Marital Stability and Intrahousehold Inequality

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Abstract

We examine which factors are predictive of unstable marriages using a unique panel data set of Japanese couples. We employ several machine learning and econometric techniques to identify characteristics of the couple pertaining to their consumption allocations, labor supply, savings decisions, and stated satisfaction that are associated with a higher divorce probability. We find time-varying characteristics of the couple, such as the wife's income and labor supply, are most predictive, while characteristics of the couple at the time of marriage are less so. We further show that marriage market conditions are highly predictive of divorce. We relate these findings to the theoretical literature on the drivers of divorce.

JEL Codes: J12, D12, D13, C53.

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1 Introduction

Having a stable marriage, where both partners know they are better off remaining married rather than apart, can influence how the couple interacts. The couple's perceived risk of divorce has the potential to impact how husbands and wives invest in their financial future, allocate labor supply, and pool their resources, as uncertainty may limit the gains from marriage. Given the economic significance of these decisions and rising divorce rates in parts of the world, the policy importance of studying marital instability has also grown.

Marital stability, however, is not observable. While attempts have been made to quantify marital stability through close-ended survey questions (e.g., Booth *et al.* (1983) for a seminal attempt), there is no universally accepted measure. In contrast, divorce is an easily observable outcome and serves as a natural indicator of marital instability. In this paper, we take a comprehensive approach to identifying factors predictive of divorce—and by extension, marital stability—using a variety of methods ranging from highly parametric ones, such as the Cox proportional hazards model, to non-parametric techniques like random forests. These analyses enable us to identify which household and couple characteristics are most predictive of marital dissolution.

While there is limited empirical evidence on the drivers of divorce, there is considerable theoretical work on the topic.[1] We begin by reviewing this literature, starting with seminal work by Becker *et al.* (1977) and Becker (1981), and continues with Weiss & Willis (1997) among others. We highlight the potential role of match quality, imperfect information, marriage-market conditions, unexpected shocks that affect the balance of power within the household, and consumption inequality, and use these insights to guide our prediction analysis.

For all of our analyses, we use the Japanese Panel Survey of Consumers (JPSC), a unique dataset designed to study issues related to gender and intra-household inequality, while also including standard labor supply and demographic information. Notably, the survey includes individual savings and consumption measures, allowing us to determine the importance of intra-household dynamics in predicting divorce. For example, are couples with unequal consumption levels more likely to divorce? Are large public goods expenditures associated with more stable marriages?[2] In addition, the survey includes measures of marital satisfaction, which have previously been shown to be predictive of divorce in Germany by Arpino

[1]Past empirical studies have investigated the gap in happiness between spouses (Guven *et al.*, 2012), economic gains and the non-pecuniary quality of the match (Chiappori *et al.*, 2018), personality traits (Lundberg, 2012), negative shocks to men's earnings (Weiss & Willis, 1997), job displacement and disability (Charles & Stephens, 2004), and legal and informational constraints (Peters, 1986). See Amato (2010) for a comprehensive literature review on the empirical determinants of divorce.

[2]Lise & Yamada (2019) similarly study the behavior of married couples using the JPSC using a dynamic collective household model. Our study complements their findings by taking a more descriptive approach to identifying key factors that impact marital decisions. Kureishi *et al.* (2025) also use the JPSC to study the impact of unexpected labor market shocks–specifically the 2011 earthquake in Japan–on divorce, as well as labor and consumption allocations within the household.

et al. (2022). Finally, the panel nature of the data allows us to make predictions that account for the time-varying nature of individual and household characteristics.

We begin our empirical analysis by descriptively comparing divorced and never-divorced couples using Kaplan-Meier survival curves and event study methods. We then turn to several econometric and machine learning techniques to examine the predictors of divorce. Given the presence of right-censoring in marriage duration data, we employ methods tailored to survival analysis. Our preferred approach is DynForest, a machine learning algorithm developed by Devaux *et al.* (2023) for analyzing time-to-event data. This method is an extension of random forests, in that it is an ensemble algorithm that makes use of decision trees, random feature selection, and bagging, while also incorporating survival analysis principles. It has similarities with random survival forest of Ishwaran *et al.* (2008), but has an advantage of accommodating time-varying predictors from panel data. Despite these advantages, random forest models are somewhat of a black box and hard to interpret, as the predictions from these models are based on the aggregation of many decision trees from bootstrapped samples with a random subset of predictors used at each potential split. As a result, we complement our main analysis using a standard Cox proportional hazard model, which adds more structure and interpretability to the analysis. We further take an intermediate approach using Lasso Cox, which combines flexible variable selection with the standard Cox model. As discussed in Wang *et al.* (2019), machine learning methods have demonstrated higher predictive accuracy compared to certain parametric or semi-parametric alternatives, especially when the data are high-dimensional. Moreover, they are especially useful when the proportional hazards assumption of the Cox model is violated. Nonetheless, there are gains to not using machine learning methods in terms of interpretability of the parameter estimates, and the ability to incorporate a variety of types of covariates that DynForest cannot (i.e., time-varying discrete variables). We see value in all approaches and thus present results from each.[3]

In our random forest specification, we are able to analyze the importance of 71 characteristics of the couple including measures of consumption allocation, time use decisions, demographics, marriage market conditions, and their stated satisfaction with different aspects of their life. We quantify predictive power using Variable Importance (VIMP),[4] and our results are broadly consistent with the theoretical literature on which factors are likely to matter for marital stability. Consistent with Arpino *et al.* (2022), stated satisfaction with the relationship is an important predictor of divorce. The husband's income and the number of children present in the household are similarly important. We find characteristics at the time

[3]Our goal is not to compare the model performance of different methods, but rather to identify which factors are predictive of divorce using several methods.

[4]VIMP (Variable Importance) is a statistical measure used to quantify the contribution of each predictor variable to the predictive accuracy of a model.

of marriage (e.g., age at marriage, education, and parental characteristics) are often unrelated to divorce, suggesting that shocks that occurred during marriage are what drives marital instability.

Our most novel findings arise from our analysis of consumption. We examine the importance of consumption allocations across spouses as well as the share of consumption devoted to public goods (including children). While individually these measures are not among the most predictive variables, when we use our preferred measure of predictive power—group variable importance, which accounts for collinearity among predictors—we find these allocations have a strong relationship with future divorce.[5]

Our paper has several contributions. First, we improve upon the existing divorce-prediction literature by using a novel machine learning technique developed by Devaux *et al.* (2023) that accounts for time-varying predictors in survival models. Thus, we partially build upon Arpino *et al.* (2022) (who uses Random Survival Forest (Ishwaran *et al.*, 2008)) by incorporating time-varying predictors such as consumption allocations and exploiting the panel structure of our data. Second, we build upon the existing literature by incorporating unique consumption allocation data as predictors. Although data on demographics and labor supply are readily available, information on how consumption expenditures are allocated across household members is not. Given the importance of consumption data identified in this paper, this addition is significant. Third, we study divorce in Japan, a unique cultural context where norms regarding divorce are changing. We highlight certain characteristics of the Japanese marriage market and examine the role they play in divorce. Our study complements other recent studies on divorce in Japan including Piao (2021) and Kureishi *et al.* (2025).

Finally, it is important to note that our approach is descriptive rather than causal. While a number of existing empirical studies estimate the causal effects of various shocks (e.g., job loss or health events) on divorce or structurally model them, our goal is to use predictive methods to uncover underexplored correlates of marital instability. This allows us to better understand which factors, including those not commonly observed or studied, are most associated with divorce risk. Our findings help inform future theoretical work on marital instability and support the view of Lewbel (2019), who argues that the correlations uncovered through machine learning exercises heighten the need for structural economic models to explain them.

The remainder of the paper is organized as follows. In Section 2 we discuss the theoretical literature on marital stability and empirical studies that have tested these theories. Section 3 describes marriage and divorce in Japan. We then discuss the data in Section 4, and conduct several descriptive analyses before proceeding to our more formal prediction exercises in Section 5. Section 6 concludes.

[5]Previous work by Piao (2021) documents the relationship between the wife's income share, private consumption, and marital stability in Japan. Our empirical approach, however, is significantly different.

2 Theoretical Framework

In this section, we summarize the existing theoretical literature on the drivers of divorce and discuss corresponding empirical findings. We structure our discussion around seminal work by Becker *et al.* (1977), who develop a framework to understand why couples divorce. This literature motivates our empirical analysis and informs the selection of couple characteristics to investigate in relation to divorce.[6]

To understand why couples divorce, we must first understand why they marry. Becker (1974) sets out a model where the marriage decision hinges on whether the expected lifetime utility in marriage is greater than the lifetime utility from remaining single. As discussed in Becker *et al.* (1977), it follows that a married couple will then divorce only when the utility from remaining married is less than the utility the couple obtains should they divorce.[7] Spouses consider how a variety of factors would differ in marriage relative to divorce, including their consumption and savings, their leisure and share of household work, the costs and utility from raising children, as well as their probability of remarriage and the quality of available partners in their marriage market.

Drawing on these insights, Becker *et al.* (1977) outline several reasons couples may divorce. First, couples consider the expected gains from remaining married, which they refer to as marriage-specific capital. Second, the couple considers the likelihood of unexpected outcomes that deviate from what their expectations were at the time of marriage, i.e., unexpected shocks. We next examine these factors in greater detail.

2.1 Marriage-Specific Capital

Becker (1974) discusses marriage-specific capital, or investment that is specific to the marriage. This includes both physical capital, such as the couple's home, and non-monetary capital, such as knowledge of a partner's preferences and their shared social network.[8] These factors tend to grow over time, and tend to be higher among couples who share characteristics, such as education and religious backgrounds. Children serve a similar role in stabilizing the marriage as other joint investments, as we discuss below.

The first component of marriage-specific capital, discussed in Becker *et al.* (1977), is match quality. Couples who have equal levels of education, income, and background are likely to have more stable

[6] For survey articles on the causes of divorce, see Lyngstad & Jalovaara (2010). Recent work in this area include Rosenfeld (2018), Abdel-Sater (2022), Rosenfeld & Roesler (2024), among others.

[7] The utility from divorce is likely to differ across spouses depending on their outside options, and thus the motivation to divorce will similarly vary. If utility is not transferable upon divorce, the utility comparison becomes more complicated, and is beyond the scope of our discussion here. See Chiappori *et al.* (2015) for a detailed analysis.

[8] Becker *et al.* (1977) additionally discusses marriage specific *human* capital, which are human capital investments that are less valuable when single. Chiswick & Lehrer (1990) further make a distinction between that which is specific to a given marriage (e.g., time spent with the couple's children), and those that are transferable to other marriages (e.g., knowledge of home production tasks).

marriages, as Becker *et al.* (1977) speculate that the marital surplus is expected to be higher in these cases. This hypothesis is tested in Weiss & Willis (1997), who find that couples with the same religion and ethnicity have more stable marriages.[9] Furthermore, they find a high degree of assortative matching in education, and further see higher stability among positively assorted couples. Other characteristics couples may match on include race and age. Regarding race, Zhang & Van Hook (2009) find interracial marriages to be more unstable relative to same-race ones. With age, Lee & McKinnish (2018) find differently aged marriages to be happier at earlier stages of the relationship, but less so than homogeneous ones as the marriage duration increases.

In terms of physical capital, the role of housing prices (a joint marital asset) has been theorized to be particularly important in marital stability. Rainer & Smith (2010) study British couples and find that positive housing price shocks lower the likelihood of divorce, while negative shocks have the opposite effect. Farnham *et al.* (2011) find similar results in the United States. Lafortune & Low (2017) focus on all assets, of which housing is a major component, and demonstrate that changes in marriage rates across socioeconomic groups can be explained by differences in asset ownership. In subsequent work, Lafortune & Low (2023) develop a model to illustrate that home-ownership stabilizes the marriage and incentivizes increased specialization, and thus efficiency within the household.

While children are not a physical asset, they function similarly in stabilizing the marriage and increasing marriage-specific capital. Chiappori *et al.* (2015) illustrate this point by formulating a model that considers how the utility of public goods (such as children) varies when the couple is together compared to divorced. Given that children cannot co-reside with both parents in divorce, they form a strong deterrent to the couple separating.[10] As discussed in Becker *et al.* (1977), it follows that divorce need not be the result of an unexpected shock, since once children reach a certain age, parents may prefer to divorce even if the marriage has gone as expected to that point. A large body of literature has empirically analyzed the role of children in divorce. Waite & Lillard (1991) find young children to be especially stabilizing for the marriage, with older children less so. Kalmijn & Poortman (2006) consider which spouse initiates the divorce, and their results suggest the presence of children is especially important for the husband's motivation to remain married.[11]

Given the existing work in this area, we include a variety of predictors in these dimensions. These include measures of match quality at the time of marriage, whether the couple owns or rents, and the

[9] This finding was previously established by Lehrer & Chiswick (1993), who note that particular religions in the United States do not appear to be especially predictive of divorce (with the exception of Mormonism), but that religious homophily is correlated with marriage stability.

[10] An adjacent literature considers the role of child gender in divorce, with some evidence that having a first-born daughter is less stabilizing than having a first-born son (Dahl & Moretti, 2008). See also Kabátek & Ribar (2021).

[11] See also, Cherlin (1977), Heaton (1990), and Svarer & Verner (2008) among many other studies.

presence of children in the household, among other measures of match quality and marriage-specific capital. These factors are discussed in detail in Section 4.

2.2 Shocks to the Marriage

At the time of marriage, the couple cannot perfectly foresee the trajectory of their incomes and savings, their individual roles in household production, or the number of children they will have. Becker *et al.* (1977) suggest the variability in the distribution of possible outcomes for these measures is a key factor in the prevalence of divorce. Any deviation from the couple's expectations may result in the utility outside of marriage being higher than the utility within.

Labor market outcomes fluctuate over the course of the marriage, and thus likely to be an important factor in marital stability. Weiss & Willis (1997) investigate the role of unexpected changes in wages and find asymmetric effects by gender, with the marriage becoming more stable when the husband experiences a wage gain, and less stable when the wife's wages increase. Charles & Stephens (2004), using the Panel Study of Income Dynamics, find an increase in the probability of divorce due to a spouse being laid off. Marinescu (2016) develops a model of marital learning and similarly concludes that job loss causally increases the probability of divorce.

Labor market shocks to one spouse, to the extent they impact the spouse's bargaining power, will have a corresponding impact on the allocation of consumption and household work within the marriage. This suggests that changes in consumption and time in household production (both of which are partly determined by bargaining power) may be predictive of subsequent divorce. Olafsson & Steingrimsdottir (2020) study a government program that expanded paternity leave, and thus husbands' involvement in childcare, and find that the program reduced divorce among eligible couples. This finding is consistent with Kalmijn (1999), who finds that the wife's marital satisfaction is higher when her husband is more involved in childcare.

The allocation of consumption and how it compares to what an individual would consume outside of marriage are likely to factor into the divorce decision. Cherchye *et al.* (2021) set out a comprehensive model of household behavior in Malawi and use insights from the revealed preference literature to demonstrate the importance of consumption and marriage market characteristics in marital stability. In subsequent work, Cherchye *et al.* (2025) extend their analysis to the United States. Motivated by these findings, we expect the share of total household consumption consumed by each spouse to be predictive of divorce.

In addition to unexpected changes to economic aspects of the couple's marriage, there may also be changes to the couple's marriage market. Since the availability of high-quality, single, matches impacts the probability of remarriage, it follows that the marriage market is a key consideration in getting divorced. This idea has been tested by South & Lloyd (1995), who find that the larger number of potential partners in an individual's marriage market, the higher the likelihood of divorce. Chiappori *et al.* (2002) demonstrate this point theoretically and empirically. They find the sex ratio in each spouse's marriage market has the potential to shift bargaining power within the marriage, and thus the utility of staying married relative to getting divorced.

A related strand of literature examines the relationship between self-reported happiness and personality traits with marital status. For example, Gardner & Oswald (2006) study individual's level of psychological well-being in the years before and after divorce. Lundberg (2012) further explores the link between personality traits, such as emotional instability or extraversion, and the gains from marriage. Guven *et al.* (2012) highlight the importance of differences in happiness across spouses and finds this to be an important predictor of divorce. Our results contribute to this literature as we observe self-reported measures of the wife's satisfaction with several dimensions of her life.

The above theory and empirical literature suggest a variety of spouse-level characteristics that are likely to be predictive of divorce. These include measures of time use, such as leisure, working hours, and time in household production, as well as measures of intra-household consumption. Moreover, marriage market conditions may play an important role in shifting the balance of power within the marriage, and thus may be predictive of divorce. Motivated by the existing theory and based on the data availability, we divide our predictors in our empirical exercise into several broad categories, including 1) household resources and allocations, 2) marriage market conditions, 3) match quality, and 4) satisfaction. Match quality variables would capture marriage-specific capital, whereas the latter three categories would capture different aspects of shocks to the marriage.

3 Background: Marriage, Divorce, and Family in Japan

Empirical studies on marriage and divorce in Japan are scarce relative to what is found in the US or Europe. Japan offers a unique setting to study, as its society is neither primarily traditional nor modern, but combines various cultural elements—some modern, some traditional, some borrowed, and some uniquely Japanese—that coexist and determine the manners and customs of the Japanese people (Kumagai, 2015). The modern Japanese system can be characterized by the modified stem family, where one experiences both modern nuclear families—typically consisting of father, mother, and offspring—and stem families—typically consisting of the grandparents, the eldest married son, and their children co-residing under the authority of the male household head.

Over the past decades, the pattern of formation and dissolution of Japanese families has changed substantially. Nearly 70 percent of marriages were arranged in the 1930s. The proportions of arranged and romantic marriages had equalized in the late 1960s, and nearly 90 percent were romantic between 2005 and 2010. Notably, the meaning of "arranged" may have changed over time from "arranged by parents" to "arranged meetings set up to minimize the trouble of looking for a partner by oneself" (Tokuhiro, 2009).

Another significant trend in Japan is that marriages are occurring later and less frequently. Between 1975 and 2020, the mean ages of men and women at first marriage increased from 24.7 and 27.0 to 29.4 and 31.0, respectively. The shares of men and women who were never married by age 50 have risen from 2.1 percent to 28.3 percent for men, and from 4.3 percent to 17.8 percent for women in this period. Retherford *et al.* (2001) argue that the near-complete erosion of the institution of arranged marriage led to later and less frequent marriage in Japan.

As with marriages, Japan's divorce situation has also changed substantially. Japan's Crude Divorce Rate (CDR), which is defined as the number of divorce cases per 1,000 people in a year, was historically high, often reaching as high as three in the late 19th century. The high CDR could be attributed to the prevalence of forced arranged marriage by parents or the simplicity of divorce and marriage then, among other reasons (Kumagai, 1983; Nishida *et al.*, 1987).[12] However, after the modern Civil Code and revised Household Registration Act were implemented in 1898, the CDR started to decline. In 1940, the CDR was as low as 0.68. After the Second World War, the CDR began to creep up until 2002 when the CDR peaked at 2.3. The CDR has been trending downwards again since then and dropped to 1.5 in 2021. It should be noted, however, that marriage is not necessarily becoming more stable, because a reduction in CDR reflects not only the stability of marriage but also the incidence of marriage in preceding years (i.e., if a large share of the population is not married in the first place, the CDR is also low). Indeed, there is some evidence that the proportion of those who have ever experienced divorce over the proportion of those who were ever married has increased across cohorts (Iwasawa, 2008).

In contemporary Japan, divorce can occur by mutual agreement or through judicial procedure.[13] The former accounts for an overwhelming majority of divorce cases in Japan. As of 2021, the share of mutual agreement among all divorce cases is 86.4 percent, even though this is the lowest figure since 1900. Notably, the composition of the duration of marriage has changed over time. There has been a reduction in the divorce rate within four years of marriage from above 50 percent in 1970 and before to a little above 30

[12]For example, under the Seven Oust Rule that dates back to the Taiho Code in early eight century, husbands could unilaterally divorce his wife for reasons such as disobedience to her parents in law, infertility, adultery, jealousy, severe disease, being loudmouthed, and larceny. Similar rules existed in other parts of East Asia, including mainland China.

[13]Judicial procedure includes family court reconciliations, district court judgments, and family court judgments (Akiba & Ishikawa, 1995).

percent in the 2010s. On the other hand, the share of couples married for a long period among all divorce cases has increased. This is partly driven by the demographic changes (as baby boomers have aged). Still, it may also reflect the weakening of social stigma associated with divorce as well as policy changes in pension structure, which have enabled couples to divide one spouse's pension at divorce.

Researchers have examined the factors that correlate with marriage and divorce in Japan. For example, Kaufman & Taniguchi (2010) find that married women are happier than others in Japan. Marriage is also associated with better health, partly because healthier individuals are more likely to marry. This association may also reflect the fact that married women are less likely to work full-time, which could negatively affect health (Lim & Raymo, 2016). There have also been changes in the perception and attitudes about family in Japan, both over time and across cohorts. Lee *et al.* (2010) suggest that views about the consequences of women working have changed over time, whereas social changes in beliefs about the importance of women's work have occurred across cohorts. Yoshida (2010) finds that women in the bust cohort (aged 20-32 in 2005) were more traditional than those in the boom cohort (aged 33-49 in 2005).

Besides the factors mentioned above, education also appears to be among the most critical factors influencing marriage. Using five rounds of the Japanese National Fertility Surveys (JNFS) between 1997 and 2015, Fukuda *et al.* (2020) find that there was a negative education gradient in women's age at first marriage. But this has disappeared by 2005, and a positive gradient emerged after 2009, thanks to a decrease in marriage rates among women with low education and an increase among women with high education. Using JNFS and JPSC data, Raymo *et al.* (2013b) found that education is negatively associated with divorce within 10 years of marriage, but there was no evidence of the education gradient growing over time. It is also worth noting that there are some cultural variations across different parts of Japan due to the long history of the traditional feudal domain system (Kumagai, 2015). Nevertheless, it is not the case that the historical divorce rates persist over a long time (Kawashima & Steiner, 1960).

Finally, it is worth pointing out that Japan's CDR has been consistently low in comparison with other high-income countries in recent decades. While international comparisons are not straightforward, there may be several reasons for this. As suggested in a comparative study of divorce rates between Japan and the US by Katsurada (1997), the cost of divorce may be higher for Japanese women than that for American women due to greater childcare responsibilities and a lower prospect of remarriage. Further, divorced women, particularly with children, may be unfavorably treated in the labor market, which may make divorce a less favorable option. It seems plausible that success as a wife and mother may be viewed as more valuable than professional success, which in turn means that the potential conflict between the roles as a professional and a mother seems weaker for Japanese women than it is for American women (Katsurada, 1997). These factors could also explain Japan's low divorce rate relative to some other high-income countries to some extent.

4 Descriptive Analysis

4.1 Data

We use data from the Japanese Panel Survey of Consumers (JPSC, 1993 - 2022), which collects information on women and their families, with an emphasis on household economics, employment, and relationships.[14] The first wave of the JPSC was conducted in 1993 with 1,500 women aged 24-34 years. Since then, it has been conducted every year with younger cohorts of women added approximately every 5 years. As of 2018, subjects of the 26th survey included women aged 29 to 59 years old. Our sample consists of all nuclear families whose children are under 18 years old during the observation period (the years 1993 to 2020). After dropping couple-years with missing data for any of the covariates (discussed below), the final sample consists of 12,637 household-year observations (12,041 for never-divorced couples and 597 for divorced couples). This includes 1,655 married couples.[15] In our sample, 108 couples divorced during the observation period. The average marital duration for these couples about 10 years, and three-quarters of all divorces occur before the 14th year of marriage.

Below, we discuss several broad categories of variables that comprise our predictors. These include standard demographic data from the JPSC, as well as several novel aspects of it, such as individual consumption and savings. We also discuss how we construct key marriage market variables.

Demographic Information. The JPSC contains rich information about the demographic characteristics of the respondents as well as their parents (e.g., education and income).[16] We interpret these variables as reflecting the match quality of the marriage. There is also non-standard information regarding how many female and male friends the respondent has, and we consider these questions as reflective of the strength of the wife's social network.[17]

Consumption, Savings and Labor Supply. In addition to standard individual time use data

[14]Available from the Panel Data Research Center at Keio University. Detailed information on the JPSC data is available on its website (http://pdrc.keio.ac.jp/en).

[15]Two women married twice in this sample. For these women, we treat each marriage separately.

[16]For parental education, we chose to use categorical variables for two reasons. First, some of the parents were educated under an older education system prior to the Second World War, and the years of education before and after the old and new education systems are not comparable. Second, we have a high prevalence of missingness in parental education variables, and thus decided to have a separate category for this.

[17]Details about the social network questions are described in the Appendix.

available in most household surveys, the JPSC also features individual-level consumption spending and savings data. The expenditure data is particularly novel as it includes both standard household-level spending on food, clothing, education, healthcare, but also individual-level data measuring person-level consumption. Expenditures are classified as either (i) expenditure for the wife, (ii) expenditure for the husband, (iii) expenditure for children, (iv) expenditure for other household members, and (v) expenditure for the household as a whole. We interpret (i)–(ii) as private goods expenditure and (iii)–(v) as public goods expenditure. As highlighted in Becker (1974) and Stevenson & Wolfers (2007), consumption complementarities are an important driver of marriage. Survey questions on individual savings are structured similarly and allow us to see if spouses who anticipate future divorce increase their savings as an insurance mechanism.

Income Management and Control. In addition to private consumption and savings, the JPSC also asks a series of questions about the management of household income. From these questions, we are able to determine the proportion of income earned by each spouse that is managed by the couple either individually or jointly. Given the novelty of this information, we discuss in more depth in the Appendix.

Women's Satisfaction Measures. For women, we observe their self-reported happiness level and satisfaction with various aspects of life, including relationships, life, income, and household spending. These measures provide us with an additional measure of marital stability that we employ in our empirical analyses. Respondents choose levels ranging from 1 - 5 where 1 indicates the lowest level of satisfaction. Details on the specific questions and the construction of the variables are reported in the Appendix.

Shocks and Events. The JPSC asks the respondents whether they have experienced any of the following events in the past year. The events include: (1) Got a job; (2) Changed jobs; (3) Retired; (4) Entered school; (5) Started a new hobby; (6) Experienced a serious illness; (7) Experienced psychological illness; (8) Experienced consumer troubles; (9) Experienced an accident or disaster. We group (1) to (5) into "positive or ambiguous event for the wife" and (6) to (9) into "negative event for the wife".

Marriage Market Data. Marriage market characteristics, such as the availability of suitable new partners in a similar age range should the couple separate, play a crucial role in shaping marital stability. To incorporate this idea into our analysis, we merge marriage market data into our base sample. We follow Cherchye *et al.* (2017) and assume that a man's potential marriage market includes all marriageable women who are at most 1 year older and 10 years younger in the survey year, and who live in the same prefecture as the man did when he was 18. For women, we define their potential marriage market similarly, except define potential matches as being between 1 year younger and 10 years older. These bounds correspond to the 5th and 95th percentiles of the age difference distribution in our sample of couples.

To obtain information about the potential marriage market relevant to each individual, we compile annual data from the Vital Statistics of Japan.[18] We collected data on the age at first marriage from 1980 to 2020, as well as marriage and divorce rates per 1,000 individuals at the prefecture level, from the e-Stat website.[19] For the size of the potential marriage market, we use prefecture-level estimates of population pyramids available from the Regional Economy Society Analyzing System (RESAS).[20] We use the estimated population size for males and females in each five-year age group every five years between 1980 and 2020.

The resulting marriage market sizes are presented in Figure A2 in the Appendix, where we plot market size by age group and gender. We observe small differences in market size across men and women on average, except for individuals aged 20 to 29. Moreover, we find significant variation across couples, as illustrated by the large interquartile range across the age distribution.

Further details about the questionnaire, specific questions and answers, the construction of all the covariates that we use in the estimation, and any imputation that we did for the covariates are described in Section A.1.1 in the Appendix.

4.2 Summary Statistics

We present summary statistics in Table 1. This table includes the variables used in the prediction exercises, and includes measures of match quality, resource allocation, wife's satisfaction measures, and marriage market characteristics.[21] Across each panel, we compare characteristics of couples that stayed married throughout our observation period ("never-divorced couples") with those that got divorced ("divorced couples").

Table 1: Summary Statistics

	Never-Divorced Couples (1)	Divorced Couples (2)
Panel A: Match Quality		
Wife's Age at Marriage	26.31	25.30
Husband's Age at Marriage	28.35	27.22
Husband Older	0.65	0.64
Wife's Experience at Marriage	6.66	6.20
Husband's Experience at Marriage	8.47	8.41

Continued on next page

[18]https://www.mhlw.go.jp/english/database/db-hw/outline/index.html

[19]https://www.e-stat.go.jp/stat-search/files?page=1&toukei=00450011

[20]The population data in RESAS is only available for five-year age groups, e.g., 20–24, 25–30, etc. We assume a uniform distribution within each age group and divide the group-level population by five to impute the population for each individual age within the group.

[21]One caveat is that we omit the shock variables from our DynForest estimation, as it is unable to incorporate time-varying indicator variables.

Table 1 – continued from previous page

	Never-Divorced Couples	Divorced Couples
	(1)	(2)
Wife's Education at Marriage	13.64	13.10
Husband's Education at Marriage	13.88	12.85
Ratio of Spouse's Education	1.00	1.04
Log Parental Income	4.68	5.01
Same Prefecture for School	0.60	0.60
Condo Owner at Marriage	0.12	0.06
Homeowner at Marriage	0.22	0.14
Father's Education Low	0.72	0.75
Father's Education High	0.26	0.25
Father's Education Missing	0.02	0.00
Father-in-Law Education Low	0.23	0.25
Father-in-Law Education High	0.06	0.09
Father-in-Law Education Missing	0.71	0.65
Mother's Education Low	0.78	0.86
Mother's Education High	0.21	0.14
Mother's Education Missing	0.01	0.00
Mother-in-Law Education Low	0.24	0.31
Mother-in-Law Education High	0.03	0.02
Mother-in-Law Education Missing	0.73	0.67
Panel B: Household Resources and Allocations		
Log Expenditure (1000 yen)	3.96	3.97
Log Wife's Income (10,000 yen)	0.57	1.47
Log Husband's Income (10,000 yen)	5.45	4.88
Income Ratio (Husband/(Husband+Wife))	0.43	0.50
Wife's Hours in Housework	50.16	48.89
Wife's Hours Working	22.75	29.15
Wife's Hours in Leisure	95.07	89.74
Husband's Hours in Housework	8.51	8.68
Husband's Hours Working	63.82	64.80
Husband's Hours in Leisure	95.65	94.43
Wife's Days Off	1.82	1.79
Husband's Days Off	1.57	1.43
Difference in Days Off (Husband-Wife)	-0.26	-0.36
Children Under 6	0.50	0.48
Children 6 or Over	1.08	1.15
Wife's Share of Total Consumption	0.06	0.08
Husband's Share of Total Consumption	0.14	0.14
Public Goods Budget Share	0.81	0.79
Consumption Ratio (Husband/(Husband+Wife))	0.56	0.53
Share of Income Controlled by both Spouses	0.75	0.77
Share of Income Controlled by Wife	0.08	0.09

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Table 1 – continued from previous page

	Never-Divorced Couples	Divorced Couples
	(1)	(2)
Log Husband's Savings (1000 yen)	-1.72	-2.61
Log Wife's Savings (1000 yen)	-2.09	-2.75
Log Family Savings (1000 yen)	-0.03	-0.81
Savings Ratio (Husband/(Husband+Wife))	0.53	0.52
Number of Female Friends	15.56	16.78
Number of Male Friends	2.64	4.63
Panel C: Satisfaction Measures		
Wife's Satisfaction with Relationship	3.52	2.96
Wife's Satisfaction with Life	3.58	3.17
Wife's Satisfaction with Income	3.34	3.09
Wife's Satisfaction with Spending	3.31	3.24
Wife's Happiness	3.97	3.55
Panel D: Marriage Market Characteristics		
Husband's Marriage Market Size	800,529.92	788,153.31
Wife's Marriage Market Size	946,626.50	935,793.93
Marriage Rate	5.66	5.82
Divorce Rate	1.97	2.05
Panel E: Shocks		
Wife Got a Job	0.08	0.11
Wife Changed Jobs	0.05	0.08
Wife Retired	0.06	0.07
Wife Entered School	0.00	0.01
Wife Started a New Hobby	0.05	0.05
Wife Experienced a Serious Illness	0.01	0.03
Wife Experienced Psychological Illness	0.01	0.03
Wife Experienced Consumer Troubles	0.00	0.00
Wife Experienced an Accident or Disaster	0.02	0.04
Positive or Ambiguous Event for Wife	0.32	0.35
Negative Event for Wife	0.05	0.09
Number of Couple-Year Observations	12,041	597
Number of Couples	1,655	108
Mean Years Observed	7.28	5.53

Note: Mean values across couple-year observations. Low parental education is a dummy variable that indicates having 9 or 12 years of education, while high parental education is a dummy variable indicating having 14 or 16 years of education. Income variables include imputed values. Hours, household expenditure, and savings are all per week. The JPSC delineates between savings for (1) all of my family (2) for me (3) for my husband (4) for my children (5) for the others. Savings for family are the sum of (1), (4), and (5). "Share public goods" is the share of expenditure for family, children, and other out of total household expenditure. Homeowner and condo owner are both dummy variables. Market work hours include work, commute, and study hours. Housework hours include both household chores and childcare time. Days off measures number of days off per week. Log Husband (Wife)'s Income is Husband (Wife)'s log annual income in ten thousand yen. Savings and expenditures are in thousand yen. Happiness ranges from value 1–5: 1 "very unhappy", 2 "a little unhappy", 3 "neither happy nor unhappy", 4 "rather happy", 5 "very happy". Satisfaction measures range from value 1–5: 1 "not at all", 2 "a little", 3 "moderately", 4 "quite much", 5 "very much". Event variables are all dummy indicator variables. Shocks variables are those that happened in the past year. We group (1) Got a job (2) Changed jobs (3) Retired (4) Entered School (5) Started a new hobby into "positive or ambiguous event for wife". We group wife experiencing serious illness, psychological illness, consumer troubles and accident or disaster into "negative event for wife". Marriage and divorce rates are measured as couples per one thousand people.

Panel (A) reports measures of match quality, which we define as the characteristics of the couple at the time of marriage. Most differences between never-divorced and divorced couples are minor. However, we observe that couples who have remained married tend to have more equal education levels and are more likely to be homeowners at the time of marriage. Additionally, men tend to marry younger women, with an average age difference of around 2 years.

In Panel (B), we examine the behaviors of married couples and how they allocate their time and consumption. We find strong evidence of specialization among married Japanese couples. First, the average labor income of men is almost three times as much as that of women, despite men and women having similar years of schooling. Second, men spend more hours in the labor market and fewer hours on housework and childcare than women. However, total working hours (market plus domestic) are similar between men and women. Third, work experience at the time of marriage is comparable between men and women. Throughout the marriage, husbands accumulate more work experience than wives, as wives allocate more time to part-time jobs and housework after getting married.

A key focus of our analysis is how consumption is allocated and the role that this allocation plays in marital stability. We find a large gender asymmetry in the share of consumption between the husband and wife, with this difference being larger for never-divorced couples. Moreover, we observe greater expenditures on public goods for never-divorced couples. Across both types of couples, we find that husbands have more leisure and sleep hours compared to their wives. The difference in market work is more pronounced in couples who stay married.

A unique aspect of the data is the self-reported satisfaction measures for women in the sample. Panel (C) of Table 1 reports average satisfaction levels in five different dimensions, on a scale of 1 to 5, with 5 indicating greater happiness than 1. Unsurprisingly, there is a clear difference in stated satisfaction between women who get divorced and those who do not. This difference is especially large for satisfaction with their relationship with their husband (3.54 among never-divorced women and 2.99 among divorced women). In Panel (D) we include several marriage market characteristics that measure both the size of the marriage market and how common divorce and marriage are in the prefecture in which the couple resides.

Finally, Panel (E) of Table 1 highlights differences in shocks experienced by wives across never-divorced and divorced couples. Wives in divorced couples are more likely to report employment transitions, such as obtaining a new job (11% vs. 8%) or changing jobs (8% vs. 5%), as well as negative health events, including serious and psychological illnesses. While positive or ambiguous life events are similarly common across groups, divorced wives experience a greater frequency of negative events overall (9% vs. 5%). These patterns suggest that adverse shocks, particularly related to health and employment, are disproportionately concentrated among couples who eventually divorce.

Satisfaction measures can be interpreted as indicators of marital stability. Thus, we next examine the correlation between the five satisfaction measures and various characteristics of the couple. These results are reported in Table 2. We divide the table into two sections: Panel (A) examines how the couple allocates different resources within the marriage, and Panel (B) presents several measures of total resources. We observe a consistent negative correlation between the difference in leisure hours and the wife's satisfaction, particularly regarding her relationship and the household's income.[22] Further, we find that the wife is happier when the husband's income is higher relative to her own. In Panel (B), we observe that the wife's stated satisfaction with her relationship, life, and happiness are higher when her husband contributes more to work around the household. Moreover, the more savings the household has dedicated to the family (as opposed to for the husband or wife alone), the happier the wife is.

[22]We do not observe joint leisure, but rather only total leisure hours for each partner. Cosaert *et al.* (2023) show that joint leisure is an important measure of the gains of marriage, which we are unfortunately unable to capture.

Table 2: Correlation between Covariates and Wife's Satisfaction

	Happiness (1)	Relationship (2)	Life (3)	Income (4)	Spending (5)
Panel A: Allocations					
Household Hours Diff.: Husband - Wife	-0.04	0.03	0.01	0.01	0.03
Market Hours Diff.: Husband - Wife	0.09	0.06	0.07	0.08	0.03
Leisure Hours Diff.: Husband - Wife	-0.07	-0.11	-0.09	-0.11	-0.07
Consumption Ratio: Husband / (Husband + Wife)	-0.01	-0.03	0.01	0.04	0.00
Savings Ratio: Husband / (Husband + Wife)	0.00	-0.01	0.00	0.02	0.01
Income Ratio: Husband / (Husband + Wife)	-0.08	-0.05	-0.07	-0.08	-0.04
Panel B: Household Resources					
Wife's Household Hours	0.08	0.01	0.01	-0.01	-0.02
Wife's Market Hours	-0.09	-0.07	-0.06	-0.05	-0.02
Wife's Leisure Hours	0.00	0.06	0.04	0.07	0.04
Husband's Housework Hours	0.13	0.12	0.08	-0.01	0.03
Husband's Market Hours	0.03	0.01	0.03	0.07	0.03
Husband's Leisure Hours	-0.11	-0.07	-0.08	-0.06	-0.04
Public Goods Expenditure	-0.02	-0.03	0.01	0.08	-0.03
Household Expenditure	-0.02	-0.03	0.03	0.14	-0.01
Husband's Savings	0.01	0.01	0.04	0.10	0.05
Wife's Savings	-0.01	0.01	0.04	0.08	0.06
Family Savings	0.09	0.09	0.17	0.28	0.19
Husband's Income	0.07	0.04	0.16	0.29	0.13
Wife's Income	-0.01	0.01	0.04	0.06	0.05

Note: Columns (1)-(5) list the wife's satisfaction with different aspects of her life. Satisfaction measures range from value 1–5: 1 "not at all", 2 "a little", 3 "moderately", 4 "quite much", 5 "very much". Happiness ranges from value 1–5: 1 "very unhappy", 2 "a little unhappy", 3 "neither happy nor unhappy", 4 "rather happy", 5 "very happy". Positive values indicate increased satisfaction or happiness.

4.3 Sorting into Marriage

In their pioneering paper, Becker *et al.* (1977) suggest two general causes for marital dissolution. The first is search costs, where costlier search lowers the bar for an acceptable match. In a marriage market with high search costs, one would expect a larger deviation of chosen matches from the optimal sorting equilibrium, and thus a higher likelihood of divorce. The second general cause are "surprises" or shocks that occur after marriage. Here, we indirectly examine the importance of search costs and assortativeness by plotting Kaplan-Meier survival curves for relative education and age levels in Figure 1. In Panel (A), we classify couples into four mutually exclusive categories based on whether the husband and wife have a high (> 12 years) or low (≤ 12 years) level of education at the time of marriage. Panel (B) divides couples by the relative age of the husband and wife. The vertical axis shows the probability of divorce, while the horizontal axis plots marriage duration.

Several interesting patterns emerge. We find that both spouses having high education levels is most strongly associated with the couple staying together, while both having low education levels is most strongly associated with divorce. Thus, having similar characteristics to one's spouse is not necessarily driving marital stability. This finding is consistent with evidence from previous research. For example, Raymo *et al.* (2013a) use the Japanese National Fertility Survey in 2005 and the JPSC and find that educated women are less likely to get divorced within 10 years of marriage. Moving to relative age in Panel (B), we see that couples who are the same age (roughly 15 percent of marriages in our sample) are the most stable, though the differences across categories are less stark.

(A) Relative Education (B) Relative Age

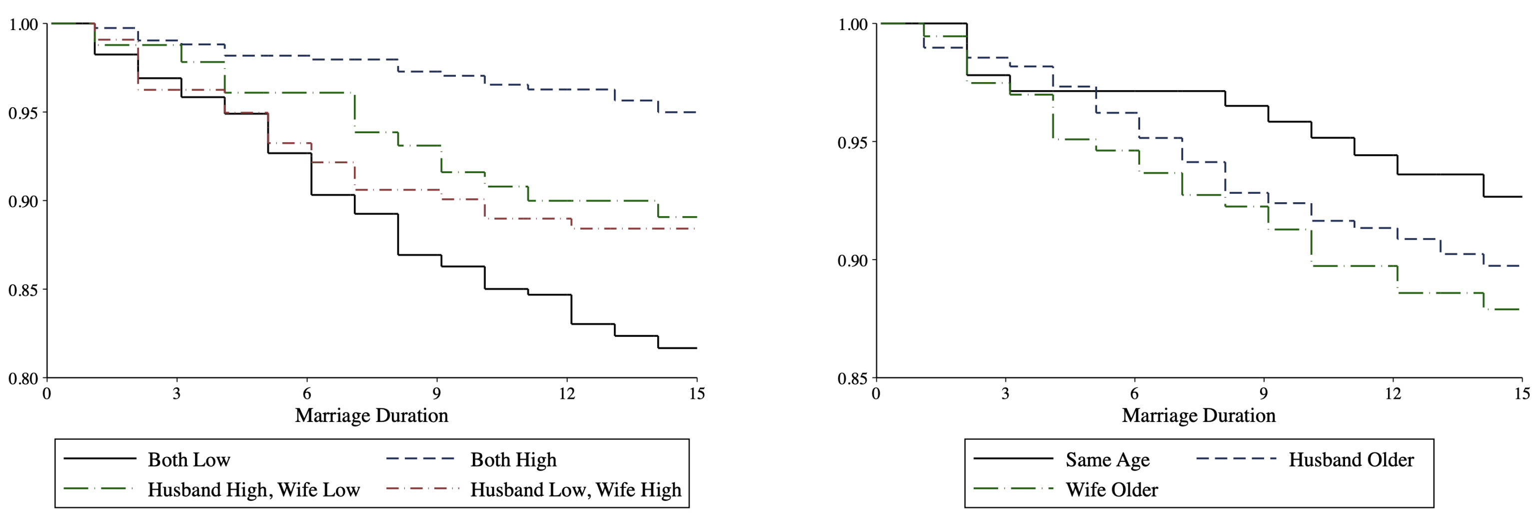


Figure 1: Kaplan-Meier Survival Curves

Note: Kaplan-Meier survival curve for the relationship between relative education and age levels of men and women, and the probability of remaining married over time. The x-axis presents the duration of the marriage in years, while the y-axis shows the probability of remaining married. Panel (A) classifies couples as both having low education (12 or fewer years) or high (more than 12 years). We restrict the maximum marriage duration presented to be 15 due few observations beyond that point.

If we compare the correlation of several couple characteristics across divorced and never-divorced couples, we see slightly higher rates of assortativeness among the never-divorced couples. The correlation of age between husbands and wives is 0.83 among couples that have yet to divorce compared to 0.77 among those that have. Similarly, we see a 0.47 correlation in years of eduction among the never-divorced compared to 0.37 among the divorced.

4.4 Evidence from Event Studies

We next analyze the evolution of certain labor, consumption, and savings measures for couples in the years leading up to their divorce. To do this, we estimate individual-level fixed-effects regressions that rely on variation within a couple in their behavior.

We denote the year of divorce for couple i by $T_i = 0$, and index three years prior to the divorce year (so event time runs from -3 to -1). Let y^g_{is} denote the outcome of interest (leisure hours, market work hours, domestic work hours, and share of consumption) for an individual of gender g in couple i in year s. Based on a specification similar to Kleven *et al.* (2019) and Foerster (2021), we run the following regressions separately for men and women for the outcome variables listed above:

$$y_{is}^{g} = \sum_{k} \beta_{k}^{g} \times I[age_{is}^{g} = k] + \sum_{z} \gamma_{z}^{g} \times I[s = z] + \sum_{q=1}^{3} \alpha_{q}^{g} \times I[T_i - s = q] + \psi_i + v_{is}, \tag{1}$$

where we include age dummies β_k^g for age k (first term on the right-hand side),[23] year dummies γ_z^g (second term), and our three event time dummies α_q^g (third term) for each gender g. The omitted period are years four and earlier to the year of divorce. Couple fixed effects and error terms are denoted by ψ_i and v_{is}, respectively.

Figure 2 plots the coefficient estimates $\hat{\alpha}_q^g$ for expenditure allocations, time use measures, savings, and income management measures separately for men and women. We present estimates for how the couples' behavior in years one, two, and three prior to divorce differ from years four and earlier. Interestingly, the couples' expenditure patterns appear to change significantly in the year prior to divorce, but not earlier. Specifically, we observe a decrease in spending on public goods in Panel (A) and an increase in the wife's consumption share in Panel (B). Together, these results suggest expenditure patterns are predictive of marital stability, though the direction of causation cannot be identified using this specification.

Moving to time use, in Panel (D) of Figure 2, we observe an increase in the wife's time in market work by nearly six hours per week relative to four years prior to divorce or earlier, consistent with existing research (Johnson & Skinner, 1986, 1988). We find the opposite pattern for husbands in Panels (G) and (I), as they decrease their market work by roughly 5 hours per week and increase their time spent on leisure by nearly 6 hours. The estimates are consistent with a gender asymmetry in how couples behave in the lead-up to divorce. Interestingly, we do not observe any change in savings behavior for the couple jointly (Panel J) or in their individual savings (Panels K and L). Finally, we find some evidence that women controlled a larger share of household income, consistent with them consuming more.

While these results are indicative of certain behaviors changing in the years leading up to divorce, it is not a systematic way of identifying the most important predictors. We delve deeper in Section 5 to further investigate these findings.

[23] For household-level outcome variables, we include age dummies for both men and women.

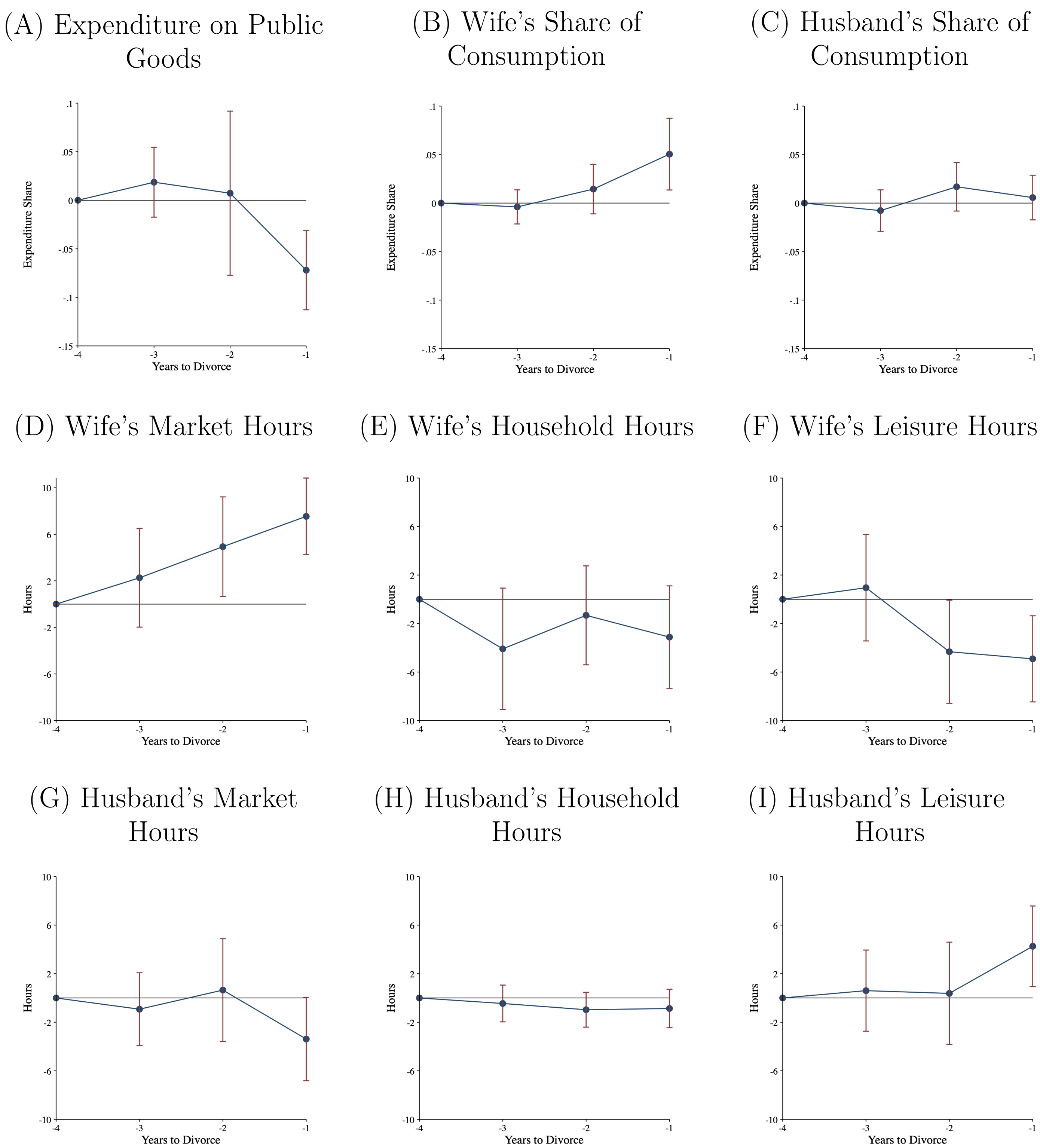
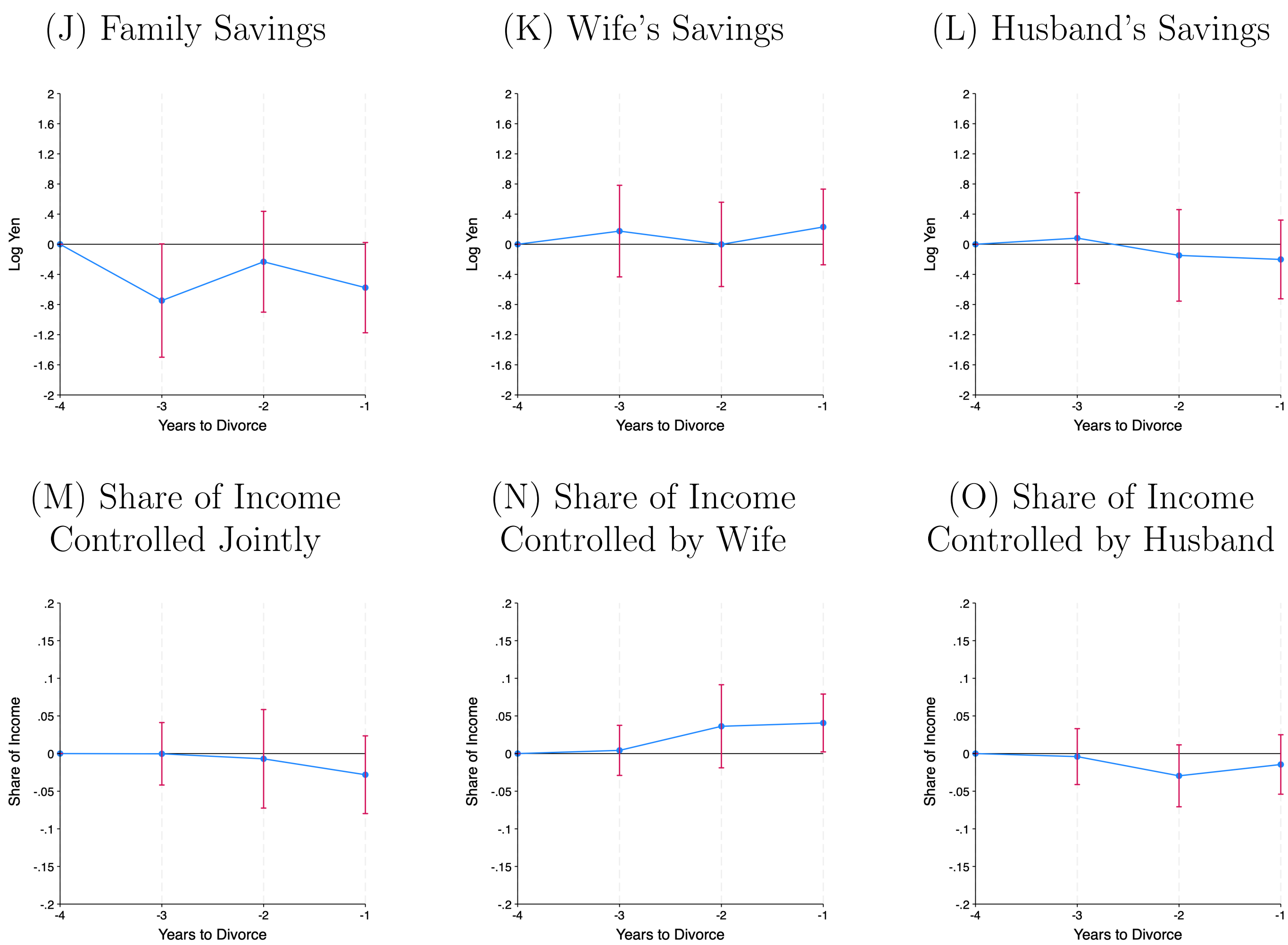


Figure 2: Evolution of Couple's Behavior Prior to Divorce

Note: The figure presents estimates on the evolution of consumption and time use measures in the lead up to divorce. We include age, year, and couple fixed effects in all specifications. We include never divorced couples to help identify age and year fixed effects. The omitted period are years 4 and earlier, which we bin together.



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Note: The figure presents estimates on the evolution of consumption and time use measures in the lead up to divorce. We include age, year, and couple fixed effects in all specifications. We include never divorced couples to help identify age and year fixed effects. The omitted period are years 4 and earlier, which we bin together.

5 Predicting Divorce: Methods and Results

The above analyses provide suggestive evidence of the role of certain couple characteristics, such as match quality, couple behavior, and unexpected shocks, in the likelihood of divorce. We now systematically analyze the importance of a variety of predictors simultaneously, with the goal of identifying which are most predictive.

5.1 Random Forest

We employ random forest as our main predictive method, owing to its flexibility in handling high-dimensional data with potentially complex interactions among covariates. The algorithm constructs an ensemble of decision trees, each trained on a bootstrapped sample of the data and a randomly selected subset of covariates. Final predictions are aggregated across trees by majority vote. This approach mitigates overfitting and is particularly well-suited to our empirical context, where many collinear, couple-level characteristics may jointly influence marital outcomes.

Our setting requires several deviations from the standard random forest approach. First, we are working with survival data, so our goal is to predict the time until divorce while accounting for the right-censoring of marriage duration in the data. This method, *random survival forest*, applies random forest to right-censored survival data (Ishwaran *et al.*, 2008). It is most commonly used in biomedical research, where the goal is to predict patient survival times or times until disease progression, but it has also been applied in social science settings, such as unemployment duration and credit risk (Fantazzini & Figini, 2009).[24] A notable contribution related to our research question is recent work by Arpino *et al.* (2022), who applied this method to analyze the predictors of divorce. However, random survival forest does not allow for time-varying covariates. This limitation leads to our second deviation: applying recent advancements in the random survival forest literature by Devaux *et al.* (2023), which accommodate these variables. Here, we provide a high-level overview of the method. Devaux *et al.* (2023) use a competing-risk random survival forest and modify the random survival forest by incorporating longitudinal predictors using linear mixed models, which can be easily estimated using the *DynForest* package in R.

Notation and Estimation Process

Suppose we observe N couples indexed by i. Let T_i be the event time (or marriage duration in our context) measured in years, with D_i being the time of divorce and t indexing years. Our analysis includes

[24]See Wang *et al.* (2019) for a survey of machine learning for survival analysis.

two types of variables; P time-independent covariates denoted X_{ip} for $p \in \{1, \ldots, P\}$, and M continuous time-dependent covariates denoted Y_{it}^{m} for $m \in \{1, \ldots, M\}$, which are measured for couple i at marriage duration time t. Examples of time-independent predictors include the couple's age difference, parental education measures, and relative education at marriage. Our time-dependent predictors, which comprise the majority of our features, include measures of labor supply, expenditure, savings, and satisfaction which vary over time.

The random forest procedure involves recursively splitting a bootstrapped sample of couples into two subgroups at nodes until the subgroups have reached a minimal size (10 in our main specification). At each node, the sample is split into two groups based on the predictor that maximizes the difference in divorce probability between them.[25] In other words, couples are divided according to the predictor that provides the strongest discrimination between the two groups at that node.

The main modification of Devaux *et al.* (2023) from the existing literature is to incorporate covariate dynamics. At each node, the trajectory of time dependent covariates is specified using a mixed model.[26] Maximum likelihood estimation of the mixed model is computed at each node. Specifically, at each node, the dynamics of each time-dependent predictor m is collapsed into a set of time-independent features using the following mixed model:

$$Y_{it}^{m} = Z^{m}(t)\beta^{m} + Z^{m}(t)b_{i}^{m} + \epsilon_{it}^{m} \tag{2}$$

where Y_{it}^{m} is the value of covariate m of couple i at marriage duration t, and Z^{m} is the vector of functions of time associated with the fixed and random effects of the mixed model.[27] b_{i}^{m} and ϵ_{it}^{m} are assumed to be mean-zero normal random errors. We assume that the trajectory of the covariates in the mixed model are quadratic in time. We experimented with alternative specifications (e.g., including a cubic term), but the results were largely unchanged. We then use the predicted values of the mixed model as time-independent features to be included as candidate features in the random forest.[28]

To summarize, the tree building process proceeds in the following steps:

1. A pre-specified number of time-independent and time-dependent candidate predictors are randomly selected.

2. The time-dependent predictors are converted into time-independent predictors using a mixed model.

[25]The difference is determined using the log-rank statistic.

[26]The estimation program used in our analysis currently can incorporate only continuous time-varying variables, though discrete ones can theoretically be added.

[27]The mixed model is estimated only with couples present at a given node.

[28]More specifically, Devaux *et al.* (2023) converts the time-dependent features to time-independent ones as the predicted couple-level deviations to the mean trajectory.

The mixed model is estimated using repeated observations from the individual couples.

3. For each candidate feature, we generate potential splits, and quantify the distance between the resulting two groups. Which features are included, and where the splits occur are decided to maximize the value of a log-rank statistic.

4. The above steps are repeated until the stopping criteria is met.[29]

5.1.1 Results

We begin by summarizing aspects of the random forest, including the model fit, and sensitivity to different hyperparameters. In Panel (A) of Figure A3 in the Appendix, we plot the out-of-bag error (OOB) by the number of variables randomly drawn at each node. Recall that the OOB is a measure of model performance calculated by averaging the prediction errors of each observation across all trees that did not include it in their bootstrap samples. The typical recommendation is to select the square root of the total number of predictors (Bernard *et al.*, 2009), which is in line with our results, as we find that the lowest OOB occurs at 9 variables. Devaux *et al.* (2023) suggest further examining the fit of the model by measuring the sensitivity of the OOB error to the node size, which determines the minimum size of the terminal nodes (leaves) in the decision trees within the forest. We plot those results in Panel (B) of Figure A3.

We then present results from the random forest model. Our main interest is which variables are most predictive of divorce. To do so, we use variable importance (VIMP), which measures how much each variable (or feature) contributes to the predictive accuracy of the model. This is determined by randomly permuting the value of a variable and seeing how the model performance changes, while holding all other variables fixed. Positive values indicate higher importance relative to negative ones. Given the large number of variables used in the analysis, we present the variables in separate figures categorized using insights from our discussion of the theoretical literature. All horizontal axes are on the same scale, so magnitudes can be easily compared across figures.

We start with match quality at the time of marriage in panel (A) of Figure 3. These include parental characteristics, education measures, work experience at the time of marriage, and the ages of the couple. Interestingly, few variables appear important. While the wife's work experience at marriage is among the top predictors among match quality variables, its VIMP is low when compared to measures of household resources (e.g., income, expenditure) and allocations (e.g., work hours) presented in panel (B). We see a

[29]The stopping criteria is based on the minimal number of couples in a node, or the number of divorces required to split the node.

similar lack of importance for relative education. The low predictive power of these measures is surprising given what we observe regarding relative age and education in Figure 1, but they have limited importance in the presence of other couple characteristics that are highly correlated with them.

panel (B) shows that marriage characteristics related to the husband's income are among the most important predictors of divorce. The husband's log income has a variable importance (VIMP) of nearly 3 percent, meaning that permuting its values increases the out-of-bag (OOB) error by that amount. Other closely related predictors, such as the difference in days off between spouses, also rank highly. Husband's income may proxy not only for direct financial resources but also for intra-household bargaining power. It may further reflect unobserved traits such as job stability or social status, both of which are likely to influence marital stability.

Having children in the household is also a major predictor of divorce, consistent with past empirical work (e.g., Becker *et al.* (1977)). Removing information on the number of children over age 6 increases the out-of-bag (OOB) error by nearly 1 percent, while doing so for children under 6 leads to a 0.5 percent increase. These results suggest that children may serve as a form of marriage-specific capital, increasing the cost of separation and reinforcing stability. However, we later show that having older children is associated with an *increase* in the likelihood of divorce (see Figure 6), casting doubt on this theory. One of the most novel aspects of the JPSC data is its inclusion of individual-level consumption measures. Both the share of expenditure devoted to public goods and the wife's private consumption share emerge as meaningful predictors of divorce, highlighting the potential importance of how resources are allocated within the household, and not just the total level of resources.

In Panels (C) and (D) of Figure 3, we present the variable importance of stated satisfaction measures and marriage market characteristics, respectively. Unsurprisingly, the wife's satisfaction with her life and her relationship emerge as strong predictors of divorce, consistent with the idea that subjective well-being captures unobserved aspects of marital quality and compatibility. Marriage market factors, such as the size of the husband's potential remarriage pool and local marriage and divorce rates, are also highly predictive. This supports theoretical models in which outside options influence the stability of existing unions (Lundberg & Pollak, 1993), suggesting that couples in environments with more favorable remarriage prospects or where divorce is more normalized—may be more likely to separate.

A drawback of variable importance in our context is that many of our predictors are highly correlated. For example, by construction, men's and women's shares of total consumption, and the share of public good expenditures, will sum to one. Thus, holding one fixed while varying others is not realistic. Group variable importance, which considers the importance of sets of variables, is a common approach to avoid these pitfalls, and thus comprise our preferred results. We present group variable importance in Figure 4. We consider two different categorizations. First, we follow Figure 3 and group all variables in a given sub-figure into a category, with the four being “match quality”, “household resources and allocations”, “satisfaction measures”, and “marriage market characteristics”. We then disaggregate these categories to provide more insights on the relative importance of, e.g., expenditure allocations and time use, which both fall under the “household resources and allocations” category. In the aggregate grouping, the results suggest resource allocations are most important, followed by the satisfaction measures. When we disaggregate these categories, we find satisfaction measures and marriage market conditions being most predictive. In terms of magnitudes, if we were to remove the link between the outcome and measures of satisfaction by random permutation, the OOB error would increase by more than 6 percent. These findings underscore that beyond economic variables, the subjective experience of the wife and external opportunities for re-partnering play central roles in predicting divorce.

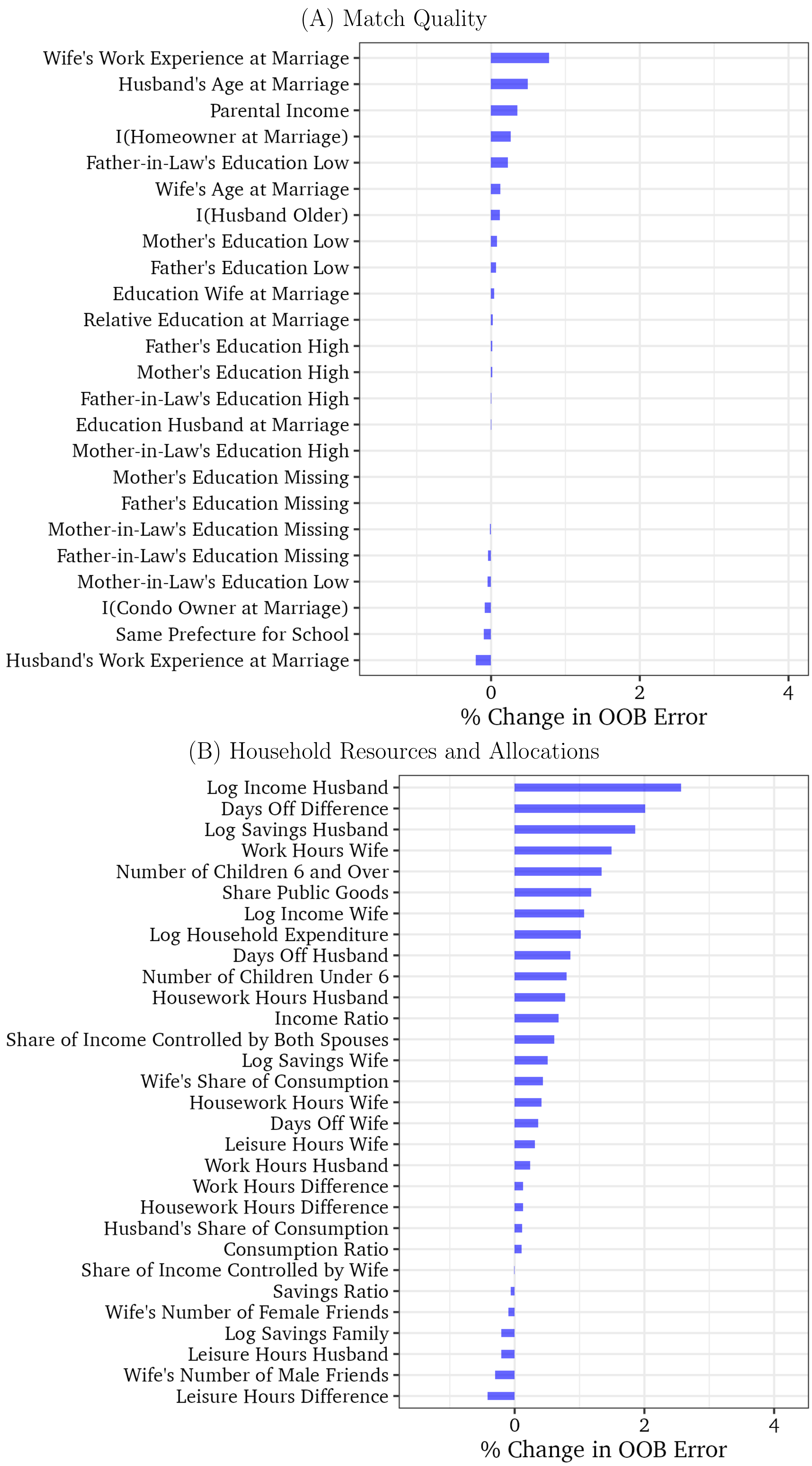

Figure 3: Variable Importance by Category

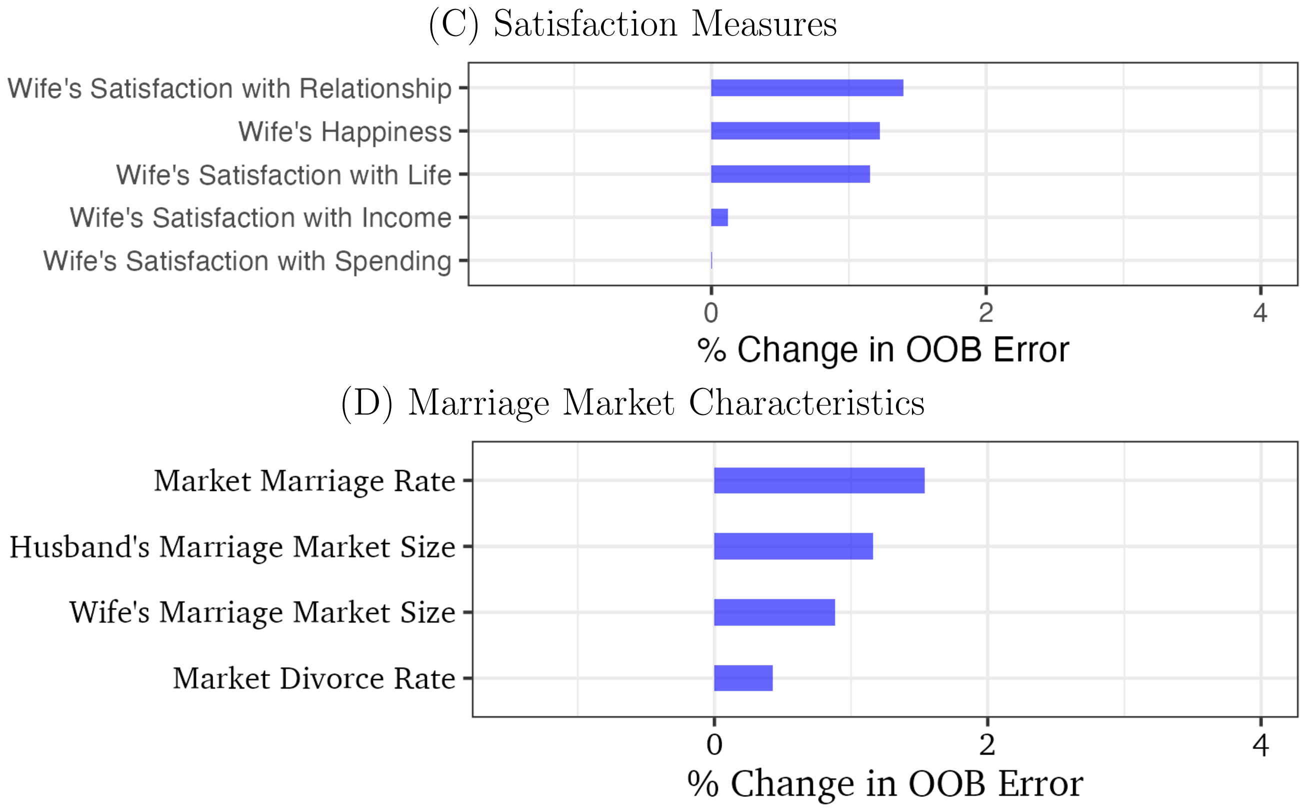

Figure 3: Variable Importance by Category

Note: Variable Importance (VIMP). VIMP is displayed as the percent change in the Out-of-Bag Error. We organize the sub-figures by variable category. Panels (A) and (B) include the wife's and husband's characteristics, respectively. panel (C) gives differences (or ratios) across spouses in several of the variables. panel (D) provides household-level characteristics. We omit region variables in the interest of clarity.

An alternative importance measure of a variable is its minimal depth in the tree. Variables that are more important are likely to appear both more frequently, and earlier in the tree-building process. To this end, we follow Devaux *et al.* (2023) and modify our main specification and make all variables available to be selected for each tree. We again include 200 trees in our analysis, and plot the average minimal depth of each variable across all trees.

These results are presented in box-plot form in Figure A4 in the Appendix. We include both the random intercept and the two coefficients from the quadratic mixed model, since disaggregating importance in this fashion is possible with minimal depth, but not VIMP. In the right-hand side of the figure, we include the number of trees that each variable appears. Variables that appear early in the tree building process (an average minimum depth of 3 or lower in our model) include the wife's satisfaction with the relationship, the wife's happiness, and her work hours. Out of these three, the wife's happiness appears in the most number of trees (146 of 200), consistent with the results presented in Figure 3.

To further examine how specific predictors relate to divorce, we use our trained random forest model to estimate survival probabilities within the testing sample. We generate dynamic predictions by fixing a landmark time, five years in this case, and using information about couples up to that point. This approach yields divorce probabilities for all subsequent years of marriage. While many predictors could be explored, we focus on a select few informed by the VIMP results (e.g., husband's income) and others with policy relevance (e.g., number of children and relative consumption).

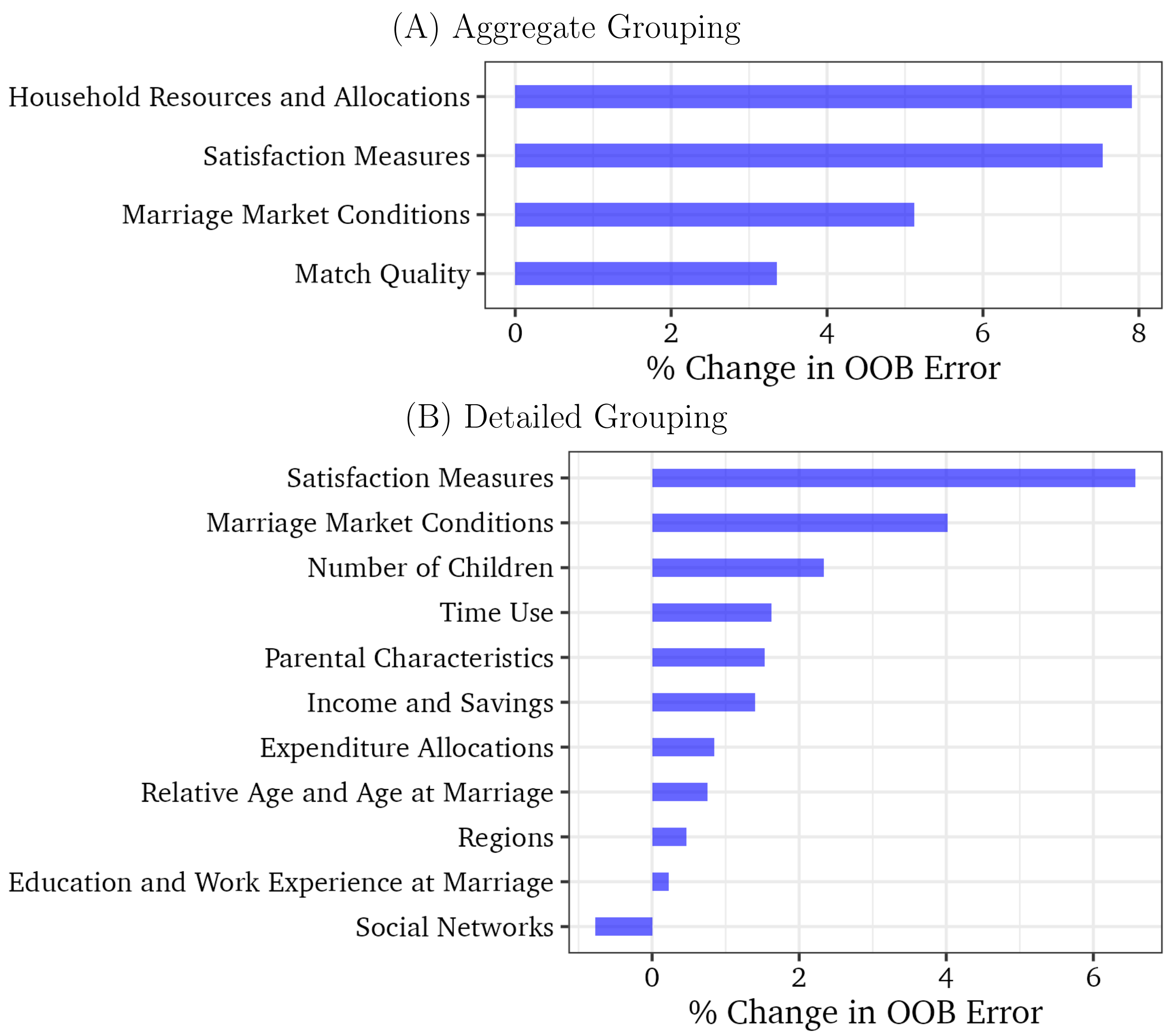

Figure 4: Group Variable Importance

Note: Group Variable Importance (gVIMP). gVIMP is displayed as the percentage loss in the Out-of-Bag Error. In panel (A), we group variables following the sub-figures of Figure 3. In panel (B) we disaggregate match quality and household resources resources and allocation into smaller categories of related variables. Income and savings include log individual incomes of both spouses, log individual and family savings, and relative income and savings. Expenditure allocations include all consumption variables, and the share of income managed by the wife and the couple jointly, respectively. Time use includes hours spent in market work, household work, and leisure, as well as differences in time spent in the categories across spouses. Time use also includes days off per week for both spouses. Social networks consists of the number of male and female friends for the wife. The remaining categories are self-explanatory.

Figure 5 presents these results graphically. panel (A) shows how the number of children under age 6 at the five-year mark relates to divorce risk.[30] We calculate average survival probabilities by marriage duration among couples still married at year five. The data indicate that childless marriages at this point are more prone to divorce, as reflected by lower survival probabilities. Having one young child offers a modest increase in stability, while marriages with two or more young children appear the most stable.

panel (B) groups marriages by the husband's income tercile, motivated by the strong predictive power of this variable in Figure 3. The results suggest that low income, rather than high income, is more strongly associated with divorce: survival probabilities are notably lower for couples in the lowest income tercile, while differences between the middle and top terciles are minimal. panel (C) turns to the consumption ratio, which measures relative private consumption within the couple. Here, we observe little variation in survival probabilities across terciles, suggesting limited predictive value of this consumption metric for divorce outcomes.

5.1.2 Sensitivity Analysis

We make several additional variable restrictions to further investigate which variables are important. First, self-reported satisfaction could be just a proxy for marital stability as opposed to a determinant. Thus, if time use was a determinant of satisfaction with one's partner, including satisfaction measures in the analysis may subsume the importance of the time use variables. As a result, we omit any self-reported satisfaction measure from the analysis and re-estimate the model. We report these results in Figure A5 in the Appendix.

In comparing the results across Figure A5 and Figure 3, several variables see significant changes in importance. First, in panel (B) of Figure A5 we observe that the importance of the number of children under six is greater, suggesting satisfaction with one's relationship is partially determined by the number of young children. Second, we see a pronounced increase in the importance of the wife's hours spent on housework. This result implies that unequal divisions of domestic labor may be a key source of underlying tension within marriages. These patterns are particularly salient in Japan, where persistent traditional gender norms may make shifts in labor supply more destabilizing to marriage than in more gender-equal contexts.

[30] We focus on young children because marriages of five years or less rarely have older children.

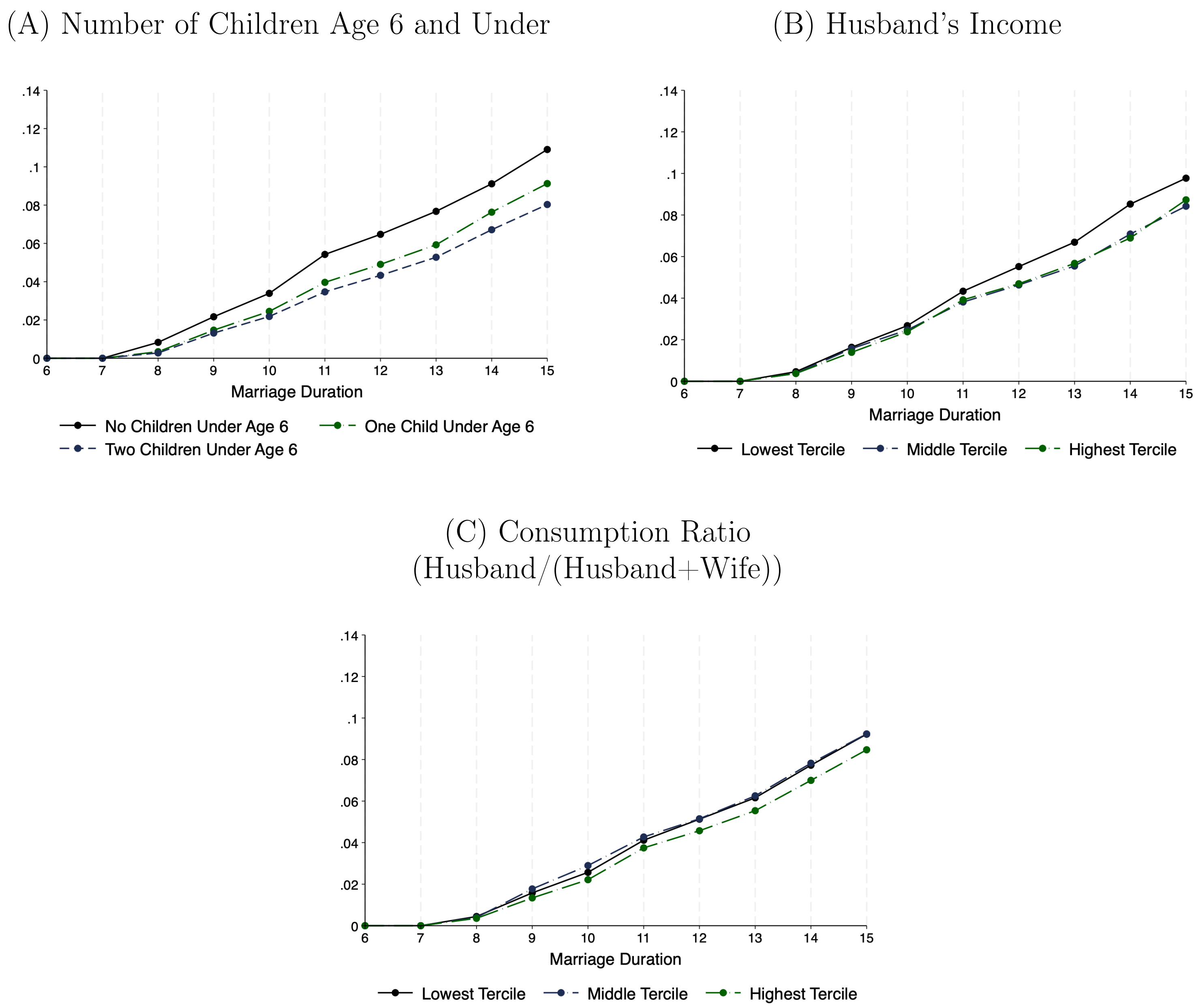

Figure 5: DynForest Predicted Survival Curves

Note: We compute probabilities of divorce in each subsequent year among couples who have been married for 5 years, applying information on the couple up to that point to our main DynForest model. We then group individuals by a given covariate value (e.g., having no children under age 6), and and calculate the average predicted probability of divorce for each subsequent year. For the continuous variables in Panels (B) and (C), we group couples into terciles based on the values of those variables in the couple's fifth year of marriage. Higher values of the resource share ratio indicate the husband is consuming more relative to his wife.

5.2 Lasso Cox Model

An important weakness of DynForest, and random forest models more generally, is that the results do not easily convey the direction of the relationship between the predictors and the outcome variable. As a result, we complement our random forest results with a Cox proportional hazard model, similar to Marinescu (2016). We estimate both the standard version of that method, as well as the least absolute shrinkage and selection operator (Lasso) applied to the Cox model (Tibshirani, 1997). Lasso Cox adds regularization to the standard model, allowing the estimation to incorporate variable selection to reduce overfitting. This addition is especially useful in our context where we have many predictors and multicollinearity is a concern. Without Lasso, we select a subset of all covariates based on characteristics that the past literature has identified as being relevant. Lasso Cox are our preferred results and are presented here, while we provide additional results for the standard Cox model in the Appendix.

In this model, we have the following log-partial likelihood function:[31]

$$\ln L(\boldsymbol{\psi}) = \sum_{t=1}^{T} \sum_{i \in D_t} \left[\mathbf{X}_i' \boldsymbol{\psi} - \log \left(\sum_{\ell \in R_t} \exp(\mathbf{X}_\ell' \boldsymbol{\psi}) \right) \right] - \lambda \sum_{p=1}^{P} |\psi_p| \tag{3}$$

where $\boldsymbol{\psi}$ is the vector of regression coefficients, $\mathbf{X}_i$ is the covariate vector for the couple experiencing the event at time t, D_t is the set of couples that get divorced within a year, R_t is the set of not-yet-divorced couples at time t, and T is the number of rounds of survey. $\lambda(\geq 0)$ is the regularization parameter controlling the strength of the penalty, and P is the number of covariates. We use an 80/20 split of the data into training and testing sets. Within the training set, we use 10-fold cross-validation to select the regularization parameter.

5.2.1 Results

In our main specification, we include 73 predictors. These predictors include all variables used in the DynForest model, as well as shock variables that were excluded because they are time-varying indicators.[32] Of the 73 predictors, Lasso Cox selects 32 with a regularization parameter of $\lambda = 0.0006$. Figure 6 presents the results where we provide the estimated hazard ratios.[33]

In our first model, we include all 73 predictors (represented with green diamonds). Similar to the DynForest results, we find self-reported satisfaction measures to be important predictors; Both the wife's satisfaction with relationship and her self-reported happiness are among the more important predictors of divorce, with hazard ratios well below 1. This suggests that lower reported satisfaction by the wife is associated with a significantly higher likelihood of marital dissolution. Two of the stronger predictors of divorce are whether an important life event occurred for the wife in the previous year. Recall that these variables indicate whether there were any significant labor market changes or health issues experienced by the wife. This result is expected, and consistent with the theory literature discussed in Section 2.

In the second model, denoted by hollow circles, we exclude satisfaction variables. The motivation behind this omissions is the same as before; We are worried that the satisfaction measures are more of an outcome measure correlated with our predictors of interest. Omitting the satisfaction measures results in the Lasso selecting 31 variables, with 23 appearing in both models. Here, we find an increase in importance of several labor market variables, including the wife's hours in market work. This can be interpreted as specialization within the marriage resulting in more stability. Alternatively, as illustrated in Figure 2,

[31]We do not interact any covariates with time. We present a standard Cox model in the Appendix that does allow for this.
[32]Recall DynForest incorporates time-varying continuous variables, but is not able to process time-varying indicator or categorical variables.
[33]Note that we do not compute confidence intervals, as is standard for Lasso estimates.

women may work more as an insurance mechanism against divorce risk.

Several match quality variables related to parental education seem highly predictive, though we do not see an obvious hypothesis for this finding. Finally, we observe several consumption measures being associated with marriage stability. Both the share of expenditure devoted to public goods and the wife's resource share are selected in each model, with marital stability increasing in the share allocated to public goods, but decreasing with the wife's expenditure share.

We complement the Cox Lasso results with a standard Cox proportional hazard model in Section A.3 of the Appendix. The benefit of this framework is that we select which variables to include, motivated by the existing literature and our descriptive results, rather than through penalization. These results are presented in Figure A7. The magnitude of the estimates is largely consistent with the Cox Lasso findings. Nonetheless, most variables have limited predictive power. We attribute this to the intrinsic difficulty in predicting divorce and the high collinearity of predictors in our analysis.

6 Conclusion

This paper provides new empirical insights into the determinants of divorce. We leverage a unique panel dataset and combine traditional econometric approaches with machine learning techniques to identify the key predictors of divorce. Our findings emphasize that time-varying characteristics, particularly related to income, labor supply, and consumption allocation, are substantially more predictive of divorce than traits observed at the time of marriage.

We make several contributions to the literature on marital stability and divorce prediction. First, we apply a novel machine learning algorithm—DynForest—to model divorce as a time-to-event outcome using panel data with time-varying covariates. This extends the existing empirical literature by allowing for a richer analysis beyond what traditional survival models or static random forest methods can accommodate. Our use of DynForest enables the identification of dynamic predictors of divorce, providing a more flexible and comprehensive modeling framework.

Second, we incorporate detailed data on intra-household consumption allocations, a dimension rarely available in existing datasets. By analyzing how private and public goods expenditures evolve and relate to divorce, we provide new evidence on the role of consumption inequality within households. Group-level variable importance measures confirm that while individual consumption variables may appear modestly predictive on their own, their collective influence is important, suggesting that how couples allocate consumption resources is fundamentally tied to marital stability. Third, we study Japan, a country undergoing notable demographic and social transitions in family formation and dissolution. By examining a setting where divorce norms are shifting and marriage rates are declining, we contribute to a better understanding of how evolving cultural environments relate to divorce outcomes.

While the machine learning methods employed here are not suited to establish causality, they offer strong predictive validity and guide future empirical and structural work. Subsequent research might seek to causally identify how shifts in intra-household allocations or policy interventions, such as childcare subsidies or labor market reforms, affect the stability of marriage.

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Figure 6: Cox Lasso Hazard Ratios

Note: Hazard ratios from the Lasso Cox model. Green diamonds indicate the model included all possible predictors. Black circles indicate the model excluded satisfaction measures. Continuous variables are standardized. Hazard ratios below one indicate a decrease in risk of divorce. We omit region variables for conciseness.

A Appendix

A.1 Data Construction

In what follows, we describe the details of the construction of variables we used in our analysis.

A.1.1 Happiness and Life Satisfaction Variables

In rounds 1–28, the JPSC survey contains 3-5 point Likert-scale questions on the wife's satisfaction with her life, income, expenses, and relationship, as well as her subjective assessment of happiness. We recode the answers such that larger numbers represent higher levels of satisfaction or happiness.

A.1.2 Social Network

The JPSC asks for the total number of female and male friends of the respondent:

How many friends do you keep company with now? Answer this question in reference to how you met. The term "friend" means here a person with whom you keep personal company (or whom you meet, exchange letters with and talk with by wire), excluding a person with whom you keep company as the members of individual groups. If you had two or more first chances of company, choose the most important.

These questions are asked in rounds 1 - 23. We impute these variables for wave 24 and forwards by using their latest information available in round 23. We interpret these two variables as reflecting the social network of the respondents.

A.1.3 Income Control Variables

The JPSC data collects the details on household income management, which allows us to identify the flow of money in the household. Through a series of questions, we know whether and what proportion of the income earned by each spouse goes to the husband's purse, the wife's purse, or the common purse, where the owner of a "purse" is the person who manages the income going there. To simplify the analysis, we define the shares of income controlled by the wife and both spouses jointly as the proportions of the income earned by the couple that eventually remain in the wife's and the common purse, respectively.

We regard the amount of money going into the purse as the money managed by the owner. However, this amount does not represent the share of the money that the owner can use freely. For example, some of the money that went into the common purse could go to the wife's or husband's purse as pocket money. Let us use Figure A1 to visualize the flow of money in the household and explain how the income control

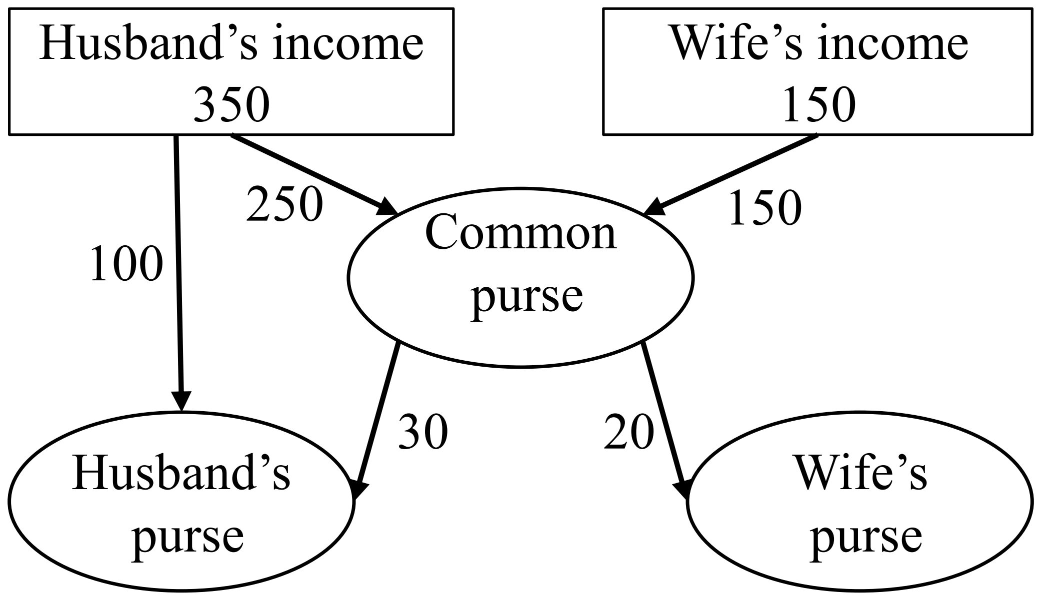


Figure A1: An example of the flow of money in the household. The numbers are in thousand yen and hypothetical.

variables are constructed. In the figure, the husband and wife earn 350 thousand yen and 150 thousand yen per month, respectively, for a total of 500 thousand yen per month. The husband puts 250 thousand yen and 100 thousand yen in the common purse and his own purse, respectively, whereas the wife puts her entire income in the common purse. The figure also shows that 30 thousand yen and 20 thousand yen flow out of the common purse to the husband and wife, respectively, as pocket money. Hence, the amount of money remaining in the common purse would be $250 + 150 - 30 - 20 = 350$, and the share of income controlled jointly is $350/500 = 0.7$. Likewise, the share of income controlled by the wife is $20/500 = 0.04$.

A.2 Additional Figures

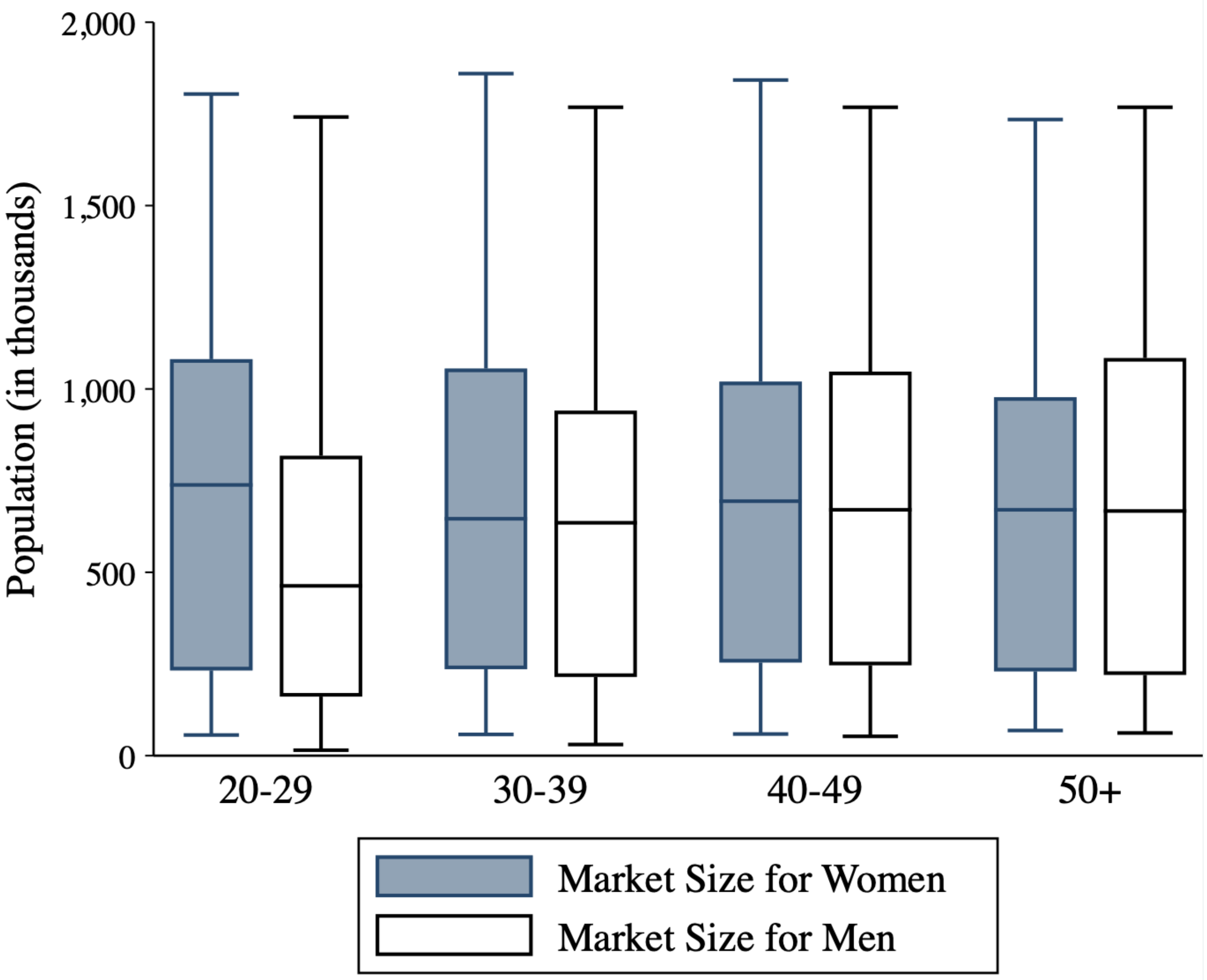
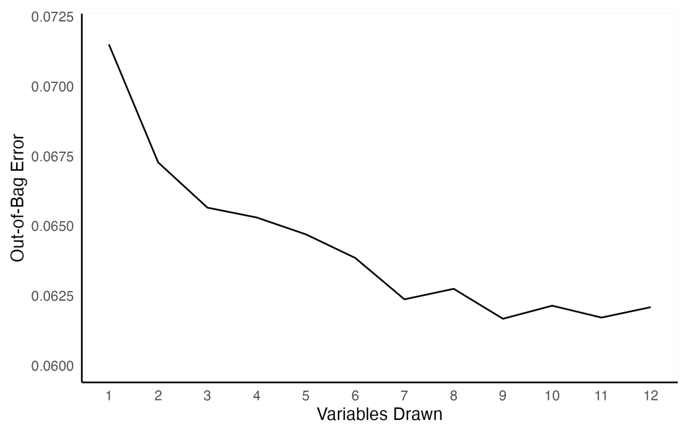


Figure A2: Marriage Market Size by Age and Gender

Note: Distribution of marriage market sizes across different age intervals for men and women. The boxes represent the interquartile range with the median marked inside each box, while the whiskers extend to the minimum and maximum values.

(A) Predictors Drawn



(B) Node Size

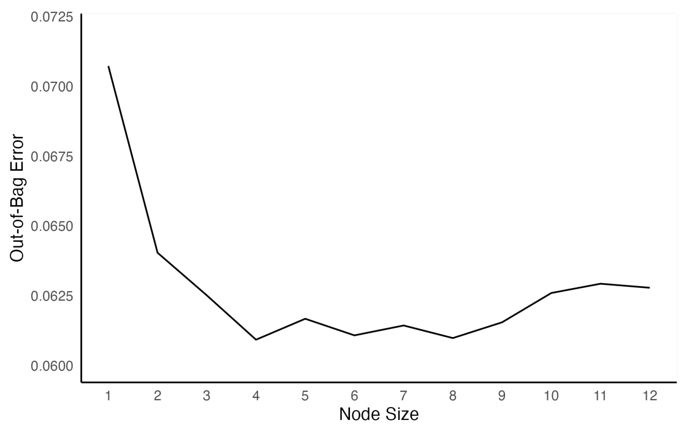


Figure A3: Sensitivity to Hyperparameters

Note: Out-of-Bag Error (OOB) for different hyperparameters. Panel A provides the OOB by the number of predictors randomly drawn at each node. The optimal value is found at 9 variables. Panel B presents the OOB by the minimum node size. The optimal value is found at 4.

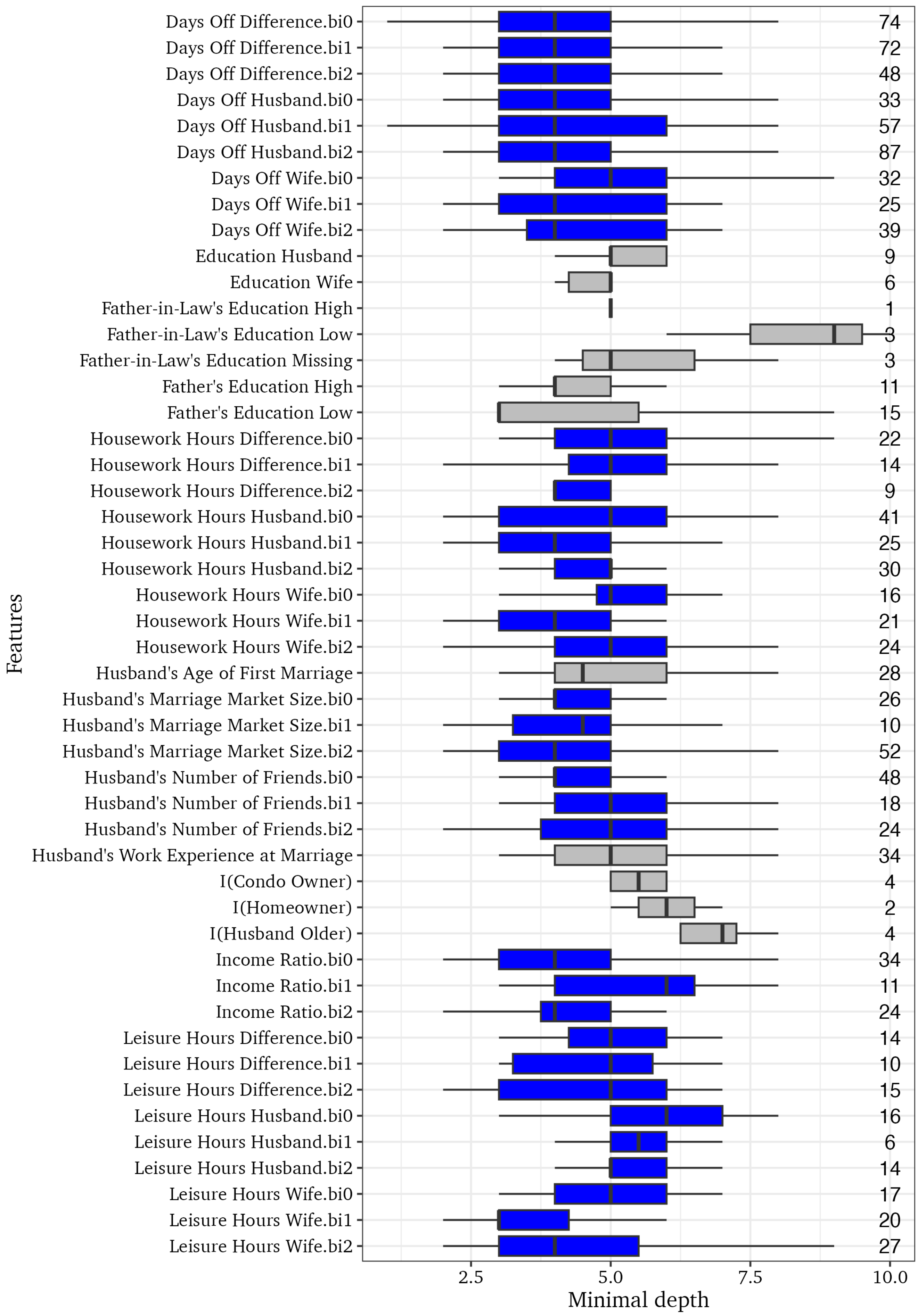


Figure A4: Minimal Depth

Note: Minimal depth computed when all variables are included across 200 trees. Blue box plots denote time-varying features, while black box plots denote time-fixed features. Variables ending in ".b0" denote the random intercept, while those ending in ".b1" denote the random slope. The number on the right-hand side indicates the number of trees out of 200 that the variable is found. Variables with a lower minimum depth, and those that appear in more trees are considered more predictive.

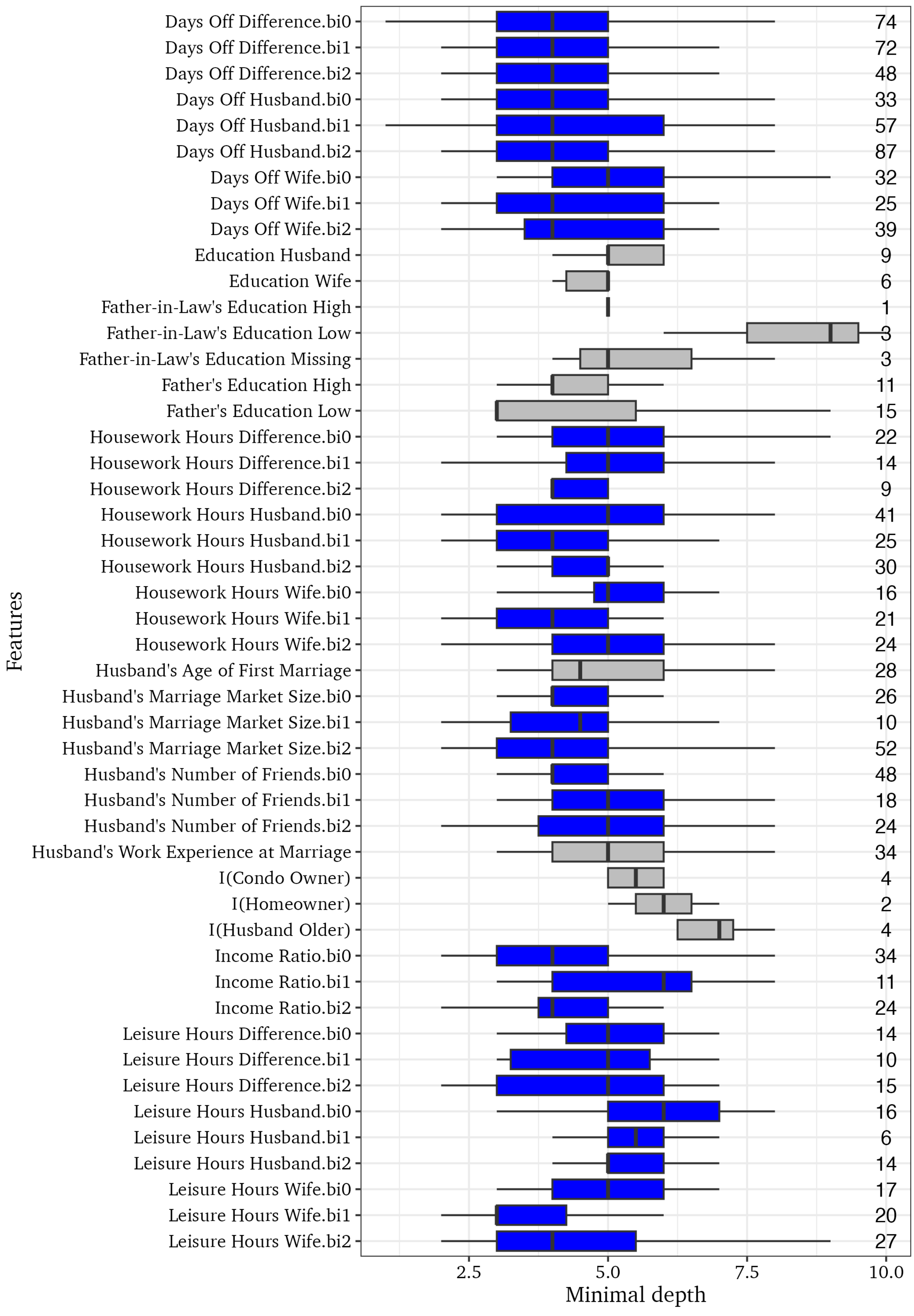


Figure A4: Minimal Depth

Note: Minimal depth computed when all variables are included across 200 trees. Blue box plots denote time-varying features, while black box plots denote time-fixed features. Variables ending in “.b0" denote the random intercept, while those ending in “.b1" denote the random slope. The number on the right-hand side indicates the number of trees out of 200 that the variable is found. Variables with a lower minimum depth, and those that appear in more trees are considered more predictive.

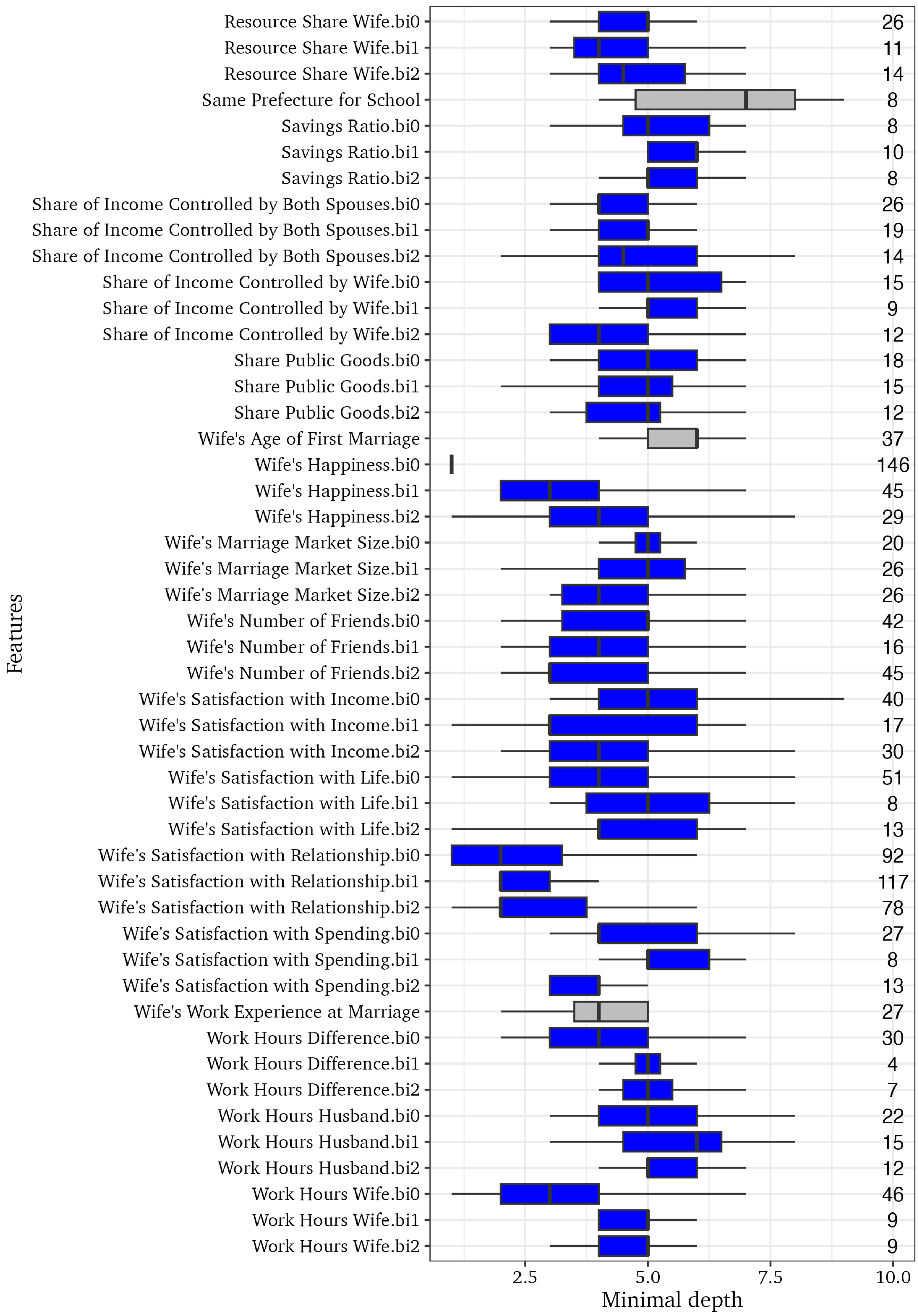


Figure A4: Minimal Depth

Note: Minimal depth computed when all variables are included across 200 trees. Blue box plots denote time-varying features, while black box plots denote time-fixed features. Variables ending in ".b0" denote the random intercept, while those ending in ".b1" denote the random slope. The number on the right-hand side indicates the number of trees out of 200 that the variable is found. Variables with a lower minimum depth, and those that appear in more trees are considered more predictive.

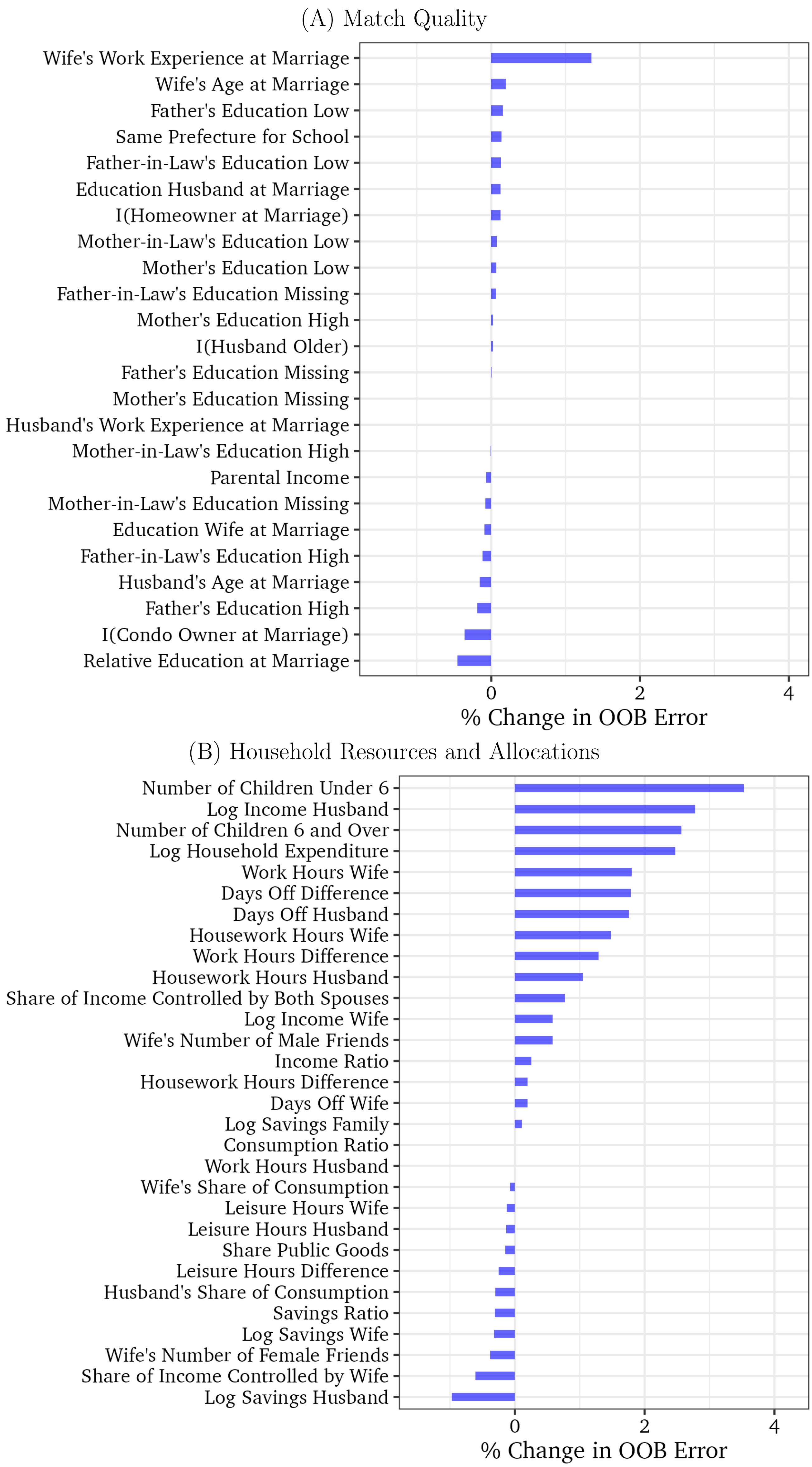


Figure A5: Variable Importance by Category (Omitting Satisfaction Measures)

(C) Marriage Market Characteristics

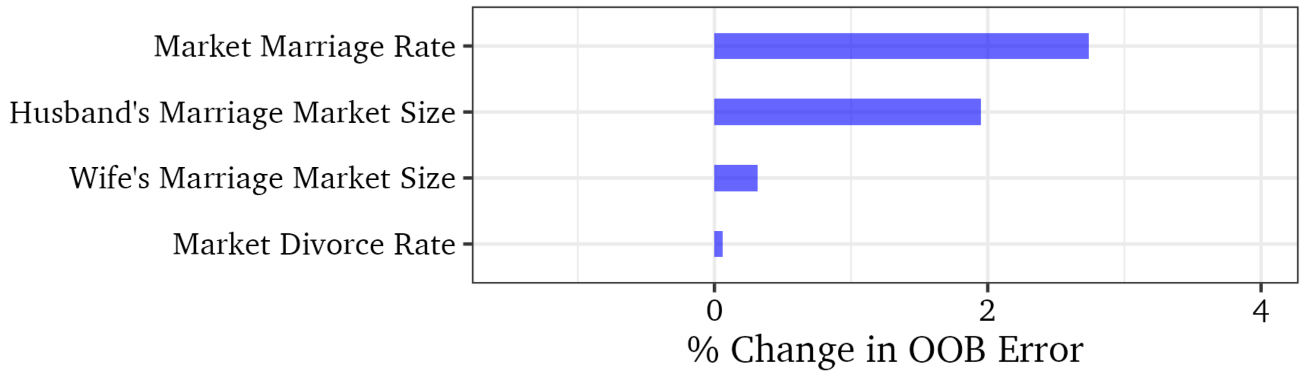
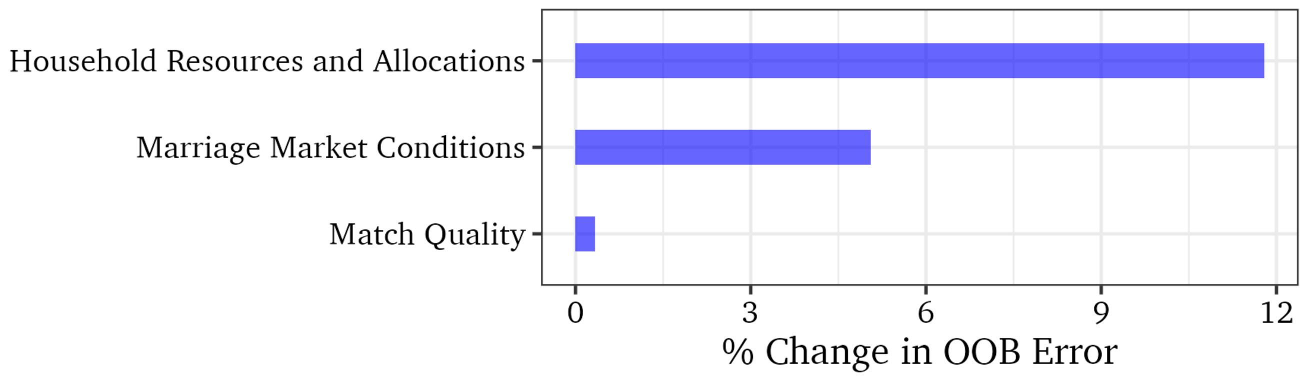


Figure A5: Variable Importance by Category (Omitting Satisfaction Measures)

Note: Variable Importance (VIMP). VIMP is displayed as the percent change in the Out-of-Bag Error. We organize the sub-figures by variable category. Panels A and B include the wife's and husband's characteristics, respectively. Panel C gives differences (or ratios) across spouses in several of the variables. Panel D provides household-level characteristics. We omit region variables in the interest of clarity.

(A) Aggregate Grouping



(B) Detailed Grouping

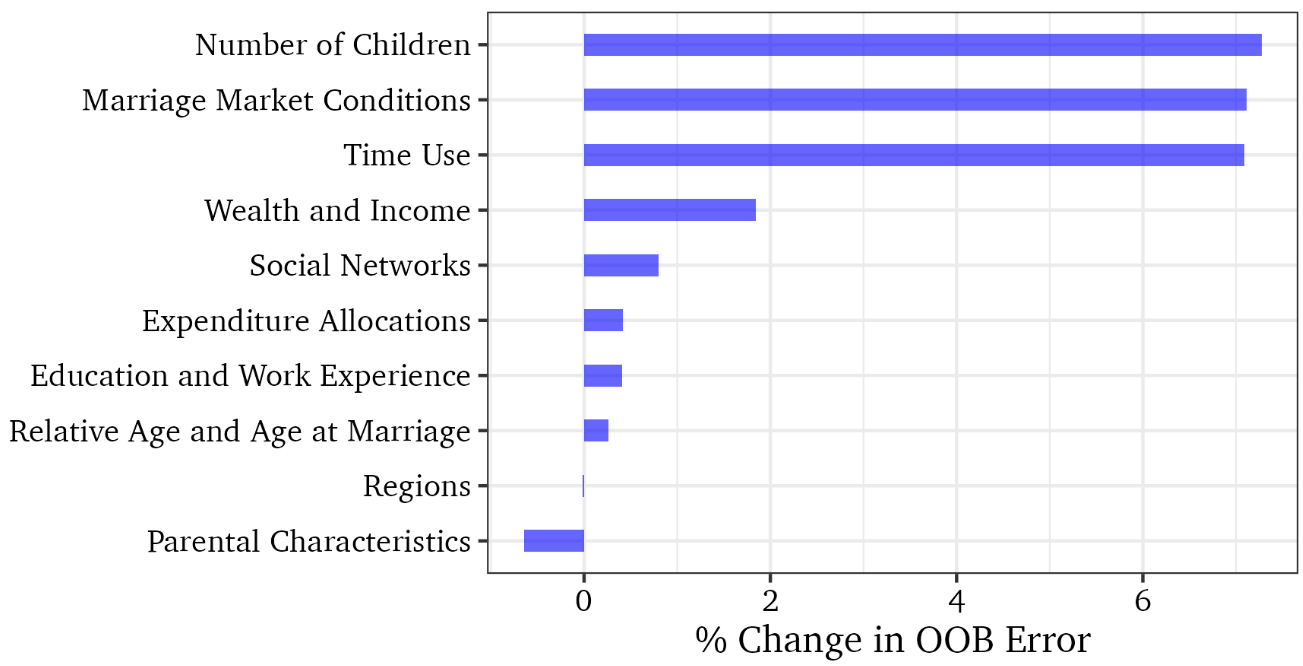


Figure A6: Group Variable Importance (Omitting Satisfaction Measures)

Note: Group Variable Importance (gVIMP). gVIMP is displayed as the percentage loss in the Out-of-Bag Error. In Panel A, we group variables following the sub-figures of Figure 3. In Panel B we disaggregate match quality and resources and allocation into smaller categories of related variables. Income and savings include log individual incomes of both spouses, log individual and family savings, and relative income and savings. Expenditure allocations include all consumption variables, and the share of income managed by the wife and the couple jointly, respectively. Time use includes hours spent in market work, household work, and leisure, as well as differences in time spent in the categories across spouses. Time use also includes days off per week for both spouses. Social networks consists of the number of male and female friends for the wife. The remaining categories are self-explanatory.

A.3 Cox Proportional Hazard Model

We supplement our main results using a Cox Proportional Hazard Model, similar to Marinescu (2016).[34] This specification has the added benefit of informing us of the sign of the relationship between the variable and the probability of divorce. The Cox proportional hazard model takes the following form (using the notation we used above), where the hazard of divorce at marriage duration t is given by $h(t, X) = h_0(t)\exp\left\{X\psi\right\}$ where $h_0(t)$ is the baseline hazard function, $X = (x_1, \ldots x_P)$ is the covariate vector, and β is the coefficient vector. The standard Cox model assumes the covariates have a proportional effect on the baseline hazard.

Given we have panel data, and are interested in how the impact of various couple characteristics vary with marriage duration, we modify the standard model as follows:

$$h(t, X, Y(t)) = h_0(t)\exp\left[\sum_{p=1}^{P}\psi_p X_p + \sum_{m=1}^{M}\gamma_m Y_m(t)\right], \tag{A1}$$

where ψ_p and γ_m are the coefficients corresponding to the p^{th} time-independent variable and the m^{th} time-dependent variable, respectively. The model is then estimated via maximum likelihood.

Figure A7 presents the estimated hazard ratios originating from the estimation of Equation A1. A value of one (highlighted by the vertical line) indicates no change in the divorce hazard with a one unit change in each variable, while values above one indicate an increase in the divorce hazard. The dots represent the point estimates and the horizontal lines indicate the 95 percent confidence interval. We include all covariates used in the estimation except for the region indicators. To avoid multicollinearity, we omit predictors that are highly correlated. This differs from our random forest estimation where multicollinearity is at least partially accounted for with random feature selection.

Overall, the results are largely similar to the findings from the random forest specification. The wife's satisfaction with the relationship is strongly predictive of divorce, with the sign of the relationship in the expected direction. Other factors that increase the probability of divorce are the wife's income, the number of children over 6, and the budget share of public goods. Given the strong correlation between public expenditures and children in the household, we caution against interpreting these coefficients in isolation.

[34] Other studies to apply the Cox model include Lehrer (1988).

Figure A7: Cox Model

Note: Relative changes the hazard rate associated with a one unit change in each variable, holding all else fixed. Continuous variables are standardized to ease the comparison across coefficients. Region fixed effects are included in the estimation, but omitted from the figure for clarity. Hazard ratios below one indicate a decrease in risk of divorce. Horizontal lines represent 95 percent confidence intervals.