Relationship Skills in the Labor and Marriage Markets

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Abstract

This paper examines the role of relationship skills in determining life cycle outcomes in the 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. In both empirical and numerical analysis, 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 fairly substitutable in the home sector: stability of marriage depends most strongly on at least *one* partner, rather than both partners, 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 affect 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 after controlling for years of schooling and the current wage, there remains an individual fixed effect which affects both marital and job dissolutions[1].

Psychologists and other researchers, including recently economists, have concluded that non-cognitive skills also affect individual outcomes. Since we are focussing on marital and job dissolutions in this paper, we consider relationship/partnering/communication skill as the non-cognitive skill of interest. Relationship skill, n, as will be shown below empirically, is a bundle of non-cognitive skills some of which are known to psychologists.

In the PSID, there is no direct measure of relationship skill, n. We observe the wage, job tenure and occupation for each job. We match occupational data from the O*NET to our PSID sample, to construct an index of partnering skill— $\widehat{n}$. 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. Our empirical proxy, $\widehat{n}$, affects both marital and job dissolutions after controlling for years of schooling and the current wage.

Moreover, the spousal $\widehat{n}'s$ are reasonably strong substitutes in decreasing the likelihood of divorce: specifically that the interaction of husband and wive's $\widehat{n}$ 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.

Substitutability of $\widehat{n}$ in determining divorce raises the question as to whether there is negative assortative matching by $\widehat{n}$ in marriage.

The above empirical evidence show that our empirical proxy, $\widehat{n}$, for relationship skills, n, affects marital matching, job and marital dissolutions. Job and occupational tenures are endogenous. We ignored this endogeneity in our construction of $\widehat{n}$. Also, the distributions of educational attainment by gender are endogenous. Thus they are also not necessarily the distributions of initial cognitive abilities in the society.

[1] This finding is consistent with Mincer and Jovanovic (1981) and inconsistent with simple search models of the labor or marriage market.

To obtain the initial bivariate distributions of skill in the population by gender, 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 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 life time returns to education on average. We back out initial distributions of relationship 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, Yamaguchi (2012a) and Yamaguchi (2012b) 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. Yamaguchi (2012b) 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. Yamaguchi (2012b) 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, Yamaguchi (2012a) and Yamaguchi (2012b) 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.[2] 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. Heckman et al. (2006) found that early

[2]Empirically, 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..

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, Lindqvist and Vestman (2011) show that non-cognitive ability, based on a psychological assessment, is actually a better 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, Lundberg (2010) 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. Weiss and Willis (1997), using the PSID, show that the likelihood of divorce rises with negative wage shocks experienced by one member of the couple and Singleton (2009) shows the same effect, albeit more weakly, for for disability shocks using the SIPP. Using Canadian longitudinal data, Gallipoli and Turner (2013) 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 the roles of observable economic vs. unobservable shocks, and of earning ability vs. personality, in determining the incidence of divorce. Consistent with recent findings by Marinescu (2012), 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, 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. Using a PSID sample for the years 1975 to 2009, 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.

   In order to identify a set of negative job separations, 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 Kambourov and Manovskii (2009), we identify an employer switch for an individual if reported employer tenure falls by more than 12 months prior to the current interview.[3] 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

[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).

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 preceeding two years in the old job.[4] 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.[5]

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.[6] 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.[7] We limit the sample to married men and women (specifically 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

[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] So 93% experienced a positive switch or did not switch employers.

[6] 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. This type of transition accounts for less than one percent of total marital separations.

[7] 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 in the PSID sample longer may tend to have more stable relationships but will also mechanically have higher numbers of countable prior separations in later years. The coefficient on this variable is negative and significant in all the regressions, but the main results are robust to excluding it.

of 50 when first observed.[8]

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 Mincer and Jovanovic (1981)'s findings, while the likelihood of divorce declines with marriage tenure, also as expected. The key results are reported in the final two rows of the tables. The results demonstrate that the number of previous negative job terminations and the number of previous marital terminations are independent predictors of the likelihood of a *current* negative job switch 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 men in the sample in both the linear probability and probit models. These estimated effects hold own spot wages constant.

Table 3 also shows results from similar regressions using wage growth ($\Delta \ln$ wage between the previous and current sample year as the dependent variable. For men, again both the tally of previous job losses and of previous marital separations has negative implications for wage growth. 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 predicted growth in ln wage. One potential explanation is selection: nearly all men work but not all women, particularly early in our time period. Women who expect to experience marital breakdown are more likely to be attached (by necessity) to the labor force, which in turn can result in higher wages. We later return to this issue in the context of 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 variety of demographic and life cycle information,[9], 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

[8]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.

[9]The average household in our sample is observed in nineteen different (usually but not always sequential) years

Table 1: Separation likelihood and previous separations: Men

	Linear probability model		Probit model	
	Job sep	Marriage sep	Job sep	Marriage sep
	(1)	(2)	(3)	(4)
age	-.065	-.023	-.328	-.208
	(.016)***	(.010)**	(.111)***	(.126)
age^2	.001	.0005	.007	.005
	(.0004)***	(.0003)*	(.003)**	(.003)
age^3	-9.74e-06	-3.64e-06	-.00004	-.00004
	(3.07e-06)***	(2.01e-06)*	(.00002)*	(.00003)
job tenure	-.00006		-.0009	
	(.00003)**		(.0003)***	
marriage tenure		-.001		-.019
		(.0004)***		(.003)***
educ	-.0004	-.002	-.005	-.026
	(.0006)	(.0003)***	(.005)	(.005)***
lag ln wage	-.026	-.005	-.192	-.061
	(.002)***	(.001)***	(.016)***	(.017)***
previous job switches	.024	.002	.166	.031
	(.001)***	(.0006)***	(.006)***	(.008)***
previous divorces	.018	.029	.124	.234
	(.003)***	(.004)***	(.018)***	(.028)***

Table 2: Separation likelihood and previous separations: Women

	Linear probability model		Probit model	
	Job sep	Marriage sep	Job sep	Marriage sep
	(1)	(2)	(3)	(4)
age	-.018	-.014	-.032	-.116
	(.017)	(.012)	(.106)	(.135)
age^2	.0004	.0003	.0007	.003
	(.0004)	(.0003)	(.003)	(.004)
age^3	-2.58e-06	-1.87e-06	-6.84e-06	-.00002
	(3.47e-06)	(2.33e-06)	(.00002)	(.00003)
job tenure	-.0006		-.006	
	(.00004)***		(.0006)***	
marriage tenure		-.002		-.025
		(.0004)***		(.003)***
educ	.001	-.003	-.003	-.039
	(.0009)	(.0005)***	(.006)	(.007)***
lag ln wage	-.054	-.002	-.282	-.014
	(.004)***	(.001)	(.020)***	(.018)
previous job switches	.006	.004	.044	.056
	(.002)***	(.001)***	(.010)***	(.010)***
previous divorces	.018	.023	.107	.177
	(.003)***	(.004)***	(.019)***	(.026)***
e(N)	36198	36386	36184	36386

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 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

Table 3: ln wage growth and previous separations

	Δ ln wage: men	Δ ln wage: women
	(1)	(2)
age	.028	.110
	(.021)	(.041)***
age^2	-.0005	-.002
	(.0005)	(.001)**
age^3	2.51e-06	.00002
	(4.15e-06)	(8.54e-06)**
job tenure	.0002	.002
	(.00006)**	(.0002)***
educ	.038	.130
	(.002)***	(.004)***
previous job switches	-.021	-.069
	(.002)***	(.006)***
previous divorces	-.025	.018
	(.006)***	(.012)

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.[10] 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 relevant O*NET code.

To gain a measure of relationship or "partnering" skill for PSID respondents, we use an argument similar to Yamaguchi (2012b): 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

[10]This 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.

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: Lundberg (2010) 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" 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

Table 4: Four criteria for $\hat{n}$

Both spouses at least 10%	Joint sig at least 5%	Joint sig, Controlling for "social"	At least one sig controlling for all $\hat{n}$
Persistence	Persistence	Persistence	Persistence
Adaptability	Adaptability	Adaptability	Adaptability
Integrity	Integrity	Integrity	Integrity
Independence	Independence	Independence	Independence
	Concern for others	Concern for others	
	Dependability	Dependability	
		Cooperation	Cooperation
		Effort	

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 $\tilde{n}$s. The bottom row of the table reports the p-value from an F test of the three terms containing the partners' $\hat{\hat{n}}$s.

2.2.2 Interpreting n

From table 5, we observe a common pattern in the regressions with respect to the common factor $\tilde{n}$s: 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.

As well, we believe our $\tilde{n}$ have a fairly clean, intuitive interpretation as bundling characteristics that allow individuals to succeed in relationships by, essentially, *avoiding conflict* (as opposed, for instance, to managing it). While there is no direct link between our qualifying $\hat{n}$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

Table 5: Divorce likelihood and relationship skill: using a common factors Model

	(1)	(2)	(3)	(4)
husband's n	-.006	-.008	-.008	-.006
	(.003)**	(.003)***	(.003)***	(.003)**
wife's n	-.006	-.007	-.010	-.008
	(.003)**	(.003)***	(.003)***	(.003)***
hus $\times$ wife's n	.005	.006	.006	.006
	(.004)	(.004)*	(.003)*	(.004)*
husband's educ	.005	.006	.005	.006
	(.001)***	(.001)***	(.001)***	(.001)***
wife's educ	.003	.004	.003	.003
	(.001)**	(.001)***	(.001)**	(.001)**
hus $\times$ wife's educ	-.0004	-.0004	-.0004	-.0004
	(.0001)***	(.0001)***	(.00009)***	(.0001)***
marriage tenure	-.002	-.002	-.002	-.002
	(.0002)***	(.0002)***	(.0002)***	(.0002)***

the measures in the first four rows of table 5 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 $\tilde{n}$ individuals, across jobs that demand "high" and "low" $\tilde{n}$ 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 ν, where higher ν jobs demand high n workers. Using our preferred criterion (criterion 4), low $\tilde{n}$ workers experience annual negative separation rates of 8.5% from high ν and 8.1% from medium- and low-ν jobs, while high $\tilde{n}$ workers experience annual negative separations rates of 5.6% from high ν jobs, 6.6% from medium ν jobs, and 7.2% from low ν jobs. While this information is at least partially by construction of $\tilde{n}$, it is consistent with our interpretation of n *in the work context*, where the ability to maintain a collegial relationship affects the likelihood of experiencing a negative separation. Specifically, low-$\tilde{n}$ 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-ν jobs that, by definition, require them.

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 $\{\Omega_0^f, \Omega_0^m\}$ which are discreet joint distributions of k_0 and n, each characterized by a σ_{kn^g} 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" $\kappa \in \{1, 4\}$ and relationship skill requirement $\nu \in \{1, 2, 3\}$, 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

$$\begin{aligned} k_1 = f(k_0, s, \epsilon_s) &= k_0^{\alpha} s^{1-\alpha} \epsilon_s(n) \\ \epsilon(n) &\sim \beta(p(n), 1) \\ p(n) &= \sigma_{\epsilon_s(n)} n \end{aligned} \tag{1}$$

where $\epsilon_s \ in(0, 1)$ is a shock realized at the end of the chosen education period which depends on n. ϵ_s is drawn from a power distribution: $f(\epsilon_s) = constant \cdot p(n) \epsilon^{p(n)-1}$, which is a special case of the beta distribution. p is increasing in n. We interpret this to mean that education offers a potential or "optimal" return of $k_0^{\alpha} s^{1-\alpha}$ if fully utilized. Individuals with greater relationship skills on average can realize more of the potential returns on their education (because, for instance, they are more persistent and conscientious or because they engage more easily and advantageously with their professors). The power distribution is useful because of its flexibility and the single-crossing property of its pdf with respect to p: as p increases, the mean of the distribution, $\frac{p}{p+1}$, increases and the variance first increases then decreases. As will be seen, however, over the range of p calculated in our model, the variance of ϵ_s is decreasing in n, implying that individuals with strong relationship skills receive higher *and* less variable returns to investments in education on average.

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. Education is costly. While receiving education, individuals receive their income from unemployment insurance (described below) which is increasing in k_0. There is also a direct period cost of education which varies across individuals and reflects both non-pecuniary costs like distaste for studying or differential access to tuition funding. These costs are randomly distributed across the population with mean $\underline{C}$ and variance $\sigma^2_{\underline{C}}$.

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 $k_1(\underline{j})$, where $\underline{j}$ 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 Π. A job offer is characterized by the vector $\{\kappa, \hat{} \nu\}$. Workers make take it or leave it offers to potential employers and so extract all the surplus in the form of wages W:

$$\begin{aligned} W(k_1, \kappa, n, \nu) &= a_g\big((\gamma_0 k_1)^{\gamma_1} + ((1-\gamma_0)\kappa)^{\gamma_1}\big)^{\frac{1}{\gamma_1}} \epsilon_W(n, \nu) \\ \epsilon_W(n, \nu) &\sim \beta\big(p(n, \nu), 1\big) \\ p(n, \nu) &= \sigma_{\epsilon_W}(1 + \phi_0 n + \phi_1 \nu + \alpha_2 n\nu] \end{aligned} \tag{2}$$

Output from a matched job consists of a fixed and a variable component. The difference in men and women's wages differ exogenously by a factor of a_g, which also pins down the mean wage for both genders. a_g can be taken either as a true productivity differential or as a discrimination factor.[11] The fixed component depends on the match between learned skill

[11] We prefer the latter interpretation on the grounds that differences in productivity should arise mainly through women's lower participation rates, which translate into lower k_1 over the working life, conditional

("human capital" broadly defined) and the productivity/complexity of capital κ according to a nested CES with share parameter γ_0 and substitution elasticity γ_1. Production each two-month period is subject to a standard exponential IID shock $\epsilon_W \in (0,1)$ which, like education, is drawn from a β distribution and depends on the "relationship skill" match of n to the occupation-level demand for these skills ν in the current job. The relative contributions and substitutability of n and ν is governed by a linear model with parameters ϕ_0, ϕ_1, ϕ_2 governing the contributions of n and ν to variance σ_{ϵ_W}. The properties and interpretation of the β distribution for realizing the output of a productive team (worker and job) are similar to those for education. 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 of jobs Π 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 κ or higher ν) job. 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 ϵ_W is sufficiently negative to make a period of unemployment more attractive. Unemployment benefits, which are also study and retirement benefits, are simply given by $a_g\gamma_0 k_1^{\gamma_1}$, reflecting the fact that unemployment benefit are typically based on potential earnings. Finally, while employed, employed individuals receive a permanent unit increment to k_1 at the start of each year with probability $p_K = p_K^0 + p_K^1\kappa$ due to learning by doing on their current job. The rate of learning increases in k so as to reflect the fact that wages rise more quickly for highly-educated individuals during the first half of the life cycle. Unemployed workers are not eligible for experience-based increases in k_1.

Family After finishing school as singles, individuals meet potential mates each year with probability π 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:

$$S^g = W(k_1, \kappa, n, \nu)\epsilon_S$$
$$\epsilon_S(n) \sim \beta\big(\sigma_S, 1\big) \tag{3}$$

Utility is given by:

$$U_g^S = \ln\left(S^g\right) - \psi^g I_{work} \tag{4}$$

Equations 3 and 4 say that singles enjoy consumption from earned income, according to a

on education.

stochastic "equivalence" shock ϵ_S that depends positively on n and distributed $\beta\big(\sigma_{\epsilon_S} n, 1\big)$. People with better relationship skills are able to better enjoy their own output, for example through sharing the experience of consumption with good friends. In addition to their consumption utility, individuals experience disutility from working (when I_{work} is equal to 1) given by gender-specific parameter ψ^g.

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

$$\begin{aligned} M &= \big((\chi_0 W_f)^{\chi_1} + (\chi_0 W_M)^{\chi_1}\big)^{\frac{1}{\chi_1}} \epsilon_M(n_f, n_m) \\ \epsilon_M(n_f, n_m) &\sim \beta\big(p(n_f, n_m), 1\big) \\ p(n_f, n_m) &= \sigma_M\big(\lambda_0 n_f + \lambda_1 n_m + \lambda_2 n_f n_m\big) \end{aligned} \tag{5}$$

Each spouse's individual utility is given by

$$U_g^M = \ln(M) - \psi^g I_{work} \tag{6}$$

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. $\chi_1 \in (-\infty, 1]$ captures the degree of substitutability in spousal incomes: the higher χ_1, the more substitutable in marital utility are spousal incomes as suggested in Becker (1974) and Becker (1991): when $\chi_0 = .5$ and $\chi = 1$ spousal contributions to household income are perfect substitutes. In the same manner as for singles, ϵ_M is a transitory exogenous shock to M (capturing the degree to which M is enjoyed or converted into utility within the period) that is experienced by couples who have been married at least one year. The distribution of the shock is governed by σ_M and depends on both husband's and wife's relationship skills n, the relative importance of which are determined by a (saturated) linear relationship $\lambda_0 n_f + \lambda_1 n_m + \lambda_2 n_f n_m$. The equation for M imples that couples with higher incomes are more able to deal with transitory conflicts implied by low draws of ϵ_M.

Single individuals meet other single individuals of the opposite gender at rate η (that is, with probability η per year). Matched pairs marry if the value of being married to the current matched partner and receiving M plus the continuation value of the match 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 ϵ_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 n, which takes the same form as the unemployment benefits. 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:

$$\begin{aligned} V_g^S(j, k_1, n, 0, 0) = {} & \ln S + \beta\Big(\big(1-\eta\big)\big((1-p_0)V_g^S(j+\frac{1}{6}, k_1, n, 0, 0) \\ & + p_0 \sum_{\hat{\kappa}\in\{1,4\}} \sum_{\hat{\nu}\in\{1,3\}} q(\hat{\kappa},\hat{\nu}) V_g^S(j+\frac{1}{6}, k_1, n, \hat{\kappa}^*, \hat{\nu}^*)\big) \\ & + \eta\big((1-p_0)\sum_{X_{-g}} \varrho(x_{-g}) V_g^M(j+\frac{1}{6}, k_1, n, 0, 0, x_{-g}) \\ & + p_0 \sum_{\hat{\kappa}\in\{1,4\}} \sum_{\hat{\nu}\in\{1,3\}} q(\hat{\kappa},\hat{\nu}) \sum_{X_{-g}} \varrho(x_{-g}) V_g^M(j+\frac{1}{6}, k_1, n, \hat{\kappa}^*, \hat{\nu}^*, x_{-g})\big)\Big) \end{aligned} \tag{7}$$

where $\hat{\kappa}^*, \hat{\nu}^* = \text{argmax}[V_g^S(j+\frac{1}{6}, k_1, n, \hat{\kappa}, \hat{\nu}), V_g^S(j+\frac{1}{6}, k_1, n, 0, 0)]$; 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 ϱ, 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 κ into four 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:

$$
\begin{aligned}
V_g^S(j, k_1, n, 0, 0) = \ln(S) + \beta\big(1 - p_0)V_g^S(j + \frac{1}{6}, k_1, n, 0, 0) \\
+ p_0 \sum_{\hat{\kappa}\in\{1,4\}} \sum_{\hat{\nu}\in\{1,3\}} q(\hat{\kappa}, \hat{\nu})V_g^S(j + \frac{1}{4}, k_1, n, \hat{\kappa}^*, \hat{\nu}^*)\big)
\end{aligned}
\tag{8}
$$

where, as before $\hat{\kappa}^*, \hat{\nu}^* = \text{argmax}[V_g^S(j + \frac{1}{6}, k_1, n, \hat{\kappa}, \hat{\nu}), V_g^S(j, k_1, n, 0, 0)]$. 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:

$$
\begin{aligned}
V_g^S(j, k_1, n, \kappa, \nu) = ln(S) - \psi^g + \beta \int_{\epsilon_W} \sum_{k_1'=k_1}^{k_1+\iota_k} \Big[\tilde{p}(k_1, k_1')\Big(\big((1-\eta)\big((1-p_1)V_g^S(j + \frac{1}{6}, k_1', n, \kappa^*, \nu^*) \\
+ p_1 \sum_{\hat{\kappa}\in\{1,4\}} \sum_{\hat{\nu}\in\{1,3\}} q(\hat{\kappa}, \hat{\nu})V_g^S(j + \frac{1}{6}, k_1', n, \kappa^{**}, \nu^{**})\big) \\
+ \eta\big((1-p_1) \sum_{X_{-g}} \varrho(x_{-g})V_g^M(j + \frac{1}{6}, k_1', n, \kappa^*, \nu^*, x_{-g}) \\
+ p_1 \sum_{\hat{\kappa}\in\{1,4\}} \sum_{\hat{\nu}\in\{1,3\}} q(\hat{\kappa}, \hat{\nu}) \sum_{X_{-g}} \varrho(x_{-g})V_g^M(j + \frac{1}{6}, k_1', n, \kappa^{**}, \nu^{**}, x_{-g})\big)\big)\Big)\Big]
\end{aligned}
\tag{9}
$$

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 ϵ_W in their current job. If no job offer is received, then

$$
\{\kappa^*, \nu^*\} = \text{argmax}\{V_g^S(j + \frac{1}{6}, k_1', n, \kappa, \nu), V_g^S(j + \frac{1}{6}, k_1', n, 0, 0\}
$$

If a job offer $\{\hat{\kappa}, \hat{\nu}\}$ is received, we define

$$\{\tilde{\kappa^{**}}, \tilde{\nu^{**}}\} = \text{argmax}\{EV_g^S(j+\frac{1}{6}, k_1', n, \hat{\kappa}^*, \hat{\nu}^*), EV_g^S(j+\frac{1}{6}, k_1', n, \kappa^*, \nu^*)\}$$

where the expectation is taken over the wage shock e_W is either the old or new job. Finally,

$$\{\kappa^{**}, \nu^{**}\} = \text{argmax}\{V_g^S(j+\frac{1}{6}, k_1', n, \tilde{\kappa^{**}}, \tilde{\nu^{**}}), V_g^S(j+\frac{1}{6}, k_1', n, 0, 0\}$$

Note that this sequence implies that job offers are received first, before the realization of ϵ_W: the decision to change jobs is made prior to the decision to quit either the old or new job. Then, as previously stated, marriage offers arrive only after the job transition decisions are made. Third, with probability $\tilde{p}(k_1, k_1 + \iota_k) = p_K$, working individuals receive a positive increment of ι_k to their adult learned human capital from learning by doing on the current job[12]: since this improvement in k_1 is based on work in the previous subperiods, this increment accrues even if the individual is unlucky and draws a negative wage shock ϵ_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:

$$U_M = V_f^M(x_M) + V_m^M(x_M) \tag{10}$$

where $x_M = \{x_f, x_m, \epsilon_M\}$. Spouse g's individual value function in subperiod 5 of 6 is given

[12]and $\tilde{p}(k_1, k_1) = 1 - p_K$. $\tilde{p}$ is of course a function of k_1 and κ. The notation is introduced simply to shorten notation in the value function.

by

$$
\begin{aligned}
V_g^M(j,k_1,n,\kappa,\nu,x_{-g},\epsilon_M) &= \ln(M) - \psi^g I_{work} + \beta \int_{\epsilon_M'} \int_{\epsilon_W'} \int_{\epsilon_W'} \sum_{k_1'=k_1}^{k_1+\iota_k} \Big[\tilde{p}(k_1,k_1') \sum_{k_{1-g}'=k_{1-g}}^{k_{1-g}+\iota_k} \Big[\tilde{p}(k_{1-g},k_{1-g}') \\
&\Big((1-\mathcal{P}_g)(1-\mathcal{P}_{-g})\Big(\varphi_g(x_M')\max\big[V_g^M(j+\frac{1}{6},k_1',n,\kappa^*,\nu^*,x_{-g}^*,\epsilon_M'),V_g^S(j+\frac{1}{6},k_1',n^*,\kappa^*,\nu)\big] \\
&\quad + (1-\varphi_g(x_M'))V_g^S(j+\frac{1}{6},k_1',n,\kappa^*,\nu^*)\Big) \\
&+\mathcal{P}_g(1-\mathcal{P}_{-g})\sum_{\hat{\kappa}}\sum_{\hat{\nu}} q(\hat{\kappa},\hat{\nu})\Big(\varphi_g'(x_M')\max[V_g^M(j+\frac{1}{6},k_1',n,\hat{\kappa}^{**},\hat{\nu}^{**},x_{-g}^*,\epsilon_M'),V_g^S(j+\frac{1}{6},k_1',n,\hat{\kappa}^{**},\hat{\nu}^{**})] \\
&\quad + (1-\varphi_g(x_M'))V_g^S(j+\frac{1}{6},k_1',n,\hat{\kappa}^{**},\hat{\nu}^{**})\Big) \\
&+(1-\mathcal{P}_g)\mathcal{P}_{-g}\sum_{\hat{\kappa}_{-g}}\sum_{\hat{\nu}_{-g}} q(\hat{\kappa}_{-g},\hat{\nu}_{-g})\Big(\varphi_g'(x_M')\max\big[V_g^M(j+\frac{1}{6},k_1',n,\kappa^*,\nu^*,x_{-g}^{**},\epsilon_M'),V_g^S(j+\frac{1}{6},k_1',n,\kappa^*,\nu^*)\big] \\
&\quad + (1-\varphi_g(x_M'))V_g^S(j+\frac{1}{6},k_1',n,\kappa^*,\nu^*)\Big) \\
&+(1-\mathcal{P}_g)(1-\mathcal{P}_{-g})\sum_{\hat{\kappa}}\sum_{\hat{\nu}}\sum_{\hat{\kappa}_{-g}}\sum_{\hat{\nu}_{-g}} q(\hat{\kappa},\hat{\nu})q(\hat{\kappa}_{-g},\hat{\nu}_{-g}) \\
&\quad \Big(\varphi_g(x_M')\max\big[V_g^M(j+\frac{1}{6},k_1',n,\hat{\kappa}^{**},\hat{\nu}^{**},x_{-g}^{**},\epsilon_M'),V_g^S(j+\frac{1}{6},k_1',n,\hat{\kappa}^{**},\hat{\nu}^{**})\big] \\
&\quad + (1-\varphi_g(x_M'))V_g^S(j+\frac{1}{6},k_1',n,\hat{\kappa}^{**},\hat{\nu}^{**})\Big)\Big)\Big]
\end{aligned} \tag{11}
$$

To generalize the above expression for both one-earner, two-earner and non-working couples, we combine the probabilities of receiving a job offer and of losing a job into a single variable, letting $\mathcal{P}_g = p_0$ if spouse g is unemployed and $\mathcal{P}_g = p_1$ if he or she is employed. Also, to reduce notation we omit the summing over $\hat{\kappa} \in \{1,4\}$ and $\hat{\nu} \in \{1,3\}$.

The bellman equation (11), which captures spouse g's individual payoff from his marriage, has nine parts. Spouse g enjoys marital consumption output $\ln(M)$ and faces disutility ψ if she works. Besides the transitory shock to the current wage, each spouse experiences an increment to current human capital of ι_k with independent probabilities $\tilde{p}(k_{1g}, k_{1g}+\iota, \kappa_g) = p_K(\kappa)$ if $\kappa_g \geq k$ and zero otherwise (and necessarily when unemployed). With probability $(1-\mathcal{P}_g)(1-\mathcal{P}_{-g})$, neither spouse receives a job offer and employment decisions are taken jointly at the household level only over whether each partner should quit or remain in the current job given $\{\epsilon_W^f, \epsilon_W^m\}$, which are independent. That is

$$
\begin{aligned}
\{\kappa_f^*, \nu_f^*, \kappa_m^*, \nu_m^*\} = \operatorname{argmax}\{&U_M(k_f', n_f, k_m', n_m, \kappa_f, \nu_f, \kappa_m, \nu_m), U_M(k_f', n_f, k_m', n_m, 0, 0, \kappa_m, \nu_m), \\
&U_M(k_f', n_f, k_m', n_m, \kappa_f, \nu_f, 0, 0), U_M(k_f', n_f, k_m', n_m, 0, 0, 0, 0)\}
\end{aligned}
$$

Once employment decisions are taken, ϵ_M' is realized and either spouse may choose to unilaterally terminate the marriage. From the perspective of spouse g, $\varphi(x_M')$ is an indicator function for whether spouse $-g$ finds it optimal to continue in the marriage next period given x'_M. If spouse $-g$ wishes to continue the current union, spouse g chooses whether or not he wishes to continue it, by solving (unilaterally) the maximization problem in the square brackets.

The same set-up governs the continuation problem if either or both spouses receive job offers (corresponding to the remaining six terms of (11)). If only the wife receives an offer, $\{\hat{\kappa}_f, \hat{\nu}_f\}$, we have

$$\begin{aligned}\{\tilde{\kappa}_f^{**}, \tilde{\nu}_f^{**}, \kappa_m^*, \nu_m^*\} = \text{argmax}\{&EU_M(k'_f, n_f, k'_m, n_m, \kappa_f^*, \nu_f^*, \kappa_m^*, \nu_m^*),\\ &EU_M(k'_f, n_f, k'_m, n_m, \hat{\kappa}_f^*, \hat{\nu}_f^*, \kappa_m^*, \nu_m^*)\}\end{aligned}$$

where $\{\tilde{\kappa}_f^*, \tilde{\nu}_f^*\}$ is the solution to the first stage problem over whether or not the wife accepts her current offer or stays put and the expectation operator is over the *final* choice of $\{\kappa_f, \nu_f\}$. Then

$$\begin{aligned}\{\kappa_f^{**}, \nu_f^{**}, \kappa_m^*, \nu_m^*\} = \text{argmax}\{&U_M(k'_f, n_f, k'_m, n_m, \tilde{\kappa}_f^{**}, \tilde{\nu}_f^{**}, \kappa_m, \nu_m), U_M(k'_f, n_f, k'_m, n_m, 0, 0, \kappa_m, \nu_m)\\ &U_M(k'_f, n_f, k'_m, n_m, \tilde{\kappa}_f^{**}, \tilde{\nu}_f^{**}, 0, 0), U_M(k'_f, n_f, k'_m, n_m, 0, 0, 0, 0)\}\end{aligned}$$

and vice versa if only the husband receives an offer. The problem in which both spouses receive an offer is similar and is omitted for space.

As for singles, occupational decisions are made prior to marriage decisions, and the decision to continue or terminate the marriage is made conditional on the household's jointly optimal career decisions. In contrast to job decisions, divorce decisions are made unilaterally by each spouse. However, the "household" may make collective decisions on occupation taking the likelihood of divorce into account. For instance, if one partner's promotion makes a divorce more likely to the detriment of the other partner, then the household may collectively opt to turn down the promotion even if that spouse would unilaterally prefer to accept it.

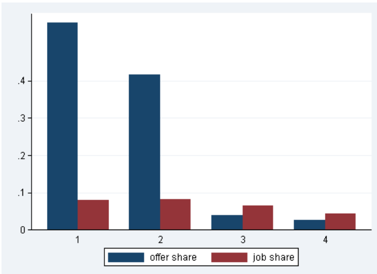
4 Parametrization and identification

The main parameters of the models, along with their estimates, are summarized in table 6 and in figures 1 (which shows the distribution of job offers) and 2 (which shows the unconditional distribution of k_0 for men and women and k_1 for later ages). In this section, we summarize the information, taken from our merged PSID-O*NET file, used to estimate the model and describe the identification process.

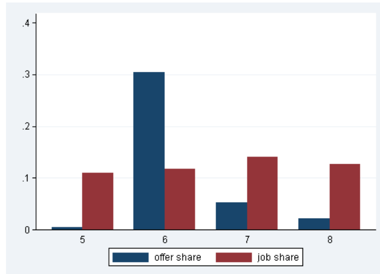
Table 6: Parameters

Parameter	Estimate: benchmark	Interpretation
α	0.807	relative contribution of k_0 to k_1 in (1)
σ_s	0.433	mean of shocks to k_1 in (1)
$\underline{C}$	0.795	mean cost of schooling
$\sigma^2_{\underline{C}}$	0.106	variance of schooling costs across the population
p_0	0.467	arrival rate of job offers while unemployed
p_1	0.316	arrival rate of job offers while employed
p_K	-0.001+ 0.002k	incidence of on-the-job-learning
ψ^f	1.222	disutility of working for women
ψ^m	0.311	disutility of working for men
η	0.226	arrival rate of marriage offers for singles
a_f	1.708	wage coefficient for women
a_m	1.803	wage coefficient for men
γ_0	0.500	share of k in deterministic part of (2)
γ_1	-0.359	substitution elasticity of k and κ in (2)
σ_W	2.739	variance of the wage shock
ϕ_0	-0.082	return to n in stochastic part of (2) (2)
ϕ_1	-0.281	return to ν in stochastic part of (2)
ϕ_2	0.548	complementarity of n and ν in stochastic part of in (2)
σ_S	0.433	variance of the shock to S
χ_0	0.500	share of wife's income in deterministic part of (5)
χ_1	-1.226	substitution elasticity of spouses' incomes in (5)
σ_M	3.041	variance of the shock to M
λ_0	0.133	return to wife's n in stochastic part of (5)
λ_1	0.472	return to husband's n in stochastic part of (5)
λ_2	0.012	complementarity of husband's and wife's n in (5)
σ_n	1.451	difference in n (ν) between high and low n individuals (jobs)
σ_{kn^f}	0.164	correlation of n and k_0 among women
σ_{kn^m}	0.279	correlation of n and k_0 among men

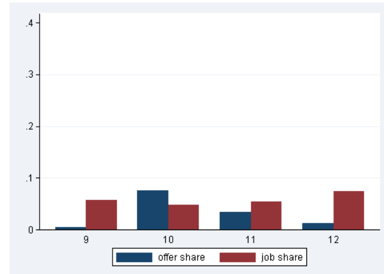
Figure 1: Filled Job and Job Offer shares



(a) $\nu = 1$

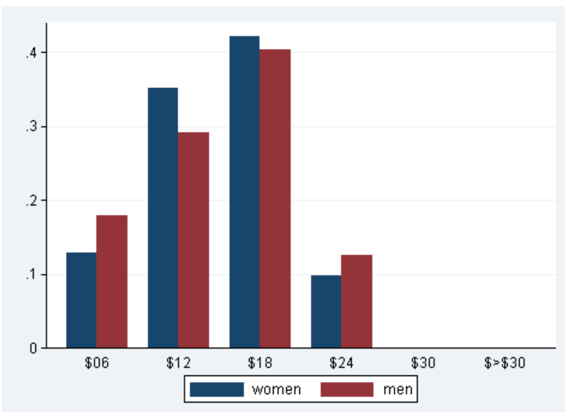


(b) $\nu = 2$

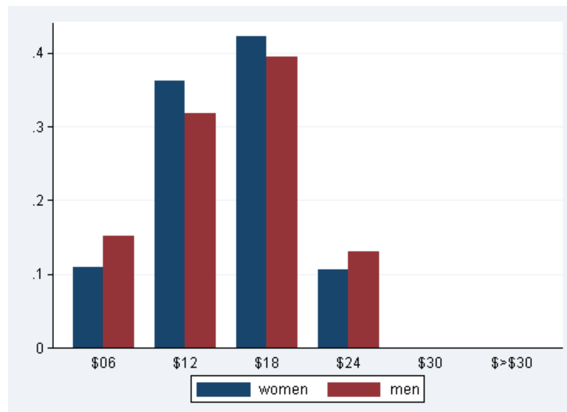


(c) $\nu = 3$

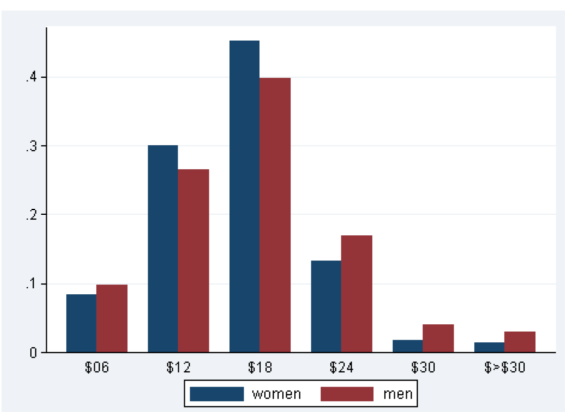
Figure 2: Distribution of human capital by gender



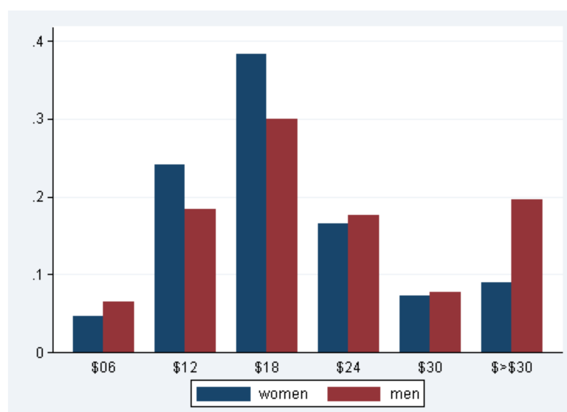
(a) K_0 by gender



(b) K_1 by gender at labor market entry



(c) K_1 by gender after 15 years experience



(d) K_1 by gender after 30 years experience

1. *Job shares and the job offer distribution.* We divide our PSID sample into twelve bins each corresponding to a range of the wage distribution (top and bottom 5%, next 20%, next 25%, excluding the top 1% and 99% of wage realizations) and a ν. Then, κ is

discretized into six grid points, taking the mean value of the wage in each of the six wage bins. Along the ν dimension, occupations are discretized as "high" ($\nu = 2$) and "low" ($\nu = 1$) social jobs according to whether they lie above or below the median importance of (or demand for) $\tilde{n}$ among all observed jobs in the PSID sample. Because the wage is not determined solely by κ (and κ itself is not observed in the data), the shares of filled job by κ are not exactly the shares of filled jobs by wage.

Figure 3 shows the distribution of occupations across ν and wage bins among currently employed workers starting in 1975. The figure shows that ν and and the wage (hence ν and κ) are positively correlated: the lowest wage jobs tend also to be low-ν jobs while jobs in the top of the wage distribution are much more likely to be high-ν jobs. We use this distribution of observed (filled) jobs to target the *offer distribution*: that is, the distribution from which wage offers are randomly drawn. Given our discretization, this gives twelve moments. The resulting job and offer distributions across $\{\kappa, \nu\}$ are shown in figure 1. The results suggest that job offers are much more highly skewed toward the lowest-paying jobs than are filled jobs, making high-κ jobs extremely valuable.

Rate of positive job separations among workers. Positive job separations include employer switches that do not satisfy either of the conditions for negative job separation: the worker does not transition through unemployment *and* experiences a higher real hourly wage than in his previous job, averaged over the two years following the switch for years before 1997 and in the year of the switch after 1997. The total rate of positive job separation as an annual rate is 6% (about 40% of all switches).

2. *Participation and exit hazard from unemployment.* An individual is a "participant" in a given year if he supplies positive hours of work. Among men and women aged 25-56, the annual participation rates in our PSID sample are 95% and 75% respectively, yielding two targets. To calculate the bi-monthly employment exit hazard we calculate the share of unemployment spells among participants (averaged across gender) that last less than two months, which comes out to 52%. This target, along with the rate of positive separations, allows us to directly identify p_0 and p_1 in the model.

3. *Negative separation rates by ν.* In the previous section, we calculated negative separation rates for high, medium and low ν occupations, which we use as six additional targets. To repeat, low $\tilde{n}$ workers experience annual negative separation rates of 8.5% from high ν and 8.1% from low ν jobs, while high $\tilde{n}$ workers experience annual negative separations rates of 5.6% from high ν jobs and 7.2% from low ν jobs. These targets have direct implications for the identification of ϕ_0, ϕ_1 ϕ_2, and σ^2_W.

4. *Wages by gender and wage returns to age and education.* We take the wages of single

and married men and women in our sample as four targets. Single women have a mean (unconditional, CPI-adjusted) rounded wage in the sample of \$15 and married women of \$14. For men, the corresponding wages by marital status are \$16 and \$22. These four targets help identify a_f, a_m, and χ_0. Next, we regress workers' wages in logs on a quadratic in age and interactions of age and age squared with education. The return to age allows us to identify the two terms in $p_k = p_k^0 + p_k^1 k$, the arrival rate of human capital gains from learning by doing for workers. The targets are reported in equation (12). In general, promotions (and wage gains) come quicker for workers who begin their careers further up the wage hierarchy, who are the workers with more education, reflected in the positive estimated values of p_k^1. Matching the variance of the residual from this regression gives the conditional variance of wages of .38, a determinant of σ_W. Finally, we calculate the degree of correlation between education and wage among workers in the PSID to be .28 for workers under 30. This correlation helps identify α, the role of innate ability k_0 in producing adult ability, k_1, and also ϵ_S.

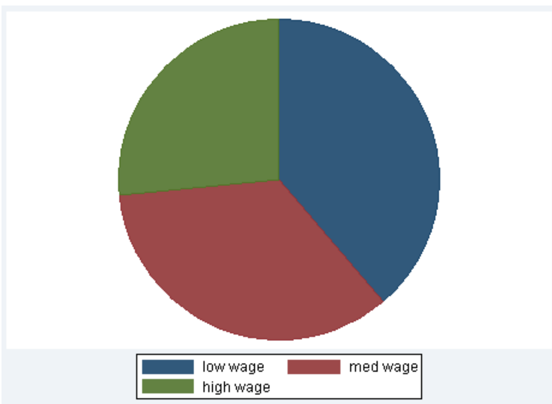
$$\begin{aligned} \ln \hat{wage} = constant - .00860 age + .0000413 age^2 \\ + .00501 educ \times age - .0000465 educ \times age^2 \end{aligned} \tag{12}$$

The second, third and fourth panels of figure 2 show how human capital increases over the life cycle for men and women due to educational investments and learning-by-doing. The growth of k_1 over the life cycle is faster for men due to their higher average labor market attachment.

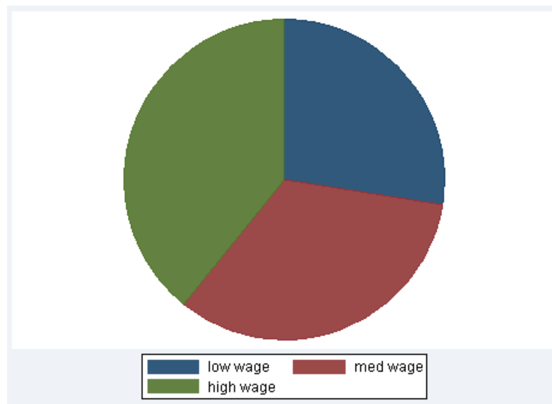
5. *Educational shares by sex and n.* We target the shares of PSID men and women obtaining less than high school, high school, college, undergraduate university and post graduate education, and the correlation between our measure of n and educational attainment in the PSID, a total of twelve targets. Variation in educational attainment allows us to identify our measures of $\underline{C}$ and $\sigma^2_{\underline{C}}$ along with the sex-specific distributions of k_0 and the correlation between k_0 and n for men and women respectively. In the model k_1 can take eight values corresponding to bands of \$6, with a lower bound of \$6. k_0 takes four values, corresponding to the first four levels of k_1. Figure 4 shows the targeted and estimated shares of education for men and women. The correlation between $\tilde{n}$ and education for men and women are .48 and .40 respectively, which – along with the job separation and divorce rates – help us identify σ_n, σ_{kn^f} and σ_{kn^f}.

6. *Marriage, divorce rates and spousal correlations.* In our PSID sample, 60% of household heads between 25 and 56 are married. As described in section 2, divorce rates vary with the ns of the spouses: the incidence of divorce among high n pairs (including common-law splits) is .027 and among low n pairs is .046. Among mixed pairs, the incidence is .027 when the husband has high n and .035 when the wife has high n. The within-couple correlation of $\tilde{n}$ is .18 and of education is .55. Together, these marriage statistics help identify σ_S, σ_M, χ_1 and λ_0, λ_1 and λ_2.

Figure 3: Filled jobs by κ and ν

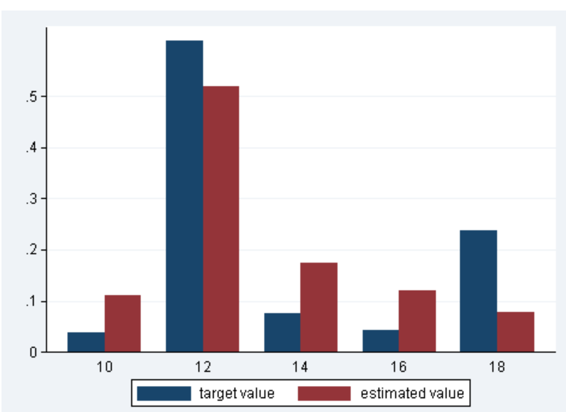


(a) filled jobs: $\nu = 1$

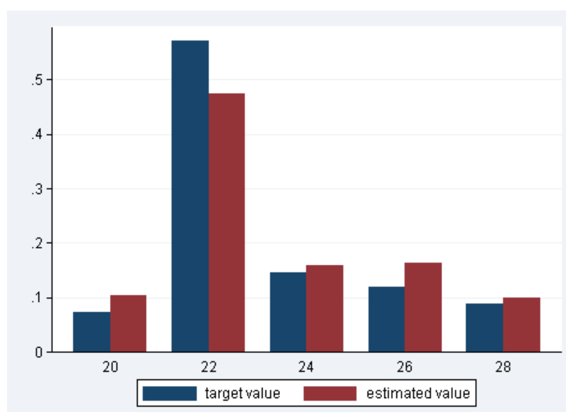


(b) filled jobs: $\nu = 3$

Figure 4: Educational shares



(a) men



(b) women

5 Results and discussion

In this section, we discuss the implications of our estimation results, specifically on their implications for the role of relationship skills n in the economy.

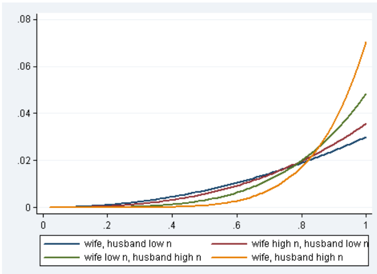
5.1 The role to n in the marriage, labor and education markets

Table 6 shows that, unsurprisingly, n and k_0 are highly positively correlated in the population of high school-age individuals: individuals with higher n also have higher human capital levels on average.

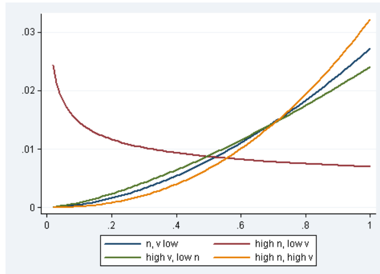
Figure 5 shows the pdfs (left panel) and cdfs (right panel) of the estimated stochastic distribution of returns to marriage utility, wage earning power and returns to education as a function of n and ν. The figures show the distribution of the "attained" portion of total output as a function of the relevant inputs of relationship skills (of the partners in a marriage in the first panel; of the individual and his job in the second panel; of the individual student in the third panel). In all three markets – marriage, labor and educational markets – relationship skills play a major role in determining average returns. The largest role of n, however, is in the education market, in which roughly 20% of high n students reap the "complete" return to education compared to only 3% of low-n students. Relationship skills thus play a very substantial role in determining the returns to education, consistent with Heckman et al. (2006)'s finding of a strong impact of non-cognitive skill on educational attainment, though our results refer to the intensive (return conditional on years) as well as the extensive (number of years) education margins. In the marriage market, unions between high n partners yield the highest consistent returns and unions between low n partners to the least consistent returns, with the n of the wife more important that the n of the husband. In the job market, high n workers produce more (realize more of attainable output) on average in both types of jobs, while high n jobs matched to high ν jobs have the highest stochastic returns. Importantly, mismatch between high ν jobs and low n workers yields the worst stochastic outcomes on average (the red line) as we would expect. These types of matches in the workplace produce least and are least stable, as in the data.

To further assess the role of n on returns to education, table 7 provides estimates of the returns to schooling for high $\tilde{n}$ and low $\tilde{n}$ individuals both in the model and in the data. Though the model underestimates the overall wage returns to education, the estimates from the PSID data indicate that high $\tilde{n}$ individuals experience higher returns to years of schooling than low $\tilde{n}$ individuals, a fact replicated in the model. We also report using the "true" n in the model, which are even stronger. There are three factors underlying this result. First, as seen

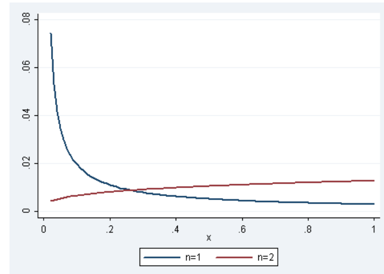
Figure 5: Realized returns to n in the marriage, job and education markets



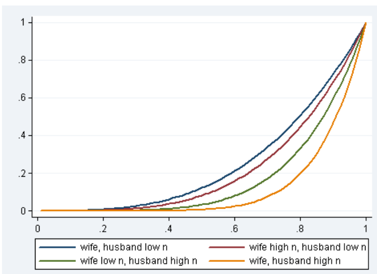
(a) marriage returns: pdf



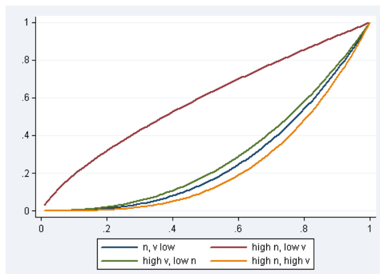
(b) wage returns: pdf



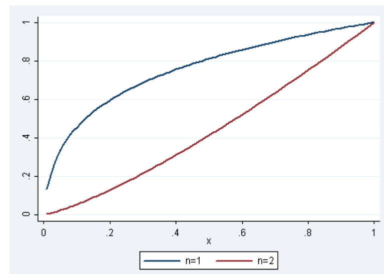
(c) education returns: pdf



(d) marriage returns: cdf



(e) wage returns: cdf



(f) education returns: cdf

in figure 5, high n individuals experience higher expected returns to education *conditional* on years of educational attainment, meaning they enter the labor force with higher k_1 on average than low n peers with the same degree. Second, given the relative scarcity of high κ jobs, high n individuals who match match with these jobs are keep them for longer durations on average because they are less likely to draw a low return to production that necessitates a split. Third, returns to learning-by-doing are themselves increasing in k_1, as reflected by the value of p^1_k needed to match the wage return over the life cycle. Since higher n individuals are more likely to enter the labor force with higher k_1, they climb the career ladder more quickly.

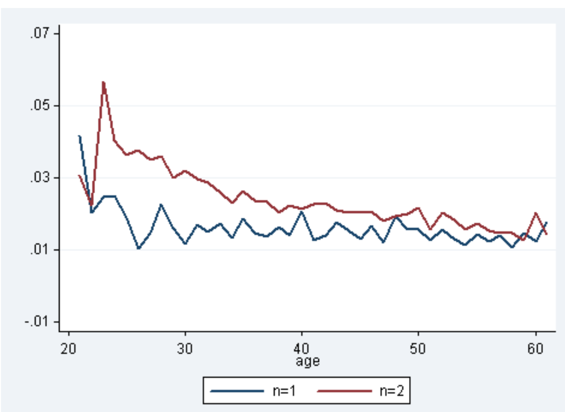
The latter two effects should imply higher not only higher returns to education at the start of life but also higher (log) *wage growth* over the working life for high-n individuals. Figure 6 shows that this is indeed the case. Wage growth is higher for the young of both genders, as we would expect, and higher on average for high n individuals of both genders. Average growth in ln wages is .005% per year higher for men and .007% higher per year for women. For both men and women, the effects of n are concentrated early in the life cycle when the effects of job turnover and promotion are largest.[13]

[13] The likelihood of changing jobs falls from .141 at age 25 to .030 at age 55 in the data, and from .144 at age 25 to .032 at age 55 in the model.

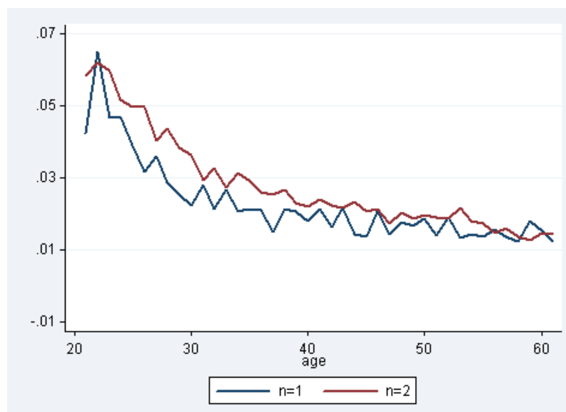
Table 7: Returns to Schooling and n

	PSID: low n	PSID: high n	Model: low $\hat{n}$	Model: high $\hat{n}$	Model: low n	Model: high n
	(1)	(2)	(3)	(4)	(5)	(6)
educ	.082	.118	.051	.062	.048	.084
	(.001)***	(.001)***	(.0004)***	(.0003)***	(.0005)***	(.0003)***
age	.066	.064	.048	.037	.053	.031
	(.007)***	(.007)***	(.006)***	(.007)***	(.006)***	(.007)***
age^2	-.001	-.0007	-.0006	-.0002	-.0008	-.00006
	(.0002)***	(.0002)***	(.0002)***	(.0002)	(.0002)***	(.0002)
age^3	6.44e-06	9.99e-07	3.23e-06	-4.64e-07	4.69e-06	-1.98e-06
	(1.47e-06)***	(1.55e-06)	(1.31e-06)**	(1.36e-06)	(1.28e-06)***	(1.40e-06)
sex	-.384	-.419	-.807	-.831	-.851	-.823
	(.004)***	(.004)***	(.001)***	(.001)***	(.001)***	(.002)***

Figure 6: Life cycle of ln wages by n



(a) life cycle ln wage growth by n: women



(b) life cycle ln wage growth by n: men

5.2 Replication: n as a fixed effect

In this section we provide some some validating evidence of our specific interpretation of n as a fixed effect. To do so, we replicate the results from tables 1 and 2 for our benchmark model and examine how including measures of $\tilde{n}$ changes the results of the tables for both the model and the PSID samples.

Consider Tables 8 and 9 which summarize the effect of n on the (linear) probability of negative job separations for men and women, respectively. Returns to age, years in the panel, and lagged ln wage are included in the regressions as before but are suppressed for clarity. Similar to the results presented in Tables 1 and 2, the results in column (1) show that the number of previous splits (here adding together negative job separations and marriage separation to simplify the comparison) increases the probability of a negative job separation in our PSID sample. Column (2), which reports the results once we add our measure $\tilde{n}$ inferred from the data, shows that those with a high $\tilde{n}$ have a lower probability of a negative job separation and the effect is significant conditional on summed previous separations. Furthermore, once we incorporate our measure of n into the regression, the effect of number of previous splits diminishes: by only about 4% for men, and by about 12% for women. Columns (3) and (4) report results from the same regressions on the model-generated data. In particular, $\tilde{n}$ in the model generated data is inferred using exactly the same procedure as in the data (i.e. generating a measure $\tilde{n}$ based on job history where $\nu \in \{1, 2, 3\}$ stands for indexes of the relationship skills provided by the O*NET). It is clear that the overall pattern of results is similar to those in the data. First, from column (3), previous number of splits positively affects the probability of a negative job separation for both genders, though the coefficients are smaller in absolute value from those in the model. Second, from column (4), high $\hat{n}$ individuals are less likely to experience a negative job separation than low $\hat{n}$ individuals.

Column 5 of tables 8 and 9 provides some evidence on the "noisiness" of $\hat{n}$. In column 5 we provide the results form the same regression as in column 4 but using the actual individual n in the model rather than the $\hat{n}$ constructed from job histories. The results in column 5 show it is still the case that (i) high n individuals have a lower probability of a negative job separation, and (ii) once we include n in the regression analysis, the effect of number of previous splits nearly disappears. The results are substantially stronger when we use the actual n rather than the one inferred using the same procedure as in the data, indicating that our measure of $\tilde{n}$ is a moderately noisy signal of "true" n, as we expect. Indeed, the correlation of n and $\tilde{n}$ is .7 for men and .6 for women in the model. Consequently, including the "true" n substantially reduces the estimated effect of previous separations on the likelihood of a current separation while constructed $\tilde{n}$, has typically much smaller effects, especially for men. The results therefore give us some confidence that we are in fact identifying an important individual factor that can explain a significant part of individuals' career and social histories.

Tables 10 and 11 repeat the same validation exercise for the divorce hazards. The results are similar to those for negative job switches. Including our measure of $\tilde{n}$ in the PSID regressions reduces the power of previous separations (the sum of job and marriage separations) in predicting a current separation, with the effect larger for women (a roughly 20% reduction in the size of the coefficient on previous switches from .01 to .008). The same

Table 8: Job switch hazards in model and data: Men

	Data	Data $+\hat{n}$	Model	Model + constructed $\hat{n}$	Model + real n
	(1)	(2)	(3)	(4)	(5)
educ	-.001	.0001	.003	.002	.003
	(.0005)**	(.0006)	(.0004)***	(.0004)***	(.0004)***
tenure	-.0002	-.0002	-.002	-.002	-.002
	(9.84e-06)***	(9.93e-06)***	(.00007)***	(.00007)***	(.00007)***
prev splits	.022	.021	.009	.007	.002
	(.001)***	(.001)***	(.0008)***	(.001)***	(.001)*
n		-.014		-.009	-.013
		(.003)***		(.001)***	(.001)***

Table 9: Job switch hazards in model and data: Women

	Data	Data $+\hat{n}$	Model	Model + constructed $\hat{n}$	Model + real n
	(1)	(2)	(3)	(4)	(5)
educ	-.0009	-.0002	.003	.003	.002
	(.0008)	(.0009)	(.0002)***	(.0003)***	(.0003)***
tenure	-.0004	-.0004	-.002	-.002	-.002
	(.00002)***	(.00002)***	(.00007)***	(.00007)***	(.00007)***
prev splits	.010	.008	.005	.004	.002
	(.001)***	(.001)***	(.0009)***	(.0009)***	(.0009)***
n		-.007		-.007	-.009
		(.004)**		(.001)***	(.001)***

result obtains when including $\tilde{n}$ in the identical model regressions. Including the true n has even larger effects in the model regressions for likelihood of marital separation than the effects for negative job switches, both in terms of its own predictive power and its ability to reduce the predictive power of previous separations. Again, the evidence is consistent with our interpretation of n as a fixed individual effect that operates on individuals' ability to maintain relationships, be it with a boss or firm, or with a partner.

Table 10: Divorce hazards in model and data: Men

	Data	Data $+\hat{n}$	Model	Model + constructed $\hat{n}$	Model + real n
	(1)	(2)	(3)	(4)	(5)
educ	-.002	-.001	-.0004	-.0004	-.0003
	(.0004)***	(.0004)***	(.0001)***	(.0001)***	(.0001)***
marr tenure	-.003	-.003	-.002	-.002	-.002
	(.0003)***	(.0003)***	(.00007)***	(.00007)***	(.00007)***
prev splits	.004	.003	.002	.002	.001
	(.0007)***	(.0007)***	(.0007)***	(.0009)**	(.0006)**
n		-.006		-.002	-.003
		(.002)***		(.0007)***	(.0009)***

Table 11: Divorce hazards in model and data: Women

	Data	Data $+\hat{n}$	Model	Model + constructed $\hat{n}$	Model + real n
	(1)	(2)	(3)	(4)	(5)
educ	-.003	-.003	-.0004	-.0003	-.0002
	(.0005)***	(.0005)***	(.00008)***	(.00009)***	(.0001)
marr tenure	-.003	-.003	-.001	-.001	-.001
	(.0003)***	(.0003)***	(.00006)***	(.00006)***	(.00006)***
prev splits	.006	.004	.004	.002	.0006
	(.0009)***	(.0009)***	(.0003)**	(.001)**	(.0003)**
n		-.004		-.0009	-.002
		(.002)**		(.0005)*	(.0006)***

5.3 Welfare analysis

We have established that partnering skill n is an important determinant of economic outcomes in our benchmark model. An obvious question is how these economic outcomes translate into utility measures. Table 12 reports how much individuals at different levels of

k_0 would be willing to pay as a share of per-period lifetime consumption to be born with high n rather than low n. The last two columns of the table report how much low n and high n individuals would be willing to pay to be born with k_0 index 3 rather than k_0 index 1. Recall that, while the k_0 do not directly map into earning ability since they must be combined with education, they correspond to human capital increments of $6 of "raw" human capital, while high n (n=2) individuals have σ_n more relationship skill relative to low-n (n=1) individuals (where we normalized the units of low n to zero units).

Table 12: Welfare effects of n

	low n to high n				k_0 1 to k_0 3	
	k_0 1	k_0 2	k_0 3	k_0 4	low n	high n
Compensating (-) change in consumption per period: men	0.9%	1.2%	4.2%	6.3%	3.9%	4.5%
Compensating (-) change in consumption per period: women	0.6%	0.9%	6.6%	15.5%	4.5%	10.2%

Table 12 shows that n does in fact have substantial welfare effects that reflect its economic implications. On average, individuals would give up about 6% of consumption per period to have good relationship skills. The welfare effects are much larger for women. Inspection of the results implies this result is largely due to the fact that high n effectively allows women options over whether to work or not. Indeed, the participation rate of high n women is 10% lower among high n women than among low n women (though – consistent with the data – the participation rates are identical by $\tilde{n}$ since some high n women working in relatively lower-skill, low-ν jobs are categorized as low $\tilde{n}$ in the algorithm used to assess n.) The welfare benefits are also increasing in k_0 for both genders, while the benefits of high k_0 are increasing in n (columns 5 and 6). This result is largely due to the fact that the highest κ jobs also tend to be the highest ν jobs. Given the complementarity of k and κ in production ($\gamma_1 = -.35$) individuals must be both high κ and high ν to benefit. The increase in the return to n by education is also higher for women since higher k allows these women to match with high n and high k spouses, which reduces their necessity of working more than for low-k women whose marriages tend to be with less economically secure men.

6 Robustness

[forthcoming]

7 Conclusion

[forthcoming]

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