in Online Appendix A show that the point estimates are always the largest for two

Table 1: Estimated coefficients for cross-market effects of instability for men

	Number of job changes			Number of relationship changes		
	OLS	FE	GFE, $G = 5$	OLS	FE	GFE, $G = 4$
	(1)	(2)	(3)	(4)	(5)	(6)
Number of relationship changes	0.388***	0.290***	0.096***			
	[0.055]	[0.041]	[0.021]			
Number of job changes				0.047***	0.052***	0.005*
				[0.007]	[0.008]	[0.003]
Constant	-2.442***			1.275***		
	[0.740]			[0.264]		
R-squared	0.192			0.097		
Observations	126,033					

Standard errors clustered at the individual level in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Columns (1)–(3): Estimated coefficients from a regression of the number of job changes on the number of spousal relationship changes obtained from OLS (1), OLS with individual-specific fixed-effects (2) and GFE estimator with $G = 5$ (3). Columns (4)–(6): Estimated coefficients from a regression of the number of spousal relationship changes on the number of job changes obtained from OLS (4), OLS with individual-specific fixed-effects (5), and GFE estimator with $G = 4$ (6). Time constant controls: education, childhood SES, father absent, being in very good/excellent health, self-assessed math and language skills during childhood. Time-varying controls: number of children aged 0-5, 6-15, and 16+, number of health conditions, log GDP, country and birth cohort-fixed-effects, and country-specific linear time trends. OLS models additionally control for age-fixed-effects.

Table 2 presents the estimated relationship between breakups and job changes for women. An increase in the number of breakups significantly increases the number of job changes, regardless of the specification, see Columns (1)–(3). As for men, the estimated coefficient reduces in magnitude when the restrictions on systematic unobserved heterogeneity are relaxed. When allowing for grouped fixed-effects, we obtain an increase in the number of job changes by 0.16 for one additional relationship breakup. This corresponds to a mean increase in the number of job changes by 9.7 percent for one additional breakup. Columns (4)–(6) of Table 2 show the results for the impact of job changes on relationship breakups. Again, the estimated coefficient is considerably reduced in magnitude when controlling for grouped fixed-effects. An additional job change significantly increases the number of relationship breakups among women

groups, $G = 2$, and decrease with an increasing number of groups. The coefficients tend to stabilize once the number of groups chosen by the BIC has been reached. This behavior is in line with the discussions in the literature, see Bonhomme and Manresa (2015) and Bonhomme et al. (2022).

Table 2: Estimated coefficients for cross-market effects of instability for women

	Number of job changes			Number of relationship changes		
	OLS	FE	GFE, $G = 5$	OLS	FE	GFE, $G = 4$
	(1)	(2)	(3)	(4)	(5)	(6)
Number of relationship changes	0.522***	0.392***	0.157***			
	[0.058]	[0.040]	[0.023]			
Number of job changes				0.068***	0.074***	0.007***
				[0.008]	[0.007]	[0.003]
Constant	0.392			1.718***		
	[0.718]			[0.295]		
R-squared	0.219			0.129		
Observations			110,295			

Standard errors clustered at the individual level in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Columns (1)–(3): Estimated coefficients from a regression of the number of job changes on the number of spousal relationship changes obtained from OLS (1), OLS with individual-specific fixed-effects (2) and GFE estimator with $G = 5$ (3). Columns (4)–(6): Estimated coefficients from a regression of the number of spousal relationship changes on the number of job changes obtained from OLS (4), OLS with individual-specific fixed-effects (5), and GFE estimator with $G = 4$ (6). Time constant controls: education, childhood SES, father absent, being in very good/excellent health, self-assessed math and language skills during childhood. Time-varying controls: number of children aged 0-5, 6-15, and 16+, number of health conditions, log GDP, country and birth cohort-fixed-effects, and country-specific linear time trends. OLS models additionally control for age-fixed-effects.

by 0.007 or 2.0 percent at the sample mean. Again, this result suggests that unobserved stability types absorb the direct effects of job instability on relationship instability to a large extent.[21]

For both genders, the estimated coefficients of relationship breakups on job instability are larger than the other way around. This implies that quitting the relationship is the more significant event, as it more likely leads to a reorganization of the job, for instance, by moving. By contrast, job changes may be solely made for career reasons and regardless of a change in private life.

Since our measures of instability are aggregate measures, they may mask considerable heterogeneity in the way instability in both markets is related to each other. One important source of heterogeneity is the circumstances under which individuals leave

[21] Tables A.18 and A.19 in Online Appendix A show the estimated coefficients for control variables. The results are robust to specifications without time-varying covariates that are potentially endogenous (Angrist and Evans, 1998).

a relationship. For instance, a job change resulting from firing could affect relationship stability differently than a job change due to a better job offer.[22] To shed light on this, define a measure of "negative job changes" that result from negative employer separations (due to lay-offs or being fired) or that lead to wages lower than in the previous job and re-estimate our main GFE specification. The results are presented in Table A.20. We find an impact of relationship breakups on job changes that is considerably lower (about one-third for men and one-half for women) than in specifications with all job changes, see Column (1) of Table A.20. This result is intuitive because negative job changes mostly contain firings and lay-offs, which are often unexpected and thus less likely to be driven by relationship instability. Column (2) of Table A.20 presents the estimated impact of negative job changes on relationship instability. The estimated coefficients are somewhat bigger in magnitude than those from our main specifications. This implies that negative job changes have more severe consequences on relationships than other types of job changes. This is in line with Charles and Stephens (2004) who argue that a job loss carries information about the partner's quality.

There are many other potential heterogeneities that may not be reflected by our aggregate instability measures. Examples are differences in the significance and severity of job and spousal relationship changes, differences in the timelines of relationship changes, or differences in the distribution of relationship changes. While it would be interesting to investigate such heterogeneities, it is unlikely that they invalidate our GFE estimates. First, we include a large number of controls, such as the number of children at different ages, and we account for individual-specific fixed-effects. Second, our stability measures are of a cumulative nature that change their value (in ascending order) in the year of a job change or breakup. Thus, they take account of heterogeneity in the timeline (timing and duration) of job or relationship changes over the life cycle. Third, the GFE estimator controls for grouped patterns of unobserved heterogeneity over the life cycle. Thus, as long as we maintain the assumption that individuals can be grouped, we are not concerned about heterogeneities emerging from these examples.

Overall, our results show that there are significant and sizeable impacts of instability in one market on the other. Allowing for grouped fixed-effects reduces the magnitude of

[22]Similarly, individuals may leave a marriage voluntarily, or they may be left by their partners. We do not have data on the marriage matching quality or reasons or circumstances for quitting a spousal relationship, and thus cannot investigate potential heterogeneity in this response.

the estimated coefficients but leaves them mostly statistically significant. This finding has two implications. First, there are direct cross-market effects of instability, a finding that is in line with Ahituv and Lerman (2011) showing that job instability increases marital instability and vice versa. Second, cross-market correlations are largely driven by latent stability types, and the relationship skill of these types may evolve differently over the life cycle. Like Kambourov et al. (2015), our cross-market effects can, to a large extent, be explained by unobserved stability types.

4.2 Model dynamics

The models described in Equations (3) and (4) assume that there is no feedback from instability in one market to instability in the other market. However, it has been shown that shocks in the job market can alter subsequent relationship stability, which in turn may affect job stability (see, for instance, Charles and Stephens, 2004; Eliason, 2012).

To address potential concerns with such feedback, we estimate dynamic versions of Equations (3) and (4) and allow main instability regressors to be predetermined. By controlling for lagged outcomes, we analyze the effect of instability in one market on instability innovations in the other market. As instruments, we use deeper lags of the lagged dependent variables and the predetermined regressors.[23]

Table 3 presents the estimated relationship between breakups and job changes as well as the corresponding state dependence coefficients for men (Panel A) and women (Panel B). As expected, there is significant and high state dependence, ranging between 0.65 and 0.86, depending on the specification. Column (1) of Table 3 presents the estimated effects of relationship instability on job instability. For men, an additional breakup significantly increases job instability by 0.08 job changes. Women experience a significant increase of about 0.09 job changes for one additional breakup. Compared to our main results in Tables 1 and 2, the estimated coefficients are lower for both men and women when feedback mechanisms are taken into account. Yet, the estimated

[23]Since our instability measures are highly persistent, we add the second lag of the dependent variables to the right-hand side and instrument it with deeper lags. With such a specification, we fail to reject the null hypothesis of zero second-order autocorrelation. We also fail to reject the null hypothesis of IV exogeneity with relatively high p-values, which provides suggestive evidence that the chosen lags are (jointly) valid instruments.

Table 3: Estimated coefficients of cross-market effects of instability, dynamic GFE estimator for $G = 5$ for job changes and $G = 4$ for relationship changes

	Number of job changes (1)	Number of relationship changes (2)
A.Men		
Number of relationship changes	0.076**	
	[0.036]	
Number of job changes		0.007*
		[0.004]
Number of job changes, $t-1$	0.648***	
	[0.215]	
Number of relationship changes, $t-1$		0.855***
		[0.227]
Observations	117,240	
B.Women		
Number of relationship changes	0.093**	
	[0.037]	
Number of job changes		0.083*
		[0.005]
Number of job changes, $t-1$	0.857***	
	[0.041]	
Number of relationship changes, $t-1$		0.864***
		[0.046]
Observations	102,600	

Standard errors clustered at the individual level in brackets; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Estimated coefficients obtained from specifications with the first and second lag of the dependent variable, predetermined regressor and grouped fixed-effects in an Arellano-Bond framework (Arellano and Bond, 1991). Levels of deeper lags of the lagged dependent variables and the predetermined regressor are used as instruments. Specifications for Column (1): $jobch_{it} = \pi_1 jobch_{it-1} + \pi_2 jobch_{it-2} + \beta relch_{it} + \boldsymbol{x}'_{it}\boldsymbol{\gamma} + \alpha_i + \alpha_{g_i t} + \xi_{it}$; Specifications for Column (2): $relch_{it} = \rho_1 relch_{it-1} + \rho_2 relch_{it-2} + \delta jobch_{it} + \boldsymbol{x}'_{it}\boldsymbol{\theta} + \eta_i + \eta_{g_i t} + \vartheta_{it}$; First differencing and controlling for the first and second lag of the dependent variable reduces the sample size by $t = 3$ periods (first three periods). Controls: number of children aged 0-5, 6-15, and 16+, number of health conditions, log GDP, country and birth cohort-fixed-effects, and country-specific linear time trends.

coefficients are still statistically significant at the 5% level, suggesting that there is a strong contemporaneous relationship between job and spousal relationship instability.

Column (2) of Table 3 shows the estimated effects of the number of job changes on the number of relationship changes. Compared to our main specifications, the estimated coefficients are slightly larger for both genders when taking into account potential feedback mechanisms. The estimated coefficient for men is now significant at the 10% level. For women, we find an impact of 0.008 additional relationships for one job change which is significant on the 10% level. Again, the estimated coefficients are very similar to those we obtained from our specifications without feedback.

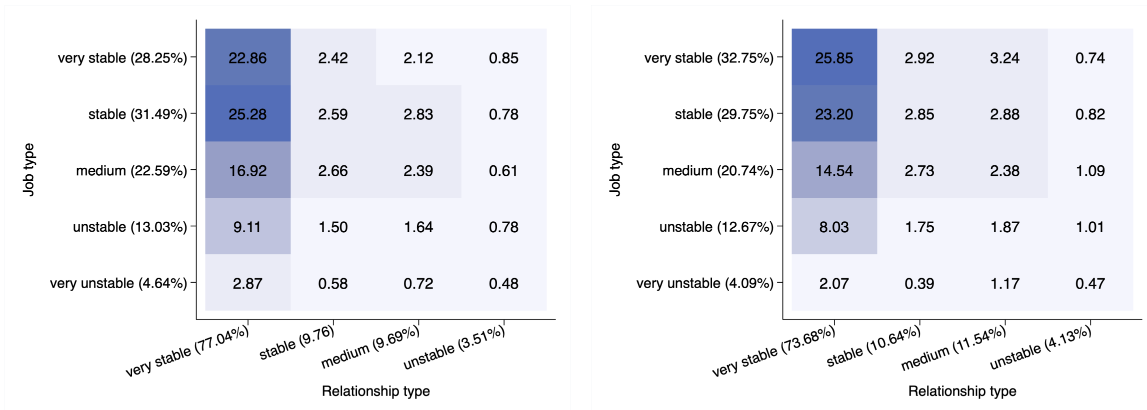
Overall, the results imply that feedback does not significantly alter the estimated contemporaneous cross-market effects of instability. One potential explanation for this finding could be that controlling for grouped patterns of unobserved heterogeneity absorbs considerable variation in the outcome process.

4.3 Group-specific profiles and group assignment

The GFE estimator also provides us with the estimated group assignments and the grouped patterns of time-varying unobserved heterogeneity. Figure 3 plots the joint and marginal (in brackets at labels) distribution for five job types and four relationship types to which we assumed that individuals could be assigned to.

Figure 3(a) reveals that the majority of men (about 77 percent) are assigned to the very stable relationship stability group, and only a few men (about 3.5 percent) are classified as unstable relationship types. Job stability types are somewhat more evenly distributed. About 60 (28.25 + 31.49) percent are assigned to the very high or high job stability group, 22.6 percent to the medium stability group, and about 18 (13.03 + 4.64) percent of men are unstable or very unstable job stability types. When considering the joint distribution of both markets, we find that about 53 percent of men in our sample are of the stable or very stable types in both jobs and relationships. Among very stable relationship types, 17 percent are medium stable job types, 9 percent are unstable job types, and about 3 percent are very unstable job types. Around 6.6 percent of men are medium stable or (very) unstable types in both markets with only about 1.3 percent of men who are unstable or very unstable types in both markets.

Figure 3: Joint distribution of estimated group assignments to stability types in job and relationship markets.



(a) Men (b) Women

Note: Figure shows the share of observations in each category. The classification is obtained from the GFE estimator using 5 job groups and 4 relationship groups as suggested by the BIC criterion.

Figure 3(b) shows the group assignments for women. The distributions of job and marital stability are similar to that of men, with women being slightly less often stable relationship types. About 74 percent of women are very stable relationship types, and 4.1 percent are classified as unstable relationship types. Regarding job changes, women are only somewhat more stable job types than men (62.5 percent of women and 60 percent of men). Also, the joint distribution of both markets is similar to that of men. About 54.8 percent of women are very stable or stable types in both markets. About 1.5 percent belong to the unstable and very unstable groups in both markets. These numbers indicate that individuals who are considered unstable in the job market are also more likely to be unstable types in the marriage market. Indeed, correlations between stability types across markets are 26 percent for men and 29 percent for women and are highly significant. The correlation between the latent instability types in marriage and labor markets is significant and positive (26 percent for men and 29 percent for women). Thus, individuals who have problems maintaining stable relationships in one market are also likely to face instability in the other market.

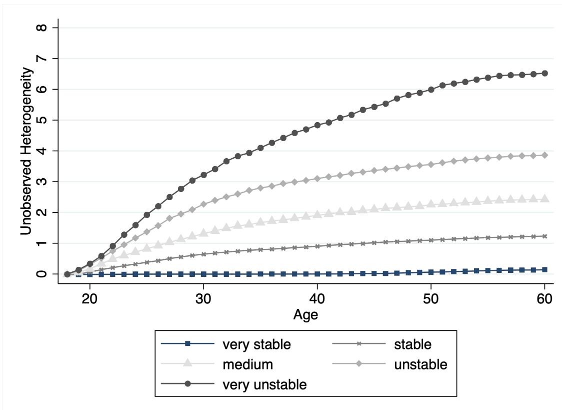
Figure 3 shows that men and women have very similar distributions of stability types. However, these shares are generated from different underlying distributions of instability, such that men and women may differ in the distribution of stability types in the population. As discussed in Section 2, women change jobs less frequently than men, on average. Moreover, men have up to seven breakups over the life cycle, while women have up to four breakups. This implies that women might be more stable relative to men. To investigate this hypothesis, we re-estimate the group assignment on a joint sample of men and women. Table A.21 in Online Appendix A shows the differences in the group assignment between the full sample of men and women and separate samples by gender. While the group assignment is very similar for the different samples (indicated by the zeros on the off-diagonals), women tend to be more often assigned to the lower job stability group with the female-only sample compared to using the sample with both genders.

The GFE estimator also estimates the heterogeneity profiles for the different job and relationship stability types. Figure 4 presents these estimated age profiles for five job stability types over the life cycle. The profiles look very similar for men and women. All stability types start from a similar level of unobserved heterogeneity. With increasing age, differences across stability types become more and more pronounced, indicating that there is substantial heterogeneity across different job stability types. Individuals assigned to the highest job stability type exhibit profiles that are almost flat and time-constant. By contrast, the group with the highest job instability exhibits a profile that steeply increases at younger ages and flattens out at the end of the life cycle. Profiles of more stable types follow a similar pattern as that of the high instability type but with a less steep increase at younger ages and a flatter trajectory at older ages. After the age of 50, these types mostly differ by levels of unobserved heterogeneity.

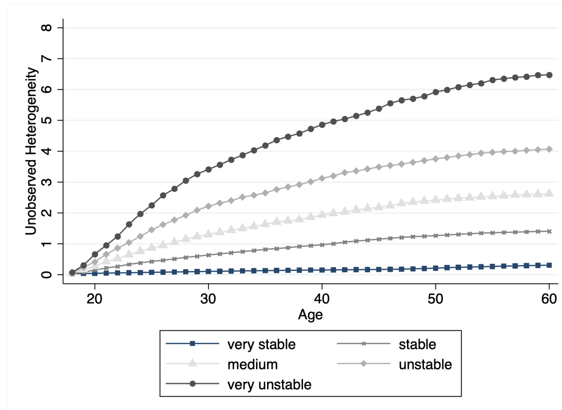
Figure 5 presents the unobserved heterogeneity profiles of different relationship stability types. While all profiles start at the same level, regardless of gender, there is, again, substantial heterogeneity across stability types. Types of very high relationship stability have an entirely flat profile, meaning that the unobserved heterogeneity contributing to the number of breakups is time-constant and almost zero. For more medium stable types, the unobserved heterogeneity profiles mostly differ by the timing at which relationship changes take place. With increasing age, the unobserved heterogeneity profiles of these stability types coincide.

The results in this section have important implications. First, there are considerable level and slope differences in age profiles across latent stability types. Thus, unobserved

Figure 4: Unobserved heterogeneity profiles for latent job stability types.



(a) Men



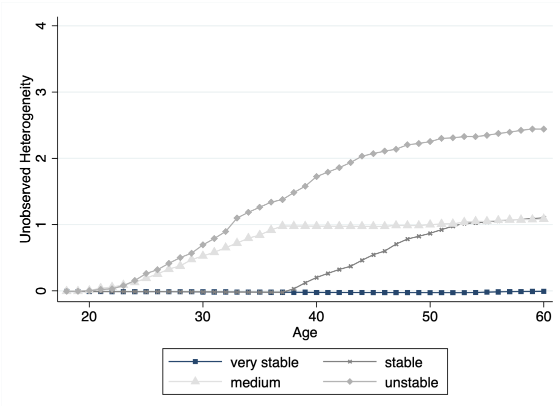
(b) Women

heterogeneity cannot be assumed to be time-constant. According to our interpretation, this implies that for a non-negligible share of individuals, there exists an unobserved relationship skill that varies over the life cycle and across latent stability types. Second, a small, but not negligible share of men and women are considered as latent unstable job or relationship types, thus being endowed with low relationship skills. Ignoring these differences across individuals would necessarily lead to a wrong assessment of how job and relationship stability are related to each other. Moreover, a small but non-negligible share of men and women are unstable or very unstable types in both markets.

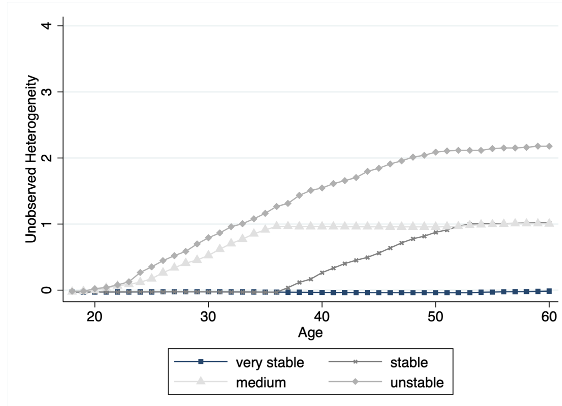
5 Latent stability types, individual characteristics and lifetime costs

In this section, we investigate how latent stability types relate to measures of personality traits, social preferences, and childhood circumstances (Section 5.1). Finally, we explore whether the latent stability types are associated with well-being at the end of the life cycle, which is measured with life satisfaction on a 10-point scale and log net household wealth (Section 5.2). This part of our analysis is not aimed at detecting causal effects

Figure 5: Unobserved heterogeneity profiles for latent spousal relationship stability types.



(a) Men



(b) Women

but rather at analyzing and interpreting associations.[24]

For the empirical analysis in this section, we combine the stability types from the job and marriage markets into a variable with four categories reflecting (in)stability in both markets jointly. We first classify individuals from the very unstable and unstable stability groups in jobs as unstable. We classify individuals from the unstable relationship category as unstable. We then make four categories: unstable in both markets, stable in relationships and unstable in jobs, unstable in relationships and stable in jobs, and stable in both markets.

5.1 Stability types, personality traits and preferences

To investigate how personality traits, preferences, early life conditions, and cognitive skills are related to different stability types, we estimate a multinomial model on types of different stability reflecting different relationship skills. The base outcome is the

[24]There are several issues threatening the interpretation of such associations as causal effects. First, we only have a one-time measurement of the measures of well-being. Thus we cannot account for reverse causality, e.g., that individuals who are in general unhappy are more likely to leave their jobs and relationships (see also Luhmann et al., 2013). Second, the measures of late-life well-being are likely correlated with unobserved factors that also shape instability that we cannot control due to the lack of panel data.

relationship type that is stable in both domains.

Tables 4 and 5 show the estimated relative ratios for men and women, respectively. We find that the unobserved stability types are related to personality traits. For both men and women, conscientiousness significantly increases the relative risk of being a stable type. Increasing conscientiousness by one standard deviation at the mean significantly decreases the chance of being an unstable type in both markets relative to being an overall stable type (44.5% times the chance at the mean of conscientiousness for men and 71.4% times the chance at the mean of conscientiousness for women). Thus, conscientiousness seems to be an important component of the relationship skill. This result is in line with the literature that singles out conscientiousness as the "super trait" because of its predictive power in both labor and marriage markets (Gensowski et al., 2021).

In addition, being more extroverted, open (only for women), or neurotic (only for men) is a significant predictor for being an unstable type in at least one market. This is in line with findings by Lundberg (2012) and Boertien et al. (2017), who show that openness increases the hazard of being divorced regardless of gender. These studies also show, in line with our findings, that men's risk of marriage instability (divorce) increases with extraversion and decreases with conscientiousness. Several studies have found that higher levels of extraversion are associated with more frequent switching of organizations and more initiative in searching for alternative employment (see, for instance, Kanfer et al., 2001; Wille et al., 2010; Almlund et al., 2011).

Regarding other social preferences, being more trusting is associated with lower instability for men and women. Being one standard deviation more trusting significantly decreases the chance of being an unstable type in both markets rather than being an overall stable type for men. For both genders, the chances of being an unstable relationship type but a stable job type are lower compared to being stable in both markets the more trusting an individual is. This suggests that trust is an important determinant of being a stable relationship type, which is in line with findings in the literature that trust is a crucial determinant of engaging and maintaining long-term cooperation (Gambetta, 2000). We do not find any significant associations between stability types and our measure of risk aversion.

Socio-economic conditions during childhood also play a role in individuals' stability types. While for men and women, a low SES during childhood is associated with a lower chance of being a stable job and unstable relationship type compared to those with medium SES, those with high SES backgrounds have a higher chance of being this type relative to being an overall stable type. Very good/excellent childhood health increases the odds of being a stable type, in particular for women. The fact that the absence of the father at age 10 is associated with a higher chance of being an overall unstable type points to the perpetuating effect of instability across generations.

Table 4: Relative risk ratios from a multinomial model that relates stability types to personality traits, preferences, and measures of childhood circumstance for men

	stable job, unstable rel (1)	unstable job, stable rel (2)	unstable both (3)
A. Preferences			
Risk aversion	0.918	0.915	0.936
	[0.107]	[0.054]	[0.187]
Trust	0.740**	0.921	0.543***
	[0.103]	[0.059]	[0.110]
B. Personality traits			
Extraversion	1.129	1.195***	1.170
	[0.173]	[0.077]	[0.242]
Agreeableness	1.004	1.055	1.124
	[0.146]	[0.067]	[0.301]
Conscientiousness	0.835	0.938	0.445***
	[0.107]	[0.059]	[0.080]
Neuroticism	0.886	0.947	1.477*
	[0.133]	[0.060]	[0.296]
Openness	0.886	1.059	1.027
	[0.132]	[0.070]	[0.250]
C. Childhood conditions and cognitive skills			
SES low	0.376**	1.333*	2.139
	[0.172]	[0.197]	[1.031]
SES high	2.016**	0.984	1.045
	[0.617]	[0.155]	[0.520]
Father absent at age 10	0.978	1.313	2.369*
	[0.439]	[0.238]	[1.123]
Very good/excellent health	0.729	0.940	1.039
	[0.211]	[0.121]	[0.463]
Self-assessed math skills	0.759	0.846**	1.030
	[0.135]	[0.065]	[0.265]
Self-assessed language skills	0.834	0.996	2.376***
	[0.162]	[0.081]	[0.724]
Low education	0.946	0.805	0.163**
	[0.298]	[0.119]	[0.123]
High education	0.666	0.984	1.240
	[0.253]	[0.158]	[0.649]

Robust standard errors in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Relative risk ratios obtained from multinomial regression of stability types on personality traits, social preferences, childhood conditions, and cognitive skills. Time constant controls: education, childhood SES, father absent, being in very good/excellent health, self-assessed math and language skills during childhood. Includes country and birth cohort-fixed-effects.

Table 5: Relative risk ratios from a multinomial model that relates stability types to personality traits, preferences, and measures of childhood circumstance for women

	stable job, unstable rel (1)	unstable job, stable rel (2)	unstable both (3)
A. Preferences			
Risk aversion	1.138	1.059	0.828
	[0.204]	[0.070]	[0.132]
Trust	0.682***	1.022	1.035
	[0.096]	[0.077]	[0.247]
B. Personality traits			
Extraversion	1.073	1.067	1.569**
	[0.197]	[0.075]	[0.301]
Agreeableness	0.917	0.935	1.407
	[0.125]	[0.067]	[0.313]
Conscientiousness	0.801	0.970	0.714**
	[0.113]	[0.071]	[0.119]
Neuroticism	0.935	1.031	1.279
	[0.154]	[0.075]	[0.261]
Openness	1.276	1.194**	1.094
	[0.220]	[0.093]	[0.259]
C. Childhood conditions and cognitive skills			
SES low	0.272**	0.924	0.535
	[0.165]	[0.164]	[0.351]
SES high	1.687*	0.929	1.404
	[0.527]	[0.154]	[0.559]
Father absent at age 10	0.730	1.106	2.975**
	[0.354]	[0.234]	[1.438]
Very good/excellent health	0.614*	0.644***	0.649
	[0.173]	[0.090]	[0.263]
Self-assessed math skills	0.836	0.935	0.897
	[0.165]	[0.083]	[0.188]
Self-assessed language skills	1.079	1.038	1.012
	[0.211]	[0.096]	[0.242]
Low education	0.822	1.023	0.588
	[0.290]	[0.163]	[0.273]
High education	0.886	0.861	0.441
	[0.294]	[0.163]	[0.227]

Robust standard errors in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Relative risk ratios obtained from multinomial regression of stability types on personality traits, social preferences, childhood conditions, and cognitive skills. Time constant controls: education, childhood SES, father absent, being in very good/excellent health, self-assessed math and language skills during childhood. Includes country and birth cohort-fixed-effects.

5.2 Does instability predict late-life well-being?

We finally investigate whether relationship stability is associated with life satisfaction and household wealth at ages 55–65, which serve as proxies of late-life well-being.

Columns (1)–(2) of Table 6 present the estimated coefficients of being an unstable type in either or both markets on life satisfaction for men and women. Being a stable job type and an unstable relationship type is associated with 0.50 (0.76) points lower life satisfaction for men (women) compared to being a stable type in both domains. Being an unstable job type but a stable relationship type is associated with 0.23 (0.24) points less life satisfaction than being an overall stable type. Being unstable in both domains is associated with a 0.70 points lower life satisfaction for men and a 0.72 lower life satisfaction for women. While the estimated associations are similar for both genders, the coefficient for males is not significantly different from zero. The strong negative correlation between being an unstable type and life satisfaction is consistent with findings in the literature. For instance, Roberson et al. (2018) show that individuals with multiple relationship transitions report a significantly worse quality of life compared to individuals with none or one transition. Studies also find that temporary contracts or unemployment events predict lower levels of job satisfaction (e.g., Booth et al., 2002; Kassenboehmer and Haisken-DeNew, 2009). Such experiences could have shaped relationship skills towards more instability and thus partly explain the findings for life satisfaction.

Columns (3)–(4) of Table 6 present the results for log net household wealth. Being a stable job and an unstable relationship type is associated with 4.8 (45) percent lower household net wealth relative to being stable in both domains. Being an unstable job and a stable relationship type is associated with lower reductions in household wealth, of 2.8 percent lower household wealth for men and a statistically insignificant reduction for women. Being unstable in both domains is associated with quite large reductions of 10 percent for men and 54 percent for women. This result is in line with, e.g., Light and McGarry (1998) showing that wage trajectories of workers with high job mobility are lower than those of less mobile workers. It also shows that instability seems to be particularly harmful for women. Their reduction in wealth is enormous but consistent with findings in the literature. For instance, Leopold (2018) shows that women lose about 40 percent of their pre-divorce household income in the year of divorce. Five years after divorce, the loss has halved but is still 25 percent less than their pre-divorce income. Strikingly, women's risk of crossing the poverty line sharply increases in the year of divorce from about 6 percent to more than 45 percent and still is 25 percent five years after divorce. By contrast, the former husband's poverty risk remains largely unchanged during the divorce process.[25]

Table 6: Estimated associations between life satisfaction, wealth (age 55–65) and estimated instability types

	Life satisfaction		log HH net wealth	
	Men	Women	Men	Women
	(1)	(2)	(3)	(4)
Stable job, unstable relationship	-0.495**	-0.759***	-0.048***	-0.450***
	[0.241]	[0.271]	[0.018]	[0.090]
Unstable job, stable relationship	-0.232**	-0.244**	-0.028***	-0.050
	[0.094]	[0.109]	[0.010]	[0.047]
Unstable in both	-0.704	-0.724**	-0.103***	-0.544***
	[0.428]	[0.292]	[0.032]	[0.129]
Constant	7.802***	7.585***	14.491***	12.056***
	[0.334]	[0.417]	[0.033]	[0.183]
Observations	2,047	1,830	2,047	1,830
R-squared	0.082	0.095	0.159	0.181

Robust standard errors in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Estimated coefficients from OLS regressions of life satisfaction and log net household wealth at age 55–65 on stability types. The reference category is being stable in the job and the marriage market. Time constant controls: education, childhood SES, father absent, being in very good/excellent health, self-assessed math and language skills during childhood. Includes country and birth cohort-fixed-effects.

[25] As an alternative wealth measure, we use the log of the net value of the house (home value minus mortgage). Table A.22 in Online Appendix A shows the results. The results are similar to the ones for household wealth.

6 Conclusion

We use longitudinal data from six Western European countries to establish the relationship between individual behavior in labor and marriage markets. This is motivated by a large literature in economics that acknowledges that behavior in both markets follows similar patterns. We show that there are direct cross-market effects in instability. However, these direct effects get smaller when grouped patterns of unobserved heterogeneity are taken into account. We interpret the unobserved heterogeneity as latent types of individuals who have a distinct evolution of an unobserved relationship skill over the life cycle. In accordance with our hypothesis that this relationship skill affects behavior in both markets, these latent stability types obtained for both markets show a large overlap. The types are related to measures of personality and social preferences. Furthermore, we show that instability is associated with costs, as measured by large negative effects on household wealth and life satisfaction. This result aligns well with Kuhn and Ploj (2020) finding long-lasting negative effects of job instability on late-life well-being.

From a policy perspective, our results emphasize the strong link between marriage and labor markets. Our analysis shows that unstable types keep changing relationships in both markets up until the later stages of life. This is important to acknowledge since we show that relationship instability is costly both in terms of wealth accumulation as well as life satisfaction. Our results show that there may even be a perpetuating effect of instability across generations since the latent instability profile is associated with the absence of the father during youth.

We relate the latent instability types to personality traits and social preferences. The Big-Five is a standard inventory developed by psychologists that is more and more included in bigger social science surveys and could indeed be used to spot individuals at risk. Important from the policy perspective is that personality traits are malleable through investments and policy interventions, in particular during (early) childhood (Borghans et al., 2008). In addition, there is a large literature in psychology showing that relationship stability can be strengthened through therapy, and thus, relationship stability can be changed through interventions (Dunn and Schwebel, 1995; Nathan D. Wood and Law, 2005; Spengler and Wittenborn, 2022). These interventions may also have positive implications on labor markets both through direct impact and through changing latent stability profiles.

Given our results, an interesting avenue for future research would be to investigate whether relationship stability extends to other markets requiring cooperation, such as long-term relationships between friends, tenants and renters, clients and banks, or firms.

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Online Appendix for
"Relationship Stability: Evidence from Labor and Marriage Markets"

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A Additional Tables

Table A.1: Variable description: number of job changes and relationship changes

VARIABLE	Question	Scale
Number of job changes	*I'm going to ask you about each paid job that lasted for 6 months or more. A series of short-term jobs for different employers that were essentially the same role counts as 1 job. In which year did you start your [first/next] paid job (as employee or self-employed), which lasted for 6 months or more?".*[26]	open
Number of relationship changes	*When did your relationship with [partner name] start?*	open

For the question eliciting the number of job changes, SHARE interviewers are supposed to code only employer changes. They are, however, allowed to also code changes in roles if the respondent wishes so. (Instructions: "In general, you should code when the respondent changed employer, although you can count a change in roles for the same employer if the respondent wishes.")

Table A.2: Descriptive statistics for job changing and relationship changing

	Female	Male
Number of job changes	1.616	1.755
	(1.679)	(1.726)
Number of breakups	0.345	0.325
	(0.610)	(0.653)
Number of divorces	0.274	0.245
	(0.516)	(0.499)
Number of cohabiting breakups	0.071	0.081
	(0.291)	(0.346)
Number of individuals	2,565	2,931
Number of observations	110,295	126,033

Standard deviations in parentheses.

Table A.3: Number of observations and sample means of job and relationship changes by country

Country	N	Number of job changes	Number of relationship changes
Austria	958	1.402	0.390
		(1.498)	(0.680)
Belgium	1248	1.343	0.364
		(1.454)	(0.651)
France	856	1.717	0.314
		(1.782)	(0.618)
Germany	1209	1.633	0.299
		(1.6436)	(0.617)
Netherlands	458	1.924	0.216
		(1.692)	(0.528)
Switzerland	767	2.536	0.365
		(2.024)	(0.636)

Standard deviations in parentheses.

Table A.4: Average number of jobs Eurostat vs. SHARE

	Eurobarometer		SHARE	
Country	N	Number of jobs	N	Number of jobs
Austria	584	2.445	958	2.471
		(2.393)		(1.558)
Belgium	728	2.023	1248	2.394
		(2.447)		(1.498)
France	818	2.641	856	2.782
		(3.484)		(1.825)
Germany	863	2.687	1209	2.686
		(2.825)		(1.668)
Netherlands	817	3.122	458	3.074
		(3.040)		(1.756)

Standard deviations in parentheses. Eurobarometer data pools the years 2005, 2006, and 2008.

Table A.5: Divorce rates - Eurostat vs. SHARE, marriage cohorts 1960-1980

	divorce rates marriage cohorts 1960–1980		
country	lowest (1)	highest (2)	SHARE sample (3)
Austria	18.00%	32.00%	25.69%
Belgium	26.00%	34.00%	27.88%
France	16.00%	33.00%	22.89%
Germany	18.00%	33.00%	21.95%
Netherlands	17.00%	31.00%	16.00%
Switzerland	19.00%	33.00%	26.69%

The term marriage cohort refers to the year of marriage, not the year of birth of those who marry. The lowest divorce rate for those marriage cohorts can be found in Column (1), and the highest rates in Column (2) (Source: Table 2 in Eurostat (1997)). Column (3) shows the divorce rates from our sample of SHARE respondents.

Table A.6: Variable description: Attitude variables

VARIABLE	Question	Scale
Risk aversion	*Please look at card 46. When people invest their savings they can choose between assets that give low return with little risk to lose money, for instance, a bank account or a safe bond, or assets with a high return but also a higher risk of losing, for instance, stocks and shares. Which of the statements on the card comes closest to the amount of financial risk that you are willing to take when you save or make investments?* (higher value indicates higher risk aversion)	1-4
Trust	*Finally, I would now like to ask a question about how you view other people. Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people? Not looking at card 50 anymore, please tell me on a scale from 0 to 10, where 0 means you can't be too careful and 10 means that most people can be trusted.*	1-10

Table A.7: Variable description: Personality variables

VARIABLE	Question	Scale
I am now going to read out some statements concerning characteristics that may or may not apply to you. After each statement please indicate whether you strongly disagree, disagree a little, neither agree nor disagree, agree a little, or agree strongly. I see myself as someone who ...		
Big-5 Openness	*... has few artistic interests, I see myself as someone who has an active imagination*	1-5
Big-5 Conscientiousness	*... tends to be lazy, I see myself as someone who does a thorough job*	1-5
Big-5 Extraversion	*... is reserved, I see myself as someone who is outgoing, sociable*	1-5
Big-5 Agreeableness	*... is generally trusting, I see myself as someone who tends to find fault with others*	1-5
Big-5 Neuroticism	*... is relaxed, handles stress well, I see myself as someone who gets nervous easily*	1-5

Table A.8: Descriptive statistics for personality traits and preferences

	Female	Male
Big-Five personality traits		
Big-Five: Openness	3.600	3.408
	(0.973)	(0.966)
Big-Five: Conscientiousness	4.235	4.121
	(0.744)	(0.774)
Big-Five: Extraversion	3.502	3.466
	(0.928)	(0.912)
Big-Five: Agreeableness	3.609	3.493
	(0.792)	(0.800)
Big-Five: Neuroticism	2.806	2.414
	(1.036)	(0.954)
Measures for preferences		
Risk aversion	3.750	3.596
	(0.494)	(0.608)
Trust	5.895	5.827
	(2.274)	(2.206)
Number of individuals	2,565	2,931

Standard deviations in parentheses.

Table A.9: Variable description: childhood cognitive skill measures and endowments

VARIABLE	Question	Scale
Low and high education	*How many years have you been in full-time education?* From this we compute the categories for each country separately. An individual's education is classified as low if the years of education are lower than the 25% percentile of the country-specific years of education. An individual's education is classified as high if the years of education are greater than the 75% percentile of the country-specific years of education.	0/1
Low and high childhood SES	Factor analysis of number of books in household, number of rooms per person, features at home (running water, number of books, etc.), and occupation of the main breadwinner. We classify SES as low if an individual's score is lower than the 25% percentile of the country-specific SES score distribution and high if an individual's score is greater than the 75% percentile.	0/1
Very good/ excellent childhood health	*Would you say that your health during your childhood was in general excellent, very good, good, fair, or poor?* (Ranked on a scale from 1-5, a higher value indicates better health, dummy equals one for very good/excellent health, so if score greater than 3)	0/1
Father absent	*Please look at SHOWCARD 8. Which of the people on this card did you live with at this accommodation when you were 10?* Here: *Biological father*	0/1
Math skills	*Now I would like you to think back to your time in school when you were 10 years old. How did you perform in Maths compared to other children in your class? Did you perform much better, better, about the same, worse, or much worse than the average?* (higher value indicates better math performance)	1-5
Language skills	*And how did you perform in compared to other children in (enter country language) in your class? Did you perform much better, better, about the same, worse or much worse than the average?*(higher value indicates better language performance)	1-5

Table A.10: Descriptive statistics time-invariant controls

	Female	Male
Childhood conditions and cognitive skills		
SES low	0.221	0.252
	(0.415)	(0.434)
SES high	0.307	0.259
	(0.461)	(0.438)
Excellent/very good health	0.583	0.619
	(0.493)	(0.486)
Father absent at age 10	0.112	0.117
	(0.315)	(0.322)
High education	0.195	0.253
	(0.396)	(0.435)
Low education	0.313	0.312
	(0.464)	(0.463)
Self-assessed math skills	3.273	3.383
	(0.867)	(0.884)
Self-assessed language skills	3.543	3.322
	(0.841)	(0.880)
Number of individuals	2,565	2,931
Number of observations	110,295	126,033

Standard deviations in parentheses.

Table A.11: Variable description: life satisfaction and wealth in late-life

VARIABLE	Question	Scale
Life satisfaction	*On a scale from 0 to 10 where 0 means completely dissatisfied and 10 means completely satisfied, how satisfied are you with your life?*	0-10
Household wealth	Sum of household net financial assets (bank accounts, bonds, stocks, funds, savings for long-term investments) and household real assets (real estate, businesses, and cars minus mortgages), answered by financial respondent	open
Net house value	Value of main residence minus mortgage on main residence	open

Table A.12: Descriptive statistics for life satisfaction and wealth in late-life

	Female	Male
Life satisfaction at age 55–65	7.86	7.97
	(1.57)	(1.50)
Household wealth at age 55–65	389,529	431,504
	(548,395)	(731,499)
Number of individuals	1,830	2,047

Standard deviations in parentheses.

Table A.13: Variable description: time-varying controls

VARIABLE	Question	Scale
Children in age groups	*In which year was [CH004_FirstNameOfChild] born?*	0/1
Number of current health conditions	Using data on the periods of ill health or disability, and their start dates together with the conditions named from a list, from SHARELIFE.	0-8
Log GDP	uses data from the Maddison historical database: Maddison Project Database, version 2020. Bolt, Jutta, and Jan Luiten van Zanden (2020), "Maddison style estimates of the evolution of the world economy. A new 2020 update "	open

Table A.14: Descriptive statistics for time-varying controls

	Female	Male
Number of current health conditions	0.076	0.06
	(0.473)	(0.43)
log GDP	10.052	10.05
	(0.350)	(0.35)
Number children 0–5	0.130	0.13
	(0.446)	(0.45)
Number children 6–15	0.219	0.22
	(0.624)	(0.62)
Number children $\geq$16	0.388	0.34
	(0.927)	(0.86)
Number of individuals	2,565	2,931
Number of observations	110,295	126,033

Standard deviations in parentheses.

Table A.15: BIC obtained from the GFE estimator with individual-specific fixed-effects and for $G = 2 - 6$ and $G = 10$ groups

	Bayesian Information Criterion (BIC)					
Dependent variable	$G = 2$	$G = 3$	$G = 4$	$G = 5$	$G = 6$	$G = 10$
A. Men						
Number of job changes	0.762	0.551	0.489	0.473	0.492	0.618
Number of relationship changes	0.081	0.060	0.055	0.057	0.058	0.071
B. Women						
Number of job changes	0.676	0.505	0.446	0.437	0.459	0.583
Number of relationship changes	0.070	0.055	0.044	0.044	0.046	0.057

Table A.16: Estimated coefficients for cross-market effects of instability using the GFE estimator with different number of groups, men

	GFE				
	$G = 2$	$G = 3$	$G = 4$	$G = 5$	$G = 6$
	(1)	(2)	(3)	(4)	(5)
Panel A	Number of job changes				
Number of relationship changes	0.167***	0.115***	0.121***	0.096***	0.082***
	[0.030]	[0.024]	[0.024]	[0.021]	[0.019]
Panel B	Number of relationship changes				
Number of job changes	0.014***	0.002	0.005*	0.006**	0.001
	[0.005]	[0.003]	[0.003]	[0.003]	[0.002]
Observations	126,033				

Standard errors clustered at the individual level in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Panel A: Estimated coefficients from a regression of the number of job changes on the number of spousal relationship changes using the GFE estimator with individual-specific fixed-effects and different number of groups. Panel B: Estimated coefficients from a regression of the number of spousal relationship changes on the number of job changes using the GFE estimator with individual-specific fixed-effects and different number of groups. Time constant controls: education, childhood SES, father absent, being in very good/excellent health, self-assessed math and language skills during childhood. Time-varying controls: number of children aged 0-5, 6-15, and 16+, number of health conditions, log GDP, country and birth cohort-fixed-effects, and country-specific linear time trends.

Table A.17: Estimated coefficients for cross-market effects of instability using the GFE estimator with different number of groups, women

	GFE				
	$G = 2$	$G = 3$	$G = 4$	$G = 5$	$G = 6$
	(1)	(2)	(3)	(4)	(5)
Panel A	Number of job changes				
Number of relationship changes					
	0.221***	0.172***	0.164***	0.157***	0.123***
	[0.028]	[0.025]	[0.024]	[0.023]	[0.020]
Panel B	Number of relationship changes				
Number of job changes	0.025***	0.017***	0.007***	0.007***	0.006***
	[0.005]	[0.004]	[0.003]	[0.003]	[0.002]
Observations	110,295				

Standard errors clustered at the individual level in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Panel A: Estimated coefficients from a regression of the number of job changes on the number of spousal relationship changes using the GFE estimator with individual-specific fixed-effects and different number of groups. Panel B: Estimated coefficients from a regression of the number of spousal relationship changes on the number of job changes using the GFE estimator with individual-specific fixed-effects and different number of groups. Time constant controls: education, childhood SES, father absent, being in very good/excellent health, self-assessed math and language skills during childhood. Time-varying controls: number of children aged 0-5, 6-15, and 16+, number of health conditions, log GDP, country and birth cohort-fixed-effects, and country-specific linear time trends.

Table A.18: All estimated coefficients for cross-market effects of instability, men

	Number of job changes			Number of relationship changes		
	OLS	FE	GFE, $G = 5$	OLS	FE	GFE, $G = 4$
	(1)	(2)	(3)	(4)	(5)	(6)
Number of relationship changes	0.388***	0.290***	0.096***			
	[0.055]	[0.041]	[0.021]			
Number of job changes				0.047***	0.052***	0.005*
				[0.007]	[0.008]	[0.003]
Low education	-0.138***			0.004		
	[0.050]			[0.016]		
High education	-0.096*			-0.018		
	[0.053]			[0.017]		
Low SES	0.150***			-0.022		
	[0.051]			[0.015]		
High SES	0.013			0.075***		
	[0.051]			[0.017]		
Father absent at age 10	0.120*			0.041*		
	[0.063]			[0.022]		
Very good/excellent	-0.015			-0.027**		
childhood health	[0.043]			[0.014]		
Self-assessed math skills	-0.051*			-0.012		
	[0.027]			[0.010]		
Self-assessed language skills	0.004			0.013		
	[0.028]			[0.010]		
Number children 0-5	0.034*	0.039***	0.026***	-0.001	-0.005	-0.002
	[0.020]	[0.014]	[0.007]	[0.006]	[0.005]	[0.002]
Number children 6-15	0.047**	0.045***	0.017**	-0.016**	-0.018***	-0.002
	[0.020]	[0.017]	[0.008]	[0.007]	[0.006]	[0.002]
Number children $\geq$16	0.065**	0.055**	0.012	-0.034***	-0.032***	-0.004
	[0.028]	[0.023]	[0.011]	[0.008]	[0.008]	[0.003]
Number health conditions	0.034	0.007	-0.008	0.053**	0.032**	0.002
	[0.041]	[0.021]	[0.012]	[0.027]	[0.015]	[0.005]
Log GDP	0.317***	0.315***	-0.073	-0.148***	-0.150***	-0.012
	[0.085]	[0.082]	[0.052]	[0.030]	[0.029]	[0.016]
Constant	-2.442***			1.275***		
	[0.740]			[0.264]		
R-squared	0.192			0.097		
Observations	126,033					

Standard errors clustered at the individual level in brackets; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Columns (1)–(3): Estimated coefficients from a regression of the number of job changes on the number of spousal relationship changes obtained from OLS (1), OLS with individual-specific fixed-effects (2) and GFE estimator with $G = 5$ (3). Columns (4)–(6): Estimated coefficients from a regression of the number of spousal relationship changes on the number of job changes obtained from OLS (4), OLS with individual-specific fixed-effects (5), and GFE estimator with $G = 4$ (6). Time constant controls: education, childhood SES, father absent, being in very good/excellent health, self-assessed math and language skills during childhood. Time-varying controls: number of children aged 0-5, 6-15, and 16+, number of health conditions, log GDP, country and birth cohort-fixed-effects, and country-specific linear time trends. OLS models additionally control for age-fixed-effects.

Table A.19: All estimated coefficients for cross-market effects of instability, women

	Number of job changes			Number of relationship changes		
	OLS	FE	GFE, $G = 5$	OLS	FE	GFE, $G = 4$
	(1)	(2)	(3)	(4)	(5)	(6)
Number of relationship changes	0.522***	0.392***	0.157***			
	[0.058]	[0.040]	[0.023]			
Number of job changes				0.068***	0.074***	0.007***
				[0.008]	[0.007]	[0.003]
Low education	-0.034			-0.021		
	[0.049]			[0.016]		
High education	-0.168***			0.004		
	[0.055]			[0.020]		
Low SES	0.025			-0.003		
	[0.054]			[0.016]		
High SES	-0.056			0.039**		
	[0.049]			[0.017]		
Father absent at age 10	0.082			0.036*		
	[0.071]			[0.022]		
Very good/excellent	-0.083*			-0.010		
childhood health	[0.044]			[0.015]		
Self-assessed math skills	0.004			-0.027***		
	[0.027]			[0.009]		
Self-assessed language skills	0.019			0.015		
	[0.029]			[0.010]		
Number children 0-5	-0.008	-0.032**	-0.024***	-0.006	-0.026***	-0.006***
	[0.017]	[0.013]	[0.007]	[0.005]	[0.004]	[0.002]
Number children 6-15	-0.022	-0.041***	-0.033***	-0.011*	-0.029***	-0.003
	[0.017]	[0.015]	[0.008]	[0.006]	[0.006]	[0.002]
Number children $\geq$16	-0.027	-0.038*	-0.021**	0.001	-0.025***	0.001
	[0.023]	[0.020]	[0.008]	[0.009]	[0.008]	[0.002]
Number health conditions	0.101**	0.050**	-0.010	0.019	0.020**	0.002
	[0.042]	[0.023]	[0.012]	[0.014]	[0.010]	[0.003]
Log GDP	-0.044	-0.085	-0.026	-0.194***	-0.161***	-0.045***
	[0.081]	[0.079]	[0.052]	[0.033]	[0.032]	[0.018]
Constant	0.392			1.718***		
	[0.718]			[0.295]		
R-squared	0.219			0.129		
Observations	110,295					

Standard errors clustered at the individual level in brackets; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Columns (1)–(3): Estimated coefficients from a regression of the number of job changes on the number of spousal relationship changes obtained from OLS (1), OLS with individual-specific fixed-effects (2) and GFE estimator with $G = 5$ (3). Columns (4)–(6): Estimated coefficients from a regression of the number of spousal relationship changes on the number of job changes obtained from OLS (4), OLS with individual-specific fixed-effects (5), and GFE estimator with $G = 4$ (6). Time constant controls: education, childhood SES, father absent, being in very good/excellent health, self-assessed math and language skills during childhood. Time-varying controls: number of children aged 0-5, 6-15, and 16+, number of health conditions, log GDP, country and birth cohort-fixed-effects, and country-specific linear time trends. OLS models additionally control for age-fixed-effects.

Table A.20: Estimated coefficients of cross-market effects of instability using the number of negative job changes, GFE estimates with $G = 5$ (jobs) and $G = 4$ (relationships)

	Number of negative job changes (1)	Number of relationship changes (2)
A.Men		
Number of relationship changes	0.039***	
	[0.012]	
Number of negative job changes		0.008
		[0.005]
Observations	126,033	
B.Women		
Number of relationship changes	0.082***	
	[0.017]	
Number of negative job changes		0.010***
		[0.004]
Observations	110,295	

Standard errors clustered at the individual level in brackets; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Columns (1)–(3): Estimated coefficients obtained from the GFE estimator with individual fixed-effects. Time constant controls: education, childhood SES, father absent, being in very good/excellent health, self-assessed math and language skills during childhood. Time-varying controls: number of children aged 0-5, 6-15, and 16+, number of health conditions, log GDP, country and birth cohort-fixed-effects, and country-specific linear time trends. OLS models additionally control for age-fixed-effects.

Table A.21: Differences in stability grouping - separate versus joint estimation

		estimation separately by gender								
		job type					*relationship type*			
		very stable	stable	medium	unstable	very unstable	very stable	stable	medium	unstable
estimation both gender jointly	*A. Men*									
	very stable	27.98%	0.00%	0.00%	0.00%	0.00%	77.04%	0.00%	0.00%	0.00%
	stable	0.27%	31.35%	0.07%	0.00%	0.00%	0.00%	9.69%	0.55%	0.00%
	medium	0.00%	0.14%	22.24%	0.00%	0.00%	0.00%	0.00%	8.87%	0.00%
	unstable	0.00%	0.00%	0.27%	13.00%	0.03%	0.00%	0.07%	0.27%	3.51%
	very unstable	0.00%	0.00%	0.00%	0.03%	4.61%	/	/	/	/
	B. Women									
	very stable	32.75%	0.12%	0.00%	0.00%	0.00%	73.68%	0.00%	0.00%	0.00%
	stable	0.00%	29.63%	0.70%	0.00%	0.00%	0.00%	10.64%	0.00%	0.00%
	medium	0.00%	0.00%	20.04%	0.51%	0.00%	0.00%	0.00%	11.54%	0.00%
	unstable	0.00%	0.00%	0.00%	12.16%	0.16%	0.00%	0.00%	0.00%	4.14%
	very unstable	0.00%	0.00%	0.00%	0.00%	3.94%	/	/	/	/

Table A.22: Estimated associations between between net house value (age 55–65) and estimated instability types

	Log net house value	
	Men	Women
	(1)	(2)
Stable job, unstable relationship	-0.108*	-0.184***
	[0.056]	[0.045]
Unstable job, stable relationship	-0.057*	-0.080*
	[0.031]	[0.048]
Unstable in both	-0.321***	-0.298***
	[0.101]	[0.050]
Constant	12.583***	12.766***
	[0.130]	[0.086]
Observations	2,047	1,830
R-squared	0.069	0.075

Robust standard errors in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Estimated coefficients from OLS regressions of net house value at age 55–65 on being a stable type in the labor market and unstable in the marriage, an unstable type in the labor market and stable in the marriage, and unstable in both markets. Unstable job types are the groups very unstable and unstable. Unstable relationship types are unstable. Time constant controls: education, childhood SES, father absent, being in very good/excellent health, self-assessed math and language skills during childhood. Includes country and birth cohort-fixed-effects.