Relationship Skill in the Labor and Marriage Market

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Abstract

This paper examines the role of relationship skills, in conjunction with more general human capital, in determining economic outcomes in labor and marriage markets. Relationship, or “partnering”, skill is understood in our framework as the ability to maintain long-term relationships, both in the formal job market and the home sector. Using a Mincer-Jovanovic (1981) framework and evidence on job and marital separations in the PSID, we argue that relationship skills are naturally modeled as an individual fixed factor that increase the durability of relationships both in the formal work and informal household sectors. Next, we use data from the Occupational Information Network to extract and develop a common factor from measures of non-cognitive skills that reduce divorce and job loss likelihood conditional on partners’ wages and education. We show that this factor operates differently in the market and home sectors in that it is highly complementary in the market sector (jobs that require relationship skills are only productive when filled by workers with this skill, while jobs that do not require partnering skill offer no return to it) but substitutable in the home sector: stability of marriage depends most strongly on one partner being endowed with strong partnering skills. It therefore stands in contrast to measures of more general human capital, such as educational attainment that are highly complementary. We use the PSID to develop and estimate a life cycle model of schooling, job search and marriage that allows us to quantitatively test the importance of partnering skills, including their implications for optimal schooling and occupational decisions, and the joint distribution of relationship skills and human capital in the population.

PRELIMINARY AND INCOMPLETE

1 Introduction

Individual attributes of team members affect team outcomes in three ways: First, the level of team output is affected. Second, the likelihood of team dissolution is also affected. Third, due to the previous two effects, individual attributes also affects who matches with whom.
This paper develops a two-factor model of market- and home-production in which individuals contribute both general human capital and relationship, or “partnering”, skill to their unions at work and at home. Although cognitive skill affects the three team outcomes listed above, our initial empirical evidence show that (i) controlling for years of schooling and the current wage, there remains an individual fixed effect which affects both marital and job dissolutions\(^1\) and (ii), controlling for years of schooling and the current wage, our empirical proxy for relationship skill also affects both marital and job dissolutions.

Using the PSID, we observe the wage, job tenure and occupation for each job. We use the occupations an individual chooses over their career to construct a proxy for the relationship skill of that individual. We do not observe the co-workers who the individual is working with. In the marriage sector, we observe who the individual is matched with if any, and tenure of the relationship. We do not observe home/marital output. Since both skills affect unions in both sectors, we can use outcomes from both sectors to estimate our model.

Since there is no non-cognitive skills module in the PSID, we match occupational data from the O*NET to our PSID sample, to construct an index of partnering skill—what we call \(n\). To do so, we construct individual occupational histories and search for traits implied by the histories that reduce the likelihood that a marital match terminates conditional on current and occupation-predicted wages, marriage tenure and other covariates for the couple. We find evidence that characteristics such as “integrity”, “persistence”, ”adaptability” and, for women but not men, “cooperation” and “concern for others”, are the most robust predictors of successful marriages. We derive a common factor from these which is our measure of partnering skill. We find moreover that the spousal \(n\)'s are reasonably strong substitutes in decreasing the likelihood of divorce: specifically that the interaction of husband and wife’s \(n\) is positive and (usually) significant in contrast to the interaction of the spouses’ wages, which is insignificant, and education, which is negative and highly significant.

Even in a market with search frictions, substitutability of \(n\) implies that some degree of “opposites attract” matching is socially optimal. Finally, we also show that our measure of \(n\) is highly sensitive to measures of extraversion – the desire to work with and be around other people which, as in [7], is highly correlated with the likelihood of divorce. Once we control for extraversion, traits that reflect both “people skills” and “partnering skills” become highly significant negative predictors of divorce, particularly for women.

Based on these findings, we turn to estimating a life cycle search model of the labor and marriage markets using a variety of demographic information to identify the parameters of

\(^1\)This finding is consistent with [9] and inconsistent with simple search models of the labor or marriage market.
the model, including moments of the schooling and occupational distributions, the profile of average wages over the life cycle, and marital sorting across education and $n$. Individuals with higher $n$ are more likely to remain longer in school and receive higher lifetime returns to education on average. We back out initial distributions of social and cognitive skills and study differences in these initial distribution across gender. Finally we do some counterfactual experiments to show how much partnering skills matter vis a vis human capital in explaining why people make the choices they do and the relative value of partnering skills for life outcomes.

Our paper is related to and builds on several recent strands of the economics and psychology literature. Most recently, [12] and [13] also map job histories to individual skill sets using the PSID merged to data from the Dictionary of Occupational Titles, the predecessor to the O*NET. [13] uses this mapping to study the long-term decline in the gender wage gap as returns to cognitively skills, in which neither gender has a strong comparative advantage, rises relative to the return to motor skills in which men have a comparative advantage. [13] estimates the return to skills over the life cycle and rationalizes the steeper slope of the life cycle wage profile of high educated workers to the relatively slow depreciation of cognitive skills, relative to manual skills, with age. Like us, Yamaguchi argues that life cycle occupational profiles provide a noisy measure of an individual’s skills, since individuals will seek out those occupations (understood as task bundles) that offer the highest return to an individual’s skill bundle. Yamaguchi’s work differs from our model in four major ways. First, unlike us, [12] and [13] consider a frictionless job search environment. Second, Yamaguchi considers cognitive and motor skills as his two factor model of individual labor market productivity. We consider cognitive and relationship skills. Third, his empirical work, and thus identification strategies, uses data only from the labor market. Our empirical work and identification strategy use data from both the labor and marriage market. Finally, he is focused on occupational matching in the labor market whereas we focus on firm matching in the labor market. So there are several broad similarities and differences between our papers, and his papers are complementary to ours.

Also related to our project, there is a large literature on the effect of non-cognitive ability on labor market and other social outcomes. [4] found that early childhood intervention can effect children’s outcomes in terms of schooling completion, risky behavior and labor market outcomes by raising their non-cognitive ability, even with IQ fixed. Recently, [6] show that non-cognitive ability, based on a psychological assessment, is actually a better

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2Empirically, part of our relationship skill is embedded in his cognitive skill measure. We ignore motor skills primarily because we want the two skills to be operative in the marriage market as well.
predictor of labor market attachment than cognitive ability among Swedish men. Their finding relies on the fact that non-cognitive skills affect all jobs that men in their sample may have, while strong cognitive skills are important only for a relatively refined subset of jobs. In a recent working paper, [7] reports similar findings on the importance of non-cognitive traits for the marriage market: among the “big five” personality traits which are measured for all participants in the German Socio Economic Panel Survey, she finds evidence that certain traits are positive predictors of marriage and negative predictors of divorce, while extroversion (for men) and neuroticism (for women) are positive predictors of both marriage and of divorce conditional on marrying.

Finally, several previous papers attempt to integrate marriage market and labor market outcomes. [11], using the PSID, show that the likelihood of divorce rises with negative wage shocks experienced by one member of the couple and [10] shows the same effect, albeit more weakly, for for disability shocks using the SIPP. Using Canadian longitudinal data, [3] argue that negative shocks (both wage or disability shocks) experienced by one member of a couple may lead to a renegotiation of the marital surplus away from that member and toward the healthier/more productive spouse as well as raising the likelihood of divorce, and that approximately 40% of marital terminations can be attributable to observable changes in the relative economic situations of the spouses. Our paper follows these papers in developing a framework that sheds light on the relative roles of observable economic vs. unobservable shocks, and of earning ability vs. personality, in determining the incidence of divorce. Consistent with recent findings by [8], non-cognitive traits are fully observable to spouses (and household consumption is public and hence non-renegotiable) but match quality evolves over time, with couples with worse non-cognitive traits being more prone to negative shocks to match quality, as well as to economic disruptions such as job loss. While we do not explicitly consider a measure of non-cognitive skill or “personality traits” from the psychological literature, our framework therefore allows us to gain insight into the relative contribution to ex-ante (expected) match quality of both partners’ partnering skills as well as whether the partners’ social capacities are substitutes or complements in the production of marital surplus.

The layout of the paper is as follows. In section 3.1, we develop our life cycle model with education, marriage, work and retirement. Section 2 describes our data sources. Section ?? presents preliminary results from the model. Conclusions are omitted for the time being.
2 Empirical evidence: job separations, marital breakdowns and relationship skill

In this section we describe our data sources and some of the motivating evidence for our model.

2.1 Job separations and marital breakdowns in the PSID

We begin by assessing a possible fixed effect determining both negative job separations and marital separations in the PSID, where the two concepts are defined in detail below. [9] presented an early challenge the standard Markov labor search model by reporting results from a regression of current job separation status among a sample of relatively young workers in the PSID on a vector of covariates including age, education and tenure with the present employer and a variable capturing the number of prior job separations. In a purely Markov framework, the number of prior separations should have no effect on the likelihood of a current separation. However, the authors show that the number of prior separations in fact has a positive and significant effect on the likelihood of separating today. Mincer interprets this finding as evidence against the historyless model of job search: workers may have fixed, unobservable, characteristics that make the likelihood of separation more likely for them than for other workers.

Using a modified PSID sample for the years 1975 to 2009, we extend Mincer’s regressions to examine both job and marriage separations. Specifically, we run a pair of regressions in which the dependent variable is (1) an indicator of negative job switching; (2) an indicator of impending marital separation.

1. Negative job separations. A “negative’ job separation is one that can be identified as either involuntary or leaving the job holder in worse shape economically after the separation. In general, it is not straightforward to identify this type of worker-employer separation in the PSID. In particular, there is no single variable that or set of variables that directly measures whether a job switch was due to the worker being laid off or fired from her previous job, or if the separation occurred in response to a better opportunity elsewhere. More generally, we can not directly observe whether a job switch was desirable, economically, for the worker experiencing it.

To circumvent this problem, we combine information from several variables available in the PSID. First, we identify an employer switch using information on a worker’s reported tenure with the current employer. Following the definition in [5], we identify
an employer switch for an individual if reported employer tenure falls by more than 12 months prior to the current interview. Next, to distinguish likely beneficial from likely negative splits, we use two indicators, either of which we assume is sufficient to identify a negative switch. First, a negative switch is indicated if the individual reports spending more than a week in search unemployment during the year the switch was reported, since moves through search unemployment are generally inconsistent with job switches arising from successful on-the-job search. Second, a negative split is indicated if the the worker’s hourly wage averaged across the year following the switch and the subsequent sample period is lower than the hourly wage reported averaged over the preceding two years in the old job. If neither condition is met when the worker changes jobs—that is, if he spends no time in unemployment and experiences a medium-term increase in his hourly wage—we identify the job change was a “positive” move up the career ladder. The negative switch rate is roughly 7% per year and slightly higher for women than for men.

2. **Marital separations.** To construct a measure of marital separation, we simply follow individuals’ reported marital status. A marital separation is indicated whenever an individual reports her marital status as “married” (which includes cohabiting) in one year but either unmarried or divorced (but not widowed) in the following period she is observed. We do not consider individuals who continuously report being married but whose spouse’s personal identifier changes, suggesting a (generally desirable) marriage-to-marriage transition. The share of divorces among total married observations in the sample, which we also take as the unconditional divorce hazard, is 2.2%.

In the regressions, that follow, the independent variables include age, education, the ln wage in the previous year (prior to the switch in (1)), tenure in the current job (in (1)) and the current marriage (in (2)) and measures of the number of total prior negative job losses and divorces of the individual. We limit the sample to married men and women (specifically

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3 Under this definition, we include switches to previous employers or secondary jobs, though the vast majority (over 90%) of observed switches are to new jobs with tenure less than 12 months (or 24 months after 1997).

4 If wage information is missing in any of the four years that enter the calculation, we omit the year from the calculation. This relaxation is especially important after 1997 because the period over which pre- and post-wages are calculated spans up to eight years. If no wage is observed in either the year following the switch because the worker left his new job and remained unemployed, the the switch is counted as negative. However, since the switch is identified by a change of employers, exits from an old job into unemployment are not counted as switches. In general, these may be positive or negative separations and are omitted by construction.

5 This type of transition accounts for less than one percent of total marital separations.

6 We also include, but do not report, year dummies a measure of the current number of periods we have observed an individual in the sample to control for attrition bias. Specifically, individuals who remain
heads and wives of PSID families) between the ages of 25 and 56 who worked in the previous year and report being in the labor force (either working or searching for work) in the current year; who have been observed for at least eight sample periods; and who were under the age of 50 when first observed.7

Linear probability and probit results are reported separately for men and women in tables 1 and 2. The results across the two estimators are similar. Likelihood of negative job loss and of divorce both decline significantly in age and education for both genders. The likelihood of job termination also declines with tenure in the current job, consistent with [9]’s findings, while the likelihood of divorce declines with marriage tenure, also as expected.

The key results are reported in the final three rows of the tables.

First, conditional on the lag ln wage and other covariates, the effect of schooling on negative job separations is statistically insignificant for both men and women. To a first order, the lag wage captures the general human capital effect on job separations (we probably need at least a footnote to show that education matters when we do not include the wage). In contrast, conditional on the lag ln wage and other covariates, the effect of schooling on the incidence of divorce is negative and statistically significant. Our interpretation is general human capital, as proxied by schooling, has a negative effect on divorce which is not mediated through the wage. In fact, conditional on the other covariates, the wage has no effect on divorce.

Second, the results demonstrate that Mincer’s criticism of Markov job search models extends to the household sector: specifically, the number of previous negative job terminations and the number of previous marital terminations are independent predictors of the likelihood of a current job switches for both men and women. Previous negative job switches and previous marital terminations are also strong independent predictors of the likelihood of a current divorce for both men and women in both the linear probability and probit models.

Table 3 also shows results from similar regressions using the ln wage as the dependent variable. For men, again both the tally of previous job losses and of previous marital separations has negative implications for the current wage, even conditional on the wage observed last period. For women, the situation is slightly different: lagged job losses negatively effect the predicted current wage, but lagged divorces have a positive, insignificant effect on the

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7 Between 1969 and 1997, PSID households were interviewed annually. Since 1997, households are interviewed only every two years, though the reference period (over which retrospective information is gathered) remains one year. In practice, since we consider only individuals who have already appeared at least eight times in the sample, the earliest year in our regressions is 1976.
Table 1: Separation likelihood and previous separations: Men

<table>
<thead>
<tr>
<th></th>
<th>Linear probability model</th>
<th></th>
<th>Probit model</th>
<th></th>
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<td>Marriage sep</td>
<td>Job sep</td>
<td>Marriage sep</td>
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<td>(2)</td>
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<td>(4)</td>
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<td>-.020 (.010)**</td>
<td>-.329 (.111)***</td>
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<td>.0004 (.0002)*</td>
<td>.007 (.003)**</td>
<td>.004 (.003)</td>
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<td>age^3</td>
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<td>-.00003 (.00003)</td>
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<td>-.0009 (.0003)**</td>
<td>-</td>
<td></td>
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<tr>
<td>marriage tenure</td>
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<td>-.036 (.004)***</td>
<td></td>
</tr>
<tr>
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<td>-.001 (.0003)***</td>
<td>-.006 (.005)</td>
<td>-.023 (.005)***</td>
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<td>lag ln wage</td>
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<td>-.005 (.001)***</td>
<td>-.193 (.016)***</td>
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<tr>
<td>previous job switches</td>
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<td>.001 (.006)**</td>
<td>.167 (.006)***</td>
<td>.023 (.009)***</td>
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<tr>
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<td>.025 (.004)***</td>
<td>.109 (.019)***</td>
<td>.201 (.031)***</td>
</tr>
</tbody>
</table>

predicted current ln wage. One potential explanation is selection. A large body of evidence show that women suffer significantly greater economic losses from divorce than than men. Anticipating this loss, women who are more at risk of divorce are more likely to be attached to the labor force (Johnson and Skinner 1986), which in turn lead to higher wages. We return to this issue in the context of our model in section ?? [Laura: reminder to redo table as wage changes. also create a predicted negative separation index from tables 1 and 2 as a covariate. this will make the interpretation closer to our model]

2.2 Identifying relationship skill in the PSID and O*NET

Our second major data source is the U.S. Department of Labor’s Occupational Information Network, the O*NET. While the PSID follows households over time and provides a wide va-
### Table 2: Separation likelihood and previous separations: Women

<table>
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<tr>
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<td>Marriage sep</td>
<td>Job sep</td>
<td>Marriage sep</td>
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<td>-.006</td>
<td>-.029</td>
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<td>(.0004)***</td>
<td>(.003)***</td>
<td>(.003)***</td>
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<td>marriage tenure</td>
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<td>-.002</td>
<td>-.029</td>
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<td>(.0004)***</td>
<td>(.003)***</td>
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<td>(.006)</td>
<td>(.007)***</td>
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<td>-.282</td>
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<tr>
<td></td>
<td>(.04)***</td>
<td>(.01)</td>
<td>(.020)***</td>
<td>(.018)</td>
</tr>
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</table>

previous job switches | .006                     | .003                  | .042         | .036                 |
|                      | (.002)***                | (.009)***             | (.010)***    | (.010)***            |

previous divorces    | .022                     | .022                  | .129         | .183                 |
|                      | (.004)***                | (.004)***             | (.021)***    | (.030)***            |

The variety of demographic and life cycle information, the O*NET provides detailed information at the occupational level for each of about 800 occupations, which can be mapped easily, though with some loss of information, into the 2000 US census categories at the 3-digit level. This information includes the set of tasks that workers in the occupation are required to perform, and measures of the the skills, interests, and personal attributes that promote success in the occupation. For each occupation, the “importance” of different skills and attributes, and the “relevance” of different tasks are reported along numeric scales typically taking values between 1 and 5, where 1 means “unimportant/irrelevant” and 5 means “extremely important/relevant”. Data is provided by subjective responses from a random sample of workers within occupations (“occupational incumbents”) and in some cases by

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8 The average household in our sample is observed in nineteen different (usually but not always sequential) years
outside occupational or human resource experts ("analysts"). In what follows, we focus on the information provided by occupational incumbents in the Work Contexts file, on different personality traits or attributes that are important to success in the occupation.

We merge the O*NET to the PSID on occupation for each person-year observation. Occupation in the PSID is reported at the three-digit level using census codes. From 1969 to 2001, occupation follows 1970 census classification codes, after which it switches to the 2000 census codes. We use crosswalks provided by IPUMS (and supplemented in a few cases by subjective matching based on examination of the occupational definitions) to map 1970 into 2000 census codes and then to map the 2000 codes into six-digit O*NET-SOC codes. The O*NET-SOC codes are then used to merge the O*NET data to the PSID sample. We are able to match over 99.5% of PSID respondents who report a current occupation to the

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Table 3: ln wages and previous separations

<table>
<thead>
<tr>
<th></th>
<th>ln wage: men</th>
<th>ln wage: women</th>
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<td>job tenure</td>
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<td></td>
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<tr>
<td></td>
<td>(.007)***</td>
<td>(.007)</td>
</tr>
</tbody>
</table>

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9This is a many-to-one match: there are roughly 500 three-digit census occupational codes compared to 800 O*NET-SOC codes. The ONET-SOC codes are nine-digit codes with the final three digits providing a further level of disaggregation than what is available in the census. We are not able to use the information provided by the final three digits of the ONET-SOC codes.
To gain a measure of relationship or “partnering” skill for PSID respondents, we use an argument similar to [13]: that we can observe a noisy measure of various individual attributes or skills by examining individuals’ job histories: in particular the amount of time they spend, and their apparent success, in occupations requiring interpersonal skills that reflect a given concept of partnering or relationship skill, which we call $n$. We construct candidate measures of $n$, called $\hat{n}$, using the following simple algorithm: for each individual in the PSID, we calculate the average of the given measure of $n$ associated to his occupation in a given year across all years in which he reports an occupation, weighting by the length of the job spell so that the $\hat{n}$ of longer spells is given (linearly) higher weight. An individual is then categorized as “high $\hat{n}$” if his average $\hat{n}$ lies above the gender-specific 50th percentile in the distribution of $\hat{n}$ in the entire PSID sample. Once $\hat{n}$s is constructed for each worker in the sample, we examine how it affects the likelihood of separation among PSID couples. Since we observe different $\hat{n}$s for both partners in a marriage (conditional on both partners having some labor market attachment over the course of the panel), this is a two-sided analysis that may be informative about how partners’ $n$ jointly affect the stability of marriage. Since the $\hat{n}$s are fixed effects, we believe we can credibly argue that they affect marriage only through their implications about the partners’ characters rather than their economic implications, conditional on the partners’ permanent occupational wages. We also test whether the $\hat{n}$ are negatively related to the likelihood of job switching during an individual’s career, though this is only suggestive since jobs that demand high $\hat{n}$ may have exogenously higher or lower turnover rates that will obviously be correlated with the estimated $\hat{n}$.

### 2.2.1 Constructing $n$

To construct different candidate measures of $n$--$\hat{n}$s--we examine measures of individual characteristics from the Work Contexts O*NET file. The work context file has several attractive properties from our perspective: first, it ascertains from occupational incumbents information on personality traits that are likely inherent rather than formally learned and can be related to standard psychological measures such as the “Big Five” personality traits. Second, it provides a manageable amount of information for analysis. There are sixteen metrics arranged into five broad categories. They are:

- Effort, Persistence
- Initiative, Leadership
- Cooperation, Concern for others, Social orientation
- Self control, Stress tolerance, Adaptability/flexibility
- Dependability, Attention to detail, Integrity
- Independence
- Innovation, Analytical thinking

For each married couple in our PSID sample, we construct the sixteen alternative $\hat{n}$ for both the husband and the wife, using the procedure outlined above. We then regress the likelihood that the marriage terminates in the subsequent sample period (i.e. that the couple is no longer cohabiting in the subsequent wave of the PSID) on the partners’ $\hat{n}$s, along with controls for the education, age, and race of each spouse and their interactions, current marriage tenure, permanent occupational ln wage (calculated for each individual in the same way as $\hat{n}$ using occupational history), current ln wage and year dummies. We extract the O*NET variables for which one or both spouses’ $\hat{n}$ significantly reduce the couple’s likelihood of divorce (subject to criteria described below) and use them to create a common factor, which we will call $\tilde{n}$, our preferred measure of which is the measure of relationship skill used to calibrate the model through indirect inference.

We use four different criteria to identify the $\hat{n}$s that negatively affect the likelihood of divorce. These are listed in the four columns of tale 4. In the first approach (column 1), both partners’ $\hat{n}$ must have negative coefficients in the divorce likelihood regression and must be individually and jointly significant at the 10% level. The four “candidates” that satisfy this criterion are “persistence”, “adaptability”, “integrity” and “independence”, all of which in fact continue to show up as significant under the alternative criteria of the next three columns. In the second approach (column 2) the individual $\hat{n}$ must have negative coefficients but only must be jointly significant at the 5% level: a somewhat weaker criterion for inclusion that increases the “qualifying” $\hat{n}$ to include “dependability” and “concern for others” (the former is individually significant for husbands and the latter for wives). In the third approach (column 3), we use the same significance criterion as in column 2, but also control for “Social Orientation” characteristic, which for husbands actually has a positive significant coefficient on divorce likelihood in the regressions reported in columns 1 and 2. This result is not surprising: [7] shows that divorce likelihood is increasing in husbands’ measured level of extroversion, which itself is correlated with other “social” indicators. Consequently, many of the social characteristics we would expect to reduce divorce likelihood, such as cooperation, may be swamped by this correlation; in fact this appears to be the case. Finally, in our fourth criterion (column 4), we include all the candidate $\hat{n}$s in a single regression, retaining those candidates for which at least one spouse’s $\hat{n}$ is a significant negative predictor of the divorce at the 10% level. In what follows, this last approach is the one we use to calibrate the model. Regardless of the approach, “persistence”, “adaptability”, “integrity”
Table 4: Four criteria for $\hat{n}$

<table>
<thead>
<tr>
<th>Both spouses at least 10%</th>
<th>Joint sig at least 5%</th>
<th>Joint sig, Controlling for “social”</th>
<th>At least one sig controlling for all $\hat{n}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Persistence</td>
<td>Persistence</td>
<td>Persistence</td>
<td>Persistence</td>
</tr>
<tr>
<td>Adaptability</td>
<td>Adaptability</td>
<td>Adaptability</td>
<td>Adaptability</td>
</tr>
<tr>
<td>Integrity</td>
<td>Integrity</td>
<td>Integrity</td>
<td>Integrity</td>
</tr>
<tr>
<td>Independence</td>
<td>Independence</td>
<td>Dependability</td>
<td>Cooperation</td>
</tr>
<tr>
<td>Concern for others</td>
<td>Concern for others</td>
<td>Cooperation</td>
<td></td>
</tr>
<tr>
<td>Dependability</td>
<td>Dependability</td>
<td>Effort</td>
<td></td>
</tr>
</tbody>
</table>

and “independence” emerge consistently as negative predictors of divorce, conditional on age, education, race, marital tenure and current wage and occupation-predicted permanent wage. For women, cooperation is also a strong predictor of divorce likelihood conditioning on all other candidates. From each of the four approaches we next derive a common factor $\tilde{n}$ using simple principle component analysis and using the first principle component of the included $\hat{n}$s from each approach, and repeat our analysis with this common factor as our “candidate” $n$. The results from the resulting regressions are reported in Table 5. The regressions are the same as in the individual “candidate” regressions except that we now include not only $\tilde{n}$ for the husband and the wife but also the interaction of the spousal $\hat{n}$s. The bottom row of the table reports the p-value from an $F$ test of the three terms containing the partners’ $\hat{n}$s.

2.2.2 Interpreting $n$

From table 5, we observe a common pattern in the regressions with respect to the common factor $\tilde{n}$: an increase in the trait for either spouse decreases the likelihood of divorce as expected, but the interaction of husband and wife’s trait is positive, and (except for cooperation) significant. This implies that our measure of “relationship skill” can be thought of as a positive substitute trait (or bundle of reinforcing traits), i.e. that one partner’s $\tilde{n}$ is more important to marital surplus when the other spouse’s $\tilde{n}$ is low. Though each interaction is significant only at the 10% level, the pattern is persistent across the different combinations of traits. The functional form for marital output $M$ in our model will allow us to estimate the extent of this substitutability.

Although the coefficients of own schooling on divorce is positive, the marginal effect of own schooling, holding spousal school at 10 years, is negative because the interaction effect is negative. Since most spouses have more than 10 years of schooling, the marginal effect of
Table 5: Divorce likelihood and relationship skill: using a common factors

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>husband's n</td>
<td>-.006**</td>
<td>-.008***</td>
<td>-.008***</td>
<td>-.006***</td>
</tr>
<tr>
<td></td>
<td>(.003)**</td>
<td>(.003)***</td>
<td>(.003)***</td>
<td>(.003)**</td>
</tr>
<tr>
<td>wife's n</td>
<td>-.006</td>
<td>-.007</td>
<td>-.010</td>
<td>-.008</td>
</tr>
<tr>
<td></td>
<td>(.003)**</td>
<td>(.003)***</td>
<td>(.003)***</td>
<td>(.003)***</td>
</tr>
<tr>
<td>hus x wife's n</td>
<td>.005***</td>
<td>.006***</td>
<td>.006***</td>
<td>.006***</td>
</tr>
<tr>
<td></td>
<td>(.004)***</td>
<td>(.004)***</td>
<td>(.003)***</td>
<td>(.004)***</td>
</tr>
<tr>
<td>husband's educ</td>
<td>.005***</td>
<td>.006***</td>
<td>.005***</td>
<td>.006***</td>
</tr>
<tr>
<td></td>
<td>(.001)***</td>
<td>(.001)***</td>
<td>(.001)***</td>
<td>(.001)***</td>
</tr>
<tr>
<td>wife's educ</td>
<td>.003***</td>
<td>.004***</td>
<td>.003***</td>
<td>.003***</td>
</tr>
<tr>
<td></td>
<td>(.001)***</td>
<td>(.001)***</td>
<td>(.001)***</td>
<td>(.001)***</td>
</tr>
<tr>
<td>hus x wife's educ</td>
<td>-.0004</td>
<td>-.0004</td>
<td>-.0004</td>
<td>-.0004</td>
</tr>
<tr>
<td></td>
<td>(.0001)***</td>
<td>(.0001)***</td>
<td>(.00009)***</td>
<td>(.0001)***</td>
</tr>
<tr>
<td>marriage tenure</td>
<td>-.002</td>
<td>-.002</td>
<td>-.002</td>
<td>-.002</td>
</tr>
<tr>
<td></td>
<td>(.0002)***</td>
<td>(.0002)***</td>
<td>(.0002)***</td>
<td>(.0002)***</td>
</tr>
</tbody>
</table>

own schooling on divorce is negative. [Laura: what is the years of mean education in the table?]

While there is no direct link between our qualifying $\bar{n}$s and more standard psychological measures, persistence and integrity are often linked to conscientiousness, one of the “Big Five” personality traits that has been previously found to reduce divorce likelihood, and improve labor market outcomes, for both men and women. Both “adaptability” and “cooperation” are linked to agreeableness, another Big Five characteristic. Independence is likely linked to the absence of neuroticism which, especially for women, Lundberg finds to increase the likelihood of divorce. Factor analysis suggests that the measures in the first four rows of table ?? are highly interdependent with a Kaiser-Meyer-Olkin score of .65.

Finally, we examine the likelihood of experiencing negative job separations for high and low $\bar{n}$ individuals, across jobs that demand “high” and “low” $\bar{n}$ workers based on the O*NET data and using the same 50% cutoff across the entire distribution of filled jobs in the PSID sample. Below, we define the demand for $n$ as $\nu$, where high $\nu$ jobs demand high $n$ workers. Using our preferred criterion (criterion 4), low $\bar{n}$ workers experience annual negative separation rates of 8.5% from high $\nu$ and 8.1% from low $\nu$ jobs, while high $\bar{n}$ workers experience annual negative separations rates of 5.6% from high $\nu$ jobs and 7.2% from low $\nu$ jobs. The effect of $\bar{n}$ on negative separations is consistent with our interpretation of $n$ in the work context, where relationship skills also affects the likelihood of experiencing a negative separation. Specifically, low-$\bar{n}$ individuals are less likely to keep jobs overall, but the effect
of having good relationship skills is more important (by 2.9% vs. 0.9%) to the probability of maintaining high-\(\nu\) jobs that, by definition, require them.

Summarizing, we first create measures of individual’s fixed characteristics based on averaging the characteristics associated with an individual’s occupational histories. We then create an index \(\bar{n}\) summarizing an individual’s relationship skill by combining spouses’ fixed characteristics which predicts couples’ likelihood of divorce holding their schooling, wages, marital tenure and other covariates constant.

3 The model

In this section, we develop a dynamic life cycle model of education, work and marriage to quantify the role of relationship skills and human capital in determining welfare and predicting outcomes.

3.1 Life cycle

Individuals’ lives are divided into three stages: education, working adulthood, and retirement. At all ages \((j)\), adult (post education) individuals differ by their gender \(g\), their human capital \(k_1(j)\), and their relationship or partnering skill \(n\). \(k_1(j)\) is determined by an initial human capital endowment \(k_0\), a schooling investment \(s\), and time spent working as an adult. \(n\) is a fixed endowment that does not vary with age, schooling or labor market attachment. \(k_0\) and \(n\) are drawn from gender-specific distributions \(\{\Omega_0^g, \Omega_n^g\}\) which are discreet joint distributions of \(k_0\) and \(n\), each characterized by a \(\sigma_{k_0n}^2\) measuring the within-gender correlation between \(k_0\) and \(n\). As adults (post education) individuals may be unemployed or employed with a job defined by “complexity” \(\kappa \in \{1, 6\}\) and relationship skill requirement \(\nu \in \{1, 2\}\), with \(\kappa = \nu = 0\) when the individual is unemployed. Adult individuals may be married \(M\) or single \(S\).

3.1.1 Stage 1: Education

At age 16, individuals know their \(k_0\) and \(n\) and make an education decision, which is a discreet choice over the amount of time to remain in school: \(s \in \{0, 2, 4, 6, 8, 10\}\), roughly corresponding to dropping out of high school, finishing high school, going to college, going to university, going for a Masters or business degree, or going for a technical post graduate degree such as medical or law school, or a PhD. The investment returns final human capital
$k_1$ according to

$$k_1 = f(k_0, s, \epsilon_s) = k_0^0 s^{1-\alpha} \exp(\epsilon_s)$$

(1)

where $\epsilon_s \sim N(0, \sigma_s^2)$ is a shock realized at the end of the chosen education period. Since individuals do not receive job offers during the education phase, their optimal choice of education decision does not change until their education is complete. Note that $k_1$ does not directly depend on social skills $n$. Individuals with high $n$ may choose to invest more years of schooling.

$\epsilon_s$ allows the individual to have $k_1$ not be a deterministic function of $k_0$ and $n$. It will also generate long run differences in wages across individuals which are not due to differences in $k_0$ and $n$.

Education is costly in three ways. First, there is a direct period cost of education per period which varies across individuals and reflects both non-pecuniary costs like distaste for studying or differential access to tuition funding. The direct cost per period, $C$, is randomly distributed across individuals with mean $\overline{C}$ and variance $\sigma_C^2$. Second, the individual incurs an indirect cost which is the opportunity cost of not working in the labor market for that period. Finally, while receiving education, individuals receive their income from unemployment insurance (described below) which is increasing in productive skills $k_0$ and $n$. Thus the net indirect cost of schooling per period is lower than what it otherwise would be. A model period is 2 months. But we only allow schooling choices by increments of two years to reduce the state space.

3.1.2 Stage 2: Adulthood, work and family

Once individuals finish their education, they enter the labor market and begin searching for work. They simultaneously enter the marriage market and begin searching for a partner. During adulthood, individuals can marry a new partner or divorce a current partner only at the beginning of each year. Job decisions, in response to new offers, are however made bi-monthly so as to achieve a realistic model of employment transitions and unemployment.

**Work** Individuals enter the labor market unemployed with human capital $k_1(j)$, where $j$ is the first age after completed education. While unemployed, they receive a single job offer every two months with probability $p_0$, drawn from the distribution of available job openings $\Pi$. A job offer is characterized by the doubleton $(\kappa, \nu)$. Workers make take it or leave it offers to potential employers and so extract all the surplus in the form of per period wages.
Production depends equally on both the worker and job characteristics (in both learned skill and relationship skill) according to a nested CES, where for simplicity the relative contributions to output of the learned skill-capital complexity match and the relationship skill match follow a Cobb-Douglas specification. Production each two-month period is subject to a standard exponential IID shock $\epsilon_W$, and jobs with higher skill demands have higher fixed capital costs governed by $f_0$ and $f_1$. The latter feature ensures that low skilled workers may not accept high $(\kappa, \nu)$ jobs because they may not be able to overcome the capital costs of those jobs. When employed, workers supply one unit of fixed labor time to each job. Jobs are assumed to never die while the distribution of worker types in the economy is constant. Therefore the distribution $\Pi$ is time-invariant.

Once matched, a worker remains on the job until one of two things happen. First, the worker may leave for a higher-paying (higher $\kappa$ or higher $\nu$) job, though the attractiveness of these jobs depends on $k$ and $n$ due to their fixed costs. Job offers drawn from the (endogenous) distribution of vacancies arrive for employed workers with probability $p_1$. Second, the job may terminate because the wage shock $\epsilon_W$ is sufficiently negative to make unemployment more attractive.

Unemployment benefits, which are also study and retirement benefits, are simply given by $(.5k_1)^{\varepsilon}(.5n)^{1-\varepsilon}$, reflecting the fact that unemployment benefit are typically based on potential earnings.

Also while employed, individuals inside the “frontier” of their learned skill – that is, with $\kappa \geq k$ receive a permanent unit increment to $k_1$ at the start of each year with probability $p_k$ due to learning by doing on their current job. Unemployed workers and workers working in jobs off their skill “frontier” are not eligible for experience increases in $k_1$.

**Family** After finishing school as singles, individuals meet potential mates each year with probability $\pi$ while single and zero while married. There is perfect assortative mating by age. While single, individual $g$ (of gender $g = m$ or $g = f$) at age $j$ generates output given by:

$$S^g = W(k_1, \kappa, n, \nu)^{\lambda_1} n^{1-\lambda_1}$$

Utility is given by:

$$U_g^S = \ln \left( W(k_1, \kappa, n, \nu)^{\lambda_1} n^{1-\lambda_1} \right) - \psi^g I_{work}$$

$$W(k_1, \kappa, n, \nu) = a_g \left( 5(k_1^2 + \kappa^2)^{\frac{\varepsilon}{2}} \right)^{\varepsilon} \left( 5(n^0 + \nu^0)^{\frac{1}{2}} \right)^{1-\varepsilon} \exp(\epsilon_W) - f_0 \kappa f_1 \nu^{1-f_1}$$

$$\epsilon_W \sim (N, \sigma_w^2)$$

(2)
Equations 3 and 4 say that singles enjoy consumption from earned income and from their relationship skill (which affects their enjoyment of leisure) and experience disutility from working (when $I_{work}$ is equal to 1).

Marriages produce output $M$ which is shared by both members of the couple:

$$M = M(W_f, W_m, n_f, n_m, \epsilon_M)$$

$$= \left(b(0.5W_f^\phi + 0.5W_m^\phi)^{\frac{1}{\lambda}}\right)^{\lambda M} \left((0.5n_f^\chi + 0.5n_m^\chi)^{\frac{1}{\chi}}\right)^{1-\lambda M} \exp(\epsilon_M)$$

(5)

$\epsilon_M \sim (N, \sigma_M^2)$

Each spouse’s individual utility is given by

$$U_g^M = \ln(M) - \psi^g I_{work}$$

(6)

Equation (5) has a similar construction to equation (2) governing the wage: it determines the production of utility within a two member household or husband wife team. $b$ is a scale factor capturing economies of scale in consumption in the marriage. $\phi \in (-\infty, 1]$ captures the degree of substitutability in spousal incomes: the higher $\phi$, the more substitutable in marital utility are spousal incomes as suggested in [1] and [2]. The same argument applies to $\lambda$ which governs the degree of substitutability in relationship skill $n$. $\epsilon_M$ is a transitory exogenous shock to $M$ which is experienced by couples who have been married at least one year. The variance of this “conflict” shock depends on the social capacity $n$ of both the partners in a way we allow to be pinned down in the model. Couples with higher levels of $M$ are more able to deal with transitory conflicts implied by low values of $\epsilon_M$.

Matched pairs marry if the value of being married to the current matched partner and receiving $M$ is greater than the continuation value of remaining single and drawing new potential mates in the future. In the first year of marriage we assume that $\epsilon_M = 0$. Similarly, a marriage continues so long as the continuation value of the current marriage (following the realization of $\epsilon_M$) is greater for both partners than the continuation value of re-entering singlehood and searching for a new mate. Marriage decisions are sketched out in section 3.2 below.

3.1.3 Stage 3: Retirement

At age 66 individuals retire and receive a pension based on their final human capital $k_1(66)$ and $g$ which is the same as the unemployment benefits, depending only on $k_1$ and $n$. Married and single output is the same as before. Everybody dies with certainty at age 80.
3.2 Individual Optimization

Next we sketch the individual value functions associated with the life cycle problem for each type of adult worker: married and unmarried, employed and unemployed.

**Single unemployed.** During the working life, a single unemployed individual of gender \( g \) has state vector \( x_g = \{j, k_1, n, \kappa, \nu\} = \{j, k_1, n, 0, 0\} \) where \( j \) indexes age. We begin by defining the value function that governs optimal behavior in subperiod 5 of 6:

\[
V_g^S(j, k_1, n, 0, 0) = \ln S + \beta \left( (1 - \eta) \left( (1 - p_0) V_g^S(j + \frac{1}{6}, k_1, n, 0, 0) \right) + p_0 \sum_{\hat{\kappa} \in \{1, 5\}} \sum_{\hat{\nu} \in \{1, 2\}} q(\hat{\kappa}, \hat{\nu}) V_g^S(j + \frac{1}{6}, k_1, n, \hat{\kappa}^*, \hat{\nu}^*) \right) + \eta \left( (1 - p_0) \sum_{X_{-g}} \varrho(x_{-g}) V_g^M(j + \frac{1}{6}, k_1, n, 0, 0, x_{-g}) \right) + p_0 \sum_{\hat{\kappa} \in \{1, 5\}} \sum_{\hat{\nu} \in \{1, 2\}} q(\hat{\kappa}, \hat{\nu}) \sum_{X_{-g}} \varrho(x_{-g}) V_g^M(j + \frac{1}{6}, k_1, n, \hat{\kappa}^*, \hat{\nu}^*, x_{-g}) \right) \right) \tag{7}
\]

where \( \hat{\kappa}^*, \hat{\nu}^* = \arg\max [V_g^S(j + \frac{1}{6}, k_1, n, \hat{\kappa}, \hat{\nu}), V_g^S(j + \frac{1}{6}, k_1, n, 0, 0)] \); \( V_g^M \) is the value function of a married individual, defined below; \( X_{-g} \) is the set of individuals of the opposite gender who are “marriageable”: that is, who are willing to marry individual \( g \) next period given his own vector \( x'_{g} \equiv \{k_1, n, \hat{\kappa}^*, \hat{\nu}^*\} \) and who he finds it optimal to marry in state \( x'_{g} \). The distribution of singles in the population, and resulting conditional densities \( \varrho \), are determined endogenously through marriage decisions. The distribution of vacant jobs, and resulting unconditional densities \( q \), are also determined endogenously given an overall time-invariant distribution of jobs. Note that the value functions incorporate the discretization of \( \kappa \) into six levels used in the simulations.

The bellman equation (7) therefore has five parts. The individual receives an immediate payoff \( \ln S \) from consuming the bundle of commodities \( S \) produced from his income and social activity. His future payoff depends on whether he receives a job offer next period and whether he meets a marriageable partner. If neither event occurs, he ages by two months and remains single and unemployed. If he receives a job offer \( \{\hat{\kappa}, \hat{\nu}\} \), he chooses whether to take the job or remain unemployed and wait for a better offer. If, conditional on his job offers and acceptance decisions, he meets a marriageable mate, they form a household. For analytical simplicity and to avoid non-cooperative game-playing among potential spouses, job offers and marriage offers occur sequentially at the start of the year: the individual first makes his work decision and then his marriage decision conditional on his new work status.
In each of the other 5 subperiods of the year, the individual solves a simpler problem:

\[
V_g^S(j, k_1, n, 0, 0) = \ln(S) - \psi^g + \beta \sum_{k_i=k_1}^{k_1+i_k} \left( \tilde{p}(k_1, k_1') \left( \left( 1 - \eta \right) \left( 1 - p_1 \right) V_g^S(j + \frac{1}{6}, k_1', n, \kappa^*, \nu^*) \right) \right)
\]

\[
+ p_1 \int_{\epsilon_w} \sum_{\kappa \in \{1, 2\}} \sum_{\nu \in \{1, 2\}} q(\kappa, \nu) V_g^S(j + \frac{1}{6}, k_1', n, \kappa^*, \nu^*)
\]

\[
+ \eta \left( (1 - p_1) \sum_{X_{-g}} q(x_{-g}) V_g^M(j + \frac{1}{6}, k_1', n, \kappa^*, \nu^*, x_{-g}) \right)
\]

\[
+ p_1 \sum_{\kappa \in \{1, 2\}} \sum_{\nu \in \{1, 2\}} q(\kappa, \nu) \sum_{X_{-g}} q(x_{-g}) V_g^M(j + \frac{1}{6}, k_1', n, \kappa^*, \nu^*, x_{-g})) \right)
\]

(8)

where, as before, \( \kappa^*, \nu^* = \arg\max[V_g^S(j + \frac{1}{6}, k_1, n, \kappa, \nu), V_g^S(j, k_1, n, 0, 0)] \). the maximization governs the individuals’ optimal job search strategy in between marriage opportunities which arise only at the start of every year.

The value function for a single worker with a job characterized by \( \{\kappa, \nu\} \) is given by:

\[
V_g^S(j, k_1, n, \kappa, \nu) = \ln(S) - \psi^g + \beta \sum_{k_i=k_1}^{k_1+i_k} \left( \tilde{p}(k_1, k_1') \left( \left( 1 - \eta \right) \left( 1 - p_1 \right) V_g^S(j + \frac{1}{6}, k_1', n, \kappa^*, \nu^*) \right) \right)
\]

\[
+ p_1 \int_{\epsilon_w} \sum_{\kappa \in \{1, 2\}} \sum_{\nu \in \{1, 2\}} q(\kappa, \nu) V_g^S(j + \frac{1}{6}, k_1', n, \kappa^*, \nu^*)
\]

\[
+ \eta \left( (1 - p_1) \sum_{X_{-g}} q(x_{-g}) V_g^M(j + \frac{1}{6}, k_1', n, \kappa^*, \nu^*, x_{-g}) \right)
\]

\[
+ p_1 \sum_{\kappa \in \{1, 2\}} \sum_{\nu \in \{1, 2\}} q(\kappa, \nu) \sum_{X_{-g}} q(x_{-g}) V_g^M(j + \frac{1}{6}, k_1', n, \kappa^*, \nu^*, x_{-g})) \right)
\]

(9)

There are three differences between (9) and (7). First, individuals face job arrival probability \( p_1 \) rather than \( p_0 \), which is the arrival rate of job offers among the employed. In general, individuals will only take advantage of new job opportunities if their expected income over the expected duration of the job is greater than the same expected income over the same duration of time from keeping their current job. Second, individuals experience wage shock \( \epsilon_w \) in their current job. If no job offer is received, then \( \{\kappa^*, \nu^*\} \) is equal to \( \arg\max\{V_g^S(j + \frac{1}{6}, k_1', n, \kappa, \nu), V_g^S(j + \frac{1}{6}, k_1', n, 0, 0)\} \). If a job offer is received, \( \{\kappa^*, \nu^*\} \) is equal to \( \arg\max\{V_g^S(j + \frac{1}{6}, k_1', n, \kappa^*, \nu^*), V_g^S(j + \frac{1}{6}, k_1', n, \kappa^*, \nu^*)\} \), where \( \kappa^*, \nu^* \) has the same meaning as given above for (7). Note that this implies that job offers are received first, before the realization of \( \epsilon_w \): the decision to change jobs is made prior to the decision to quit either the old or new job. Lastly, as previously stated, marriage offers arrive only after the job transition decisions are made. Third, with probability \( \tilde{p}(k_1, k_1 + i_k) = p_K \), working individuals receive a positive increment of \( t_k \) to their adult learned human capital from learning by doing on the current job\(^{10}\): since this improvement in \( k_1 \) is based on work in the previous

\(^{10}\)and \( \tilde{p}(k_1, k_1) = 1 - p_K \). \( \tilde{p} \) is of course a function of \( k_1 \) and \( \kappa \). The notation is introduced
subperiods, this increment accrues even if the individual is unlucky and draws a negative wage shock $\epsilon_W$ in the current period that induces him to quit the current job.

The sub-period Bellman equation is also identical to (8), subject to the same three modifications described directly above. We omit it for space.

We next turn to the value functions for married individuals. A married household maximizes a household-level utility function $U_M$:

simply to shorten notation in the value function.
References


