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 education, labor and marriage markets. We posit a two-factor model with human capital and "relationship" or "partnering" skill. Relationship 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 increases the durability of relationships in multiple 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. It is highly complementary in the market sector but fairly substitutable in the home sector: that is, stability of marriage depends most strongly on at least *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 inputs into marriage. To explore the quantitative implications of relationship skill, we use the PSID to develop and estimate a two-factor life cycle model of schooling, job search and marriage that allows us to 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, they influence the level of team output. Second, they affect the likelihood of team dissolution. 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 standard measures of human capital affect the three team outcomes listed above, our initial empirical evidence shows that after controlling for years of schooling and the current wage, there remains an individual fixed effect which affects both marital and job dissolutions. This finding is consistent with Mincer and Jovanovic (1981) and with the general class of mover-stayer models but inconsistent with more traditional search models of the labor or marriage markets.

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” or “partnering” 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— $\tilde{n}$. 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, especially for women, “cooperation” 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, $\tilde{n}$, affects both marital and job dissolutions after controlling for years of schooling and the current wage.

Moreover, we find that the spousal $\tilde{n}s$ are reasonably strong substitutes in decreasing the likelihood of divorce: specifically that the interaction of husband and wive's $\tilde{n}$ is positive and consistently marginally significant in contrast to the interaction of the spouses' wages, which is insignificant, and education, which is negative and highly significant. Substitutability of $\tilde{n}$ in determining divorce raises the question as to whether there is negative assortative matching by $\tilde{n}$ in marriage conditional on education, We find that lack of a marital bargaining mechanism means that n is positively sorted, though less strongly than education or human capital.

We are also interested in the initial distribution of n with human capital (k) in the population. We obtain estimates of the initial bivariate distributions of skill in the population by gender by developing and 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 much more likely to remain longer in school and receive higher life time returns per year of education on average. We back out initial distributions of relationship and cognitive skills and study differences in these initial distribution across gender, which are relatively small. 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 importance of partnering skills for life outcomes.

Our paper is related to and builds on several recent strands of the economics and psychology literatures. First, 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, which is also consistent with the evidence in Borghans et al. (2008). 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, while we consider a general measure of human capital, which is closely related but not synonymous with cognitive skills, and relationship skills.[1] 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.

Second, recently Altonji et al. (2013) estimate a two factor model of labor market wages, hours of work and transitions also using data from the PSID in order to study the deter-

[1]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.

minants of life cycle variation in hours and earnings. They allow for two individual specific factors – a general ability factor and a "propensity to move" factor – as well as a rich assortment of persistent job- and individual-specific factors that we believe together capture much of the variation we attribute to n. With reference to the labor market, our paper differs from their work in four major ways. (1) We include data on both men and women in our analysis whereas they focus on black and white men. (2) We construct an empirical proxy for relationship skill, that is in general correlated with measures of human capital, whereas they leave their "propensity to move" factor as unobservable and independent of their fixed ability factor. (3) We estimate a structural model whereas they estimate a behaviorally motivated statistical model. They are therefore able to estimate a model with a much richer array of idiosyncratic shocks. On the other hand, we can use our structural model to discuss policy and behavioral issues which are not feasible without such a model and to study the co-determination of two fixed factors and endogenous effects across multiple markets.

Also related to our project, there is a large literature on the effect of non-cognitive ability on labor market and other social outcomes. While this literature has generally produced inconclusive evidence on the importance of different personality-based attributes for wages and earnings (see the discussion in Borghans et al. (2008)) Heckman et al. (2006) found that early childhood intervention can effect children's outcomes in terms of schooling completion, risky behavior and labor market outcomes by raising a broadly-defined measure of non-cognitive skill, 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. Focusing on a more traditional economic measure of personality, Compton (2009) shows that smokers – individuals with high time discount rates – are more likely to divorce.

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 the output of the match changes over time, with couples with worse non-cognitive traits being more prone to negative shocks to household efficiency, 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.

The layout of the paper is as follows. Section 2 describes our data sources and empirical motivation. In section 3, we develop our life cycle model with education, marriage, work and retirement. Section 4 describes the parameterization and estimation of the model while section 5 presents preliminary results, focussing on the role of relationship skills in life cycle outcomes. Section 6 studies the evidence of the model in favor of our interpretation of n as a multi-sector fixed effect. Section **??** offers tentative conclusions.

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, 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 cannot 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 − a switch is identified if the reported employer tenure is lower than the time period between the two consecutive interview dates.[2] 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 any time 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 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.[3] If neither condition is met when the worker changes jobs − that is, if she spends no time in unemployment and experiences a medium-term increase in her hourly wage − we identify the job change as a "positive" move up the career ladder. The negative switch rate is roughly 8% per year among all adults 25-56 and 9.5% among adults who worked in the previous year. It is slightly (1.5 pp) higher for female than for male workers.

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

[2]Under this definition, we exclude 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. See Kambourov and Manovskii (2009) for a discussion of this and other related ways to identify employer switches in the PSID.

[3]If wage information is missing in any of the four years that enter the calculation, we omit the year from the calculation.

observed.[4] The share of divorces among total married observations 25-56 in the sample is 4.3%.

In the regressions, that follow, the independent variables include age, education, the ln wage in the previous year (prior to the switch in column (1)), tenure in the current job (in column (1)) and the current marriage (in column (2)) and measures of the number of total prior negative job losses and divorces of the individual.[5] 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 of 50 when first observed.[6]

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 switch and of divorce both decline in age and education for both genders. The likelihood of negative employer separation declines with job tenure in the year before the potential split while the likelihood of divorce declines with marriage tenure, also as expected. The lagged ln wage is only significantly negative for the likelihood of divorce, though it becomes strongly significant in the job switch regressions if job tenure is omitted. 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 and women in the sample in both the linear probability and probit models.

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, both the tally of previous job losses and of previous marital separations have independent negative

[4] 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.

[5] We also include, but do not report, year dummies and 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.

[6] 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.

implications for wage growth, conditional on ln wage in the previous year. For women, the situation is slightly different: lagged job losses negatively affect the predicted current wage, but lagged divorces have a positive, insignificant effect on the predicted growth in the wage. One potential explanation is selection: nearly all men work but not all women, particularly earlier in our sample period. Women who expect to experience marital breakdown may be more likely to be attached (by necessity) to the labor force, or women with high labor market attachment (and wage growth) may be willing to exit bad marriages. In section 6 we return to this implication in the context of our model.

This evidence is suggestive of the existence of an individual fixed effect, observed both in the labor and in the marriage markets, that affects individuals' ability to prevent breakdowns in relationships. Two important issues arise at this point. First, is it possible to describe this fixed effect in greater detail and map it into some of the observable individual characteristics that such datasets as the U.S. Department of Labor's Occupational Information Network, the O*NET, have tried to measure? Second, what are the exact mechanisms through which these "relationship" skills affect individuals' labor and marriage market histories over the life cycle and how quantitatively important are they? We turn to the first issue in the next subsection. The second issue is addressed by building a life-cycle model with education, labor, and marriage market decisions that explicitly incorporates the various channels through which "relationship" skills affect individuals.

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[7], 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 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

[7] 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	-.034	-.023	-.025	-.021
	(.016)**	(.010)**	(.016)	(.013)*
age^2	.0007	.0005	.0006	.0005
	(.0004)*	(.0003)**	(.004)	(.003)
age^3	-4.93e-06	-3.73e-06	-4.25e-06	-3.50e-06
	(3.03e-06)	(1.99e-06)*	(2.93e-06)	(1.80e-06)
job tenure	-.003		-.003	
	(.0002)***		(.0001)***	
marriage tenure		-.001		-.001
		(.0004)***		(.0002)***
educ	-.003	-.002	-.002	-.001
	(.0005)***	(.0004)***	(.0004)***	(.0003)***
lag ln wage	-.0008	-.006	-.0008	-.005
	(.003)	(.002)***	(.001)	(.0001)***
previous job switches	.016	.002	.007	.002
	(.001)***	(.0007)***	(.0007)***	(.0006)***
previous divorces	.014	.029	.008	.015
	(.003)***	(.004)***	(.002)***	(.002)***

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	-.011	-.016	-.009	-.014
	(.015)	(.012)	(.014)	(.013)
age^2	.0002	.0003	.0009	.003
	(.0004)	(.0003)	(.004)	(.004)
age^3	-1.50e-06	-2.34e-06	-6.92e-06	-.00003
	(3.06e-06)	(2.34e-06)	(.00003)	(.00003)
job tenure	-.003		-.004	
	(.0002)***		(.0003)***	
marriage tenure		-.002		-.002
		(.0004)***		(.0001)***
educ	-.003	-.003	-.003	-.003
	(.0007)***	(.0005)***	(.0006)***	(.0005)***
lag ln wage	.003	-.003	.004	-.002
	(.003)	(.002)	(.002)	(.002)
previous job switches	.013	.003	.007	.003
	(.002)***	(.001)***	(.001)***	(.0008)***
previous divorces	.010	.021	.007	.011
	(.003)***	(.004)***	(.002)***	(.002)***

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.[8] The O*NET-SOC codes are then used to merge the O*NET data to the PSID sample. We

[8]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.

Table 3: ln wage growth and previous separations: Both genders

	Δ ln wage: men	Δ ln wage: women
age	.025	.036
	(.015)	(.019)*
age^2	-.0005	-.0008
	(.0004)	(.0005)*
age^3	3.25e-06	5.85e-06
	(3.06e-06)	(3.92e-06)
job tenure	.001	.005
	(.0003)***	(.0005)***
educ	.025	.038
	(.001)***	(.002)***
previous job switches	-.010	-.009
	(.002)***	(.002)***
previous divorces	-.014	.002
	(.004)***	(.005)

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, n. We construct candidate measures of n, called $\hat{n}$, for each individual using the following simple algorithm: for each PSID person-year for which an occupation is reported, we assign the measure of the "importance" of a given potential relationship skill (described below) for this occupation from the O*NET, and then average this measure across all years in which the individual reports an occupation, weighting by the length of the job spell so that longer spells in a given occupation are 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 the $\hat{n}$s are constructed for each worker in the sample, we examine how they affect the likelihood of marital 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 household-level analysis with the potential to be informative about how partners' $\hat{n}$s *jointly* affect the stability of marriage. Since the $\hat{n}$s measure fixed effects, we believe we can credibly argue that they affect marriage through their implications about the partners' characters rather than their economic implications, conditional on the partners' current wages and permanent predicted based on their job history.[9] 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 and estimating n

To construct different candidate measures of n–the $\hat{n}$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 qualitatively related to standard psychological measures such as the "Big Five" personality traits. Second, it provides a manageable amount of information for analysis. We focus on the mean reported "importance" of each skill to the occupation, ranked from one to five. There are sixteen skill 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 at least one member of the couple reports that they are 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 (see footnote 9), current ln wage and year dummies. We extract the O*NET variables for which one or both spouses' $\hat{n}$s significantly reduce the couple's likelihood of divorce (subject

[9]To calculate the permanent predicted wage of an individual with a given job history we use the same algorithm as used to calculate the $\hat{n}$s, using average wage in the occupation in place of reported skill, and averaging over the person's entire occupational work history.

to various criteria described below) and use them to create a common factor, which we will call $\tilde{n}$. We will use our preferred measure of $\tilde{n}$ to calibrate and estimate 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 table 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 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 the *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. The increase in qualifying $\hat{n}$s in column 3 suggest this is in fact the case. Finally, under our fourth criterion (column 4), we include *all* the $\hat{n}$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 conditional on all the others. In what follows, the principle component obtained from the qualifying $\hat{n}$s using this last criterion is the one we use to calibrate the model.

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. We then repeat the divorce regressions with this common factor calculated for each spouse as our measure of n. The results 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 $\tilde{n}$s as the independent variables of interest. The bottom row of the table reports the p-value from an F test of the three terms containing the partners' $\tilde{n}$s.

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

Table 4: Four criteria for divorce effects of candidate ns

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	

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 × 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 × wife's educ	-.0004	-.0004	-.0004	-.0004
	(.0001)***	(.0001)***	(.00009)***	(.0001)***
marriage tenure	-.002	-.002	-.002	-.002
	(.0002)***	(.0002)***	(.0002)***	(.0002)***

as expected, but the *interaction* of husband and wife's trait is positive and consistently marginally 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.

2.2.2 Interpreting n

Since work and marriage relationships can be terminated by either partner, $\tilde{n}$ may increase the duration of relationships due to two mechanisms. First, an individual may have skills which directly increases the duration of a relationship, for example the ability to cooperate or follow through on promises, which reduces the rate at which frictions arise in the relationship. The second mechanism is indirect. Some attributes may make that person an attractive partner and therefore an individual with those attributes is unlikely to face divorce even during frictional periods.

From our empirical analysis above, we showed that persistence, adaptability, integrity, and independence are consistent, important components which determine $\tilde{n}$ and increase the observed stability of marriage. For women, concern for others and cooperation are also strong predictors of divorce likelihood conditioning on other measures of social orientation. Relationship specific capital is, to a large extent, built on trust and reliability. Thus it is not surprising that persistence and integrity will be important components of $\tilde{n}$. Adaptability allows partners to adapt to new circumstances, mitigate and diffuse conflict. So adaptability have both direct and indirect effects in building relationships. There is no obvious direct role by which independence builds relationships. However, independent individuals (the effect is modestly stronger for wives in the regressions) may be more attractive to the partner. As well, independence can be seen as the opposite of neuroticism, which **?** shows to raise the divorce hazards of women.[10] Factor analysis suggests that 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

[10] In general, there is no direct quantifiable link between our qualifying $\hat{n}$s and more standard psychological measures. Besides independence, however, 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.

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 finding 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 $k(j)$, and their relationship or partnering skill n. $k(j)$ 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 discrete joint distributions of k_0 and n, each characterized by a σ_{kn}^g measuring the within-gender correlation between k_0 and n.[11] As adults (post education) individuals may be unemployed or employed with a job defined by "complexity" κ and relationship skill requirement ν, with $\nu = 0$ and $\kappa = \underline{\kappa}$ when the individual is unemployed. Adult individuals may be married M or single S.

[11]In our PSID sample, we cannot observe the initial distribution of k_0, but we do observe that almost exactly 50% of men and 50% of women are high n. Since *observed* n and *true* n (our $\tilde{n}$) differ, we allow the actual shares of high-n men and women to differ. In practice only women's share of true n differs from the share of $\tilde{n}$. The share of high n women entering adulthood is N_f and is estimated as a parameter of the model.

3.1.1 Stage 1: Education

At age 16, individuals know their k_0 and n and make an education decision, which is a discrete 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 according to

$$\begin{aligned} k = f(k_0, s, \epsilon_s) &= k_0^{\alpha} s^{1-\alpha} \epsilon_s(n) \\ \epsilon_s(n) &\sim \beta(p(n), 1) \\ p(n) &= \sigma_S(1 + \psi n) \end{aligned} \tag{1}$$

where $\epsilon_s \in (0, 1)$ is a shock realized at the end of the chosen education period. ϵ_s is drawn from a power distribution: $f(\epsilon_s) = \mathit{constant} \cdot p(n)\epsilon^{p(n)-1}$, which is a special case of the beta distribution, and the constant normalizes the distribution between 0 and 1 and is otherwise unimportant to the analysis. p varies with 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 (or, in principle, less but ψ turns out to be very positive) 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. The same holds for the other stochastic components of the model that hold in other markets.

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 transfer or unemployment income (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 $\sigma^2_{\underline{C}}$.

All other thing equal, a higher k_0 and or higher n will lead to higher levels of schooling, and thus higher expected levels of adult k.

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 each period, which is two months. Job decisions, in response to new offers, are also made bi-monthly which allows us to achieve a realistic model of employment and unemployment transitions.

Work. Individuals enter the labor market unemployed with human capital $k(\underline{j})$, 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 $\tilde{\Pi}(\kappa, \nu)$, where (κ, ν) characterizes a particular job offer. Workers make take it or leave it offers to potential employers and so extract all the surplus in the form of wages W[12]:

$$\begin{aligned} W(k, \kappa, n, \nu, \epsilon_W) &= a_g\big(\gamma_0 k^{\gamma_1} + (1-\gamma_0)\kappa^{\gamma_1}\big)^{\frac{1}{\gamma_1}} \epsilon_W(n, \nu) \\ \epsilon_W(n, \nu) &\sim \beta\big(p(n, \nu), 1\big) \\ p(n, \nu) &= \sigma_W(1 + \phi_0 n + \phi_1 \nu + \phi_2 n\nu]. \end{aligned} \tag{2}$$

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.[13] The fixed component depends on the match between learned skill ("human capital" broadly defined) and the productivity/complexity of capital κ according to a CES with share parameter γ_0 and substitution elasticity γ_1. Production each two-month period is subject to an 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 the variance σ_{ϵ_W}. The properties and interpretation of the β distribution for

[12] We do not explicitly model the firms' decisions. We assume that there is an exogenously given distribution of jobs $\Pi(\kappa, \nu)$ and, given the model, some of them get filled, giving rise endogenously to a distribution of filled jobs $\hat{\Pi}(\kappa, \nu)$ and a distribution of available unfilled jobs $\tilde{\Pi}(\kappa, \nu)$. We parameterize the $\Pi(\kappa, \nu)$ distribution so that in our benchmark the model is consistent with certain targets from the data.

[13] 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 over the working life, conditional on education.

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 $\hat{\Pi}(\kappa,\nu)$ 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 $\tilde{\Pi}(\kappa,\nu)$ 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 (also student and retirement) benefits are given by () when $\kappa = \underline{\kappa}$ and $\epsilon_W = 1$. reflecting the fact that unemployment benefit are typically based on potential earnings. While employed, individuals receive a permanent unit increment to k at the start of each year with probability $p_k = p_{0,k} + p_{1,k}k^{.5}$ 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.

Finally, in the simulated economy, we assume that we observe W with error. That is, we observe a measure of wages $\hat{W} = W\exp(\epsilon_{me})$, where ϵ_{me} is distributed normally with mean zero and variance σ^2_{me}.

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:

$$\begin{aligned} S &= \left(W(k,\kappa,n,\nu,\epsilon_W)^{\chi_1} + H(k)^{\chi_1}\right)^{\frac{1}{\chi_1}}\bar{\epsilon}_S(n) \\ H(k) &= 0.1\ if\ \kappa > 0 \\ &= \eta^g k\ if\ \kappa = 0 \\ \bar{\epsilon}_S &= e_0 + e_1 n \end{aligned} \tag{3}$$

For convenience, we also define S by employment status:

$$\begin{aligned} S_U &= \left(W(k,n,\underline{\kappa},0)^{\chi_1} + \eta^g k\right)^{\frac{1}{\chi_1}}\bar{\epsilon}_S(n) \\ S_E &= \left(W(k,\kappa,n,\nu,\epsilon_W)^{\chi_1}\right)^{\frac{1}{\chi_1}}\overline{\epsilon_S}(n) \end{aligned}$$

Utility is given by:

$$U_g = \ln\left(S\right) \tag{4}$$

Expressions 3 and 4 say that singles enjoy consumption from earned income and home production, according to a deterministic equivalence scale given by $\bar{\epsilon}_S(n)$. $\bar{\epsilon}_S$ depends on n since relationship skills may impact an individual's ability to transform market and home produced goods into effective consumption even if he or she is not married, for example by affecting the quality of friendships, but we assume that the value of these less formal relationships is known. The assumption of determinism in period consumption for singles (conditional on ϵ_W is not essential to the results of the model, but simplifies the dynamic programs presented in the next section. Home production H is normalized to a small positive value for individuals who work and otherwise is increasing and concave in human capital k.

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

$$M = \big(\chi_0(W_f + W_m)^{\chi_1} + (1-\chi_0)(H_f + H_m)^{\chi_1}\big)^{\frac{1}{\chi_1}} \epsilon_M(n_f, n_m)$$

$$\begin{aligned} H_f &= 0 \; if \; \kappa_f > 0 & \qquad H_m &= 0 \; if \; \kappa_m > 0 \\ &= \eta^f k_f \; if \; \kappa_f = 0 & &= \eta^m k_m \; if \; \kappa_m = 0 \end{aligned}$$

$$\begin{aligned} \epsilon_M(n_f, n_m) &\sim \beta\big(p(n_f, n_m), 1\big) \\ p(n_f, n_m) &= \sigma_M\big(1.0 + \lambda_0 n_f + \lambda_1 n_m + \lambda_2 n_f n_m\big) \end{aligned} \tag{5}$$

Each spouse's individual utility is given by

$$U_g^M = \ln(M) \tag{6}$$

Equation (5) has a similar construction to equation (2) governing the wage: it determines the efficiency of a two member household or husband wife team. Elasticity parameter $\chi_1 \in (-\infty, 1]$ captures the degree of substitutability between home and market production and χ_0 captures their relative importance in generating marital output. Market earnings by the spouses are taken to be perfect substitutes but the spouses may have comparative advantage in either the market or home, allowing for specialization not available to singles, as suggested in Becker (1974) and Becker (1991). In contrast to $\bar{\epsilon}_S$, which is a fixed factor, ϵ_M is a transitory exogenous shock to M, capturing the degree to which M is enjoyed or converted into utility-generating consumption within the period, and over time the stream stochastic returns to marital production. The distribution of the shock depends on both husband's and wife's relationship skill 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 implies that couples with higher incomes and efficiency in home production 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 π (that is, with probability π per two-month period). Matched pairs marry if, for both members of the pair, the continuation value of being married to the matched partner exceeds the continuation value of remaining single and drawing new potential mates in future periods. 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. The interaction of marriage decisions with work decisions is 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 $k(66)$ 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 i of gender g is characterized by state vector $x_g = \{j, k, n, \kappa, \nu\} = \{j, k, n, \underline{\kappa}, 0\}$ where j indexes age in months. His value function is given by:

$$\begin{aligned} V_{g,i}^S(j,k,n,0,0) = \ln S_U + \beta\Big(&\big(1-\pi_i\big)\big((1-p_{0,i})V_{g,i}^S(j+2,k,n,0,0) \\ &+ p_{0,i}\sum_{\mathcal{J}} q(\hat{\kappa},\hat{\nu}) \int_{\epsilon'_W(\hat{\kappa},\hat{\nu})} V_{g,i}^S(j+2,k,n,\hat{\kappa}^*,\hat{\nu}^*)dF(\epsilon_W)\big) \\ &+ \pi_i\big((1-p_{0,i})\sum_{X_{-g,i}} \varrho(x_{-g,i})E_{\epsilon_{-W}}V_{g,i}^M(j+2,x_g,x_{-g}) \\ &+ p_{0,i}\sum_{\mathcal{J}} q(\hat{\kappa},\hat{\nu}) \sum_{X_{-g,i}} \varrho(x_{-g,i})E_{\epsilon_W,\epsilon_{-W}}V_{g,i}^M(j+2,x_g,x_{-g})\big)\Big) \end{aligned} \tag{7}$$

where $V_{g,i}^M$ is the value function of the individual when married, defined below.

In (7), F is the distribution function of ϵ_W. $X_{-g,i}$ is the set of singles of the opposite gender who are "marriageable": that is, who are willing to marry individual i next period given his own vector $x'_g \equiv \{k, n, \hat{\kappa}^*, \hat{\nu}^*\}$ *and* who he finds it optimal to marry in state x'_g; π_i is the individual-specific likelihood of meeting a partner in this set, which is the product of exogenous meeting probability π and the share of "marriageable" partners among the entire population of singles, which is itself determined endogenously within the model. Similarly, $\mathcal{J}$ is the set of $\{\kappa, \nu\}$ job offers that the individual would accept if they were offered; $p_{i,0}$ is the individual-specific likelihood of receiving a job offer from this set, which is the product of exogenous probability of matching p_0 and $\mathcal{J}$ as a share of all vacancies. Like the population of singles, the *unconditional* distribution of vacant jobs is determined endogenously in the model given an overall time-invariant distribution of *filled* jobs. Finally,

$$\{\hat{\kappa}^*, \hat{\nu}^*\} = \text{argmax}[S_E(\epsilon'_W) + \beta V^S_{g,i}(j+4, k, n, \hat{\kappa}, \hat{\nu}), S_U + \beta V^S_{g,i}(j+4, k, n, \underline{\kappa}, 0)]$$

which says that $\hat{\kappa}^*, \hat{\nu}^*$ is the single individual's optimal employment choice next period once match productivity ϵ'_W has been realized in job $\{\hat{\kappa}, \hat{\nu}\}$.

Equation (7) incorporates a specific timing of events within the period. The individual enters the period with all uncertainty resolved and consumes S_U. At the end of the current period, three things happen. First, the unemployed individual receives and accepts an attractive job offer for next period with probability $p_{0,i}$. Second, the individual encounters an attractive and attracting marriage opportunity with probability π_i, where π_i depends itself on whether the individual has just changed employment status since becoming employed changes the set $X_{-g,i}$. Third, if the individual is now employed, the current wage productivity shock ϵ_W is realized, at which point the individual can choose to remain and produce in his new job or decline the offer and remain in unemployment. If the individual is single, he makes this decision on his own. If he has married, the decision is a household-level decision which is defined in detail below. In this case, the payoff depends both on own and spousal ϵ'_W.

Single employed. The value function for a single worker with a job characterized by

$\{\kappa, \nu\}$ is given by:

$$
\begin{aligned}
V^S_{g,i}(j,k,n,\kappa,\nu) &= \ln(S_E) \\
&+ \beta \sum_{k'=k}^{k+\iota_k} \Big[\tilde{p}(k,k') \Big(\big(1-\pi_i\big) \big((1-p_{1,i}) \int_{\epsilon'_W(\kappa,\nu)} V^S_g(j+2,k',n,\kappa^*,\nu^*) dF(\epsilon'_W) \\
&+ p_{1,i} \sum_{\mathcal{J}} q(\hat{\kappa},\hat{\nu}) \int_{\epsilon'_W(\hat{\kappa},\hat{\nu})} V^S_g(j+2,k',n,\hat{\kappa}^*,\hat{\nu}^*) dF(\epsilon'_W) \big) \\
&+ \pi_i \big((1-p_{1,i}) \sum_{X_{-g}} \varrho(x_{-g,i}) E_{\epsilon'_W,\epsilon_{-W}} V^M_{g,i}(j+2,x_g,x_{-g}) \\
&+ p_{1,i} \sum_{\mathcal{J}} q(\hat{\kappa},\hat{\nu}) \sum_{X_{-g}} \varrho(x_{-g,i}) E_{\epsilon'_W,\epsilon_{-W}} V^M_{g,i}(j+2,x_g,x_{-g}) \big) \Big) \Big]
\end{aligned}
\tag{8}
$$

There are three differences between (8) and (7). First, at the very beginning of the period, individual i faces job arrival probability $p_{1,i}$ rather than $p_{0,i}$, where p_1 is the arrival rate of job offers among the employed and $p_{1,i}$ again is the product of p_1 an the share of attractive job offers among all potential job offers. In general, individuals will only take advantage of new job opportunities if their expected income in the current period and over the expected duration of the job is greater than the same expected income from keeping their current job, so $p_{1,i}$ is decreasing in κ. Second, with probability $\tilde{p}(k, k+\iota_k) = p_K$, individual i receives a positive increment of ι_k to his adult human capital from learning by doing on the current job.[14] This increment to capital is realized before any other decisions are made for the next period; figure 1 at the end of the section shows the timing of events within a period for singles and marrieds. Third, once job change and marriage decisions are made, at the very end of the period, all employed individuals draw their wage shock ϵ'_W and choose whether to work their current job or quit. If no job offer or marriage offer is received, we define

$$
\{\kappa^*, \nu^*\} = \text{argmax}\{S_E(\epsilon'_W) + \beta V^S_{g,i}(j+4,k',n,\kappa,\nu), S_U + \beta V^S_{g,i}(j+4,k',n,\underline{\kappa},0)\}
$$

which again depends on the realization of ϵ'_W which will in general be drawn from different distributions for depending on whether the individual changed jobs. Otherwise, after a marriage has been formed, the decision to stay or quit in the subsequent period again depends on own and spousal variables and is taken at the household level, as described next.

Married unemployed and employed. We now turn to the value functions for married individuals. A married household maximizes a household-level utility function U_M:

[14]and $\tilde{p}(k,k) = 1 - p_K$. The $\tilde{p}$ is introduced here only to reduce the notation in the value function.

$$U_M = V_f^M(x_M) + V_m^M(x_M) \tag{9}$$

where $x_M = \{x_f, x_m, \epsilon_M\}$. Spouse g's individual value function at age j is given by

$$\begin{aligned}
&V_g^M(j,k,n,\kappa,\nu,x_{-g},\epsilon_M) = \ln(M) + \beta \int_{\epsilon'_M} \sum_{k'=k_g}^{k_g+\iota_k} \Big[\tilde{p}(k_g,k'_g) \sum_{k'_{-g}=k_{-g}}^{k_{-g}+\iota_k} \Big[\tilde{p}(k_{1-g},k'_{1-g}) \\
&\quad \Big((1-\mathcal{P}_g)(1-\mathcal{P}_{-g}) \\
&\quad \Big(\varphi_g(x'_M) \max\Big[\int_{\epsilon'_W}\int_{\epsilon'_{-W}} V_g^M(j+2,x_g^{**},x_{-g}^{**},\epsilon'_M) dF(\epsilon'_W) dF(\epsilon'_{-W}), \int_{\epsilon'_W} V_g^S(j+2,x_g^*) dF(\epsilon'_W)\Big] \\
&\qquad\qquad + (1-\varphi_g(x'_M)) \int_{\epsilon'_W} V_g^S(j+2,x_g^*) dF(\epsilon'_W)\Big) \\
&\quad +\mathcal{P}_g(1-\mathcal{P}_{-g}) \sum_{\mathcal{J}} q(\hat{\kappa},\hat{\nu}) \\
&\quad \Big(\varphi'_g(x'_M) \max\Big[\int_{\epsilon'_W}\int_{\hat{\epsilon}'_{-W}} V_g^M(j+2,\hat{x}_g^{**},x_{-g}^{**},\epsilon'_M) dF(\hat{\epsilon}'_W) dF(\epsilon'_{-W}), \int_{\hat{\epsilon}'_W} V_g^S(j+2,\hat{x}_g^*) dF(\hat{\epsilon}'_W)\Big] \\
&\qquad\qquad + (1-\varphi_g(x'_M)) \int_{\hat{\epsilon}'_W} V_g^S(j+2,\hat{x}_g^*) dF(\hat{\epsilon}'_W)\Big) \\
&\quad +(1-\mathcal{P}_g)\mathcal{P}_{-g} \sum_{-\mathcal{J}} q(\hat{\kappa}_{-g},\hat{\nu}_{-g}) \\
&\quad \Big(\varphi'_g(x'_M) \max\Big[\int_{\epsilon'_{\hat{W}}}\int_{\hat{\epsilon}'_{-W}} V_g^M(j+2,x_g^{**},\hat{x}_{-g}^{**},\epsilon'_M) dF(\epsilon'_W) dF(\hat{\epsilon}'_{-W}), \int_{\epsilon'_{\hat{W}}} V_g^S(j+2,x_g^*) dF(\epsilon'_W)\Big] \\
&\qquad\qquad + (1-\varphi_g(x'_M)) \int_{\epsilon'_W} V_g^S(j+2,x_g^*) dF(\epsilon'_W)\Big) \\
&\quad +\mathcal{P}_g\mathcal{P}_{-g} \sum_{\mathcal{J}} \sum_{-\mathcal{J}} q(\hat{\kappa},\hat{\nu}) q(\hat{\kappa}_{-g},\hat{\nu}_{-g}) \\
&\quad \Big(\varphi_g(x'_M) \max\Big[\int_{\hat{\epsilon}'_W}\int_{\hat{\epsilon}'_{-W}} V_g^M(j+2,\hat{x}_g^{**},\hat{x}_{-g}^{**},\epsilon'_M) dF(\hat{\epsilon}'_W) dF(\hat{\epsilon}'_{-W}), \int_{\hat{\epsilon}'_W} V_g^S(j+2,\hat{x}_g^*) dF(\hat{\epsilon}'_W)\Big] \\
&\qquad\qquad + (1-\varphi_g(x'_M)) \int_{\hat{\epsilon}'_W} V_g^S(j+2,\hat{x}_g^*) dF(\hat{\epsilon}_W)\Big)\Big)\Big]\Big] dF(\epsilon_M)
\end{aligned} \tag{10}$$

where

$$
\begin{aligned}
x_g^{**} &= \{k_g', n_g, \kappa_g^{**}, \nu_g^{**}\} &\qquad x_{-g}^{**} &= \{k_{-g}', n_{-g}, \kappa_{-g}^{**}, \nu_{-g}^{**}\} \\
\hat{x}_g^{**} &= \{k_g', n_g, \hat{\kappa}_g^{**}, \hat{\nu}_g^{**}\} &\qquad \hat{x}_{-g}^{**} &= \{k_{-g}', n_{-g}, \hat{\kappa}_{-g}^{**}, \hat{\nu}_{-g}^{**}\} \\
x_g^{*} &= \{k', n, \kappa^{*}, \nu^{*}\} &\qquad \hat{x}_g^{*} &= \{k', n, \hat{\kappa}^{*}, \hat{\nu}^{*}\}
\end{aligned}
$$

We make several notational innovations in order to simplify and generalize the above expressions to apply to both one-earner, two-earner and non-working couples. We combine the unemployed and employed probabilities of receiving a job offer into a single variable, letting $\mathcal{P} = p_{0,i,-i}$ if spouse g is unemployed and $\mathcal{P} = p_{1,i,-i}$ if he or she is employed. The i and $-i$ indicate that the set of job offers that the individual will accept is determined jointly (collectively) with his spouse and in general will differ for every couple in the economy. We omit the individual-level notation i throughout. Variables denoted $-$ refer to the spouse. Finally, we let $\epsilon_W = \epsilon_W(\kappa, \nu)$ and $\hat{\epsilon}_W = \epsilon(\hat{\kappa}, \hat{\nu})$.

The bellman equation (10), which captures spouse g's individual payoff from his marriage, has five parts, denoting the cases in which neither, one, or both spouses receive alternative job offers for next period. The timing of events is the same as for singles. In the current period, spouse g enjoys marital consumption output $\ln(M)$. At the end of the period, each spouse experiences an increment to current human capital of ι_k with independent probabilities $\tilde{p}(k, \kappa_g) = p_{0,k} + p_{k,1}k^{.5}$ if $\kappa_g \geq \underline{\kappa}$ and zero otherwise (when unemployed). The spouses then simultaneously receive their next-period alternative job offers and choose the optimal response for both spouses jointly. Once employment decisions have been resolved, the couple first receives a marriage shock ϵ_M which determines the efficiency of the marriage in the next period.[15] At this point, the decision to leave or stay is taken simultaneously by both spouses. $\varphi(x_M')$ is an indicator function for whether spouse $-g$ finds it optimal to commit to the marriage next period given x_M' plus expected payoffs in the labor market. If $-g$ does not want to commit to another period, spouse g becomes single. If spouse $-g$ does commit to another period, spouse g solves the maximization problems given his new employment status and taking the expectation over his and his spouses' labor productivity in the period. Lastly, after marital decisions have been taken, ϵ_W' is realized for both partners, at which point they jointly (if married) choose to remain in their job and produce or quit to unemployment for at least a two-month spell.

[15]The distribution of ϵ_M does not depend on employment decisions which allows us to treat the integral over ϵ_M globally.

Figure 1: Timing of events in a two-month model period

Singles

consumption of $\ln S$	k' realized	new job offer $\{\hat{\kappa}', \hat{\nu}'\}$	new potential marriage partner	e_W realized if employed; quit decision
consumption of $\ln M$	k'_f and k'_m realized	new job offers received	ϵ'_M and divorce choice	e^f_W and e^m_W realized; for employed spouses quit decisions

Marrieds

With probability $(1 - \mathcal{P}_g)(1 - \mathcal{P}_{-g})$, neither spouse receives a job offer. In this case, the final employment status of the household is given by:

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

A similar set-up governs the continuation problem if either or both spouses receive job offers (corresponding to the remaining three continuation terms of (10)). If only the wife receives an acceptable offer, $\{\hat{\kappa}_f, \hat{\nu}_f\}$, we have

$$
\begin{aligned}
\{\hat{\kappa}^{**}_f, \hat{\nu}^{**}_f, \kappa^{**}_m, \nu^{**}_m\} = \text{argmax}\{ & U_M(k'_f, n_f, k'_m, n_m, \hat{\kappa}_f, \hat{\nu}_f, \kappa_m, \nu_m, \hat{\epsilon}^f_W, \epsilon^m_W, \epsilon_M), \\
& U_M(k'_f, n_f, k'_m, n_m, , \underline{\kappa}, 0, \kappa_m, \nu_m, \epsilon^m_W, \epsilon_M), \\
& U_M(k'_f, n_f, k'_m, n_m, \hat{\kappa}_f, \hat{\nu}_f, , \underline{\kappa}, 0, \hat{\epsilon}^f_W \epsilon_M), \\
& U_M(k'_f, n_f, k'_m, n_m, \underline{\kappa}, 0, \underline{\kappa}, 0, \epsilon_M)\}
\end{aligned}
$$

and vice versa if only the husband receives an acceptable offer. The problem in which both spouses receive acceptable offers is similar and is omitted for space. In this case, the household chooses for both spouses between unemployment ($\kappa = \underline{\kappa}, \nu = 0$) and the new job $\{\hat{\kappa}, \hat{\nu}\}$ with productivity draws $\epsilon^{\hat{}}_W$.

The timing of events within the period for marrieds and singles is summarized in figure1. Note that one implication of the sequence of events is that marriage provides immediate insurance against unemployment shocks since by the time productivity draws for the (two month) period are realized, the spouses have already committed. However, an unemployed spouse may face a divorce if he has not become re-employed by next period.

4 Parametrization and identification

Because the model is large, we descretize the values of k, n, κ and ν to take eight, two, four, and three values respectively. We estimate the model through grid search with simulated annealing, which allows us to search for a global minimum for the error term constructed from the moments (described below) given the non-convexities implied by the discretization. The grid values of k begin at \$6 and increase by increments of \$6 up to \$48. We normalize the value of high n to one and low n to zero, since an explicit value of the difference between high and low n is not identified in the model. Correspondingly, the three values of ν are normalized to $\{0.0, 0.5, 1.0\}$ and the four values of κs are equal to the wages, in 2009 US dollars, at the middle of each quartile of the PSID inflation-adjusted wage distribution for the years 1976-2009. Space constraints prevent the use of larger grids, but the results are not sensitive to small changes in the spacing of the grids.

The main parameters of the model, along with their estimates, are summarized in table 6[16] and in figures 4 (which shows the distributions of job offers and filled jobs) and 2 (which shows the unconditional distribution of k_0 for men and women and the evolution of k for later ages). Below, we summarize the information, taken from our merged PSID-O*NET file, used to estimate the model and describe the identification process.

1. *Job shares and the job offer distribution.* We divide our PSID sample into twelve bins each corresponding to a quartile of the wage distribution (excluding the top 1% and 99% of wage realizations) and a ν. "High" ($\nu = 3$), "medium" ($\nu = 2$) and "low" ($\nu = 1$) ν jobs are determined according to their tercile of the reported importance of (or demand for) $\tilde{n}$ among all observed jobs in the PSID sample between 1975 and 2009. Because the mean wage in a bin 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 shown in figure 4.

   The top panel of figure 4 shows the distribution of occupations across ν and wage bins among all currently employed workers observed between 1976 and 2009. It is clear from the figure show that ν 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. However, there is still substantial wage variation within each ν bin. The bottom panel of figure 4 shows the corresponding *offer distribution*: that is, the distribution of $\kappa - \nu$ combinations from which job offers are randomly drawn so as to generate the filled job distribution in the model. Given

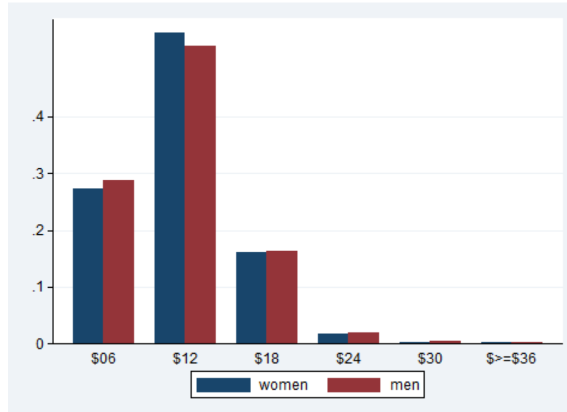
[16]Standard errors are omitted for the time being.

Table 6: Parameters

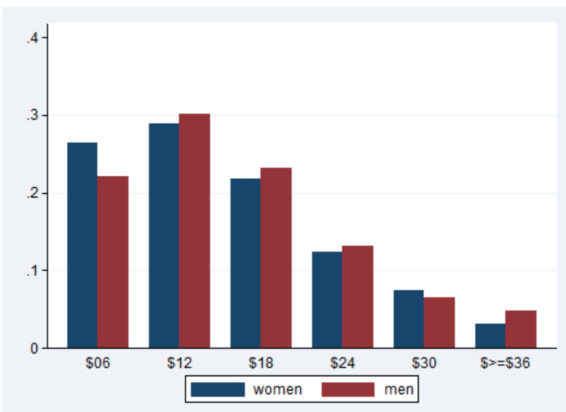
Parameter	Estimate: benchmark	Interpretation
α	0.214	relative contribution of k_0 to k_1 in (1)
σ_s	5.237	distribution of shocks to k_1 in (1)
σ_s	5.237	return to n in stochastic part in (1)
$\underline{C}$	0.501	mean cost of schooling
$\sigma^2_{\underline{C}}$	0.012	variance of schooling costs across the population
p_0	0.402	arrival rate of job offers while unemployed
p_1	0.217	arrival rate of job offers while employed
p_K	-0.008+ 0.005k	incidence of on-the-job-learning
a_f	1.154	wage coefficient for women
a_m	1.652	wage coefficient for men
γ_0	0.500	share of k in deterministic part of (2)
γ_1	-0.357	substitution elasticity of k and κ in (2)
σ_W	2.905	distributionsl parameter for shocks to wages
ϕ_0	0.188	return to n in stochastic part of (2) (2)
ϕ_1	-0.179	return to ν in stochastic part of (2)
ϕ_2	0.253	complementarity of n and ν in stochastic part of in (2)
ϵ_{me}	0.401	measurement error in bi-monthly wages
η^f	0.769	home production productivity for women
η^m	0.253	home production productivity for men
π	0.035	arrival rate of marriage offers for singles
e_0	0.970	equivalence scale for singles
e_1	0.093	increase in single equivalence scale with n
χ_0	0.402	share of home production in hh output
χ_1	0.907	substitution elasticity of market and home production
σ_M	5.485	distributional parameter of shocks to M
λ_0	0.474	return to wife's n in stochastic part of (5)
λ_1	0.661	return to husband's n in stochastic part of (5)
λ_2	-0.427	complementarity of husband's and wife's n in (5)
δ_n	1.000	difference in n (ν) btwn high and low individuals (jobs)
N_f	0.514	share of high n women at birth
σ_{kn^f}	0.546	correlation of n and k_0 among women
σ_{kn^m}	0.660	correlation of n and k_0 among men

Figure 2: Distribution of human capital by gender

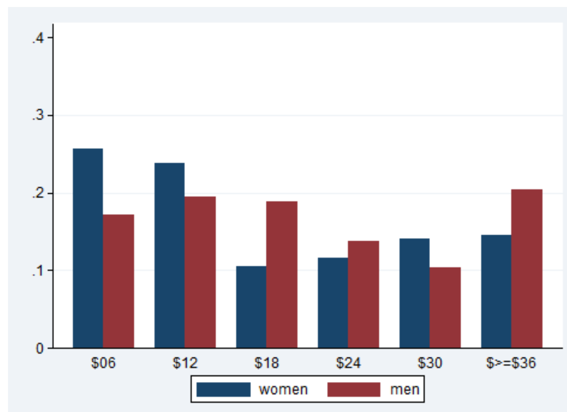
(a) K_0 by gender



(b) K by gender at labor market entry



(c) K by gender after 15 years experience

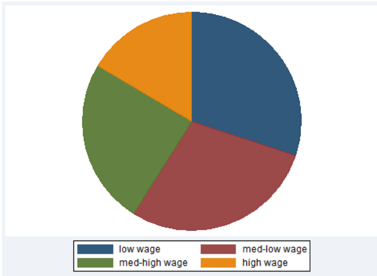


(d) K by gender after 30 years experience

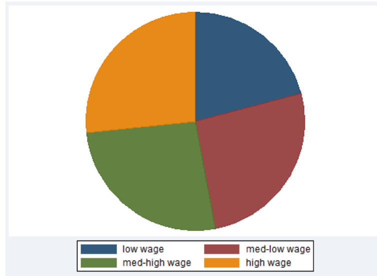
our discretization, this gives twelve moments. The offer distribution suggests that job offers are highly skewed toward the lowest-κ jobs, making high-κ jobs valuable once obtained.

2. *Participation rates and exit hazard from unemployment.* An individual is a "participant" in a given year if he supplies positive hours of work (in the model, works at least one two-month period out of the year). Among marrieds and singles aged 25-56, the annual participation rates in our PSID sample are 94% and 90% for men and 75.5% and 78.5% for women, yielding four targets. The differences in participation across gender marital status and gender help us identify η_f, η_m and χ_0. Next, 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 allows us to directly identify p_0, the arrival rate of offers for the

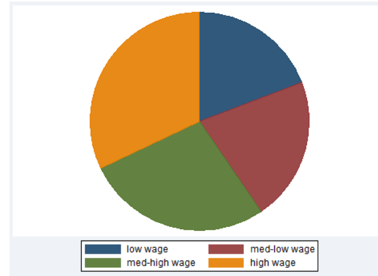
Figure 3: Filled jobs wage bin and ν



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

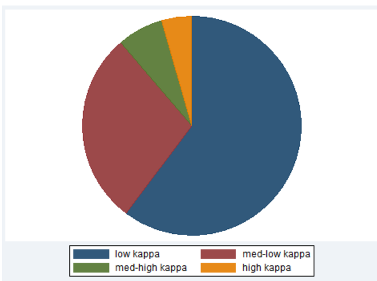


(b) filled jobs: $\nu = 2$

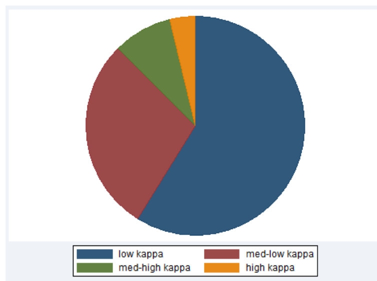


(c) filled jobs: $\nu = 3$

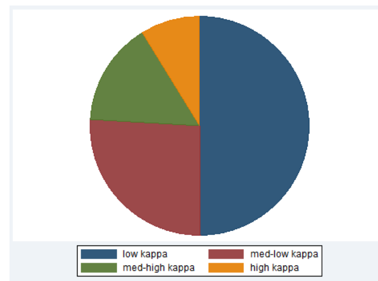
Figure 4: Offer distribution by κ and ν



(a) job offers: $\nu = 1$



(b) job offers: $\nu = 2$



(c) job offers: $\nu = 3$

unemployed, in the model which is relatively high at 83%.

3. *Negative separation rates by ν.* In section 2, we calculated negative separation rates for high, medium and low ν occupations by worker n, which we use as six additional targets. To recap,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. These targets help identify γ_1, ϕ_0, ϕ_1 ϕ_2, and σ^2_W. We note that the negative estimated value of ϕ_1 and positive value of ϕ_2 support the idea that n and ν are complementary in market production. The negative estimated value of γ_1 suggests that k and κ are also strong complements in production, as we would expect. Earlier trials suggest that γ_0 is poorly identified in the model, and so we set it to .5.

4. *Promotions and positive employer separations.* Individuals may be promoted either within their employer or successful on the job search. 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. Positive job separation

as an annual rate is 5%, or about half the rate of negative job separation. Workers may also be promoted within employer. We identify the share of *internal* promotions by the number of workers who change ν without changing employer, which is roughly three percent per year, and is roughly equally divided between individuals moving to a higher and a lower ν within employers. We assume workers face the same arrival rate of p_1 of internal promotions and external offers and are indifferent between these types of offers. A relatively high value of p_1 suggests workers sort by ν quickly and therefore that $\tilde{n}$ is a good proxy for n.

5. *Wages by gender and wage returns to age, job tenure 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 and a_f, a_m. Next, we regress workers' wages in logs on a quadratic in age, interactions of age and age squared with education, and tenure in the current job. The returns to age by education level help to identify the two terms in $p_k = p_k^0 + p_k^1 k^{.5}$, the stochastic rate of (general) human capital accumulation through learning by doing. The returns to job tenure help identify p_1, the arrival rate of offers among the employed. The targets are reported in equation (11). 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 .29, which pins down the variance of the bi-monthly measurement error σ_{me}^2. We find σ_{me}^2 to be relatively large, accounting for 47% of the variance in wage growth at annual rates, larger than the 35% suggested by Altonji et al. (2013).

   Finally, we calculate the degree of correlation between education and wage among workers in the PSID to be .31 for workers under 30. This correlation helps identify α, the role of innate ability k_0 in producing adult ability, k, and also ϵ_S.

$$\begin{aligned}\widehat{\ln wage} =& constant - .0253 age + .000196 age^2 \\ &+ .00513 educ \times age - .0000509 educ \times age^2 + .0230 \times job\ tenure \end{aligned} \qquad (11)$$

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 over the life cycle is faster for men due to their higher average labor market attachment. As well, table 6 shows that n and k_0 are positively correlated in the population of high school-age individuals: individuals with higher n also have higher human capital levels on average, with correlation coefficients between n and k_0 of .55 for women and .66 for men. Women have slightly more likely than men to be high n. 51.4% of women in the population are high n compared to 50% of men.

6. *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 by gender, 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 n for men and women respectively. k_0 takes four values, corresponding to the first four levels of k.[17] Figure 5 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}, σ_{kn^f} and ψ.

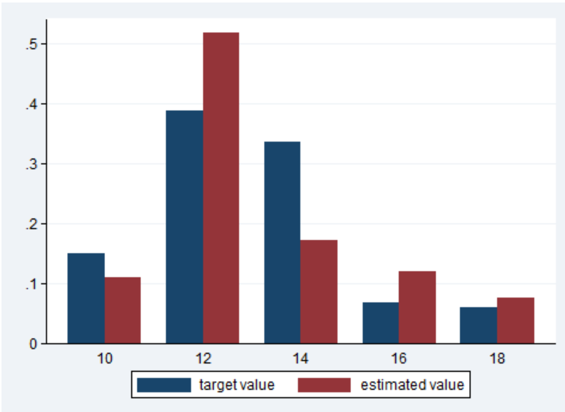
   Marriage, divorce rates and spousal correlations. In our PSID sample, 72% of low $\tilde{n}$ and 79% of high $\tilde{n}$ individuals 25-56 are married, two moments that help us identify e_0 and e_1, the equivalence scale parameters for singles. As described in section 2, divorce rates also vary with 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 .035 when the husband has high n and .040 when the wife has high n. The within-couple correlation of $\tilde{n}$ is .18 and of education (less than high school, high school, two-year college, and four-year university or more) is .33. Together, these marriage statistics help identify π, χ_1, σ_M and λ_0, λ_1 and λ_2. The positive values of λ_0 and λ_1 and the positive value of λ_2 suggest that the spousal ns are substitutes in reducing the likelihood of divorce.

5 Results

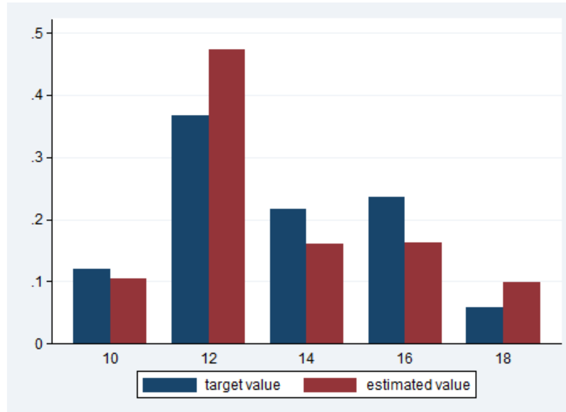
In this section, we discuss the implications of our estimation results, specifically on their implications for the role of relationship skills n in the economy.

[17] Note that k_0, unlike k, cannot be easily interpreted as wage-earning human capital since it must be combined with schooling and subject to the schooling productivity shock before it can be used to earn a wage.

Figure 5: Educational shares



(a) men



(b) women

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

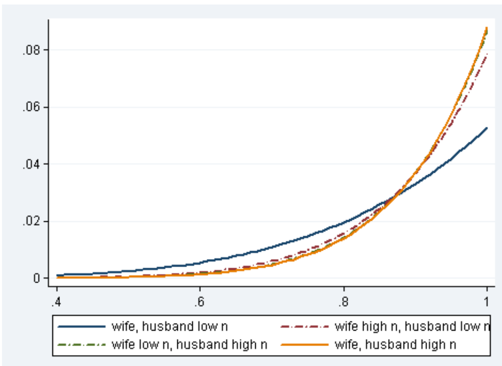
Partnering skills n plays four distinct roles in the model. It affects the deterministic returns to being single and the stochastic returns to married household output, paid employment, and education. In the model, the values of n possessed by individuals in a team (a team of spouses, a manager and worker, a student and teacher) determine how much a given *potential* output of the team is actually realized within a period on average and how much this return varies across periods. Figure 6 shows the pdfs (top panels) and cdfs (bottom panels) of the estimated stochastic distribution of these realized returns from marriage ($\epsilon_M(n_f, n_m)$), market production ($\epsilon_W(n, \nu)$) and educational attainment ($\epsilon_S(n)$) as functions 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. The more horizontal the pdf, the greater is the variance of ϵ; the more mass is concentrated on right side of the graphs, the higher is the average stochastic return.

In all three markets – marriage, labor and educational – relationship skills determine the average expected and volatility of output. However, the explicit role of n differs across type of relationship. As discussed briefly in section 4, the supply of n and demand for n (i.e. ν) in the labor market are strongly complementary: mismatch between a high ν job and a low n worker – the dashed green line – yields the lowest and most variable stochastic output a job conditional on the human capital of the worker (k) and complexity of the capital (κ). This complementary is captured by the negative estimated value of ϕ_1 and large positive estimated value of ϕ_2. In the marriage market, by contrast, n_f and n_m are substitutes in increasing the mean and decreasing the variance of stochastic output. Unions between two low n partners yield the lowest returns. The husband's n is more important that the wife's n: a marriage between two high-n spouses is only modestly more productive and less variable than a union between a low n wife and high n husband. However, the stochastic returns to the n of *both* sexes is highest when their marriage partner is low n, as captured by the negative estimated value of λ_2 reported in table 6.

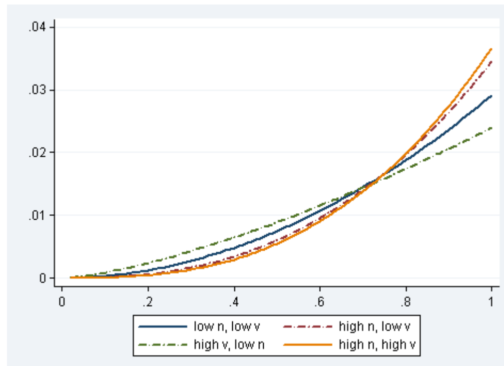
The largest effect of n arises in through stochastic returns to education through e_S; in particular the value of ψ need to generate the correlations between schooling and $\tilde{n}$ is large, and $p(high\ n)$ is about three time larger than $p(low\ n)$. From the top panel of figure 6, the resulting pdf of shock realizations shows that roughly 10% of high n students reap the "complete" return to education compared to only 2% of low-n students. Educational return for low n students are also much more variable. 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. Our results imply that not only is it more rewarding for high n individuals to go to school, but the expected and average return to any year of schooling is higher (an intensive margin effect). Though we model the extensive margin as pure choice, a plausible interpretation of our finding is that high n students are more likely to complete their marginal education choice (e.g. graduate from high school). Alternatively, high n students may be more likely to be streamed into more remunerative degrees, achieve better grades than their low n peers, or procure more positive references from teachers.

We next turn to a more explicit examination of how partnering skill n affects post-education outcomes in the labour and marriage marriages.

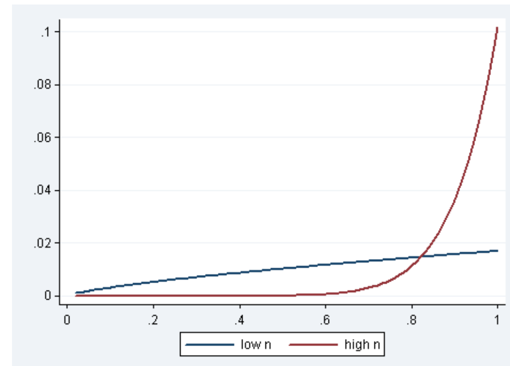
Figure 6: Realized returns to n in the marriage, job and education markets



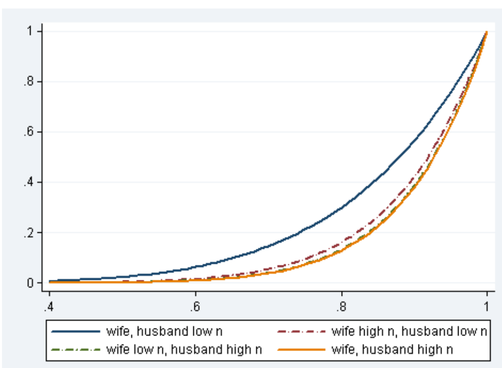
(a) marriage shock e_M: pdf



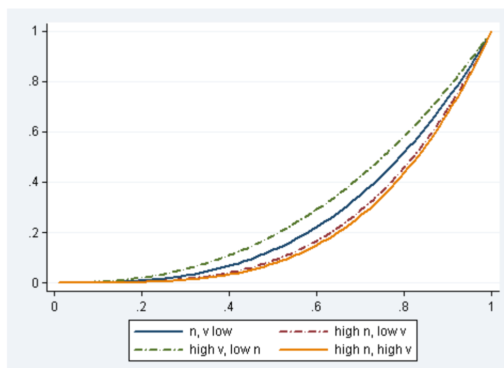
(b) wage shock e_W: pdf



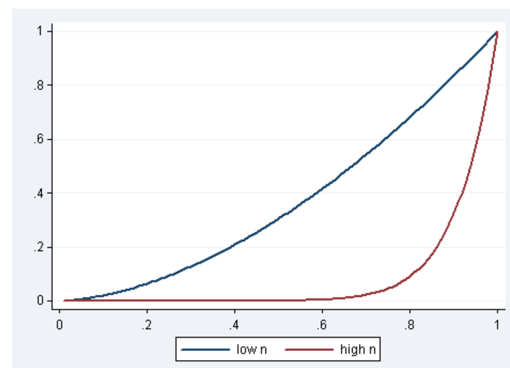
(c) education shock e_S: pdf



(d) marriage shock e_M: cdf



(e) wage shock e_W: cdf



(f) education shock e_S: cdf

5.1.1 Partnering skill and returns in the labor market.

In our model, there are five ways in which having high n increases predicted wages and earnings over the life cycle:

1. High n individuals experience higher returns per year of education, and therefore invest more in education, than their low n peers.
2. Returns to learning-by-doing are higher for individuals who enter the labor market with higher initial k (as reflected by the estimated value of p_k^1).
3. High n people experience lower rates of job turnover (fewer negative splits) on average and therefore (1) spend less time in unemployment and (2) build up more firm-specific skills through internal promotions.
4. High κ job offers are relatively scarce and the correlation between ν and κ (see figure 4) means that high n workers are generally more suited to the most remunerative jobs.
5. The realizations of e_W are higher on average for high n than for low n employees.

Table 7 and figure 7 provide some descriptive evidence for how n impacts wages over the life cycle. Table 7 reports estimates of the returns to schooling in terms of ln wages for high and low $\tilde{n}$ individuals in the data, and for high and low n individuals in the model. We see that the model matches the data quite well: higher $\tilde{n}$ individuals experience higher wage returns to education, as we would expect, in both model and data. Note, however, that when we use "true" n rather than $\tilde{n}$, wage returns to education are smaller due to correlations of education and wages with n.

Figure 7 shows post-education growth in ln wages over the life cycle by $\tilde{n}$ (top panel) and n (bottom panel) for men and women. Wage growth declines with age for both genders, is generally higher for high n individuals, especially men, early in the life cycle when the effects of job turnover and promotion are largest,[18] but is indistinguishable by n later life cycle. Averaged across ages 21-60, average annual wage growth is 0.6 percentage points higher for high n men and 0.15 percentage points higher for high n women.

Table 7 and figure 7 provide some descriptive evidence (and external validation) for the effects of n on wages, but we may be more interested in the effects of n on total lifetime earnings. Table 8 decomposes the effect of n on total lifetime earnings through the five paths described above. The earnings variable we consider is earnings averaged over all periods the individual is observed. The entries in the first row of the top and bottom panels of the

[18] 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 $\tilde{n}$	Model: high $\tilde{n}$	Model: low n	Model: high n
	(1)	(2)	(3)	(4)	(5)	(6)
educ	.068	.111	.078	.091	.066	.088
	(.001)***	(.0008)***	(.0005)***	(.001)***	(.0005)***	(.001)***
age	.073	.076	.066	.013	.047	.039
	(.005)***	(.005)***	(.011)***	(.010)	(.011)***	(.010)***
agesq	-.001	-.001	-.001	.0004	-.0007	-.0003
	(.0001)***	(.0001)***	(.0003)***	(.0003)	(.0003)***	(.0003)
agecu	8.17e-06	3.61e-06	9.98e-06	-3.88e-06	6.46e-06	1.68e-06
	(1.05e-06)***	(1.09e-06)***	(2.38e-06)***	(2.23e-06)*	(2.37e-06)***	(2.13e-06)
sex	-.342	-.337	-.174	-.391	-.226	-.382
	(.003)***	(.003)***	(.002)***	(.002)***	(.002)***	(.002)***

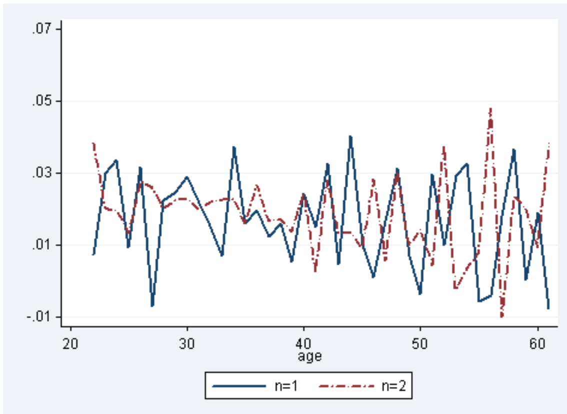
table show the simple linear relationship between each column heading and n for men and women respectively. The middle row in each panel reports the estimated coefficients from a multivariate regression of the column heading variables on total observed life time earnings. The last row in each panel gives the product of the first two rows:

$$\beta_{n,X} \times \beta_{X,earnings}$$

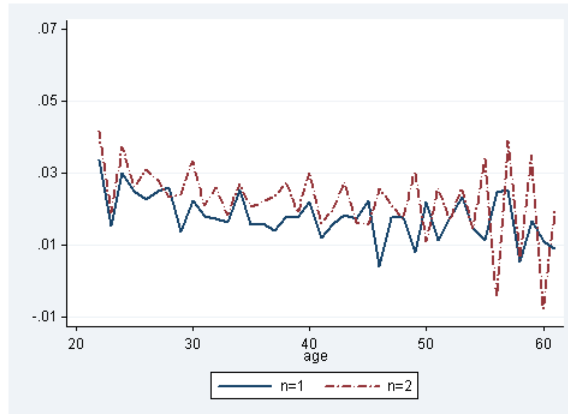
where X is the variable in the column heading (e.g. years of education). This exercise is not a true decomposition because of non-linearities in the impacts of n, but it provides instructive evidence on the relative channels through which n affects earnings for men and women respectively.

The first column of table 8 describes the effect of n on earning through chosen years of education. The second column reports the effect of n through the average increase in k realized per year of education. These two columns together give a measure of the total effect of n on earnings through education: on the extensive margin (years of education chosen) and the intensive margin (return per year of education). The third column reports the effect of n on earnings through accumulation of general skills, or the growth in k over the working life. The fourth and fifth columns describe the effects of n on earnings working through positive and negative separations, the former including both employer switches and internal promotions. The sixth column reports the effect of n on earnings operating through the total number of model periods in which the individual is unemployed. The last column reports the direct effect of n on earnings operating through the stochastic wage returns to n. The

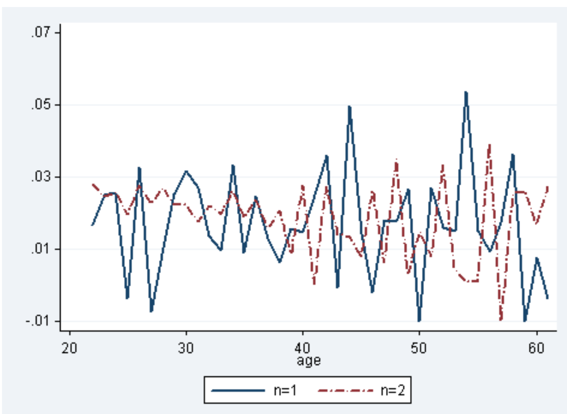
Figure 7: Life cycle wage growth by $\tilde{n}$ and n



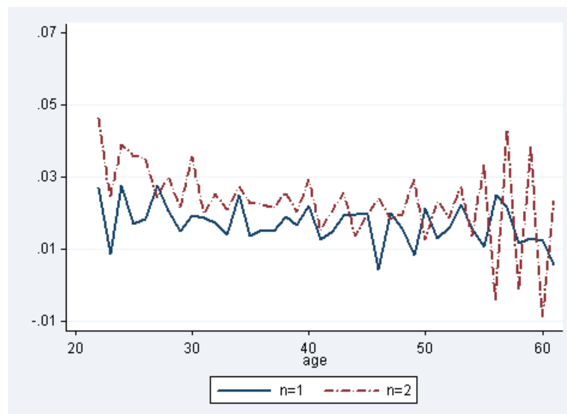
(a) change in ln wage by $\tilde{n}$: women 25-60



(b) change in ln wage by $\tilde{n}$: men 25-60



(c) change in ln wage by n: women 25-60



(d) change in ln wage by n: men 25-60

results are reported separately for men and women as shares of the average total earnings by gender in the sample.

Table 8: n and life time earnings: decomposition

	Years of education	k per year educ	Post-educ growth in k	Promotions or pos separations	Negative separations	Periods of non-employment	n
Men							
$\beta_{X earnings}$	0.045	0.095	0.096	0.075	-0.089	-0.006	0.246
$\beta_{n,X}$	0.911	-0.129	0.087	-0.059	-1.523	-6.042	1.000
(1) $\times$ (2)	0.041	-0.012	0.008	-0.004	0.135	0.038	0.246
	Correlation of n and life-time earnings: 0.370						
	Correlation of k_0 and life-time earnings: 0.379						
Women							
$\beta_{X earnings}$	0.063	0.068	0.045	0.024	-0.074	-0.010	0.134
$\beta_{n,X}$	1.565	0.019	0.229	2.534	-1.076	-54.9	1.000
(1) $\times$ (2)	0.099	0.001	0.102	0.061	0.080	0.100	0.134
	Correlation of n and life-time earnings: 0.608						
	Correlation of k_0 and life-time earnings: 0.500						

Consistent with the structural estimation results, a major effect of n on earnings arises through education. Higher n individuals receive more education on average (for men, for whom the correlation between n and education is .48, this is enough to drive the average return for years of education lower than for low n men). For men, the higher investment and returns to education among high n individuals increase total lifetime earnings by 7% and for women by 6%. The effect of n working through growth in general skills through learning by doing and through positive labor market separations or promotions are very large for women relative to men since women's labor supply is much more elastic to wage incentives. The first row of column three can be interpreted as that if wage growth doubles for a man, his average life time earning increases only 10%, due to the timing of growth and the complementarity of κ and k. For women, the same doubling of the growth of general skills increases predicted life time earnings by 44% due to participation effects. High n women have higher participation rates (row two of column 6 gives the average difference in the number of two month periods in non-employment by n for men and women) and experience much greater wage growth. n itself has *direct* effects on wages accounting for about 13% of earnings differences for men, conditional on behavior and luck. For women, the direct effect of n on earnings is 24% consistent with some of the recent literature on psychological measures and wages (e.g. Borghans et al. (2008)).

The last two rows of the top and bottom panels of table 8 reports the overall correlation between n and life time earnings and between k_0 and life time earnings. The effects are large and similar in magnitude. Initial k_0 and n are much more important determinants of life time earning for women. At first blush, the large correlation between n and earnings even for men contrasts with the results reported in Altonji et al. (2013) who, in a decomposition of earnings growth, find a "propensity to move" fixed effect to have negligible effects relative to an (uncorrelated) fixed ability factor and persistent job-specific wage shocks. However, in our model, much of the return to n in the labor market, especially for men, arises through the ability of high n individuals to match with jobs that demand n, that is with high ν jobs. This is likely to be identified as a match-specific rather than an individual-specific component. Also, the correlation of n with k_0 amplifies the effect of n, especially for education, but would be harder to identify separately from k after schooling is finished without additional data from the marriage market (see section 6.2 forthcoming).

5.1.2 Partnering skill and returns to marriage

Table 9 reports some cross-sectional statistics on marriage among working age (25-56 year old) couples by n, $\tilde{n}$ and education for the model and the data. The upper panel of the table reports marriage rates among individuals disaggregated by gender. The comparison between the model and data should be interpreted with caution given that our PSID sample is based on "heads and wives", and single women are more likely to head households than single men. Consequently, the female population has a lower marriage rate, a feature not replicated in the model. Nevertheless, some patterns are clear: low n (and to a lesser extent low $\tilde{n}$) men and women are less likely to be married. Among men, those whose $\tilde{n}$ can not be identified due to lower labor market attachment are much less likely to be married, while the same holds much more weakly (and not at all n the data) for women. Differences in marriage rates across education (using college and less than college for ease of comparison) are smaller than differences in marriage rates across $\tilde{n}$. The middle panel of table 9 reports divorce rates

Table 9: Marriage and divorce rates and marriage tenure by n, $\tilde{n}$ and education

Individual Marriage Rates: 20-65					
	Model	Data		Model	Data
Men: low n	0.701		Women: low n	0.792	
Men: high n	0.822		Women: high n	0.759	
Men: low $\tilde{n}$	0.698	0.714	Women: low $\tilde{n}$	0.760	0.678
Men: high $\tilde{n}$	0.804	0.772	Women: high $\tilde{n}$	0.791	0.729
Men: n/a $\tilde{n}$	0.333	0.611	Women: n/a $\tilde{n}$	0.731	0.733
Men: low ed	0.745	0.752	Women: low ed	0.798	0.707
Men: high ed	0.771	0.742	Women: high ed	0.761	0.706
Divorce Rates by Partners' $\tilde{n}$ and education					
	Model	Data		Model	Data
low $\tilde{n}_f$, low $\tilde{n}_m$	0.048	0.046	low ed_f, low ed_m	0.035	0.053
high $\tilde{n}_f$, low $\tilde{n}_m$	0.032	0.035	high ed_f, low ed_m	0.037	0.048
low $\tilde{n}_f$, high $\tilde{n}_m$	0.042	0.040	low ed_f, high ed_m	0.063	0.056
high $\tilde{n}_f$, high $\tilde{n}_m$	0.027	0.027	high ed_f, high ed_m	0.025	0.032
Mean Marriage Tenure by Partners' $\tilde{n}$ and education					
	Model	Data		Model	Data
low $\tilde{n}_f$, low $\tilde{n}_m$	8.4	9.5	low ed_f, low ed_m	9.2	9.1
high $\tilde{n}_f$, low $\tilde{n}_m$	8.2	9.1	high ed_f, low ed_m	7.5	9.1
low $\tilde{n}_f$, high $\tilde{n}_m$	7.7	9.9	low ed_f, high ed_m	8.2	7.2
high $\tilde{n}_f$, high $\tilde{n}_m$	8.7	9.6	high ed_f, high ed_m	8.4	8.5

among couples in which n_f and n_m can be identified. The divorce rates by spouses' $\tilde{n}$s are estimated directly in the model and fit closely. Although we don't report them, divorce rates are higher for couples in which $\tilde{n}_f$ and (especially) $\tilde{n}_m$ are not identified in both the model and the data. In the model, the reasons for the high divorce rates among non-workers are different across genders. Men whose $\tilde{n}$ is unidentified in the model are roughly equally likely to be high or low n, while women whose much more likely to be low n. Women with low attachment to the labor force are therefore less likely to be efficient in generating M, while men with low labor force attachment are simply poor providers.

The model understates the effect of education mismatch on divorce rates but otherwise captures the basic pattern in the data: marriages among high education couples are more stable. Again, the model provides an explanation for the greater stability of highly educated marriages, which is ambiguous in traditional models of marriage (e.g. Becker et al. (1977)). Couples with higher combined spousal education also tend on average to have higher combined spousal n, which protects against shocks to the efficiency of the marriage. If we further examine couples disaggregated by whether the husband is high or now n, we find that divorce rates are much more sensitive to education for couples in which the husband has low n than when he is high n, but about 1.5 percentage points in the model and .5 percentage points in the data. In the model, this is due to the fact that higher income couples can weather negative shocks to their marital efficiency easier than lower income couples.

Finally, the bottom panel reports differences in marital tenure by $\tilde{n}$ and education. In both model and data higher marital tenure is associated with more stable marriages as we would expect, but the effect is attenuated in both the model and data due to the unbalanced panel structure and shows up less strongly than the results for divorce rates.

We can also directly compare the relative effect of n on the expected output of marrieds to the effect of n on the output of singles. n increases the equivalence scale for a single household as well as for a married household (since $e_1 > 0$). From the simulated data, we calculate the output of a married household to be 18% higher, and the variance of output x% lower, on average when at least one of the partners is high n. For singles, household output for high n singles is 9.5% higher than for low n singles. Thus, while relationship skills are important in generating utility for both singles and marrieds, the effect is larger for marrieds as we would expect.

Finally, given the substitutability of n in marital production, we also examine whether or not there is evidence of assortative mating on n. The model undershoots assortative mating on both n and *educ* relative to the data, but replicates the pattern that assortative mating on education is roughly twice as high than assortative mating on $\tilde{n}$: .17 vs. .095% (compared to .33 vs. .18 in the data). However, assortative mating on n itself is basically close in magnitude to assortative mating on education at .12, and is positive for high, low and mixed education couples. This finding suggests that marriage market equilibrium is not entirely efficient: aggregate marital output would be maximized through negative assortative mating on n within education cells. The inefficiency arises through the absence of household bargaining; the results of the model, however, suggest that the absence of bargaining is, to a first approximation, realistic, since we would expect to see even lower correlation of $\tilde{n}$ within spouses and more uniform divorce rates if spouses were paid their marginal product in marriage.

6 Robustness: interpreting n as a fixed effect

In this section we provide some additional external validity in favor of our interpretation of n as a fixed effect. First, we use the model to generate results corresponding to those reported in tables 1, 2 and 3 for our benchmark model, and then examine how including $\tilde{n}$ and true n changes the results of the tables for both the model and the PSID samples. Second, we examine more closely the effect of n *across* markets, but observing what happens to the main results from the previous section when we shut down the effects of n on realized stochastic returns in the labor and marriage markets respectively [this subsection is forthcoming].

6.1 Previous splits as a proxy for n

Tables 10 and 11 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 (along with the full set of controls from tables 1 and 2 used in regressions based on the PSID) but are suppressed for clarity. We add together negative job separations and marriage separations to simplify the comparison across the columns of the table. Results based on disaggregated marital and job splits are excluded for now.[19]

Similar to the results presented in Tables 1 and 2, the results in column (1) show that the number of previous negative separations 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 and the other controls. Furthermore, once we incorporate $\tilde{n}$ into the regression, the effect of number of previous splits diminishes, though only by about 4% for men, and by about 6% for women. Columns (3) and (4) report results from the same regressions run on the model-generated data. In particular, $\tilde{n}$ in the model generated data is inferred using exactly the

[19]Current results based on disaggregated negative job and marriage splits are roughly similar to the reported results from tables 1 and 2 except that the effect of prior divorces on the likelihood of losing a job is only marginally significant for men. The tables are available upon request.

Table 10: Negative job switch hazards in model and data: Men

	Data	Data $+\tilde{n}$	Model	Model + constructed $\tilde{n}$	Model + real n
	(1)	(2)	(3)	(4)	(5)
educ	-.003	-.001	-.006	-.006	-.006
	(.0005)***	(.0005)**	(.0006)***	(.0006)***	(.0006)***
job tenure	-.002	-.002	-.002	-.002	-.002
	(.0001)***	(.0001)***	(.0002)***	(.0002)***	(.0002)***
splitcount	.022	.021	.020	.018	.016
	(.001)***	(.001)***	(.0008)***	(.0009)***	(.0009)***
n		-.014		-.017	-.018
		(.003)***		(.001)***	(.002)***

same procedure as in the data (i.e. generating a measure $\tilde{n}$ using job history based on ν). The overall pattern of results is similar between model and data. First, from column (3), previous number of total splits positively affects the probability of a negative job separation for both genders. Second, from column (4), high $\tilde{n}$ individuals are less likely to experience a negative job separation than low $\tilde{n}$ individuals.

Column 5 of tables 10 and 11 provides some evidence on the "noisiness" of $\tilde{n}$. 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 $\tilde{n}$ 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 becomes even smaller, though it remains positive and significant. The reduction in the predictive power of previous splits is stronger when we use the true n rather inferred n, indicating that our measure of $\tilde{n}$ is a strong but imperfect signal of "true" n, as we expect. Indeed, the correlation of n and $\tilde{n}$ is .86 for men and .75 for women in the model. Consequently, including the "true" n reduces the estimated effect of previous separations on the likelihood of a current separation while constructed $\tilde{n}$, has typically smaller effects, especially for men. The results therefore give us some confidence that we are in fact identifying an important individual factor that offer genuine explanatory power regarding individuals' career and social histories.

Tables 12 and 13 repeat the same validation exercise using the divorce hazards as the dependent variable. 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

Table 11: Negative job switch hazards in model and data: Women

	Data	Data $+\tilde{n}$	Model	Model + constructed $\tilde{n}$	Model + real n
	(1)	(2)	(3)	(4)	(5)
educ	-.004	-.003	-.001	-.0006	-.00005
	(.0007)***	(.0008)***	(.001)	(.001)	(.001)
job tenure	-.004	-.004	-.003	-.003	-.003
	(.0002)***	(.0002)***	(.0004)***	(.0004)***	(.0004)***
splitcount	.013	.013	.025	.023	.022
	(.001)***	(.001)***	(.001)***	(.001)***	(.001)***
n		-.008		-.016	-.020
		(.003)**		(.003)***	(.004)***

for men, account for about 25% of the total effect. A drop of similar magnitude is effected in the model when including $\tilde{n}$. 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.

Table 12: Divorce hazards in model and data: Men

	Data	Data $+\tilde{n}$	Model	Model + constructed $\tilde{n}$	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)***

Finally, table 15 and **??** show results corresponding to table 3. The only difference between these tables and the previous tables is that we now disaggregate previous separations by marriage and labor market separations (divorces and previous negative job losses) in order to demonstrate the differences that emerge across gender. Specifically, we observe that previous negative job separations reduce predicted wage growth (conditional on lagged ln wage and other covariates) for men and women, but lagged divorces significantly increase

Table 13: Divorce hazards in model and data: Women

	Data	Data $+\tilde{n}$	Model	Model + constructed $\tilde{n}$	Model + real n
	(1)	(2)	(3)	(4)	(5)
educ	-.003	-.003	-.001	-.001	-.0009
	(.0005)***	(.0006)***	(.0006)**	(.0007)*	(.0007)
marr-ten	-.003	-.003	-.005	-.005	-.005
	(.0003)***	(.0003)***	(.0004)***	(.0004)***	(.0004)***
splitcount	.007	.007	.002	.002	.001
	(.001)***	(.001)***	(.0005)***	(.0006)***	(.0006)***
n		-.005		-.004	-.007
		(.002)**		(.002)**	(.002)***

predicted wage growth only for men, and there only marginally. In fact, lagged divorces *increase* predicted wage growth for women (whereas in the results from table **??**, the effect of lagged divorces was positive but not significant). We argue there are two reasons for this finding. First, women's n is relatively abundant ($N_f = .514$) and also their n is relatively less important than husbands' n in any individual marriage. Therefore, lagged divorces are less of a bad sign for women cross-sectionally. Second, women who earn more (high n women in the model) are also more willing to leave a marginally efficient marriage.

Table 14: ln wage growth in the model and data: Men

	Data	Data $+\tilde{n}$	Model	Model + constructed $\tilde{n}$	Model + real n
	(1)	(2)	(3)	(4)	(5)
educ	.028	.024	.012	.012	.011
	(.001)***	(.001)***	(.0007)***	(.0007)***	(.0008)***
job tenure	.002	.002	-.001	-.001	-.001
	(.0003)***	(.0003)***	(.0003)***	(.0003)***	(.0003)***
lag *ln* wage	-.259	-.263	-.153	-.161	-.168
	(.007)***	(.007)***	(.002)***	(.002)***	(.002)***
previous job switches	-.012	-.011	-.026	-.023	-.022
	(.002)***	(.002)***	(.001)***	(.001)***	(.001)***
previous divorces	-.015	-.014	-.002	-.001	-.001
	(.005)***	(.005)***	(.001)**	(.0006)*	(.0006)
n		.044		.044	.061
		(.005)***		(.003)***	(.003)***

Table 15: ln wage growth in the model and data: Women

	Data	Data $+\tilde{n}$	Model	Model + constructed $\tilde{n}$	Model + real n
	(1)	(2)	(3)	(4)	(5)
educ	.043	.039	.011	.012	.010
	(.002)***	(.002)***	(.001)***	(.001)***	(.001)***
job tenure	.004	.004	.0003	.0003	.0003
	(.0005)***	(.0005)***	(.0003)	(.0003)	(.0003)
lag ln wage	-.348	-.351	-.232	-.232	-.232
	(.008)***	(.008)***	(.004)***	(.004)***	(.004)***
previous job switches	-.014	-.013	-.018	-.019	-.017
	(.002)***	(.002)***	(.001)***	(.001)***	(.001)***
previous divorces	.004	.006	.016	.016	.017
	(.005)	(.005)	(.004)***	(.004)***	(.004)***
n		.042		-.005	.014
		(.006)***		(.003)	(.004)***

6.2 Spillovers between the marriage and labor markets

[tba]

7 Conclusion

In this paper, we have examined the role of relationship or partnering skill – measured in the O*NET and constructed for the 2975-2009 PSID – in determining life cycle outcomes in a structural setting across multiple markets. We find that several desirable personality traits, such as persistence, adaptability, integrity , cooperation and independence, map into stable marriages and jobs in the PSID, conditional on observable human capital. Our structural model suggests that relationship skills are important: they have similar impacts as a measure of raw ability (what we call initial human capital) on expected labor market earnings over the life time. They are also strong predictors of divorce, and have major implications for the efficiency of marital sorting and household formation. Interestingly, relationship skills seem to have different impacts in different types of market. In the formal labor market, demand for and supply of relationship skills are strong complements, consistent with other recent papers that find a labor market return to certain desirable personality traits. In the household sector, relationship skills appear to be substitutable and within a pairing, husbands' relationship skills are the most valuable to a union.

While it is intuitive that relationship skills are important in close partnerships like marriages We have not considered the implications of relationship skill on fertility or parenting choices. We have also not considered that individuals may be paid for their relationship skill in the marriage as well as the labor market, for example through bargaining over marital surplus. We leave these extensions for future work.

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