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Relationship Stability: Evidence from Labor and Marriage Markets

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Abstract

Behavior in labor and marriage markets follows similar structures when it comes to commitment to long-term relationships. We argue that there is a joint social skill driving stability in both markets. Applying a grouped fixed-effect estimator on data from the Survey of Health, Ageing and Retirement in Europe, we identify types of individuals at risk of instability in both domains. We provide evidence on how economic preferences and personality are related to instability in both markets. We also show negative consequences of instability in terms of reduced life satisfaction and wealth late in life.

Keywords: Relationship Stability, Marriage dissolution, Job turnover, Social Skills, Non-Cognitive Skills, Grouped Fixed-Effect Estimator, Survey of Health, Ageing and Retirement in Europe
JEL-Codes:: J12, J24, J63, I31, C33

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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, in 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).

While the theoretical literature on search and matching has long recognized that relationships in marriage and labor markets follow similar patterns (Becker et al., 1977; Burdett and Coles, 1999), 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, and we investigate the role of a latent ability to maintain stable relationships in these two markets. Kambourov et al. (2015) call this ability a relationship (or teamwork) skill and argue that this skill increases returns to cooperation. We assume 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 time. While a number of aspects of personality are formed during adolescence, events such as relationship break-ups and job loss have been shown to shape an individual's personality over the life cycle (Cobb-Clark and Schurer, 2012). Relationship skills may develop more towards (in)stability through (un)favorable experiences as individuals age. There is also a literature in psychology about ways to increase cooperative skills, for example as part of higher education (Mendo-Lázaro et al., 2018). Our hypothesis is 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 seems crucial to identify individuals who are at risk of instability. Knowing about this is important since policies that aim to improve welfare by protecting marriage or reducing divorce could overlook that causality could run in the other direction, namely 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 types and economic 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 welfare.

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 time-variation in the unobserved relationship skill, we apply a grouped fixed-effects (GFE) estimator proposed by Bonhomme and Manresa (2015). The idea of the GFE estimator is that unobserved heterogeneity can be grouped into not too many groups. Individuals are assigned to these groups based on similar unobserved characteristics. Within each group, unobserved heterogeneity is allowed to vary over time and can be estimated along with the main parameters of interest. In our application, the GFE estimator assigns individuals with a similar unobserved relationship skill to the same stability type and then estimates the relationship between observed job and marital stability along with group-specific age profiles of the unobserved relationship skill.

Our empirical analysis is based on seven waves and six Western European countries (Austria, Germany, Netherlands, France, Switzerland, Belgium) of the Survey of

Health, Ageing and Retirement in Europe (SHARE).[1] 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. Based on this data, we measure relationship instability as the number of job changes and relationship break-ups an individual experiences 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 associations between job and marital stability regardless of whether we use OLS, standard time-constant individual fixed-effects, or GFE models. 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 five groups (or types). For instance, an additional break-up among men leads to 0.39 additional jobs in OLS models but reduces to 0.10 in the GFE model. Overall, the GFE effect sizes for the estimated cross-market instability coefficients are between 60 and 98 percent smaller than OLS without and with individual fixed-effects, depending on the specification. This suggests that there exists time-varying unobserved heterogeneity — an unobserved relationship skill in our interpretation — that determines the relationship between the labor and the marriage market to a large extent. This finding is robust to alternative specifications, including varying the number of groups, considering outcome dynamics, or excluding career-boosting job changes.

We next analyze the latent stability types and the unobserved heterogeneity profiles obtained from the GFE estimator in more detail. On the labor market, 60 percent of men and 62 percent of women are classified as high or very high job stability types. Only a smaller share of 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: 87 percent of men and 80 percent of women are types of high or very high relationship stability. Only 4 percent of men and 12 percent of women are classified as low or very low types. Our analysis reveals that being an unstable type in marriage and labor markets is strongly positively correlated for both men and women with 2–4 percent of

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

individuals being unstable types 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.

Which personality traits and preferences are associated with being an unstable type? Among men, 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, personality traits mainly matter for the marriage market. Being an unstable spousal relationship type is associated with lower levels of conscientiousness, neuroticism, and trust but with higher levels of openness.

Finally, we link being an unstable type to welfare measures at age 55–65. 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) who consider decisions in marriage and labor markets jointly. 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. Ahituv and Lerman (2011) only consider men up to their early 30s, thus they can neither draw inference on long-term marital and job stability nor can they analyze women's behavior. Kambourov et al. (2015) assume that individuals are endowed with a relationship skill, that determines returns to output in teams. The authors formulate and estimate a multi-market equilibrium model of labor and marriage markets in which human capital endowments and relationship skills are unobservable to the researcher. This model allows estimating returns to both factors in both markets. Kambourov et al. (2015) assume that the relationship skill is an innate and time-constant non-cognitive skill that can be proxied by a number of personality attributes that are strongly related to the Big-Five measures. By contrast, while being reduced form, our approach allows the relationship stability skill to arbitrarily change over the life cycle within stability types of individuals.

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). 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). Recently, 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).

Our study shows that marital and job instability are not only strongly directly associated with each other but that there is also an indirect relationship through a latent relationship skill. Ignoring such indirect effects would lead to an underestimation of the full costs associated with separations or job turnover. While policies increasing stability in one market may have positive spillovers to the other market, they typically do not consider that instability across markets is strongly correlated. To design policies that can fully accommodate all cross-market effects, it is important 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 relating instability in both markets. Section 5 relates the stability types to personality traits and later 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 that was established in 2004. SHARE contains nationally representative samples for 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 (see, for instance, Havari and Mazzonna, 2015, for the reliability of the retrospective childhood module in SHARELIFE).

Our main measures of relationship instability are the number of job changes and the number of break-ups 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.[2] To obtain a measure of instability in the marriage market, we use the reported number of break-ups of all cohabiting relationships. As for the job history, SHARELIFE collects the start and end dates of each cohabiting relationship.[3] Due to the relatively old sample, most cohabiting relationships are marital relationships (about 90 percent). For simplicity, we will use the term spousal relationship throughout the paper. The wording of the questions on the job and relationship history in SHARELIFE can be found in Table A.1 in Appendix A.

Using the information on job and relationship histories, we create a pseudo panel of individuals with complete job and relationship information during ages 18–60.[4] We focus on individuals born after 1939. 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 who we observe job and relationship histories for 43 years.

Figure 1 shows the distribution of the number of job changes and relationship break-ups for men and women. Figure 1(a) presents the job change distribution for men and women separately. Most men (about 29 percent) and women (about 27 percent) have one job change. The number of job changes ranges from zero up to a maximum of

[2] 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.

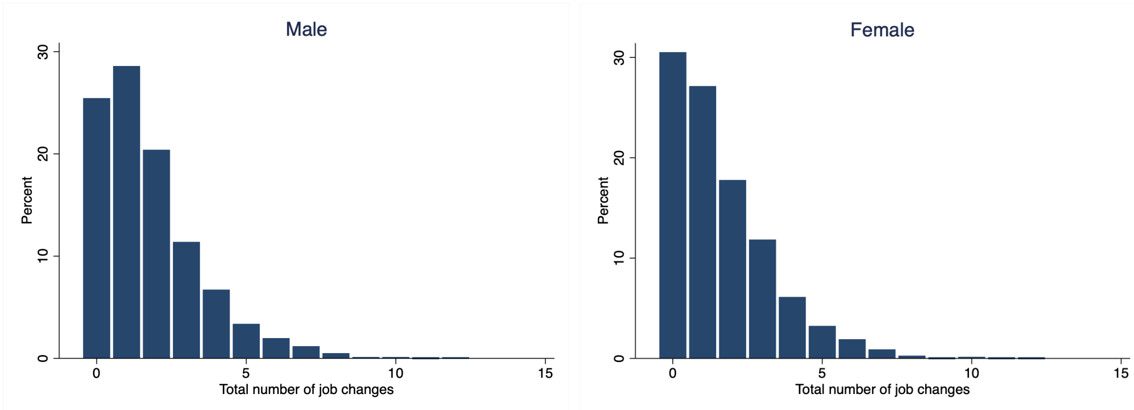
[3] We do not consider the death of a partner as a break-up. We also remove inconsistencies in the start and end dates.

[4] A pseudo-panel is the only way to use life-cycle information on both these markets since no survey exists that covers such a long period.

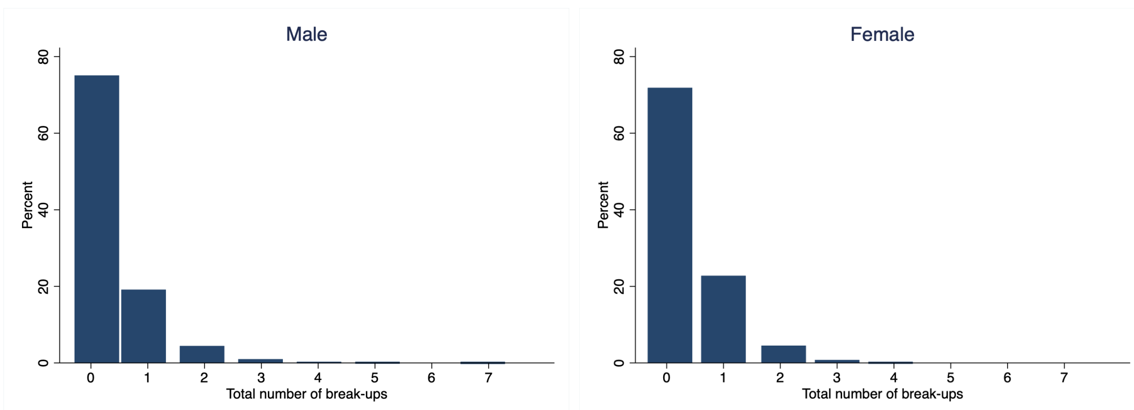
12 job changes, and about 14 percent of men and 13 percent of women have 4 job changes or more over the life cycle. On average, men have 1.75 job changes between ages 18–60. Women change the jobs about 1.62 times during this age (see Table A.2 in Appendix A). There is a considerable amount of variation in job stability in our sample. 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. About 75 percent of men and 72 percent of women have no relationship break-up in their lives. A lower share of individuals (19 percent of men and 23 percent of women) report one break-up. A minority of individuals, namely 1.3 percent of men and 0.9 percent of women had two or more relationship break-ups between ages 18–60. Men have up to 7 break-ups, and women have up to 4. The average number of break-ups is 0.33 for men and 0.35 for women.[5] Overall, Figure 1 indicates that there is more stability in the marriage market than there is in the labor market, regardless of gender.

We next assess the relationship between the number of job changes and the number of break-ups. 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 break-up over the entire life cycle. Figure 2(a) shows that men in both groups are on a similar job trajectory at young ages. From around age 25, men with relationship break-ups are on a steeper job-accumulation profile than men with no break-ups. The difference increases over age such that men without break-ups have on average experienced about 0.5 fewer job changes than men with break-ups (1.62 vs. 2.15). Figure 2(b) displays the trajectories for women. Their profiles start to diverge at a somewhat earlier age than those of men and the difference in job changes between women without and with break-ups is somewhat larger than for men. Women without break-ups have on average experienced about 0.7 fewer job changes than women with break-ups (1.42 vs. 2.11). Otherwise, the patterns found are very similar for men and women, revealing a positive association between the number of job changes and the number of break-ups over the life cycle. This provides us with first descriptive evidence that higher instability

[5]The sample average for job changes and relationship break-ups can be found in Table A.2 in Appendix A. The average relationship break-ups are driven by divorces with 0.27 for women and 0.25 for men. Table A.3 provides the number of observations per country and the sample means for the numbers of job changes and relationship break-ups for each country.



(a) Number of job changes



(b) Number of relationship break-ups

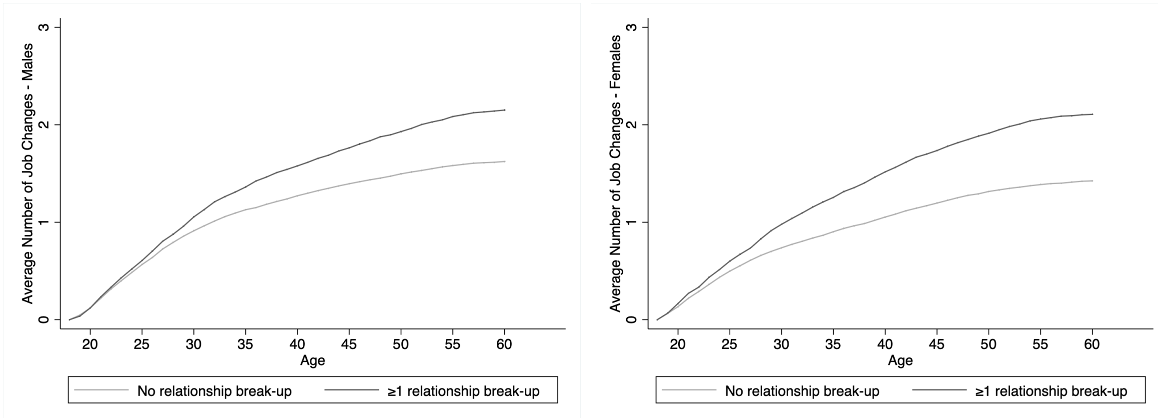
Figure 1: Number of job changes and spousal relationship changes by gender.

in the marriage market is related to higher instability in the labor market.

In Section 5, we will investigate how instability is related to non-cognitive skills and preferences. To this end, 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.[6]

To analyze the lifetime impact of being a low relationship skill type, we make use of a question about life satisfaction as a proxy of experienced utility and net household

[6]The exact wording of all questions can be found in Table A.4 and Table A.5 in Appendix A. The corresponding descriptive statistics by gender are available in Table A.6 in Appendix A.



(a) Men

(b) Women

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

wealth as a monetary measure. 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.[7] Both outcomes are measured between ages 55–65 which broadly reflects the end of the life cycle.[8] The exact wording of the questions for these variables can be found in Table A.7 in Appendix A and descriptives in Table A.8.

In all our estimations we include controls for the number of children (in three age groups: 0–5, 6–15, ≥ 16), the number of current health conditions, and log GDP. The variable description for these controls can be found in Table A.9 and descriptive statistics can be found in Table A.10 in Appendix A. In OLS specifications, we also control for measures of childhood endowment and cognitive skills.[9]

[7]To deal with negative household wealth, we take the log of household net wealth plus the absolute value of the largest negative household wealth.

[8]Ideally, one would want to measure both outcomes at age 60. However, this would lead to a considerably lower number of observations, since in SHARE individuals may not have been asked these questions exactly at age 60. We thus use the answer that is closest to the age of 60. We give priority to answers past the age of 60.

[9]Measures of childhood endowment are obtained from SHARELIFE, collecting childhood-specific information about socioeconomic status (SES), health, and presence of the father at age 10. 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). Cognitive skills are obtained from information about self-assessed math and language skills during childhood as well as respondents' educational attainment. The exact questions can be found in Table A.11 and descriptives in Table A.12 in Appendix

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,[10]

$$jobch_{it} = \beta relch_{it} + \boldsymbol{x}'_{it}\boldsymbol{\gamma} + \alpha_i + \epsilon_{it}, \tag{1}$$

$$relch_{it} = \delta jobch_{it} + \boldsymbol{x}'_{it}\boldsymbol{\theta} + \eta_i + \nu_{it}. \tag{2}$$

Equation (1) links the number of job changes of individual i at age t, $jobch_{it}$, to the number of spousal relationship break-ups $relch_{it}$, a vector of covariates $\boldsymbol{x}_{it}$, a systematic unobserved individual-specific fixed-effect α_i, and an idiosyncratic error term ϵ_{it} with mean zero.[11] Similarly, Equation (2) links the number of spousal relationship changes, $relch_{it}$ to the number of job changes $jobch_{it}$, the same set of covariates as in Equation (1), an unobserved individual-specific fixed-effect η_i, and an idiosyncratic error ν_{it} with mean zero. The main parameters of interest are β and δ which provide us with a measure of the association between the number of relationship changes and the number of job changes and vice versa.

If unobserved individual-specific heterogeneity is time constant, i.e., it is correctly specified with α_i and η_i, β and δ can be consistently estimated using a standard fixed-effects OLS estimator.[12] In our application, this would be the case if individuals were endowed with an unobserved relationship skill that is fixed before the age of 20. However, if the relationship skill is time-varying and systematically evolves over time through, e.g., the continuous experience of positive or negative events or environments, then Equations (1) and (2) do not correctly specify systematic unobserved heterogeneity and the estimates for β and δ are biased.

A.

[10] Since we observe all individuals from age 18 up to and including age 60, our panel is balanced in age.

[11] In all specifications, we control for the number of current health conditions, log GDP, the number of children ages 0–5, 6–15, ≥ 16, country and cohort fixed-effects.

[12] In a first step, we will compare results from a standard fixed-effects OLS estimator to results from OLS without fixed-effects.

To address potential concerns with time-varying unobserved heterogeneity, we estimate a grouped fixed-effects (GFE) estimator proposed by Bonhomme and Manresa (2015) and Bonhomme et al. (2022). The idea of this estimator is that individuals who share similar unobserved characteristics can be grouped together. Individuals who belong to the same group follow the same profile of unobserved heterogeneity. Within groups, unobserved heterogeneity is allowed to arbitrarily vary over time. While the GFE estimator imposes the restriction that time-varying unobserved heterogeneity can be grouped into a finite number of groups, this assumption is arguably less strict than the assumption that unobserved heterogeneity is time-constant.[13] Allowing for grouped fixed-effects leads to the following modified versions of Equations (1) and (2).

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

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

The parameters $\alpha_{g_i t}$ and $\eta_{g_i t}$ represent the time-varying unobserved heterogeneity clustered into $g \in \{1, \ldots, G\}$ groups, with g_i denoting the group membership of individual i. It implies that individuals assigned to the same group g follow the same profile of unobserved heterogeneity.

The GFE estimator for Equations (3) and (4) is defined as the solution of a least squares minimization problem and can be obtained with an iterative two-step procedure. In the assignment step, each individual is assigned to a group, $\hat{g}_i$, based on residuals from a given set of parameters. In the update step, the main parameters of interest, $\beta(\delta); \gamma(\mu)$, along with the group-specific unobserved heterogeneity profiles $\alpha_{g_i t}(\eta_{g_i t})$ are estimated. These two steps are alternated until convergence has been achieved, see Bonhomme and Manresa (2015) for details. To account for the individual-specific fixed-effects, we time-demean our data before applying the GFE estimator. Standard errors are clustered on the individual level.

The GFE estimator requires the researcher to choose the optimal number of groups G. Bonhomme and Manresa (2015) suggest a Bayesian information criterion (BIC) to

[13] Janys and Siflinger (2021) compare the identifying assumptions of the GFE estimator and the difference-in-Difference (DiD) estimator. They show that the assumptions of these two estimators are not nested. Thus, the choice of the estimator depends on the underlying shape of unobserved heterogeneity.

select the optimal number of groups.[14] For both, job changes and relationship break-ups, the BIC selects $G = 5$ groups for men and for women.[15] The fact that the BIC selects a relatively large number of groups may seem surprising given the low variation in relationship changes. As Section 4.3 will show, part of the group assignment seems to be based on the different timing of relationship break-ups, in particular for women. We therefore also estimate Equations (3) and (4) for a lower number of groups.

4 Results

In this section, we present our main results. We first discuss the estimated associations between instability in labor and marriage markets in Section 4.1. Section 4.2 shows the results from a dynamic specification. In Section 4.3, we discuss the estimated group assignments as well as the group-specific profiles of latent instability.

4.1 Stability in job and marriage markets

Tables 1 and 2 present our main estimation results for the associations of stability in job and marriage markets. In all regressions, we control for country and cohort fixed-effects as well as for the number of children in three age groups (0–5 years, 6–15 years, and 16 and older), the accumulated number of health conditions, and log GDP. In OLS models with and without individual fixed-effects, we control for age fixed-effects. In OLS models, we additionally control for a set of childhood endowments and cognitive skills. We estimate the GFE model with five groups as suggested by the BIC.

Columns (1)–(3) of Table 1 show the estimated impact of the number of break-ups on the number of job changes for men obtained from OLS, FE, and GFE estimators.

[14]The BIC for a general specification is

$$BIC(G) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it} - x'_{it}\widehat{\theta}^{(G)} - \widehat{\pi}^{(G)}_{\widehat{g}_i t}\right) + \widehat{\sigma}^2 \frac{G(T+N-G+K)}{NT}\ln(NT),$$

where y_{it} is the outcome, $\hat{\theta}$ are the estimated parameters of interest $(\beta, \delta, \gamma, \mu)$, $\widehat{\pi}_{\widehat{g}_i t}$ is the grouped fixed-effect, G is the chosen number of groups and K is the number of parameters. $\widehat{\sigma}^2$ is the estimated error variance based on a maximum feasible number of groups.

[15]The BIC for G=2–6 and 10 groups can be found in Table A.13 in Appendix A.

OLS estimates a significant increase in the number of job changes of 0.39 for one additional relationship break-up. 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 break-ups and job changes. An additional break-up 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 show that there is a considerable amount of time-varying unobserved heterogeneity in addition to individual-specific time-constant heterogeneity. Ignoring it 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 break-ups. Here, the OLS and fixed-effect estimates (Columns (4) and (5)) are similar in magnitude and highly significant. An additional job change increases the number of break-ups by 0.05. By contrast, when using the GFE, we obtain an estimated impact of the number of job changes on the number of break-ups which is close to zero (0.001 or 0.3 percent at the sample mean) and insignificant. An additional job change does thus not seem to be directly predictive for any changes in spousal relationships. Instead, the connection from job changes to relationship changes seems to be entirely absorbed by unobserved stability types.

Table 2 presents the estimated relationship between break-ups and job changes for women. As can be seen from the coefficient estimates in Columns (1)–(3), the number of break-ups significantly increases the number of job changes, regardless of the specification. As for men, the estimated coefficient reduces in magnitude with relaxing the restrictions on systematic unobserved heterogeneity. When allowing for grouped fixed-effects, we obtain an increase in the number of job changes by 0.16 for one additional relationship break-up. This corresponds to a mean increase in the number of job changes by 9.7 percent for one additional break-up. The results for the impact of job changes on relationship break-ups can be found in Columns (4)–(6). Again, the estimated coefficient considerably reduces in magnitude when controlling for grouped fixed-effects. In contrast to men though, an additional job change significantly increases the number of relationship break-ups among women by 0.01 or 2.1 percent at the sample mean, suggesting that unobserved stability types do not entirely absorb the direct effects of

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, $G = 5$
	(1)	(2)	(3)	(4)	(5)	(6)
Number of relationship changes	0.388***	0.288***	0.098***			
	[0.055]	[0.041]	[0.021]			
Number of job changes				0.047***	0.050***	0.001
				[0.007]	[0.007]	[0.002]
Constant	2.119**			0.859**		
	[0.904]			[0.398]		
R-squared	0.187			0.096		
Observations	126,033					

Standard errors clustered on 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 using OLS (1), OLS with individual-specific fixed-effects (2) and the 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 using OLS (4), OLS with individual-specific fixed-effects (5) and the GFE estimator with $G = 5$ (6). Controls: respondent's education, childhood SES, father absent, being in very good/excellent health, self-assessed math and language skills during childhood (only OLS), number of children age 0-5, number of children age 6-15, number of children aged 16 and above, the number of health conditions, log GDP, country, cohort and age fixed-effects. We do not control for age fixed-effects in the GFE specifications.

job instability on relationship instability.[16]

For both genders, the estimated coefficients of relationship break-ups 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 on 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.

We also estimate the GFE model with a different number of groups. Tables A.16 and A.17 in Appendix A present the results for men and women, respectively, for $G = 2, ..., 6$. For both outcomes that we consider, the point estimates are always the largest when we choose two groups. With an increasing number of groups, the magnitude of the estimated coefficients reduces until we choose five groups. With five or more groups the

[16]Tables A.14 and A.15 in Appendix A present the estimated coefficients for controls.

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, $G = 5$
	(1)	(2)	(3)	(4)	(5)	(6)
Number of relationship changes	0.520***	0.385***	0.157***			
	[0.058]	[0.041]	[0.022]			
Number of job changes				0.068***	0.070***	0.007***
				[0.008]	[0.007]	[0.003]
Constant	3.810***			0.032		
	[0.933]			[0.409]		
R-squared	0.213			0.126		
Observations	110,295					

Standard errors clustered on 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 using OLS (1), OLS with individual-specific fixed-effects (2) and the 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 using OLS (4), OLS with individual-specific fixed-effects (5) and the GFE estimator with $G = 5$ (6). Controls: respondent's education, childhood SES, father absent, being in very good/excellent health, self-assessed math and language skills during childhood (only OLS), number of children age 0-5, number of children age 6-15, number of children aged 16 and above, the number of health conditions, log GDP, country, cohort and age fixed-effects. We do not control for age fixed-effects in the GFE specifications.

coefficient estimates tend to stabilize. This behavior is in line with the discussions in the literature, see, Bonhomme and Manresa (2015) and Bonhomme et al. (2022).

So far, it is unclear whether our measure of job instability captures career-boosting or career-dampening job changes. To shed light on this, we now use a measure of job instability which only consists of job changes that are accompanied by a reduction in monthly wages. In our sample, such negative job changes are on average more common among women (1.03 changes) than among men (0.74 changes). The results from re-estimating Equations (3) and (4) using the GFE estimator with five groups with this alternative measure of job instability can be found in Table A.18 in Appendix A. An additional relationship break-up leads to 0.04 and 0.09 more negative job changes for men and women, respectively. For men, this implies a 5.4 percent increase in the number of negative jobs on average. Women's average number of negative job changes increase about 8.6 percent with an additional break-up. These numbers are very close to those we obtain from the main specification, which suggests that relationship instability triggers mostly negative job instability.

Overall, our results show that there are significant and sizeable associations of instability in one market on the other. Allowing for grouped fixed-effects reduces the magnitude of the estimated coefficients but leaves them mostly statistically significant. This finding has two implications. First, there are direct cross-market effects of instability, in particular for women. This finding is in line with Ahituv and Lerman (2011) who show 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 correlations can to a large extent be explained by unobserved stability types. In Section 4.3, we will investigate these relationship types in more detail.

4.2 Model dynamics

One potential concern with the findings on cross-market effects of instability in the previous section is reverse causality. For instance, a number of studies have shown that job changes lead to changes in spousal relationships which in turn affect the likelihood of a job change in the next period (see, for instance, Charles and Stephens, 2004; Eliason, 2012; Olivetti and Rotz, 2017).

To address such a concern we include the first lag of the dependent variable as an additional regressor on the right-hand side of Equations (3) and (4). To tackle the endogeneity in lagged job and relationship changes, we use their second lags as instruments and apply the GFE estimator on first differences.[17]

Table 3 presents the estimated cross-market and state dependence coefficients for men (Panel A) and women (Panel B). As expected, there is a considerable amount of state dependence in the outcomes, ranging between 0.83 and 0.90 depending on the specification. Compared to our main results (Tables 1 and 2) the estimated impact of the number of break-ups on the number of job changes is considerably lower when reverse causality is taken into account, see Column (1). It implies that past levels of job

[17] This estimation approach essentially combines the GFE estimator with an Anderson-Hiso estimator and was proposed by Bonhomme and Manresa (2015).

Table 3: Estimated coefficients of cross-market effects of instability, dynamic GFE-IV estimator for five groups

	Number of job changes (1)	Number of relationship changes (2)
A.Men		
Number of relationship changes	0.031***	
	[0.011]	
Number of job changes		0.002
		[0.002]
Number of job changes, $t-1$	0.889***	
	[0.011]	
Number of relationship changes, $t-1$		0.884***
		[0.010]
Observations	123,102	
B.Women		
Number of relationship changes	0.051***	
	[0.013]	
Number of job changes		0.011***
		[0.003]
Number of job changes, $t-1$	0.895***	
	[0.011]	
Number of relationship changes, $t-1$		0.827***
		[0.006]
Observations	107,730	

Standard errors clustered on the individual level in brackets; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Estimated coefficients obtained from an IV estimator on first differences with grouped fixed-effects. The second lag of job changes and break-ups serves as instrument for the lagged dependent variables. Controls: number of children age 0-5, number of children age 6-15, number of children aged 16 and above, the number of health conditions, log GDP, country and cohort fixed-effects.

instability are strongly correlated with current levels of relationship instability (see, e.g., Ahituv and Lerman, 2011). Yet, the estimated coefficients are still highly significant, suggesting that there is also a strong contemporaneous effect of relationship instability on job instability. Turning to the estimated impact of the number of job changes on the number of break-ups, we find similar coefficient sizes as for our main specification in Tables 1 and 2. This implies that reverse causality plays less of a role for the effect running from job changes to relationship changes.

To further address a potential concern with reverse causality, we lag the instability predictor on the right-hand side of Equations (3) and (4) by one year. Table 4 presents the estimation results. The estimated coefficients are very similar in magnitude and significance to those obtained from the main specifications which estimate the contemporaneous cross-market effects (see Tables 1 and 2). It indicates that past instability is persistent and it confirms that contemporaneous effects cannot be entirely driven by reverse causality.[18]

Table 4: Estimated coefficients of lagged cross-market effects of instability, GFE estimator for five groups

	Number of job changes (1)	Number of relationship changes (2)
A.Men		
Number of relationship changes, $t-1$	0.105***	
	[0.022]	
Number of job changes, $t-1$		-0.000
		[0.002]
Observations	123,102	
B.Women		
Number of relationship changes, $t-1$	0.162***	
	[0.023]	
Number of job changes, $t-1$		0.006***
		[0.003]
Observations	107,730	

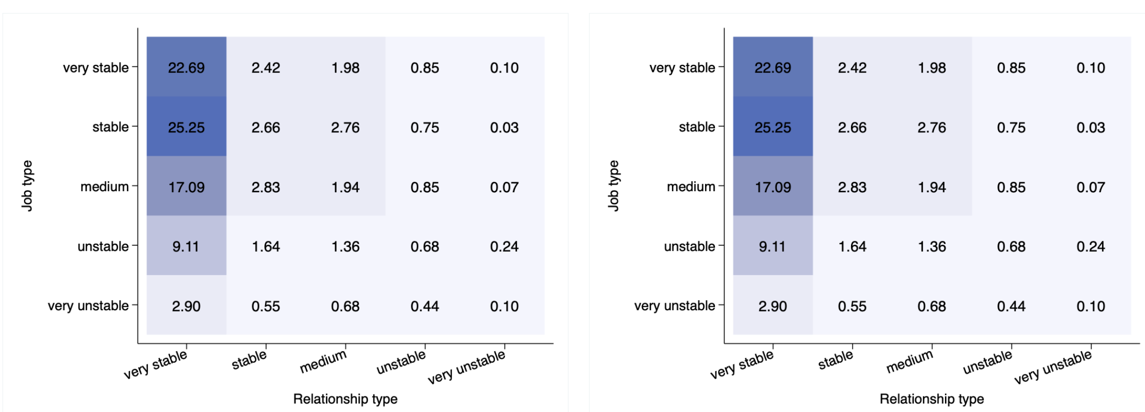
Standard errors clustered on the individual level in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Estimated coefficients of instability predictors lagged by one period obtained from the GFE estimator with individual fixed-effects. Controls: number of children age 0-5, number of children age 6-15, number of children aged 16 and above, the number of health conditions, log GDP, country and cohort fixed-effects.

[18] We also test the robustness of our results to the lag choice. Table A.19 in Appendix A presents the estimated coefficients when instability predictor are lagged by three years. The results are very similar to one-year lagged effects.

4.3 Group-specific profiles and group assignment

The GFE estimator does not only provide us with the cross-market instability effects but also with the estimated group assignments and the grouped patterns of time-varying unobserved heterogeneity. Figure 3 plots the joint distribution for five groups that we chose in the main specification.[19]

Figure 3(a) reveals that the majority of men (about 77 percent) are in the very high relationship stability group, and only very few are assigned to the low (0.6 percent) or very low relationship instability group (about 3.6 percent). Job stability types are somewhat more evenly distributed. About 60 percent are assigned to the very high or high job stability group, 23 percent to the medium stability group, and about 18 percent of men are low or very low stability types. When considering the joint distribution of both markets, we find that more than 50 percent of men in our sample are types of high or very high stability in jobs and in 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 10 percent of men are medium stable or (very) unstable types in both markets with only about 1.5 percent of men who are unstable or very unstable types in both markets.



(a) Men (b) Women

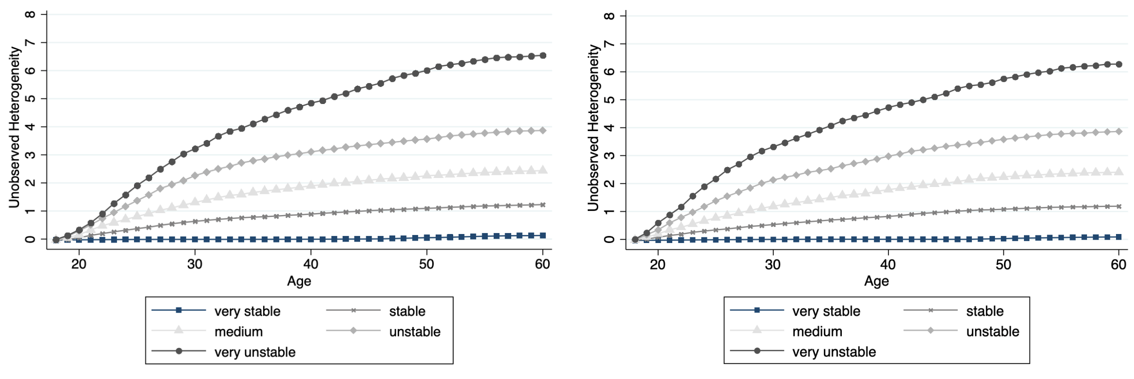
Figure 3: Joint distribution of estimated group assignments to stability types in job and relationship markets.

[19]The numbers for the joint and marginal distributions can be found in Tables A.20 and A.21 in Appendix A.

Figure 3(b) shows the corresponding group assignments for women. The distributions of job and marital stability are similar to that of men with women being somewhat less often stable relationship types. Compared to men, only 73 percent of women are very stable relationship types but more than 12 percent are unstable or very unstable relationship types. The larger share of unstable types among women however is generated from different underlying distributions of instability for men and women. While men have on average up to 7 break-ups, women have on average only up to 4 break-ups. Regarding job changes, women are only somewhat more stable job types than men (62 percent of women and 60 percent of men). Also, the joint distribution of both markets is similar to that of men. More than 50 percent of women are very stable or stable types in both markets. About 3.6 percent belong to the low and very low stability groups in both markets.

The GFE estimator also estimates the time effects for the different latent 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 for 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.

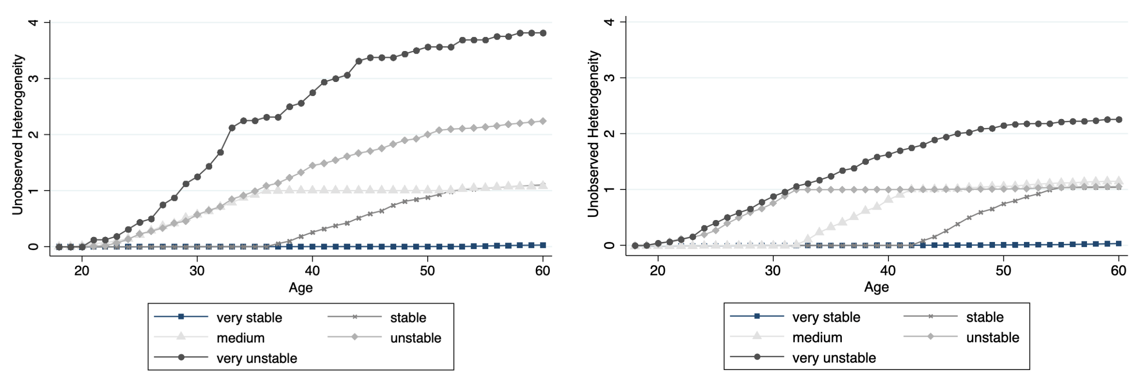
Figure 5 presents the unobserved heterogeneity profiles for the number of relationship break-ups. While the profiles of all stability types start at the same level, regardless of gender, there is again substantial heterogeneity across stability types. Types of very high relationship stability have an entirely flat profile, suggesting that the unobserved heterogeneity contributing to the number of break-ups is time-constant and almost zero. The more stable (stable, medium) types seem to be mostly determined by the timing at which unobserved heterogeneity contributes to changes in relationships. With increasing age, the unobserved heterogeneity profiles of these stability types coincide.



(a) Men (b) Women

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

While the profiles of more stable types are very similar for men and women, there are clear gender differences in more unstable types. First, a male unstable type exhibits an increasing age profile of unobserved heterogeneity, while the profile of a female unstable type shows a steep increase before the early 30s and is constant afterward. Second, there are considerable slope and level differences between men and women in the unobserved heterogeneity profile of highly unstable types. The men's profile is much steeper than the women's profile and keeps increasing over the life cycle which is not the case for women. As a consequence, there are large level differences in the unobserved heterogeneity across men and women for highly unstable relationship types.



(a) Men (b) Women

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

The results in this section have important implications. First, there are considerable level and slope differences in the unobserved heterogeneity across latent stability types. Thus, unobserved 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.[20] Second, a substantial 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. When classifying these individuals as unstable types and all others as stable types, we find a tetrachoric correlation of 27 percent (significant at the 1 percent level) between types across markets for men and women. This suggests that individuals belonging to the same type in different markets may indeed share similar unobserved characteristics that jointly determine outcomes 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 and economic preferences (Section 5.1). Finally, we explore whether being an unstable type is associated with monetary and non-monetary costs at the end of the life cycle (Section 5.2).

The empirical analysis of this section is based on three measures of stability types: whether an individual is an unstable job type, whether she is an unstable relationship type, and whether she is an unstable type in both markets. Accordingly, we define three

[20] There is an ongoing debate about whether personality traits are fixed or whether they change over time. Using longitudinal Australian data, Elkins et al. (2017) and Cobb-Clark and Schurer (2012) show that personality traits change moderately in adolescence and early adulthood but are stable for prime-age adults. By contrast, a recent study by Stillman and Velamuri (2020) shows that personality traits are rather malleable and that they change in response to specific life events, such as marital separation or financial problems.

binary variables of instability. Each of them takes the value one if an individual is an unstable or very unstable type in the labor market, the marriage market, or in both markets, and is zero otherwise. In Section 5.1 we use these three measures as outcome variables in probit regressions. In Section 5.2, we regress our cost measures on these instability type variables using OLS.

5.1 Stability types, personality traits and preferences

Table 5 shows the estimated average marginal effects (AME) for men and women from a probit regression, linking unstable types to personality types and economic preferences. For men (Panel A), higher levels of trust and conscientiousness are both negatively associated with being an unstable type in either market as well as in both markets. Men who are more extraverted and less conscientious are significantly more likely to be a type with low relationship skills on the labor market. Being extraverted increases the probability to be an unstable job type by 2.5 percentage points while being conscientious decease this probability by 2.5 percentage points. More neuroticism is related to being unstable in both domains, but the effect is only marginally significant.

For women (Panel B), higher levels of conscientiousness and neuroticism are significantly associated with a 3.2 and 2.5 percentage points lower probability of being an unstable relationship type. More trust is also associated with a 0.9 percentage point lower likelihood of being a latent unstable type in relationships. In contrast, more openness significantly predicts a higher likelihood of 1.9 percentage points of being an unstable job type and a higher likelihood of 1.4 percentage points of being a latent unstable type in relationships.

Our findings show that personality traits are related to the unobserved instability type an individual belongs to. Both genders are more likely to be unstable types in marriage markets the more open they are to experiences. This confirms previous findings. For instance, Lundberg (2012) or Boertien et al. (2017) show that openness increases the hazard of being divorced regardless of gender. Our results are also consistent with another result of these studies: men's risk of marriage instability (divorce) increases with extraversion and decreases with conscientiousness. The finding that an unstable job type is related to more extraversion is also intuitive. Dimensions of extraversion are

Table 5: Estimated associations between being a latent unstable type, personality traits and preferences

	unstable job type	unstable relationship type	unstable type in both markets
	(1)	(2)	(3)
A. Men ($N = 2,199$)			
Risk aversion	-0.016	-0.010	-0.001
	[0.012]	[0.004]	[0.004]
Trust	-0.006*	-0.005***	-0.001*
	[0.004]	[0.002]	[0.001]
Extraversion	0.025***	0.008	0.003
	[0.009]	[0.005]	[0.003]
Agreeableness	0.007	0.002	0.001
	[0.010]	[0.006]	[0.003]
Conscientiousness	-0.025**	-0.022***	-0.012***
	[0.011]	[0.005]	[0.003]
Neuroticism	-0.003	0.004	0.005*
	[0.009]	[0.005]	[0.003]
Openness	0.010	0.002	0.005*
	[0.008]	[0.005]	[0.003]
B. Women ($N = 1,954$)			
Risk aversion	0.010	-0.014	0.000
	[0.004]	[0.015]	[0.009]
Trust	0.000	-0.009***	-0.000
	[0.004]	[0.003]	[0.002]
Extraversion	0.013	-0.004	0.001
	[0.009]	[0.009]	[0.005]
Agreeableness	-0.007	0.012	0.008
	[0.011]	[0.010]	[0.006]
Conscientiousness	-0.008	-0.032***	-0.002
	[0.011]	[0.010]	[0.005]
Neuroticism	0.008	-0.025***	-0.009
	[0.008]	[0.008]	[0.005]
Openness	0.019**	0.014*	0.006
	[0.009]	[0.008]	[0.005]

Robust standard errors in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Average marginal effects obtained from probit regressions of being an unstable type on personality traits and economic preferences. Controls: country and cohort fixed-effects.

ambition, assertiveness, activity, or excitement-seeking. Thus, individuals with a high score on this personality trait may more often change their jobs and seek new job-related challenges. Several studies have found that higher levels of extraversion are associated with more frequent switching of organizations and more initiative in searching for alternative employments (see, for instance, Kanfer et al., 2001; Wille et al., 2010; Almlund et al., 2011). For conscientiousness, the direction of the association with stability is, in general, less clear. While some studies suggest that more conscientious people have higher job mobility due to being competent and self-disciplined, others have pointed out that such individuals are also more deliberate and dutiful and thus prefer to stay in the same job (Nieß and Zacher, 2015; Cohn et al., 2021). Both genders are less likely to be an unstable type if they trust more in others. This is in line with findings in the literature that trust is a crucial determinant of engaging and maintaining long-term cooperation (Gambetta, 2000). Risk aversion has been shown to lower the chances of job turnover and divorce (Argaw et al., 2017; Light and Ahn, 2010). However, while the direction of the estimated marginal effects is consistent with these findings, the association between being an unstable type and risk aversion is not significant at conventional levels.

5.2 Does instability predict welfare?

We finally investigate whether relationship stability is associated with life satisfaction and household wealth at ages 55–65. Columns (1)–(3) of Table 6 present the estimated coefficients of being an unstable type on life satisfaction for men. Being an unstable job type is associated with 0.24 points less life satisfaction compared to a stable type. Being an unstable relationship type reduces life satisfaction even by 0.53 points. Men who are unstable types in both markets experience the strongest reduction in life satisfaction. Compared to men who are stable types in at least one market, their life satisfaction is 0.58 points lower. However, due to the low number of men that fall into this category of stability, the point estimate is not significant at conventional levels.

Columns (4)–(6) of Table 6 present the results for women. We find significant impacts of being an unstable job or relationship type on women's life satisfaction. Compared to a stable type, an unstable job type reduces life satisfaction by 0.27 points. For

Table 6: Estimated associations between life satisfaction and estimated instability types

	Life satisfaction at age 55–65					
	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Unstable job type	-0.241***			-0.272***		
	[0.093]			[0.105]		
Unstable relationship type		-0.526***			-0.468***	
		[0.203]			[0.128]	
Unstable in both			-0.578			-0.357
			[0.405]			[0.212]
Constant	7.795***	7.749***	7.723***	7.568***	7.610***	7.550***
	[0.334]	[0.336]	[0.334]	[(0.417)]	[0.425]	[0.421]
Observations		2,047			1,830	
R-squared	0.078	0.080	0.077	0.087	0.093	0.085

Robust standard errors in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Estimated coefficients from OLS regressions of life satisfaction at age 55–65 on being an unstable type in the labor market, the marriage market and in both markets. Controls: respondent's education, childhood SES, father absent, being in very good/excellent health, self-assessed math and language skills during childhood, country and cohort fixed-effects.

relationship instability, we find a 0.47 points lower life satisfaction. As for men, being an unstable type in both markets is associated with strong but insignificant reductions in life satisfaction. 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.

Table 7 presents the estimated coefficients of being an unstable type on log household wealth. For men, an unstable job type is associated with 3.2 percent less household wealth (Column (1)). This result is in line with, e.g., Light and McGarry (1998) who show that wage trajectories of workers with high job mobility are lower than those of less mobile workers. An unstable relationship type has even 5.6 percent less wealth (Column (2)). The reduction in household wealth is 8.9 percent among men who are an unstable type in both markets (Column (3)).

Table 7: Estimated associations between log household wealth and estimated instability types

	Log household wealth at age 55–65					
		Men			Women	
	(1)	(2)	(3)	(4)	(5)	(6)
Unstable job type	-0.032***			-0.054		
	[0.010]			[0.045]		
Unstable relationship type		-0.056***			-0.185***	
		[0.016]			[0.049]	
Unstable in both			-0.089***			-0.224***
			[0.029]			[0.085]
Constant	14.460***	14.457***	14.452***	11.604***	11.644***	11.599***
	[0.035]	[0.035]	[0.034]	[0.184]	[0.186]	[0.185]
Observations		2,047			1,830	
R-squared	0.159	0.159	0.158	0.208	0.214	0.211

Robust standard errors in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Estimated coefficients from OLS regressions of log household wealth at age 55–65 on being an unstable type in the labor market, the marriage market and in both markets. Controls: respondent's education, childhood SES, father absent, being in very good/excellent health, self-assessed math and language skills during childhood, household size at age 55–65, country and cohort fixed-effects.

Columns (4)–(6) of Table 7 present the estimated coefficients for women. As for men, women who are unstable types have less household wealth at age 55–65 compared to stable types. The differences are particularly strong for types who are unstable in relationships or in both markets. Compared to stable types, women who are unstable relationship types have 18.5 percent less household wealth. Being unstable in both markets is associated with even 22.4 percent less household wealth. The reduction in wealth is enormous – more than three times the coefficient for men – 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.[21]

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

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 strong direct cross-market effects in instability that persist 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 economic preferences. We furthermore 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) who find long-lasting negative effects of job instability on later life welfare.

From a policy perspective, our results emphasize the strong link between marriage and labor markets, suggesting that policies affecting one market are likely to spill over onto the other market, such as divorce laws, or employment protection legislation. These spillover effects are important to take into account for the design and cost-effectiveness of policies. Relationship instability incurs indirect costs across markets which have to be factored in for policies addressing instabilities. Our analysis also shows that unstable types keep changing relationships in both markets up to late in life. This is important to acknowledge, especially in light of the costs we identified. Continuous job instability may constraint wealth accumulation, as shown by Kuhn and Ploj (2020) and thus contribute to old-age poverty.

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

wealth.

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Appendix

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?".*[22]	open
Number of relationship changes	*When did your relationship with [partner name] start?*	open

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 break-ups	0.345	0.325
	(0.610)	(0.653)
Number of divorces	0.274	0.245
	(0.516)	(0.499)
Number of cohabiting break-ups	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: 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.5: 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.6: 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.7: Variable description: life satisfaction and wealth in later 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.8: Descriptive statistics for life satisfaction and wealth in later life

	Female	Male
Life satisfaction at age 55–65	7.861	7.97
	(1.569)	(1.50)
Household wealth at age 55–65	389,529	431,504
	(548,395)	(731,499)
Number of individuals	2,199	1,954

Standard deviations in parentheses.

Table A.9: Variable description: time-varying controls

VARIABLE		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.10: 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 ≥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.11: 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.12: Descriptive statistics for time-fix controls, OLS only

	Female	Male
Childhood endowments and cognitive skills		
SES: low	0.221	0.252
	(0.415)	(0.434)
SES: high	0.307	0.259
	(0.461)	(0.438)
Health: excellent or very good	0.583	0.619
	(0.493)	(0.486)
Father absent: yes	0.112	0.117
	(0.315)	(0.322)
Education: high	0.195	0.253
	(0.396)	(0.435)
Education: low	0.313	0.312
	(0.464)	(0.463)
Math skills	3.273	3.383
	(0.867)	(0.884)
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.13: 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	0.776	0.541	0.476	0.454	0.467	0.567
Number of relationship changes	0.081	0.060	0.055	0.053	0.055	0.070
B. Women						
Number of job changes	0.692	0.496	0.431	0.414	0.428	0.519
Number of relationship changes	0.069	0.050	0.043	0.042	0.043	0.052

Table A.14: Estimated coefficients for cross-market effects of instability, men w. controls

	Number of job changes			Number of relationship changes		
	OLS	FE	GFE, $G = 5$	OLS	FE	GFE, $G = 5$
	(1)	(2)	(3)	(4)	(5)	(6)
Number of relationship changes	0.388***	0.288***	0.098***			
	[0.055]	[0.041]	[0.021]			
Number of job changes				0.047***	0.050***	0.001
				[0.007]	[0.007]	[0.002]
Low education	-0.137***			0.004		
	[0.050]			[0.016]		
High education	-0.097*			-0.017		
	[0.053]			[0.017]		
Low SES	0.149***			-0.022		
	[0.051]			[0.015]		
High SES	0.013			0.075***		
	[0.051]			[0.017]		
Father absent at age 10	0.123**			0.041*		
	[0.062]			[0.022]		
Very good/excellent	-0.016			-0.027*		
childhood health	[0.043]			[0.014]		
Self-assessed math skills	-0.051*			-0.012		
	[0.027]			[0.010]		
Self-assessed language skills	0.005			0.013		
	[0.028]			[0.010]		
Number children 0-5	0.043**	0.057***	0.025***	-0.001	-0.008	-0.003
	[0.020]	[0.014]	[0.007]	[0.006]	[0.005]	[0.003]
Number children 6-15	0.051**	0.058***	0.017**	-0.016**	-0.021**	-0.002
	[0.020]	[0.017]	[0.008]	[0.006]	[0.006]	[0.003]
Number children $\geq$16	0.065**	0.067***	0.012	-0.035***	-0.037***	-0.002
	[0.027]	[0.022]	[0.010]	[0.008]	[0.008]	[0.003]
Number health conditions	0.031	0.003	-0.008	0.053**	0.031**	-0.002
	[0.041]	[0.022]	[0.013]	[0.027]	[0.015]	[0.006]
Log GDP	-0.208**	-0.257***	-0.078	-0.100**	-0.094**	-0.005
	[0.102]	[0.094]	[0.052]	[0.045]	[0.042]	[0.017]
Constant	2.119**			0.859**		
	[0.904]			[0.398]		
R-squared	0.187			0.096		
Observations			126,033			

Standard errors clustered on 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 using OLS (1), OLS with individual-specific fixed-effects (2) and the GFE estimator with individual-specific fixed-effects and $G = 5$ (3). Columns (4)–(6): Estimated coefficients from a regression of the number of spousal relationship changes on the number of job changes using OLS (4), OLS with individual-specific fixed-effects (5) and the GFE estimator with individual-specific fixed-effects and $G = 5$ (6). Additional controls: country, cohort and age fixed-effects. We do not control for age fixed-effects in the GFE specifications.

Table A.15: Estimated coefficients for cross-market effects of instability, women w. controls

	Number of job changes			Number of relationship changes		
	OLS	FE	GFE, $G = 5$	OLS	FE	GFE, $G = 5$
	(1)	(2)	(3)	(4)	(5)	(6)
Number of relationship changes	0.520***	0.385***	0.157***			
	[0.058]	[0.041]	[0.022]			
Number of job changes				0.068***	0.070***	0.007***
				[0.008]	[0.007]	[0.003]
Low education	-0.029			-0.020		
	[0.049]			[0.016]		
High education	-0.166***			0.004		
	[0.055]			[0.020]		
Low SES	0.022			-0.003		
	[0.054]			[0.016]		
High SES	-0.054			0.039**		
	[0.049]			[0.017]		
Father absent at age 10	0.084			0.036*		
	[0.071]			[0.022]		
Very good/excellent	-0.086**			0.036*		
childhood health	[0.043]			[0.022]		
Self-assessed math skills	0.003			-0.027***		
	[0.027]			[0.009]		
Self-assessed language skills	0.020			0.015		
	[0.028]			[0.009]		
Number children 0-5	-0.009	-0.012	-0.023***	-0.004	-0.033***	-0.004**
	[0.017]	[0.013]	[0.008]	[0.005]	[0.004]	[0.002]
Number children 0-5	-0.017	-0.031	-0.031	-0.012**	-0.037***	-0.003
	[0.017]	[0.014]	[0.008]	[0.006]	[0.006]	[0.002]
Number children ≥16	-0.019	-0.017	-0.020**	-0.003	-0.036***	-0.002
	[0.022]	[0.018]	[0.008]	[0.008]	[0.008]	[0.003]
Number health conditions	0.097**	0.044*	-0.010	0.020	0.021**	-0.001
	[0.042]	[0.023]	[0.013]	[0.014]	[0.010]	[0.003]
Log GDP	-0.437***	-0.440***	-0.064	0.002	-0.019	-0.040**
	[0.105]	[0.096]	[0.057]	[0.046]	[0.042]	[0.017]
Constant	3.810***			0.032		
	[0.933]			[0.409]		
R-squared	0.213			0.126		
Observations	110,295					

Standard errors clustered on 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 using OLS (1), OLS with individual-specific fixed-effects (2) and the GFE estimator with individual-specific fixed-effects and $G = 5$ (3). Columns (4)–(6): Estimated coefficients from a regression of the number of spousal relationship changes on the number of job changes using OLS (4), OLS with individual-specific fixed-effects (5) and the GFE estimator with individual-specific fixed-effects and $G = 5$ (6). Additional controls: country, cohort and age fixed-effects. We do not control for age fixed-effects in the GFE specifications.

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	0.177***	0.117***	0.123***	0.098***	0.076***
	[0.031]	[0.024]	[0.024]	[0.021]	[0.019]
Panel B	Number of relationship changes				
Number of job changes	0.013***	0.001	0.005*	0.001	0.001
	[0.005]	[0.003]	[0.003]	[0.002]	[0.002]
Observations	126,033				

Standard errors clustered on 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 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. Controls: number of current health conditions, log GDP, number of children in specific age groups (0-5,5-15,>16), country, and cohort fixed-effects.

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***	0.164***	0.176***	0.157***	0.148***
	[0.030]	[0.026]	[0.025]	[0.022]	[0.015]
Panel B	Number of relationship changes				
Number of job changes	0.026***	0.010***	0.007***	0.007***	0.006***
	[0.005]	[0.003]	[0.003]	[0.003]	[0.002]
Observations	110,295				

Standard errors clustered on 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. Controls: number of current health conditions, log GDP, number of children in specific age groups (0-5,5-15,>16), country, and cohort fixed-effects.

Table A.18: Estimated coefficients of cross-market effects of instability using the number of negative job changes, GFE estimates with $G = 5$

	Number of negative job changes (1)	Number of relationship changes (2)
A.Men		
Number of relationship changes	0.040***	
	[0.040]	
Number of negative job changes		0.002
		[0.004]
Observations	126,033	
B.Women		
Number of relationship changes	0.086***	
	[0.016]	
Number of negative job changes		0.007**
		[0.004]
Observations	110,295	

Standard errors clustered on the individual level in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Estimated coefficients obtained from the GFE estimator with individual fixed-effects. Controls: number of children age 0-5, number of children age 6-15, number of children aged 16 and above, the number of health conditions, log GDP, country and cohort fixed-effects.

Table A.19: Estimated coefficients of lagged cross-market effects of instability, GFE estimator for five groups, 3 year lags

	Number of job changes (1)	Number of relationship changes (2)
A.Men		
Number of relationship changes, $t-3$	0.115***	
	[0.023]	
Number of job changes, $t-3$		-0.001
		[0.003]
Observations	117,240	
B.Women		
Number of relationship changes, $t-3$	0.165***	
	[0.025]	
Number of job changes, $t-3$		0.004*
		[0.003]
Observations	102,600	

Standard errors clustered on the individual level in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Estimated coefficients of instability predictors lagged by three periods obtained from the GFE estimator with individual fixed-effects. Controls: number of children age 0-5, number of children age 6-15, number of children aged 16 and above, the number of health conditions, log GDP, country and cohort fixed-effects.

Table A.20: Joint distribution of estimated group assignments, men

		Group spousal relationship stability:					
		very high	high	medium	low	very low	Total
Group job stability:	very high	22.69% (665)	2.42% (71)	1.98% (58)	0.85% (25)	0.10% (3)	28.05% (822)
	high	25.25% (740)	2.66% (78)	2.76% (81)	0.75% (22)	0.03% (1)	31.46% (922)
	medium	17.09% (501)	2.83% (83)	1.94% (57)	0.85% (25)	0.07% (2)	22.79% (668)
	low	9.11% (267)	1.64% (48)	1.36% (40)	0.68% (20)	0.24% (7)	13.03% (382)
	very low	2.9% (85)	0.55% (16)	0.68% (20)	0.44% (13)	0.10% (3)	4.67% (137)
	Total	77.04% (2258)	10.10% (296)	8.73% (256)	3.58% (105)	0.55% (16)	100% (2,931)

Table A.21: Joint distribution of estimated group assignments, women

		Group spousal relationship stability:					
		very high	high	medium	low	very low	Total
Group job stability:	very high	25.73% (660)	1.72% (44)	2.30% (59)	2.34% (60)	0.66% (17)	32.75% (840)
	high	22.77% (584)	2.03% (52)	2.07% (53)	2.03% (52)	0.74% 19)	29.63% (760)
	medium	14.58% (374)	1.52% (39)	1.99% (51)	1.75% (45)	1.13% (29)	20.97% (538)
	low	7.80% (200)	1.21% (31)	1.25% (32)	1.40% (36)	0.90% (23)	12.55% (322)
	very low	2.07% (53)	0.23% (6)	0.47% (12)	0.90% (23)	0.43% (11)	4.09% (105)
	Total	72.94% (1871)	6.71% (172)	8.07% (207)	8.42% (216)	3.86% (99)	100% (2,565)

Table A.22: Estimated associations between net house value and estimated instability types

	Log net house value at age 55–65					
		Men			Women	
	(1)	(2)	(3)	(4)	(5)	(6)
Unstable job type	-0.079**			-0.083*		
	[0.031]			[0.042]		
Unstable relationship type		-0.155***			-0.084***	
		[0.050]			[0.026]	
Unstable in both			-0.269***			-0.145***
			[0.094]			[0.045]
Constant	12.445***	12.439***	12.423***	12.540***	12.554***	12.533***
	[0.130]	[0.131]	[0.132]	[0.089]	[0.089]	[0.089]
Observations		2,047			1,830	
R-squared	0.074	0.074	0.074	0.100	0.100	0.100

Robust standard errors in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Estimated coefficients from OLS regressions of log household wealth at age 55–65 on being an unstable type in the labor market, the marriage market and in both markets. Controls: respondent's education, childhood SES, father absent, being in very good/excellent health, self-assessed math and language skills during childhood, household size at age 55–65, country and cohort fixed-effects. The calculation of log house value wealth takes into account that some respondents also report having mortgages. We therefore take the log of household net wealth plus the absolute value of the larges negative household wealth. We thereby avoid creating missing values for those with negative net house value. Those without a house are assigned net house value of 0.