Relationship Skills in the Labor and Marriage Markets*

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Abstract

This paper examines the roles of relationship skill and human capital in determining life-cycle outcomes in education, labor, and marriage markets. We find strong empirical evidence of an individual fixed factor that affects both job and marriage separation hazards and extract an index of non-cognitive skill that increases the durability of relationships in marriages and in the labor market. Using this index, we develop and estimate a two-factor life-cycle model of schooling, job search, and marriage. We find that relationship skill can explain about 40% of the persistence in employment turnover and 35% of the persistence in marriage turnover.

JEL Classification: D13, J12, J24, J64

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1 Introduction

Individuals' social skills affect life cycle outcomes by determining who interacts with whom and the returns to these interactions. Recently, economists have begun to devote significant attention to this dimension of individual heterogeneity. The economic analysis of social interaction presents theoretical and empirical challenges. Theoretically, the challenge is to construct models of social interactions in which heterogenous social skills are relevant. Empirically, the

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challenge is to distinguish social skills from other types of skills, including cognitive skills, using behavioral data.

The core idea of our paper is that social interactions are central to team production. Thus, "social skill" can profitably be studied in the narrower and more tractable context of *relationship* (or teamwork) skill. In different facets of life, including marriage and work, individuals are faced with the option to choose partners and form teams. Ex-post, individuals may also choose to dissolve poor-functioning teams so as to look for better matches or to produce alone. Thus, individuals with poor (or strong) relationship skill will likely have poor (or good) outcomes in different areas of life where relationship skill is salient.

To explore these ideas, we develop and estimate an equilibrium model with school, work, and marriage in which individuals differ in their endowments of initial human capital and relationship skill, both of which are assumed to be unobservable to the analyst. We use our model to relate these two unobserved exogenous factors to observable proxies (years of education, wages, and an index for relationship skill based on occupational history) and to mobility indicators in the labor and marriage markets. We model human capital as a persistent individual factor that evolves over the life cycle and has a positive level effect on the potential per-period returns to production: in school, in the labor market, and in household production. Relationship skill, by contrast, is a fixed factor that affects stochastic returns to output of teams, specifically by affecting *how much*, on average, of the potential output can be captured each period, and the variability of these returns.[1] Intuitively, when an individual with low relationship skill works in a team, he often creates transitory conflictual situations which prevent the team from performing to its maximum potential. That may in turn lead to a break-up of the team in order to avoid the future low returns. Negative shocks in one market can also produce feedback effects in another. For example, negative transitory shocks to a marriage such as stress at work may be exacerbated by poor spousal communications and lead to a breakup.

Our model is a two-factor multi-market equilibrium model. In the marriage market, individual decisions about with whom to match are consistent with the distribution of singles from which potential matches are drawn. Over the life cycle, individuals continuously choose which occupation to work in and who (if anybody) to live with. Their characteristics and choices affect the evolution of their existing and future matches. Since individual characteristics determine choices, and choices in turn determine the returns to characteristics, the estimated returns to relationship skill and human capital can vary, and − consistent with

[1]Although there is evidence that some personality traits, such as conscientiousness, improve with age (see Heckman and Kautz (2012)), Cobb-Clark and Schurer (2012) offer evidence that non-cognitive skills, specifically the big five skills, are stable for individuals across time in an economically meaningful sense.

evidence from the labor search literature − initial differences in outcomes due to individual heterogeneity can lead individuals into self-perpetuating bad states: unremunerative careers or unstable family life. This feature of the model reflects the situational specificity hypothesis of the psychology literature, in which estimates of the causal effects of non-cognitive and social skills on individual outcomes will vary with the context in which the outcomes are measured.[2] Our structural approach allows us to disentangle the specific ways and the magnitudes of the effects by which individual heterogeneity affects outcomes.

Our empirical work begins by providing reduced-form evidence. Using the 1980-2011 waves of the Panel Study of Income Dynamics (PSID) we show that, conditional on standard covariates that measure human capital and average team quality, measures of stocks of previous "negative" employer separations (such as layoffs or firings) and of divorces are positively correlated with the incidences of both current negative employer separations and divorces, and that this result is robust to controlling for simple forms of state dependence in the form of lagged dependent variables. We next link the fixed (negative) "mover" factor extracted from these regressions to measures of relationship skill for each individual by matching PSID observations to the U.S. Department of Labor's Occupational Information Network (O*NET) and using data on required employee attributes across an individual's career history. We find evidence that, conditional on measurable human capital such as permanent wages and education, the characteristics *persistence*, *cooperation*, *adaptability*, *dependability*, *attention to detail*, and *independence* are robust and significant predictors of stable marriage and employment outcomes. The principal factor capturing relationship skill that we extract from this exercise − which we call $\widetilde{n}$ − is both endogenous and a noisy measure of relationship skill n. We use our structural model to link n to $\widetilde{n}$.

After the reduced form analysis, we estimate our structural model. Our structural estimates show that individuals with higher n are much more likely to remain longer in school and to have more durable marriages and less negative job turnover. We also estimate the initial distributions of relationship skill and initial human capital k_0 by gender and find relatively small gender differences. n and k_0 are positively correlated across individuals, with a higher correlation for men. Both types of innate skills are strong determinants of life cycle earnings, with post-education k accounting for around 22%, n around 7%, and jointly around 44% of the variance of measured lifetime earnings averaged across the population. There is positive assortative matching in both the job and marriage market by relationship skill n and adult human capital k; however our structural estimates suggest that relationship skill is much more

[2]Particularly relevant is Caspi et al. (1987). Other examples include, in the personnel literature Morgeson et al. (2007a), or Morgeson et al. (2007b), and in the economics literature Lundberg (2013) or the discussion in Borghans et al. (2008).

complementary in the labor market (where high-n workers are most productive when matched to a job that demands n) than in the household where spouses' endowments of relationship skill are substitutes conditional on income. Returning to the analysis of separations, we use the model to show that roughly 40% of the persistence in negative employer separations and 35% of the persistence in marriage turnover can be directly attributed to individual heterogeneity in the form of n and k, with much of the rest due to state dependence by which bad outcomes (specifically job- and marital mismatch) become self-perpetuating. In contrast to earnings for which k plays the larger role, turnover in both the labor and marriage markets is most strongly determined by n. Finally, our model can account for both the robustness of state-dependence in predicting turnover in reduced-form regressions as established by Light and McGarry (1998) and Munasinghe and Sigman (2004), and for the cross-market feedback effects documented, for example, in Ahituv and Lerman (2011) and Marinescu (2012).

The layout of the paper is as follows. Section 2 discusses some of the relevant economics literature that our paper draws on and complements. Section 3 describes our data sources and empirical motivation. In section 4, we develop our life cycle model with education, marriage, and work. Section 5 describes the parameterization and estimation of the model while section 6 presents our main results, focussing on the role of relationship skill in determining life cycle outcomes. Section 7 studies the evidence of the model in favor of our interpretation of n as a multi-sector fixed effect, while section 8 concludes.

2 Literature review

Our paper is related to and builds on several recent strands in the economics literature. Our approach to identifying relationship skill from occupation histories follows Yamaguchi (2012a,b), who also maps job histories to individual skill sets using PSID data merged to data from the Dictionary of Occupational Titles (DOT), the predecessor to the O*NET, in order to explain changes in earnings across workers with different skills and across the life cycle. Like us, Yamaguchi (2012a,b) 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 conditional on his preferences, which is also consistent with the evidence in Borghans et al. (2008) and Weinberger (2014). The major difference between our paper and Yamaguchi (2012a,b) is that his empirical work, and thus identification strategies, use data only from the labor market while our empirical work and identification strategy use data from both the labor and marriage market, and we focus more on specific "team" matching and separation in a frictional environment rather than on frictionless occupational sorting.[3] Thus, we see our paper as complementary to his.

Another recent paper with implications for our work is Altonji et al. (2013), in which the authors 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 determinants 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 three major ways. First, we focus only on *negative*, rather than all, transitions across employers. Second, we construct an empirical proxy for relationship skill, that is in general correlated with measures of human capital, whereas they assume their unobservable "propensity to move" factor to be independent of their fixed ability factor. Third, we estimate a structural model whereas they estimate a behaviorally motivated statistical model that allows for a very rich array of labor-market specific idiosyncratic shocks. These three differences explain why we find a much larger quantitative role for "movers" than they do.

Also related to our project, there is a large literature on the effect of non-cognitive ability on labor market and other social outcomes. Heckman et al. (2006), Cunha et al. (2010), and Heckman et al. (2013), among others, have shown, theoretically and empirically, that early childhood interventions that raise non-cognitive ability significantly enhance education outcomes and adult outcomes including employment, earnings, marriage, health, and engagement in crime. In the context of our paper, their work already shows that there exist fixed (or quasi-fixed) non-cognitive factors that affect adult outcomes and that are distinct from both "cognitive skill" and market productivity as traditionally understood. The literature has generally produced less conclusive evidence on the importance of specific personality-based attributes for wages and earnings.[4] Recently, however, Lindqvist and Vestman (2011) show that non-cognitive ability, based on a psychological assessment, is a better predictor than cognitive skill of labor market attachment and earnings (but not wages) among Swedish men. In an approach that is complementary with ours, they make a case for non-standard measures of non-cognitive skill that link these skills directly to economic performance (in their case, suitability for the military) as more useful and powerful than standard survey data based

[3] Yamaguchi (2012a,b) also differs from ours in that he considers cognitive and motor skills as his two factor model of individual labor market productivity, while we consider a general measure of human capital and relationship skill. Empirically, part of our relationship skill is embedded in his cognitive skill measure. Similarly, our "human capital" factor is closely related, but not synonymous, with cognitive skill.

[4] See for example the discussion in Borghans et al. (2008).

on personal self-assessments.[5] Also of interest, Cattan (2013) examines the contributions of cognitive and non-cognitive traits to the gender wage gap: she finds that the gap is largest in occupations that demand traits in which men have an absolute advantage, particularly managerial jobs that require high levels of self-confidence.

Finally, our paper is complementary with several previous papers that integrate marriage market and labor market outcomes. A recent working paper by Flabbi et al. (2013) also introduces search and matching frameworks in the two markets using a non-cooperative marriage environment. Chiappori et al. (2014), Greenwood et al. (2012) and Jacquemet and Robin (2013) build on one factor search and marriage matching models which also include labor supply decisions. Knowles (2013) and Pistaferri et al. (2013) examine how household power dynamics and sharing rules have changed over time in response to changing labor market opportunities for women. Mazzocco et al. (2014) argue, and generate as a prediction of a dynamic structural model, that wives in the PSID who anticipate a divorce will raise their labor market activity to raise their human capital and thus their outside option. Marinescu (2012) argues that partners' non-cognitive traits are in general fully observable to their spouses, but the output of a match changes over time due to shocks, which is consistent with our approach. In our paper, non-cognitive skill is fully observable to spouses (though not the econometrician) and couples in which the members have worse non-cognitive traits are being prone to negative shocks to household efficiency, as well as to economic disruptions such as job loss.

3 Empirical evidence: PSID and O*NET

In this section we explore the evidence of a fixed factor determining individuals' ability to form effective or, specifically, long-lasting, teams. Our data source is the 1980-2011 PSID, which contains detailed longitudinal information on heads (anachronistically, husbands or individuals of either gender living alone) and, where present, spouses (wives) living in the mainland US. In section 3.1 we provide reduced form evidence which is consistent with our idea of a two factor model in which one of the fixed factors controls relationship stability in the labor and marriage markets. In section 3.2, we derive a measure of relationship skill for each individual in our sample by merging the PSID with the O*NET. Additional information on our data sources and sample selection are provided in appendix A.2.

[5] Our approach is also similar to the exploratory approach employed by Jencks et al. (1979) who, by explicitly searching for the most conditionally significant traits for future earnings and occupational status, found substantially larger effects of non-cognitive traits, in particular measures of leadership and executive ability, than was typical among early sociological studies.

3.1 Employer separations and marital breakdowns in the PSID

Relationship skill affects the success, and hence longevity, of teams. An unsuccessful team or one that receives a negative productivity shock is likely to end in a separation that is "negative" for at least one partner in the sense that he is worse off than before the shock arrived. Two key variables in the PSID capture our idea of negative separations: (1) "negative" employer separations (*nes*); and (2) "spouse" separations, or colloquially "divorce" (though we include terminating cohabitations in our definition).

1. A *negative employer separation (nes)* occurs when a PSID individual leaves or changes his employer, satisfying one of two conditions: (1) a transition into or through unemployment, or (2) a post-separation annual average wage which is *lower* than the pre-separation wage. In general, perfectly identifying "negative" employer transitions in the PSID is impossible given measurement error and timing effects. Following Kambourov and Manovskii (2009), we first identify *employer switches* 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.[6] We identify those switches that satisfy either (1) or (2) as negative. If neither condition is met when the worker changes employers − that is, if she reports not having spent time in unemployment and experiences a medium-term increase in her hourly wage − we identify the employer change as a "positive" move up the career ladder, likely the result of successful on the job search. Second, individuals who have been with an employer in the previous interview, but are self-employed at a lower effective hourly wage (annual earnings over annual hours) or unemployed and in the labor force at the time of the current PSID interview are considered to have experienced a negative employer separation. Under our definition, the negative separation rate is roughly 11.3% per year among wage-earners aged 20-55 and 8.3% among all workers. It is 1.1 percentage points higher for male than for female wage earners and decreases sharply with age, averaging 15.5% for wage earners between 20 and 29 and 9.9% for wage earners aged 30 to 55.

2. A *spouse separation* (divorce) is indicated by a change in the reported marital status, either (1) whenever an individual changes her marital status from "married" (which includes individuals which describe themselves as singles but report living with a spouse) in one period to either unmarried or divorced (but not widowed) in the following period; or (2) whenever a

[6] 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) and appendix A.1 for a discussion of this and other related ways to identify employer switches in the PSID.

married individual's spouse's personal identifier changes, indicating a marriage-to-marriage transition, which accounts for about 6% of all marital transitions. Some individuals in the longitudinal sample who are not part of the core PSID sample exit the PSID sample upon separation. If their former spouse (from the core PSID sample) reports a separation, these leavers are also identified as experiencing an impending divorce in their last year in the sample. Under these definitions, which include transitions out of cohabiting relationships as well as formal marriages, the annual individual-level "divorce" rate among couples aged 20-55 is 3.9% for cohabiting wage-earners and 3.7% for all cohabiting individuals.[7]

Both human capital and relationship skill should affect outcomes in the labor and marriage markets. In particular, if there is a fixed "relationship skill" then we should expect to see some individuals experience many separations while other individuals experience few, conditional on standard measures of human capital. Thus, the stock of previous separations in either market should act as a reduced-form predictor of an impending *current* separation, and moreover we expect the prediction to operate across markets: that is, an individual with many previous spousal separations may be more likely to face an impending (negative) employer separation in the current period and vice-versa. To test this idea on our PSID sample, we run the following pair of regressions:

$$nes_{i,t+1} = \beta^1 X^1_{i,t} + \zeta^{11}_{i,t} stock\ of\ previous\ nes_{it} + \zeta^{12}_{i,t} stock\ of\ previous\ divorces_{it} \quad (1)$$

$$divorce_{i,t+1} = \beta^2 X^2_{i,t} + \zeta^{21}_{i,t} stock\ of\ previous\ nes_{it} + \zeta^{22}_{i,t} stock\ of\ previous\ divorces_{it} \quad (2)$$

The vectors X include a cubic in age, years of education, an indicator if the individual is white, the current wage in logs, employer tenure and its square (in X^1) and marriage tenure and its square (in X^2), number of children in the individual's household, year dummies, indicators for the SEO and immigrant samples, and counts of of the number of periods the individual been married and the number of periods she been a wage earner (hence susceptible to an *nes*) since entering the PSID. Means and standard deviations (in brackets) for the samples used in the regressions are reported in the first two columns of table A-1 in Appendix A.2. For the results reported in tables 1-2 we limit the sample to married men and women (specifically heads and wives of all PSID families) in the years 1980 or later, between the ages of 20 and 56. The samples for the regressions in columns 1 and 3 are further restricted to those who are currently

[7]Unlike the definition of *nes* there is no obvious way to identify whether a divorce leaves an individual in the PSID worse off economically or emotionally. It is well known that, in general, divorced men and women have lower incomes and employment outcomes than their married counterparts and that divorce is often traumatic. Excluding the subset (6%) of individuals who transition marriage-to-marriage and who might be said to experience a "positive spouse transition" does not significantly affect the results.

in paid employment (i.e. wage earners).[8] The middle two columns of table A-1 report the same statistics for the entire unweighted working age PSID sample between 1980 and 2011, and the last two columns give the same statistics weighted by the individual-level PSID weights, which is approximately demographically representative for the period 1980-2011 and which we use to estimate the model.

Linear probability and probit results are reported separately for men and women in tables 1 and 2. Most variables (in particular tenure and education) have the effects we would expect: reducing the likelihood of an impending *nes* or divorce. The key results from this exercise are the values of the ζs, reported in the two rows at the end of the tables. They show that (i) the number of previous *nes* and the number of previous divorces are independent predictors of the likelihood of an impending *nes* for both men and women, and (ii) the number of previous *nes* and the number of previous divorces are also independent predictors of the likelihood of an impending divorce for men and women.

Both own and cross-market effects of previous separation stocks are quite large. Relative to the means reported in the first two columns of table A-1, the results based on the linear probability model suggest that, for men, each additional *nes* (divorce) increases the likelihood of a current impending *nes* by 17% (16%) and of a current divorce by 8% (52%). The magnitudes for women are similar. The results based on the probit model are generally smaller in magnitude for both genders but the cross-market effects are even more precisely estimated.

When we refer to "negative" separations, we mean "negative" in an economic sense. It is well known that job loss (and high job mobility in general) is associated with low wage growth and that divorce is correlated with negative economic outcomes, especially for men. Table 3 relates stocks of *nes* and divorces to wage growth, using the change in log wages between the current and subsequent sample year as the dependent variable. For men, both the stocks of previous *nes* and of divorces have independent negative implications for wage growth, conditional on the current log wage. For women, however, only the stock of previous *nes* is significantly negatively correlated with predicted wage growth. We will briefly explore this gender difference in the context of the model.

[8] While only observations from 1980 on are used in the regressions, we use individual histories back to 1968 where available to compute the stocks of previous separations. This data, however, is not available for most PSID "wives" prior to 1980. To maximize the sample size, we combine the SRC and SEO samples dropping only the recent Latino oversample. The results are less precise (especially for women) but generally robust if use only the SRC sample or the full sample weighted by the PSID individual-level weights, about a third of which are set to zero. The results in columns 2 and 4 are also robust to using only the sample of current wage earners from the regressions in columns 1 and 3.

Table 1: Likelihood of experiencing a negative separation: Men

	Linear probability model		Probit model	
	nes	divorce	nes	divorce
	(1)	(2)	(3)	(4)
age	-.030 (.009)***	-.033 (.006)***	-.016 (.007)**	-.015 (.004)***
age^2	.0007 (.0002)***	.0008 (.0002)***	.0004 (.0002)*	.0004 (.0001)***
age^3	-5.80e-06 (1.99e-06)***	-6.69e-06 (1.31e-06)***	-2.42e-06 (1.67e-06)	-3.54e-06 (1.05e-06)***
tenure	-.013 (.0006)***	-.004 (.0006)***	-.012 (.0006)***	-.003 (.0004)***
(tenure)^2	.0004 (.00002)***	.0001 (.00002)***	.0003 (.00002)***	.00009 (1.00e-05)***
yrs of education	-.004 (.0007)***	-.004 (.0004)***	-.003 (.0007)***	-.004 (.0004)***
dummy for white	.005 (.004)	-.017 (.003)***	.004 (.003)	-.012 (.002)***
log wage	.001 (.003)	-.007 (.001)***	.0005 (.002)	-.007 (.001)***
stock of prev *nes*	.018 (.001)***	.004 (.0007)***	.014 (.001)***	.004 (.0006)***
stock of prev divorce	.017 (.004)***	.025 (.003)***	.015 (.003)***	.019 (.002)***
sample size	54734	68439	54734	68439
R^2	.042	.035	.067	.083

The dependent variable in each column is an indicator for experiencing a separation within the next sample period (before $t+1$ from the perspective of t). Additional controls include number of children in the household, indicators for whether the observation is from the SEO or immigrant samples, and year dummies. Tenure refers to employer tenure in columns (1) and (3) and marriage tenure in columns (2) and (4). * (**) [***] denote significance at the 10% (5%) [1%] confidence levels. *nes* stands for 'negative employer separation.' 'Divorce' denotes a spouse separation including from cohabiting relationships. The R^2s for the probit regressions are pseudo-R^2s.

The strong predictive power of previous separations for current separations within a single market is well known in the labor search literature (see Mincer and Jovanovic (1981)) and in the marriage literature (see Becker et al. (1977) or Amato and Rogers (1997)). The fact that negative separations have strong predictive effects *across* markets has been much less explored (an exception is Ahituv and Lerman (2011)). It is consistent with our hypothesis of the presence of a fixed individual effect in "team-based" productivity, regardless of the type of team under consideration but also with the presence of occurrence state dependence in separations (Heckman and Borjas (1980)). Disentangling heterogeneity from state dependence is in general very difficult; however, previous literature has found strong evidence of "mobility effects" *within* the labor market (see e.g. Munasinghe and Sigman (2004)), due, for example, to mismatch or to the loss of firm-specific capital when changing employers or occupations.

Table 2: Likelihood of experiencing a negative separation: Women

	Linear probability model		Probit model	
	nes	divorce	nes	divorce
	(1)	(2)	(3)	(4)
age	-.019	-.029	-.009	-.015
	(.008)**	(.006)***	(.007)	(.005)***
age^2	.0004	.0007	.0001	.0004
	(.0002)*	(.0002)***	(.0002)	(.0001)***
age^3	-2.85e-06	-6.01e-06	-4.61e-07	-3.76e-06
	(1.90e-06)	(1.31e-06)***	(1.64e-06)	(1.17e-06)***
tenure	-.013	-.003	-.012	-.002
	(.0007)***	(.0006)***	(.0006)***	(.0005)***
(tenure)^2	.0004	.00009	.0004	.00006
	(.00003)***	(.00002)***	(.00003)***	(.00002)***
yrs of education	-.004	-.006	-.003	-.005
	(.0007)***	(.0005)***	(.0007)***	(.0005)***
dummy for white	.010	-.034	.010	-.028
	(.004)***	(.003)***	(.003)***	(.003)***
log wage	.012	-.0002	.011	-.0008
	(.003)***	(.001)	(.002)***	(.001)
stock of prev *nes*	.018	.006	.014	.005
	(.002)***	(.001)***	(.001)***	(.0009)***
stock of prev divorces	.016	.035	.014	.026
	(.004)***	(.004)***	(.003)***	(.002)***
sample size	45746	60144	45746	60144
R^2	.030	.036	.052	.079

The dependent variable in each column is an indicator for experiencing a separation within the next sample period (before $t+1$ from the perspective of t). Additional controls include number of children in the household, indicators for whether the observation is from the SEO or immigrant samples, and year dummies. Tenure refers to employer tenure in columns (1) and (3) and marriage tenure in columns (2) and (4). * (**) [***] denote significance at the 10% (5%) [1%] confidence levels. *nes* stands for 'negative employer separation.' 'Divorce' denotes a spouse separation including from cohabiting relationships. The R^2s for the probit regressions are pseudo-R^2s.

State dependence *across* markets is also likely – e.g., Marinescu (2012) shows using SIPP data that husbands who experience a job loss in one three-month period are much more vulnerable to divorce in the subsequent three-month period. As well, to the extent that the persistence of turnover across markets is due to fixed individual effects, the stocks of previous negative separations may be picking up a residual measure of human capital, which is not fully captured by education and mis-measured current wages, rather than, or in addition to, a separate "relationship skill".

This second possibility is difficult to test using PSID data, and we return to it in section 7 in the context of our structural model. Table A-2 in appendix A.3 reports results dealing with simple state dependence. Specifically, we introduce a lagged dependent variable for each type of separation into the specifications from tables 1 and 2, that is, an indicator for whether the

Table 3: Wage growth and previous negative separations: Both genders

	Δ log wage: men	Δ log wage: women
	(1)	(2)
age	.049	.058
	(.011)***	(.013)***
age^2	-.001	-.001
	(.0003)***	(.0003)***
age^3	7.68e-06	9.33e-06
	(2.49e-06)***	(3.02e-06)***
employer tenure	.004	.010
	(.0009)***	(.001)***
(employer tenure)^2	-.00007	-.0002
	(.00003)**	(.00005)***
yrs of education	.044	.055
	(.002)***	(.003)***
dummy for white	.081	.052
	(.007)***	(.008)***
log wage	-.367	-.426
	(.014)***	(.017)***
stock of previous *nes*	-.023	-.027
	(.002)***	(.004)***
stock of previous divorces	-.018	-.011
	(.006)***	(.007)
sample size	53720	43906
R^2	.160	.181

The dependent variable in each column is the change in log wages from period t to period $t+1$. * (**) [***] denote significance at the 10% (5%) [1%] confidence levels. *nes* stands for 'negative employer separation.' 'Divorce' denotes a spouse separation including from cohabiting relationships. All reported results are from the linear probability model. Corresponding probit results are available upon request.

individual experienced a negative separation between the previous and current period along with the stocks of previous negative separations. We find that the direct lag of *nes* (though not divorce) does increase the likelihood of experiencing a divorce or *nes* in the subsequent period conditional on the stocks of previous *nes* and divorces, but that the stocks remain strong significant predictors within and across markets. We also show that our cross market effects cease to hold when we replace *nes* with a measure of "positive employer switches": employer-to-employer transitions that result in higher observed wages and do not involve a spell of unemployment.[9] That is, only *negative* mobility in the labor market appears to predict divorce and vice-versa.

Taken as a whole, the data is consistent with, even suggestive of, an unobserved cross-market fixed "teamwork" or "relationship" factor, though this factor may act in complex ways. In particular, it may induce long-term state dependence by making individuals susceptible to self-perpetuating spells of high instability in either the job or labor markets. We return to

[9]Positive employer switches are again identified using the definition of employer switching from Kambourov and Manovskii (2009), subject to not meeting our definition of a negative switch.

explore this issue further in section 7. We now turn to finding a proxy for relationship skill and then to using this information to develop and estimate a structural model.

3.2 Mapping fixed effects into character observables

3.2.1 Relationship skill and occupational history at the individual level

To find a plausible identifier of relationship skill for individuals in the PSID, we turn to the U.S. Department of Labor's Occupational Information Network, the O*NET. The O*NET provides detailed information on the characteristics, requirements, and tasks associated with each of about 800 occupations, including measures of the skills, interests, and personal attributes that promote success in the occupation. This information can be mapped, though with some loss of information, into the 2000 U.S. Census categories at the 3-digit level which are reported for each worker in the PSID. We can therefore merge the O*NET with the PSID, based on the occupation of employment, for each individual-year observation in which occupation was reported.[10] For each occupation, the "importance" of different skills and attributes, and the "relevance" of different tasks are reported along numeric scales typically taking values between 1 and 5, where 1 means "unimportant/irrelevant" and 5 means "extremely important/relevant." Data is provided by subjective responses from a random sample of workers within occupations ("occupational incumbents") and in some cases by outside occupational or human resource experts ("analysts").

The O*NET contains over 400 occupational attributes. To narrow down our search for the relevant ones, we focus on the O*NET Work Styles file. The Work Styles file is attractive for our purposes because it ascertains from occupational incumbents information on personality traits (attributes) that are likely inherent rather than formally learned and can intuitively be related to standard psychological measures such as the "Big Five" personality traits, rather than learned skills.[11] We focus on the mean reported "importance" of each skill to the occupation, ranked from one to five. The Work Styles file reports sixteen personality attributes, a, arranged into seven broad categories. They are:

- Effort, Persistence
- Initiative, Leadership
- Cooperation, Concern for others, Social orientation

[10]See appendix A.4 for a discussion of mapping occupation from the O*NET to the PSID.

[11]"Work styles" can be understood as mapping from personality traits to actions, capturing how an individual worker chooses and performs a set of actions in order to accomplish a task based on his own strengths and preferences. Almlund et al. (2011) define actions as "*styles* of behavior that affect how tasks are accomplished" (emphasis theirs).

- Self control, Stress tolerance, Adaptability/flexibility
- Dependability, Attention to detail, Integrity
- Independence
- Innovation, Analytical thinking

We then construct our proxy for relationship skill using the following three step process:

1. For each PSID individual i and attribute a, we construct a measure of this attribute $\hat{n}_i^a = g(\hat{a}_1, .., \hat{a}_T)$ where T is the total number of PSID sample periods the individual reports an occupation, and the $\hat{a}_t$ is the reported "importance" of attribute a to the individual's reported main occupation in period t. The most intuitive choice of $g(\cdot)$ is simply the average of the $\hat{a}$ over the individual's observed work life. We calculate this mean after adjusting for gender and a quadratic in birth year. The resulting measure $\hat{n}_i^a$ should be thought of as a true, if noisy, measure of trait a for the individual.

   Once we have our sixteen traits $\hat{n}_i^a$, we now want to know what trait or combination of traits best approximates our concept of relationship skill n. In other words we search for the combination of traits $\hat{n}_i^a$ that is most strongly negatively correlated with the likelihood of separation in the labor and marriage markets. To do so, we compute the first principal factor from *all* combinations of $\hat{n}_i^a$ up to six.[12] We call these factors $\widehat{n}$, our candidate measures of n.

2. Next, to extract a compact measure of separation likelihood as a fixed effect, we estimate on our sample of PSID individuals time differenced OLS versions of equations (1) and (2) omitting the stocks (and all time-invariant parameters) as covariates, and allowing the coefficients on the time-varying covariates to differ by gender. We extract the implied individual fixed effects from these two regressions and take their principal factor, which we call $\widehat{f}_i$.[13]

3. Finally, to relate our $\widehat{n}$s to the separation fixed effects, we regress $\widehat{f}_i$ on the different candidate $\widehat{n}_i$s at the individual level along with a set of other observable individual-level fixed effects: years of education, gender (female = 1), average hourly wage over the individual's working life (normalized for gender and cohort just like the the $\hat{a}$s), race (white = 1), indicators for being in the immigrant or SEO subsamples, and the year, age, and squared age at which the individual was first observed. We run this regression once for each $\widehat{n}$, holding

[12] There are $\sum_{i=1}^{6}\prod_{j=1}^{i}(16+1-j)$ combinations.

[13] The correlation of the two fixed effects extracted from the regressions is .21.

the set of conditioning regressors constant, and search for the $\widehat{n}$s that maximize the R^2 from this second-stage regression.

Table A-3 in appendix A.4 reports the results from the second stage regression for the top eight $\widehat{n}$s. The most predictive $\widehat{n}$ are all combinations of two or more of the following six $\hat{n}^a$: *persistence*, *cooperation*, *adaptability*, *dependability*, *attention to detail*, and *independence*.[14] A more detailed discussion of these results is given in appendix A.4. Since the magnitudes and significance of the $\widehat{n}$s reported in table A-3 are all nearly identical, we choose the $\widehat{n}$ that contains all six attributes listed above − henceforth $\widetilde{n}$ − to estimate and test our model.

3.2.2 Sorting on $\widetilde{n}$

Supply and demand for n in the labor market. Since our identification of $\widetilde{n}$ is based on supply and demand − the idea that high n individuals supply their relationship or teamwork skills to the jobs or employers that demand those skills − it is useful to examine rates of *nes* across $\widetilde{n}$ and demand for n, which we construct for each occupation using the same data from the O*NET on the "importance" of the $\hat{a}$s used to construct $\widetilde{n}$. We label occupations demanding different levels of $\widetilde{n}$ by ν.[15] We should then see relatively higher rates of match failure among low $\widetilde{n}$ compared to high $\widetilde{n}$ workers employed in high ν jobs and vice versa, and of course lower negative separation rates among high $\widetilde{n}$ workers overall. This is in fact what we see: using two categories of $\widetilde{n}$, "high" and "low," and three levels of ν, "high," "medium," and "low," the negative separation rates within low ν jobs are 10.0% among low $\widetilde{n}$ workers and 10.9% among high $\widetilde{n}$ workers at the annual level. Among high ν jobs the pattern is reversed: low $\widetilde{n}$ workers experience an annual negative separation rate of 10.8% and high $\widetilde{n}$ workers of only 6.3%. Among medium ν jobs the negative separation rates are 9.2% for low $\widetilde{n}$ and 7.6% for high $\widetilde{n}$ workers. The reduced-form differences in *nes* rates by $\widetilde{n}$ are significant at the 1% level for each value of ν while high $\widetilde{n}$ workers experience overall lower negative employer annual separation rates by 2.5% compared to low $\widetilde{n}$ workers.[16]

Sorting on n in the marriage market. To assess sorting on n in the marriage market, we can ask whether marital sorting patterns in the PSID suggest that couples sort based on

[14]Two other individual $\hat{n}^a$s, *integrity* and *analytical thinking*, are significant negative predictors of $\widehat{f}_i$ at the 10% level, but are less strongly correlated with the other predictive attributes in table A-3.

[15]See section 5 for detail on how we construct ν.

[16]On average, the *nes* rates are slightly lower than those reported in table A-1 because we calculate these moments based on all workers who report an occupation in the reference year rather than only wage-earners. The patterns of *nes* across $\widetilde{n}$ and ν are even more pronounced if we consider only individuals who were wage-earners at the time of the PSID interview.

n, assuming that they also, clearly, sort on education. The correlation of $\widetilde{n}$ within couples is given by

$$\rho(\widetilde{n}_m, \widetilde{n}_f) = \frac{cov(\widetilde{n}_m, \widetilde{n}_f)}{\sigma^m_{\widetilde{n}} \sigma^f_{\widetilde{n}}}$$

where σ^g_x is the standard deviation of a random variable x normalized to have zero mean. Since for each gender, education s and $\widetilde{n}$ are correlated, we have

$$\mathbb{E}(\widetilde{n}_g | s_g) = \rho(\widetilde{n}_g, s_g) \frac{\sigma^g_{\widetilde{n}}}{\sigma^g_s} s_g$$

or

$$\widetilde{n}_g = \rho(\widetilde{n}_g, s_g) \frac{\sigma^g_{\widetilde{n}}}{\sigma^g_s} s_g + \epsilon_g$$

where ϵ_g has mean zero and is uncorrelated with s_g.

In turn, this implies that if couples do not sort on $\widetilde{n}$, then we would have

$$\begin{aligned}
\hat{\rho}(\widetilde{n}_m, \widetilde{n}_f) &= \mathbb{E}\Big(\rho(\widetilde{n}_m, s_m) \frac{\sigma^m_{\widetilde{n}}}{\sigma^m_s} s_m + \epsilon_m\Big)\Big(\rho(\widetilde{n}_f, s_f) \frac{\sigma^f_{\widetilde{n}}}{\sigma^f_s} s_f + \epsilon_f\Big) \frac{1}{\sigma^m_{\widetilde{n}} \sigma^f_{\widetilde{n}}} \\
&= \rho(\widetilde{n}_m, s_m) \frac{\sigma^m_{\widetilde{n}}}{\sigma^m_s} \rho(\widetilde{n}_f, s_f) \frac{\sigma^f_{\widetilde{n}}}{\sigma^f_s} cov(s_m, s_f) \frac{1}{\sigma^m_{\widetilde{n}} \sigma^f_{\widetilde{n}}} \\
&= \rho(\widetilde{n}_m, s_m) \rho(\widetilde{n}_f, s_f) \rho(s_m, s_f)
\end{aligned}$$

which we can calculate directly from the data.

In our PSID sample, $\rho(\widetilde{n}_m, s_m) = .45$, $\rho(\widetilde{n}_f, s_f) = .37$ and $\rho(s_m, s_f) = .61$. This gives $\hat{\rho}(\widetilde{n}_m, \widetilde{n}_f) = .102$, compared to an actual correlation of $\widetilde{n}$ within married couples of $\rho(\widetilde{n}_m, \widetilde{n}_f) = .179$, almost twice as high. We therefore see some descriptive evidence in favor of explicit, although relatively low, positive assortative mating on $\widetilde{n}$. We will return to this issue below in the context of the model.

4 The model

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

4.1 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 skill n. $k(j)$ is determined by an initial human capital endowment k_0, a schooling investment s, and stochastic learning-by-doing as a working adult. n is a fixed endowment that does not vary with age, schooling, or labor market attachment. k_0 and n are drawn from distributions $\{\Omega_0^f, \Omega_0^m\}$, each characterized by a σ_{kn}^g measuring the within-gender correlation between k_0 and n.[17] As adults, individuals may be unemployed or employed with a job defined by "complexity" κ and relationship skill requirement ν. When an individual is unemployed, we assume $\nu = \kappa = 0$ for notational simplicity. Adult individuals may be married or single.

4.1.1 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: $s \in \{0, 2, 4, 6, 8\}$, roughly corresponding to dropping out of high school, finishing high school, going to a two-year college, going to four-year university, or going for a higher post-graduate degree. The investment returns human capital $k(\underline{j})$ according to

$$\begin{aligned} k(\underline{j}) &= f(k_0, s, \epsilon_s) = k_0 s^{\alpha} \epsilon_s(n) \\ \epsilon_s(n) &\sim Beta(p_s(n), q_s) \\ p_s(n) &= \psi_0(1 + \psi_1 n); \qquad q_s = \psi_2 \end{aligned} \tag{3}$$

where $\underline{j}$ is the first age after completed education s, and $\epsilon_s \in [0, 1]$ is a shock realized at the end of the chosen education period. ϵ_s is drawn from a beta distribution with shape parameters p_s and q_s.[18] For given p_s, parameter q_s, which we take to be a constant across all individuals, pins down how close the mean of ϵ_s lies to one. Education offers a maximum return of $k_0 s^{\alpha}$ if fully utilized. Because p_s depends on n, individuals with greater relationship skill on average can realize more (or, in principle, less if $\psi_1 < 0$) of the potential returns to their education. The estimated value of q_s effectively tells us how much of the difference by n relates the the variance − the likelihood of receiving an abnormally low return to schooling investment − and how much is due to differences in the *mean* return to education by n.[19]

[17]In our PSID sample, we cannot observe the initial distribution of k_0, but we do observe that about 51% of men and 48% of women are high-$\widetilde{n}$ (using weighted estimates). Since *observed* $\widetilde{n}$ and *true* n differ, we estimate the shares of high-n men and women entering adulthood, N_f and N_m, and the mean and variance of k_0 by gender, after normalizing the mean k_0 for men.

[18]The density is given by $f(\epsilon_s) = constant \cdot \epsilon_s^{p_s(n)-1}(1-\epsilon_s)^{q_s-1}$ where the constant normalizes the distribution so that the integral of the density over the unit interval is 1. We ignore it in what follows to avoid clutter. In general, the mean of the normalized beta distribution is given by $\frac{p}{p+q}$ and the variance by $\frac{pq}{(p+q)^2(p+q+1)}$.

[19]The mean of the beta distribution is monotonically decreasing in q and increasing in p. The coefficient of variation is is decreasing in $p+q$ so long as $p^2 - p < (q+1)^2$ which is satisfied by the estimated parameters

Individuals commit to their optimal education at the start of life and do not receive marriage or job offers until they have completed their education. Education therefore imposes an opportunity cost in terms of lost earnings and delayed marriage. During education, individuals receive an income

$$B^s = \Big(b_0^s s + b_1^s n + b_2^s k_0\Big)\Big(\exp(\epsilon_s^B)\Big) \tag{4}$$

where ϵ_s^B is normally distributed across the population with mean zero and variance σ_B^2. The per-period income received during school depends both on how much schooling an individual chooses to obtain and her innate productive characteristics. We would expect schooling income to increase with k_0 and n if, for example, better-endowed children come from higher-income families or if they derive more consumption value from learning because they have a knack for it.[20]

4.1.2 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 in a two-month period allowing us to achieve a realistic model of employment and non-employment transitions.

Work. Individuals enter the labor market non-employed with human capital $k(\underline{j})$. While non-employed, they receive a single job offer every two months with probability τ_0^s or τ_0^l, depending on whether their non-employment spell has been "short term" (one model period) or "long-term" (more than one model period).[21] The job offer they receive is 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

of the model for education, marriage and labor markets.

[20]In general, when we refer to "innate" skills or endowments, we are referring to skills at 16, which depend both on raw endowments and environmental factors during childhood that we do not observe.

[21]We use the term "non-employment" to emphasize the fact that, in the model, there is no clear distinction between unemployment and non-participation. While non-employment is generally sub-optimal, some individuals in the model, particularly women who have relatively high non-employment productivity, endogenously choose to be long-term non-employed by turning down job offers.

the form of wages W[22]:

$$
\begin{aligned}
W_g(k, \kappa, n, \nu, \epsilon_W) &= a_g\big(\gamma_0 k^{\gamma_1} + (1-\gamma_0)\kappa^{\gamma_1}\big)^{\frac{1}{\gamma_1}} \epsilon_W(n, \nu) \\
\epsilon_W(n, \nu) &\sim Beta\big(p_W(n, \nu), q_W\big) \\
p_W(n, \nu) &= \phi_0(1 + \phi_1 n + \phi_2 \nu + \phi_3 n\nu); \quad q_W = \phi_4
\end{aligned} \tag{5}
$$

Gross output from a matched job for a worker of gender g consists of a fixed and a variable component. The fixed component depends on the match between k (productive human capital) and the complexity of physical capital κ, according to a CES production function with share parameter γ_0, substitution elasticity γ_1, and a gender-specific TFP factor a_g (with a_m normalized to one). Production each two-month period is subject to an IID shock $\epsilon_W \in [0, 1]$ which, like education, is drawn from a beta distribution and depends on the "relationship skill" match of n to the occupation-level demand for this skill ν in the current job. The mean, variance, and relative contributions of n and ν to the shock are governed by a linear model with parameters $\{\phi_0, \phi_1, \phi_2, \phi_3, \phi_4\}$. The properties and interpretation of the beta distribution for realizing the output of a worker-job team are similar to those for education. When employed, workers supply one unit of fixed labor time to their job.[23]

Once matched, a worker remains on the job until one of two things happen. First, the worker may leave for a better (either higher κ or better-matched ν) job. Note that this "new" job may be with the same employer; the worker is indifferent to his employer given the characteristics of the job. Job offers drawn from the $\tilde{\Pi}(\kappa, \nu)$ distribution of vacancies arrive for employed workers with probability τ_1. Second, the job may terminate because the wage shock ϵ_W is sufficiently low as to make a period of non-employment attractive.[24]

Non-employment incomes for women and men are given by

$$B_f^{ne} = (b_1^{ne} + b_2^{ne} I_{long\ term}) W_f(k, \overline{\kappa}, n, \overline{\nu}, 1) \tag{6}$$

$$B_m^{ne} = (b_3^{ne} + b_4^{ne} I_{long\ term}) W_f(k, \overline{\kappa}, n, \overline{\nu}, 1) \tag{7}$$

[22] We do not explicitly model 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 $\tilde{\Pi}$ distribution so that the $\hat{\Pi}$ that arises in the model is consistent with that observed in the data.

[23] The simplifying assumption of deterministic returns to k and κ is not strictly necessary for identification of our model. We could, for instance, construct a $\widetilde{k}$, similar to $\widetilde{n}$ for each PSID worker and use *nes* rates among occupations of different complexities to identify a separate, independent, stochastic shock to W reflecting variation in returns that is due to factors other than personal conflict. While likely realistic, this extension would add substantial computational cost and complexity without, we believe, shedding much additional light on the role of relationship skill in determining career outcomes.

[24] Low et al. (2010) use a model with job arrival and job destruction shocks to study wage and employment risk over the life cycle. Low draws of the shock can also imply that the firm goes out of business.

where $I_{long\,term}$ indicates that the individual is in long-term non-employment and $\{\overline{\kappa}, \overline{\nu}\}$ are the average values of κ and ν in the economy. B^{ne} is increasing in potential earnings to reflect the facts that (1) unemployment benefits are typically based on previous earnings; and (2) k is a likely input into home production, including child-care.[25] Non-employment productivity differs by gender and short- vs. long-term non-employment to reflect possible comparative advantages for women in childbearing and related non-employment activities which may require low labor market attachment for an extended period of time.

While employed, individuals receive a permanent unit increment to k at the start of each year with probability $p_k = p_{k,0}k(j)^{p_{k,1}} + p_{k,2}j$ due to learning by doing in the labor market. Non-employed workers are not eligible for experience-based increases in k.

Finally, in the simulated economy, we assume that both W and ν are observed with error. That is, we observe a measure of wages $\widehat{W} = W \exp(\epsilon_{me})$ and a value of ν such that $\widehat{\nu} = \nu + \epsilon_\nu$, where ϵ_{me} and ϵ_ν are each distributed normally with mean zero and variance σ^2_{me} and σ^2_ν.[26]

Family. After finishing school individuals of both genders ($g = f$ or $g = m$) begin searching for a partner. While single, individuals generate output, denoted by S, which can take two forms depending on whether the individual is working or not:

$$
\begin{aligned}
S_g^U &= B_g^{ne} \\
S_g^E &= W_g(k, \kappa, n, \nu, \epsilon_W).
\end{aligned}
$$

Utility is given by:

$$
U_g^S = \log\big(S\big). \tag{8}
$$

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

$$
M = \big(\chi_0 I_f^{\chi_1} + (1-\chi_0) I_m^{\chi_1}\big)^{\frac{1}{\chi_1}} \epsilon_M(n_f, n_m)
$$

$$
\begin{aligned}
&\epsilon_M(n_f, n_m) \sim Beta\big(p_M(n_f, n_m), q_M\big) \\
&p(n_f, n_m) = \lambda_0\big(1 + \lambda_1 n_f + \lambda_2 n_m + \lambda_3 n_f n_m\big); \qquad q_M = \lambda_4
\end{aligned} \tag{9}
$$

Each spouse's individual utility is given by

$$
U_g^M = \log(\ell_g M), \tag{10}
$$

[25] Note that, since home production output is not subject to shocks ($\epsilon_W = 1$), it does not depend directly on n.

[26] See Kambourov and Manovskii (2009) on the issue of measurement error in occupation in the PSID.

Equation (9) has a similar construction to equation (5) governing the wage: it determines the efficiency of a two member household or husband-wife team as a function of their characteristics. The elasticity parameter $\chi_1 \in (-\infty, 1]$ captures the degree of substitutability between the income I (either wage or non-employment income) generated by the wife and husband, and χ_0 captures the share that the wife contributes to marital output. Given the shape of preferences, ℓ_g can be thought of as either a consumption equivalence scale (which can vary by gender depending on how spouses divide output) or a gender-specific non-pecuniary gain from being married that increases utility conditional on the couple's joint income. The $\epsilon_M \in [0, 1]$ is a transitory multiplicative shock capturing the degree to which deterministic (potential) marital output is converted to (intangible) marital income in a given period. We assume that the distribution of the shock depends on both husband's and wife's relationship skill n, the importance and substitutability of which are determined by parameters $\{\lambda_0, \lambda_1, \lambda_2, \lambda_3, \lambda_4\}$. While n affects both the expected level and the volatility of marital enjoyment, it is also clear that couples with higher incomes are better able to deal with transitory conflicts caused by low draws of ϵ_M. Also, even though the effects of the spousal ks on M are deterministic, changes in the spouses' relative k can still induce divorce.

Single individuals meet potential mates each year with probability π. There is perfect assortative mating by age. 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. In contrast to the job market, there is no on-the-marriage search. The timing and interaction of marriage decisions with work decisions is sketched out in section 4.2 below.

4.1.3 Stage 3: Retirement

At age 66 individuals retire and receive a pension based on their final human capital $k(66)$, which is the same as the non-employment benefit during the working life. Married and single output is the same as before. Everybody dies with certainty at age 80.

4.2 Individual optimization and timing in the model

Figure 1 shows timing of events within a model period for married and unmarried individuals. Individuals enter a period with all uncertainty resolved and committed to their current jobs

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

SINGLE				
production and consumption of S	k' realized	new job offer $\{\hat{\kappa}', \hat{\nu}'\}$	new potential marriage partner	e'_W realized if employed; quit decision
production and and consumption of M	k'_f and k'_m realized	new job offers received	ϵ'_M and divorce choice	$e'_{W,f}$ and $e'_{W,m}$ realized for employed spouses; quit decisions
MARRIED				

and marital states. They produce in their current jobs given the current realization of ϵ_W. Singles consume their output S and married partners produce and consume M.

At the end of the current period, individuals are subject to five potential shocks. First, individuals who worked in the period either do or do not receive (and observe) an increment ι to their current stock of human capital k. Second, the individuals do or do not receive a new job offer for next period. If the job offer is more attractive than the current employment status, individuals accept the new offer. Third, singles do or do not meet a potential mate for next period. Fourth, partnered households (married couples and newly matched couples) receive their stochastic realization ϵ'_M for next period, prompting some couples to separate. Fifth and finally, if the individual is employed (in either an old or a new job), the match productivity shock for the job ϵ'_W is realized, at which point the individual can choose to remain and produce in his new job during the next period or decline the offer and enter (short-term) non-employment. If the individual is single, he makes this last decision on his own. If partnered, the quit decisions for both spouses (and the earlier job-change decisions for marrieds) are household-level decisions that the couple makes simultaneously as a function of both partners' ϵ'_W and on ϵ'_M.

Note that one important implication of the sequence of events described is that marriage provides immediate insurance against non-employment shocks since by the time productivity draws for the (two month) period are realized, the spouses have already committed for the subsequent period. However, a non-employed spouse may face a higher likelihood of divorce in the subsequent (two-month) period if he has not become successfully re-employed. The timing of events also implies that some employment and domestic matchings will be very short (more like an unsuccessful interview or first date) since job and "marriage" offers arrive before the immediate productivity of the match is known. If the individual accepts a new job (or relationship) and then immediately quits (or separates), then we assume that we do not observe the transition in the data and we treat the individual as if he did not change job or marital status.

Though computationally straightforward, the Bellman equations for married and single workers and non-workers are somewhat cumbersome and are relegated to appendix B where they are described in detail.

5 Parametrization and identification

To compute the model, we discretize the values of k, n, κ, and ν to take ten, two, two, and three values, respectively. 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 set to $\{0.0, 0.5, 1.0\}$ and the two values of κ are equal to the third and seventh grids of k.[27] Computational constraints prevent the use of larger grids, but the results are not sensitive to small changes in the spacing of the grids.

The model is estimated through simulated method of moments using 56 moments taken from the PSID-O*NET sample in addition to the ζs from columns (1) and (2) of tables 1 and 2 for a total of 64 moments. For each draw of parameters we solve for marriage market equilibrium.[28] The moments identify 51 parameters discussed in the previous section. To make the simulated economy as close as possible to the US economy over the period 1980-2011, we simulate the model to match moments calculated using the individual-level PSID weights, corresponding to the population described in columns (5) and (6) of table A-1. To replicate the sampling of the PSID, we simulate 4500 individuals and their (possibly multiple) spouses corresponding (roughly) to the SRC sample. For each of these simulated individuals we draw a random sample of years from their life so as to replicate the mean and standard deviation of the individual record (row 3 of table A-1). These data are used to estimate the parameters of the model. We then simulate a further 3000 individuals drawn from a different mean-shifted distribution of k_0 and n to proxy the SEO and immigrant subsamples. Our regression analysis is performed on the combined sample of 7500 simulated households.[29]

The parameters of the model, along with their estimates and standard errors from ten

[27] Strictly speaking, these are not normalizations, but the model parameters, in particular γ_0 will adjust to establish the proper share of capital in production. The grid for k takes ten values ranging from 5 to 86 in increasing increments.

[28] The imposition of marriage market equilibrium is similar to Fernández and Wong (2014). For each parameter draw we iterate to a fixed point at which single searchers have rational expectations over the population of potential mates from which they draw, and marriage and divorce decisions reproduce that distribution.

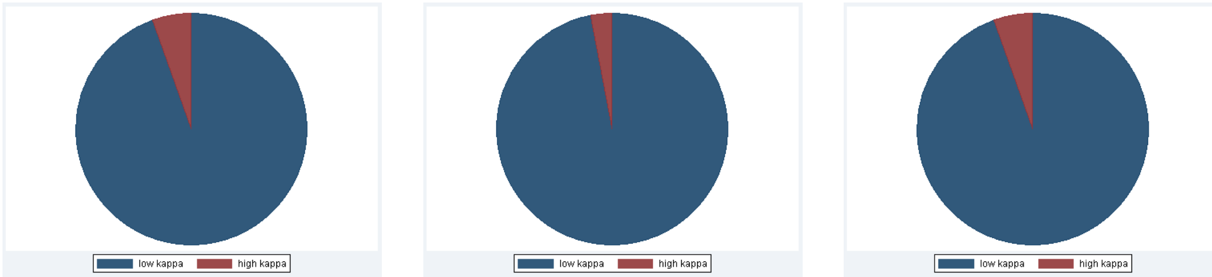
[29] Drawing an "SEO" sample from a distribution of n the mean of which is 10pp below and a distribution of k_0 the mean of which is .12 standard deviations below the values estimated for the main sample produces an overall simulated population with mean characteristics close to those in columns 3 and 4 of table A-1. With respect to $\widetilde{n}$ (not shown in table A-1), the mean value is .494 in the representative sample and .460 in the combined sample, a difference we replicate in the model.

Table 4: Parameters

Parameter	Estimate: benchmark	Interpretation
α	0.503 (0.015)	return to s in (3)
$p_s(n)$	$1.873(1+1.114n)$ (0.165) (0.029)	distribution of shocks to $k(\underline{j})$ in (3)
q_s	3.958 (0.199)	shape parameter for stochastic part of (3)
B^s	$-0.761s + 8.468n + 1.465k_0$ (0.114) (1.243) (0.284)	deterministic part of schooling consumption
σ_B^2	5.739 (0.869)	variance of exponential schooling consumption shock
τ_0^s	0.578 (0.021)	arrival rate of job offers while non-employed
τ_0^l	0.093 (0.011)	arrival rate of job offers while long-term non-employed
τ_1	0.165 (0.013)	arrival rate of job offers while employed
μ	0.541 (0.004)	share of τ_1 from on-the-job search (vs. promotions)
p_K	$0.0068k^{0.589} - 0.0007j$ (0.0005) (0.010) (0.0002)	incidence of on-the-job-learning
a_f	0.844 (0.015)	wage penalty for women
γ_0	0.459 (0.037)	share of k in wage given by (5)
γ_1	-0.983 (0.072)	substitutability of k and κ in (5)†
$p_W(n,\nu)$	$0.366(1+0.113n-0.148\nu+0.199n\nu)$ (0.045) (0.008) (0.017) (0.019)	distribution of shocks to W in (5)
q_W	0.116 (0.017)	shape parameter for stochastic part of (5)
σ_{me}^2	0.225 (0.005)	variance of measurement error in log wages
σ_ν^2	0.270 (0.020)	variance of measurement error in latent occupation
B_f^{ne}	$0.185 + 0.464 \times \textit{long term}$ (0.018) (0.051)	non-employment productivity for women
B_m^{ne}	$0.366 + 0.109 \times \textit{long term}$ (0.016) (0.023)	non-employment productivity for men
π	0.019 (0.002)	arrival rate of marriage offers for singles
ℓ_f	2.554 (0.078)	marriage equivalence scale for women
ℓ_m	2.807 (0.119)	marriage equivalence scale for men
χ_0	0.333 (0.033)	share of wife's earnings in hh output given by (9)
χ_1	-0.163 (0.045)	substitutability of husband's and wife's incomes in (9)††
$p_M(n_f,n_m)$	$0.259(1+0.419n_f+0.299n_m-0.286n_f n_m)$ (0.039) (0.047) (0.046) (0.060)	distribution of shocks to M in (9)
q_M	0.088 (0.017)	shape parameter for stochastic part of (9)
N_f	0.503 (0.012)	share of high n women at birth
N_m	0.543 (0.009)	share of high n men at birth
σ_{kn}^f	0.217 (0.021)	correlation of n and k_0 among women
σ_{kn}^m	0.282 (0.023)	correlation of n and k_0 among men

† The elasticity of substitution between k and κ is given by $\frac{1}{1-\gamma_1}$. †† The elasticity of substitution between I_f and I_m is given by $\frac{1}{1-\chi_1}$.

Figure 2: Job offer distribution, by κ and ν, model



(a) $\nu = 1$, 22.2% of job offers (b) $\nu = 2$: 56.1% of job offers (c) $\nu = 3$: 21.7% of job offers

replications (in brackets), are summarized in table 4 and figure 2. Figure 3 in the next section shows the initial distribution of k_0 for men and women. The fit of the model to the PSID moments is given in appendix tables A-4, and in figures A-1 and A-2, showing, respectively, the distribution of filled jobs and the distribution of education by gender. The fit is quite close across most of the moments, and in particular the model captures the basic patterns of nes by $\widetilde{n}$ and ν and divorce by spousal $\widetilde{n}$. The simulated sample differs from the PSID sample, however, in that we underestimate the within-couple correlation of education and n and overestimate the within-couple correlation of log wages. The discrepancy could arise because education provides additional non-pecuniary returns that we are not capturing in the model, and on which spouses sort. As well, many couples meet in school, something we do not allow for directly in the model.

A detailed discussion of the identification process, linking the moments to the specific targets, is provided in appendix C.

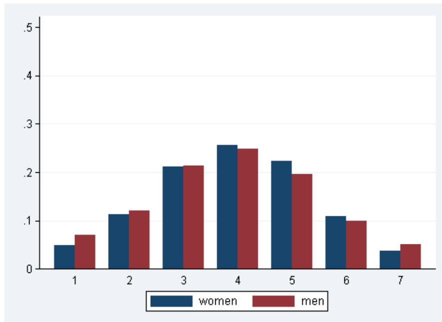
6 Results

In this section, we discuss the implications of our estimation results, in particular the role of relationship skill n in determining life cycle outcomes. We begin by examining the distributions of n and k within the population by gender. Then we examine the effects of n in each of the three markets it plays a role: the labor, marriage, and education markets.

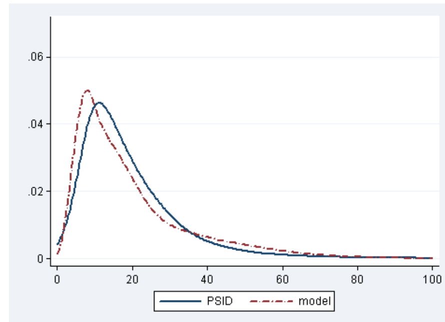
6.1 Gender differences in the distributions of k_0 and n

The first panel of figure 3 shows the distributions of k_0 for men and women which we assume to be normally distributed for both genders. For men, the mean of k_0 is normalized and we

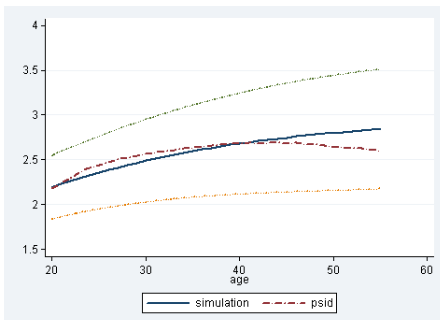
Figure 3: Initial distributions of human capital and life cycle wages by gender



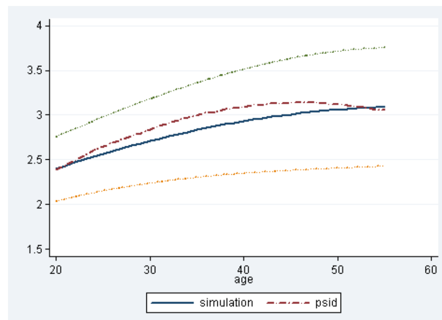
(a) k_0 by gender



(b) unconditional wage distribution



(c) life cycle profile of log wages: women



(d) life cycle profile of log wages: men

estimate the variance for men and the mean and variance for women.[30] The distributions of k_0 are very similar across gender though the distribution for men has slightly fatter tails, consistent with the evidence reported, using a completely different methodology, in Cattan (2013). The second panel of figure 3 shows that the model generates a left-skewed unconditional distribution of wages very similar to the same distribution calculated from the PSID. The bottom two panels show the life cycle evolution of the mean and variance of wages for men and women. The solid blue and dashed red lines shows the mean log wage at every age from the simulation and the PSID. The dotted green and yellow lines show the log wage one standard deviation above and below the mean in the simulation. In both the simulated and real data, the growth of wages over the life cycle is faster for men on average due to their higher average labor market attachment, which generates growth in k, and the variance of log wages increases with age for both genders. Additionally, the last two rows of table 4 report that n and k_0 are positively correlated: sixteen year olds with higher n also have greater raw ability on average, with correlation coefficients between n and k_0 of .28 for men and .22 for women. Consistent with their very slightly higher observed $\widetilde{n}$, men are also slightly more

[30] We normalize male k_0 to a value of 20. k_0 has no direct economic meaning because it must be combined with schooling and subject to the schooling productivity shock before it can be used to earn a wage.

likely to be born with high n which is sensible given that the gender-specific correlations of participation with $\widetilde{n}$ are small (see table A-4).

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

In addition to raising the direct utility received from education, relationship skill n plays three distinct roles in the model. It affects the stochastic returns to couples' marital output, to individual paid employment, and to education. The values of n possessed by individuals in a team (married spouses, a manager and worker, a student and teacher) determine how much a given potential output of the team is actually realized on average within a period and how much this return varies across periods. Figure 4 shows the cdfs of the estimated stochastic distributions 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 skill into production.

Two results stand out. First, in the labor and marriage market subfigures, we can observe that about half of the mass of the distribution lies where $\epsilon > .99$ indicating that the mean returns to production are high and the dominant effect of low n is on increasing the riskiness (variance) of the stochastic returns, generating occasional very low productivity draws. By contrast, the mean return to education is lower overall and strongly dependent on n. Indeed, we can see that nearly 80% of low n students reap less than 40% of their "potential" returns to education while only about 40% of high-n students do. Relationship skill thus plays a very substantial role in determining mean returns per year of education, consistent with much of the recent literature on non-cognitive skills and education.[31] This effect could be due to high n students being streamed into more remunerative degrees, achieving better grades than their low n peers, or procuring more positive references from teachers.[32]

Second, for adults, the explicit role of n differs between personal and professional relationships. The labor market supply of n and demand for n (i.e. ν) are strongly complementary: mismatch between a high ν job and a low n worker − the dashed green line − yields the lowest and most variable (closest to horizontal) stochastic output in a job conditional on the human capital of the worker (k) and complexity of the capital (κ). This complementarity is captured

[31] See, for instance, Cunha et al. (2010) for the effects of non-cognitive skill formation on education choices, or Lundberg (2013) on personality as a predictor of college attendance.

[32] Another interesting example of an intensive-margin return to education based on non-cognitive skill in the literature concerns the returns to a GED vs. high school grduation. Using a latent factor model with sequential schooling choice, Heckman et al. (2011) find that GED recipients have approximately similar cognitive skills, but significantly lower non-cognitive skills, than high school graduates. GED recipients also, on average, derive much smaller benefit from their degree in terms of labor market outcomes, even though they nominally have the same educational attainment as high school graduates who did not go on to college.

by the negative estimated value of ϕ_2 (the coefficient on ν) and the positive estimated value of ϕ_3 (the coefficient on $n \times \nu$) from table 4. In the marriage market, by contrast, n_f and n_m are substitutes, conditional on spousal incomes. Unions between two low n partners (the blue line) yield the lowest stochastic returns on average and the marginal return to n is highest for both sexes when their marriage partner is low n, as captured by the negative estimated value of λ_3 reported in table 4.

We now turn to a more explicit examination of how the relationship skill n affects post-education outcomes in the labor and marriage markets.

6.2.1 Relationship skill and returns in the labor market.

In our model, there are six ways in which high n can increase wages and earnings over the life cycle: (1) high n individuals choose, on average, more education; (2) high n individuals experience higher returns per year of education; (3) returns to learning-by-doing are higher for high n individuals who enter the labor market with higher initial k (since $p_{k,1} > 0$); (4) high n individuals work more complex (high κ jobs) due to their higher average k and the lower *nes* rate, which allows them to benefit from on the job search or promotions; (5) high n people spend less time in non-employment (the gender-specific correlations of participation and $\widetilde{n}$ are positive); and (6) the realizations of ϵ_W may be better on average for high n than for low n employees, a direct wage effect.

Table 5 decomposes the effect of n on total log life time earnings of an individual over the sample period through these six paths as well as through the positive correlation of n and k_0 (which we call path zero). Labeling each of the channels x_i, we can write

$$\mathit{log\ earnings} = G(x_0, ...x_6) \approx c + \sum_{i=0}^{6} x_i b_i$$

then

$$\frac{d\ \mathit{log\ earnings}}{d\ n} = \sum_{i=0}^{6} G_{x_i} \frac{d\ x_i}{d\ n}$$

where G_{x_i} is simply the regression coefficient from the multivariate regression of observed life time earnings on the xs (the column heading variables), and the $\frac{d\,x_i}{d\,n}$ are simply the linear projections of x_i on n, which are easily computed using the model data. These results are reported in rows 1 and 2 of the top and bottom panels of table 5 for men and women respectively. The last row in each panel gives the product of the first two rows:

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

The regressions are log-log (except for n which is a binary) and so the coefficients can be roughly interpreted as the percentage change in y due to a 1% change in x.

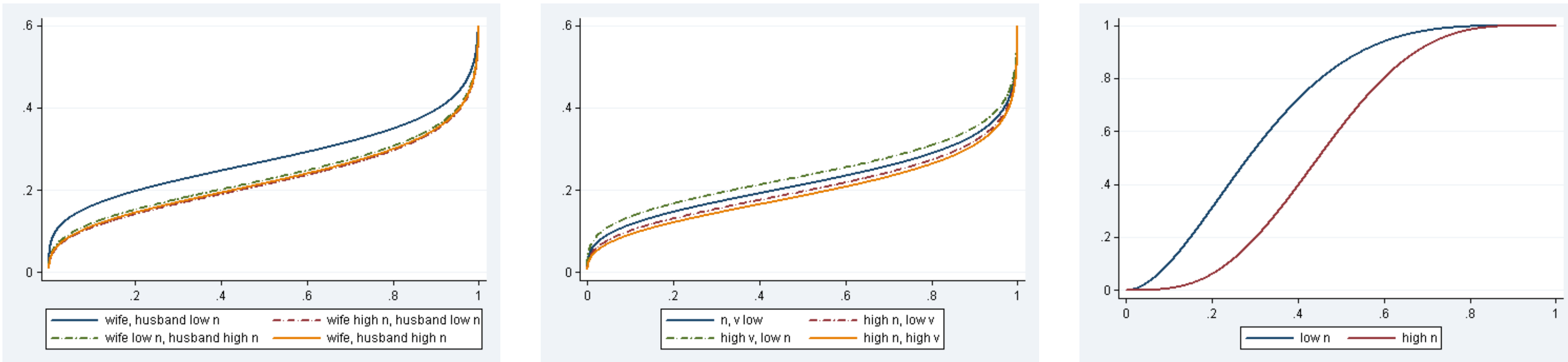
Table 5 tells us that the largest effect of n on earnings for both men and women comes through education, and in particular through the higher return of human capital per year of education (the intensive margin), consistent with the evidence from the previous subsection. The second major effect of n on log earnings comes through learning by doing: higher n workers enter the labor force with higher k and continue to build on this advantage. The remaining effects are relatively small. We find no direct effect of n, which makes sense given that n mainly affects the variance rather than the mean of wages. The effect of n on earnings through occupational complexity κ is modest due to the small correlation between n and κ shown in row 2.[33] A somewhat more substantial effect of n works through participation (path 5). It is larger for women, for two reasons. First, there is more sorting into non-employment on n for women relative to men (see table A-4); and second, a 1% increase in non-employed time has a bigger average impact on women's life time earnings all else equal since women have a comparative advantage at home and may choose long-term non-employment over relatively unremunerative work. By contrast, men enter non-employment only in periods when their earnings would otherwise be very low due to a negative productivity shock.

The last two rows in the top and bottom panels of table 5 report the share of the variance of observed life time earnings accounted for by n, by k measured at the start of the working life, and by both together. A standard variance decomposition from a regression of average annual log earnings on n and $k(\underline{j})$ shows that n explains about 7% and 6% of the variance in observed earnings for men and women respectively, while $k(\underline{j})$ accounts for about 22%. Because n and $k(\underline{j})$ are correlated, they jointly explain about 44% of the total variance of earnings by gender, slightly more for men than for women. The portion of the variance explained directly by relationship skill n relative to adult human capital $k(\underline{j})$ is substantial, and the results for men are broadly consistent with some other recent findings in the literature comparing the importance of personality or non-cognitive with cognitive skills. For instance Mueller and Plug (2006) (using the big five taxonomy) find personality measures explain about 5% of the variance in hourly earnings compared to 10% for IQ among men, while personality and IQ each explain about 5% of the variation in hourly earnings among women. Direct comparisons of our results are not possible, however, since our measures of n and k differ from other researchers' measures of non-cognitive and cognitive skills.

Finally, if we replace $k(\underline{j})$ with k_0 in the decomposition, the total share of earnings ex-

[33] The correlation between n and κ is much smaller than the correlation between k and κ, which is .12. Also, from figure 2, there is little difference in the share of high κ offers across ν.

Figure 4: Realized returns to n in the marriage, job and education markets



(a) marriage shock ϵ_M: cdf (b) wage shock ϵ_W: cdf (c) education shock ϵ_s: cdf

Table 5: n and life time earnings: decomposition

	Initial hc k_0	Years of education s	Return per year educ $(k(\underline{j}) - k_0)/s$	Learning by doing $k(\bar{j}) - k(\underline{j})$	Average occupational complexity κ	Periods of non-employment	Direct effect of n
i	(0)	(1)	(2)	(3)	(4)	(5)	(6)
Men							
b_{x_i}	$0.038^{\dagger}$	0.296	0.288	0.076	0.517	-0.049	$0.001^{\dagger}$
$\frac{d\,x_i}{d\,n}$	0.153	0.196	1.336	3.934	0.026	-1.264	1.000
row (1) $\times$ row (2)	0.006	0.058	0.384	0.300	0.014	0.062	0.001
	Variance of life-time earnings explained by n: 0.068						
	Variance of life-time earnings explained by $k(\underline{j})$: 0.222						
	Variance of life-time earnings explained by n and $k(\underline{j})$: 0.446						
Women							
b_{x_i}	0.084	$0.023^{\dagger}$	0.312	0.072	0.542	-0.067	$-0.005^{\dagger}$
$\frac{d\,x_i}{d\,n}$	0.093	0.178	1.305	3.801	0.023	-1.642	1.000
row (1) $\times$ row (2)	0.008	0.004	0.407	0.274	0.012	0.111	-0.005
	Variance of life-time earnings explained by n: 0.058						
	Variance of life-time earnings explained by $k(\underline{j})$: 0.223						
	Variance of life-time earnings explained by n and $k(\underline{j})$: 0.434						

All reported estimates in rows (1) and (2) are significant at the five percent level except those marked †.

plained by individual heterogeneity drops to 36% for both men and women, with the direct effect of n accounting for about 65% of the total explained sum of squares. The larger role for n when paired with "innate" human capital k_0 is due to its large effect on educational attainment. The total share of earnings accountable by individual fixed factors is thus in line with, though on the high end, of recent literature decomposing residual earnings inequality into initial ability differences, permanent and transitory shocks. For example, Lochner and Shin (2014) find that initial ability differences accounted for around 20 to 30 percent of lifetime residual earnings variation in the eighties, 10 percent in the nineties.

6.2.2 Relationship skill and returns in the marriage market

While the regressions linking $\widetilde{n}$ to separation fixed effects in section 3 are performed at the individual level, we can also use our PSID sample of heads and wives to examine the effect of $\widetilde{n}$ on the likelihood of divorce at the household level and link it to our estimation results. Using couple-by-year observations, we regress an indicator for whether the marriage ends in divorce before the next interview on the partners' $\widetilde{n}$s and their interaction, along with controls for the education and age of each spouse and their interactions, current marriage tenure, mean lifetime log wages of both spouses, and year dummies.[34] We can then repeat the estimation on our simulated sample, excluding the year dummies and age interaction terms which are not allowed for in the model. In both the simulated and PSID regressions, we cluster the standard errors by couple.

The results of this exercise on the PSID sample, on the simulated sample using $\widetilde{n}$, and on the simulated sample using true n, are reported in table 6. In the PSID sample, $\widetilde{n}$ of both husband and wife are negative significant predictors of divorce, but the sign of the interaction term of spousal $\widetilde{n}$ is positive, suggesting that n is a substitutable trait contributing to marital stability. These results are consistent with the (very) reduced-form evidence from section 2.3: matching on $\widetilde{n}$ exists but is much weaker than matching on education as the latter is a complementary trait in increasing marital stability.

When we run the same regression on our simulated data with husband and wife's $\widetilde{n}$ as regressors (column (2)), we see similar patterns: both husband's and wife's $\widetilde{n}$ negatively predict divorce but their interaction is positive (though, as in the PSID, imprecisely estimated) suggesting substituability, while education appears to be a strongly complementary trait. These patterns − in particular the substitutability of spousal n − become more pronounced if we replace $\widetilde{n}$ by n in the regression as in column (3), which is to be expected if $\widetilde{n}$ measures

[34] Year dummies are very important since the likelihood that a marriage ends during the sample period nearly doubles after 1997 when the sample period becomes biannual.

n with error. Put another way, n is more important for marriage market behavior than what the estimates in column (1) suggests. The substitutability of n among spouses conditional on earning ability is to be expected, given our model estimate of $\lambda_3 < 0$.[35]

Table 6: Relationship skill and divorce among couples: PSID and simulation

	PSID couples	Simulation: $\widetilde{n}$	Simulation: n
	(1)	(2)	(3)
Husband's n	-.0026	-.0050	-.0423
	(.0011)**	(.0013)***	(.0045)***
Wife's n	-.0054	-.0032	-.0433
	(.0010)***	(.0013)**	(.0048)***
Husband $\times$ wife's n	.0012	.0015	.0104
	(.0010)	(.0011)	(.0027)***
Husband's educ	.0086	.0335	.0385
	(.0025)***	(.0021)***	(.0023)***
Wife's educ	.0079	.0346	.0397
	(.0027)***	(.0022)***	(.0023)***
Husband $\times$ wife's educ	-.0007	-.0027	-.0029
	(.0002)***	(.0002)***	(.0002)***
Husband's average log wage	-.0210	-.0111	-.0023
	(.0020)***	(.0016)***	(.0016)
Wife's average log wage	.0029	-.0127	-.0048
	(.0018)*	(.0016)***	(.0016)***
Obs.	78075	81144	81144
R^2	.027	.0237	.029

Why is n a substitute trait in the marriage market but complementary with ν in the labor market? In our formulation, n affects spouses' stochastic ability to enjoy their output. Divorces are triggered in part by very low realizations of this ability, which could be the result of conflict which is typically unobservable to the econometrician: Amato and Rogers (1997) use longitudinal data on spouses' reported problems with each other to show that reports of non-social behavior and conflict by both themselves and their partner are indeed highly correlated with subsequent divorce. In our model, production in the marriage market is different from production in the labor market because there is relatively little scope for specialization. Competition in the labor market leads firms to offer jobs tailored to both high n and low n workers; workers then sort into the jobs that best suit their skills. A monogamous marriage market – at least one in which the main output of a marriage is joint consumption – does not offer the same opportunities for specialization.

[35]One discrepancy between the simulated and PSID results is that the lifetime average log wage of the wife has a negative effect on the likelihood of divorce, in contrast to what we observe among PSID couples. This discrepancy may reflect the fact that we are imperfectly capturing home production opportunities for women in marriage.

7 Why lagged stocks affect current separations

The evidence presented in section 3, as well as much evidence from previous economics and psychology literature surveyed in section 2, suggests that unobserved heterogeneity plays a role in explaining the persistence of negative separations in labor and marriage markets over an individual's life cycle. Nonetheless, much previous literature on labor and marriage market mobility (e.g. Munasinghe and Sigman (2004), Light and McGarry (1998), Ahituv and Lerman (2011)) has also empirically detected a role for state dependence. Is the empirical presence of state dependence due to the researchers' inability to fully control for unobserved heterogeneity?

Within the context of our model, the answer to the above question is no. In this section, we address the question by revisiting the reduced form separation regressions from section 3. First, we show that our model generates reduced form separation regressions, for both *nes* and divorce, which are broadly consistent with those reported in section 3. Then we show, using our simulated data, that even when we control directly for n and k in the reduced form separation regressions, stocks of previous negative separations continue to predict future negative separations. The reduced-form effects of the stocks, however, are attenuated, both for labor and marriage market separations, and this reduction in explanatory power allows us to quantify, albeit informally, how much unobserved heterogeneity accounts for the persistence of separations.

Our explanation for the continued role of separation state dependence is straightforward. Current negative separations are explained by n, k, and characteristics of the current job and the partner. Controlling for individual unobserved personal characteristics, n and k, along with relationship tenure and wages, does not fully span all the time varying state variables, many of which (κ, ν and the unobserved characteristics of the partner) are not fully observable in data. State dependence persists even though we do not allow for reverse causation by which a history of bad relationship shocks could reduce n as suggested, for example, by Caspi et al. (1987). The stocks of previous negative separations continue to predict an individual's future negative separations by changing the average quality of his current job and marriage. Moreover, we show that these effects are persistent enough not to be captured only by the direct lag of separations but also by the stock of previous negative separations.

7.1 Previous separations as proxies for n and k

Tables 7 (for *nes*) and 8 (for divorce) summarize the reduced form effects of stocks of previous *nes* and divorces, of the direct lag of *nes*, and of individual heterogeneity measures n and

$\log k$ on the (linear) probability of a current separation.[36] The regressions are essentially the same as those reported in section 3, except we simplify and compress the analysis by pooling men and women together and also add together the stocks of negative employer and spouse separations into a single stock of "previous negative separations" (*pns*).[37] Corresponding results disaggregated by gender and by type of separation stock are provided in appendix D, tables A-5 – A-8.

The first column in each of tables 7 and 8 reports the estimates from our PSID sample. Column (2) reports the same result when we add our empirical measure of $\widetilde{n}$ to the PSID regression. Conditional on stocks of previous negative separations and the lag of *nes*, individuals with a high $\widetilde{n}$ have a lower probability of experiencing an *nes* or a divorce in the subsequent sample period. (The significance of $\widetilde{n}$ at the 5% confidence level or higher holds when we disaggregate by gender and type of previous separation as shown in tables A-5-A-8). The inclusion of $\widetilde{n}$ in the regressions, however, has only a very small effect on the coefficient on *pns* or the contribution of this stock to the R^2, which is shown in the final row of the tables.[38] Comparing columns (1) and (2), the contribution of the stock of *pns* to the R^2 falls by 1.7% for *nes* and by 4.3% for divorce once we include $\widetilde{n}$ as a regressor.

Columns (3) and (4) report results from the same regressions run on the model-generated data.[39] In the model, $\widetilde{n}$ is inferred using exactly the same procedure as in the data based on job history of (observed) ν for each individual with a work history. In general, we understate the degree of persistence in turnover relative to the PSID, especially for divorce. Comparing column (3) to column (1), we are able to account for 92% of the measured persistence in *nes* and 53% of the persistence of turnover in divorce, using the ΔR^2 from *pns* as a metric. Otherwise, the overall patterns are similar. First, from column (3), the stock of previous negative separations increases the linear probability of an impending *nes* or divorce. Second, from column (4), high $\widetilde{n}$ individuals are less likely to experience an *nes* or a divorce in the subsequent period than low $\widetilde{n}$ individuals, conditional on the number of previous negative separations and other covariates. Lastly, as in the PSID regressions, including $\widetilde{n}$ reduces the predictive power of the stock of *pns* in terms of the magnitude of its coefficient and its

[36] Recall that the direct lag of divorce is not significant in table A-2, so we exclude it here.

[37] To facilitate comparisons across the columns, we also exclude individuals for which we cannot compute $\widetilde{n}$ in both simulated and PSID data from all the regressions.

[38] Urzua (2008) notes that simply comparing the change in the coefficient on *pns* across more and less rich specifications is a crude way to measure its importance. Therefore we consider as well the contribution of *pns* to the share of total variance in the dependent variable explained in each of the specifications, i.e. the difference in the R^2 when *pns* is included as a regressor compared to when it is omitted. In the model, we know that the stock of *pns*, by construction, proxies the current state variables rather than vice-versa, so we can be sure that the contribution of *pns*, rather than n and $\log k$, to the R^2 is spurious.

[39] The model regressions also include a cubic in age and counts of number of previous years the individual has been a worker and has been married.

Table 7: *nes* hazards in model and data: Men and women

	Data	Data + $\widetilde{n}$	Model	Model + $\widetilde{n}$	Model + n	Model + $\log k$	Model + $f(n, \log k)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
educ	-.0037	-.0028	-.0051	-.0041	.0002	-.0039	.0003
	(.0005)***	(.0005)***	(.0004)***	(.0004)***	(.0005)	(.0005)***	(.0005)
employer tenure	-.0098	-.0098	-.0143	-.0142	-.0138	-.0143	-.0136
	(.0004)***	(.0004)***	(.0004)***	(.0004)***	(.0004)***	(.0004)***	(.0004)***
tenure squared	.0003	.0003	.0004	.0004	.0004	.0004	.0004
	(.00002)***	(.00002)***	(1.00e-05)***	(1.00e-05)***	(1.00e-05)***	(1.00e-05)***	(1.00e-05)***
log wage	.0077	.0082	-.0338	-.0336	-.0273	-.0275	-.0236
	(.0019)***	(.0019)***	(.0012)***	(.0012)***	(.0012)***	(.0016)***	(.0016)***
stock of *pns*	.0154	.0153	.0153	.0147	.0124	.0153	.0114
	(.0010)***	(.0010)***	(.0010)***	(.0010)***	(.0011)***	(.0010)***	(.0011)***
nes last period	.0761	.0760	.0483	.0483	.0484	.0484	.0475
	(.0053)***	(.0053)***	(.0059)***	(.0059)***	(.0058)***	(.0059)***	(.0058)***
n		-.0042		-.0155	-.0475		-.1156
		(.0011)***		(.0017)***	(.0021)***		(.0077)***
$\log k$						-.0086	-.0991
						(.0016)***	(.0080)***
$\log k^2$							.0100
							(.0014)***
$n \times \log k$							.0262
							(.0028)***
Obs.	97788	97788	116650	116650	116650	116650	116650
R^2	.0399	.0400	.0841	.0848	.0883	.0844	.0908
ΔR^2 from *pns*	.00348	.00342	.00320	.00291	.00204	.00318	.00171

Dependent variable is an indicator for experiencing an *nes* between t and $t+1$ at time t. Columns 1-3 report estimates based on married wage workers from the 1980-2011 PSID. Columns 4-9 report estimates based on married workers in the benchmark simulation. All regressions control for a cubic in age, number of periods the individual has previously been observed married, and number of periods the individual has previously been observed working for an employer. The regressions in columns 1-3 also include a dummy for race (1=white), number of children in the household, and year and sample dummies. ΔR^2 from *pns* reports the contribution of the stock of previous negative separations to the R^2 in each regression specification. *** denotes significance at the 1% confidence level. * denotes significance at the 10% confidence level. ** denotes significance at the 5% confidence level. *** denotes significance at the 1% confidence level.

Table 8: Divorce hazards in model and data: Men and women

	Data	Data + $\widetilde{n}$	Model	Model + $\widetilde{n}$	Model + n	Model + $\log k$	Model + $f(n, \log k)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
educ	-.0044	-.0037	-.0025	-.0020	.0005	-.0009	.0008
	(.0003)***	(.0004)***	(.0003)***	(.0003)***	(.0003)*	(.0003)***	(.0003)**
marriage tenure	-.0049	-.0048	-.0080	-.0079	-.0078	-.0079	-.0077
	(.0004)***	(.0004)***	(.0006)***	(.0006)***	(.0006)***	(.0006)***	(.0006)***
tenure squared	.00008	.00008	.0002	.0002	.0002	.0002	.0002
	(1.00e-05)***	(1.00e-05)***	(1.00e-05)***	(1.00e-05)***	(1.00e-05)***	(1.00e-05)***	(1.00e-05)***
log wage	-.0034	-.0031	-.0074	-.0073	-.0037	.0009	-.0005
	(.0010)***	(.0010)***	(.0008)***	(.0008)***	(.0008)***	(.0010)	(.0010)
stock of pns	.0071	.0070	.0038	.0035	.0021	.0037	.0021
	(.0006)***	(.0006)***	(.0005)***	(.0005)***	(.0005)***	(.0005)***	(.0005)***
nes last period	.0088	.0088	-.0003	-.0004	-.0010	-.0003	-.0010
	(.0028)***	(.0028)***	(.0022)	(.0022)	(.0022)	(.0022)	(.0022)
n		-.0037		-.0072	-.0258		-.0533
		(.0009)***		(.0010)***	(.0013)***		(.0044)***
$\log k$						-.0110	.0065
						(.0009)***	(.0046)
$\log k^2$							-.0048
							(.0008)***
$n \times \log k$							.0107
							(.0015)***
Obs.	125250	125250	123339	123339	123339	123339	123339
R^2	.0306	.0308	.0235	.0239	.0269	.0245	.0274
ΔR^2 from pns	.00138	.00132	.000728	.000623	.000224	.000702	.000224

Dependent variable is an indicator for experiencing a divorce between t and $t+1$ at time t. Columns 1-3 report estimates based on married men and women from the 1980-2011 PSID. Columns 4-9 report estimates based on married men and women in the benchmark simulation. All regressions control for a cubic in age, number of periods the individual has previously been observed married, and number of periods the individual has previously been observed working for an employer. The regressions in columns 1-3 also include a dummy for race (1=white), number children in the household, and year and sample dummies. ΔR^2 from pns reports the contribution of the stock of previous negative separations to the R^2 in each regression specification. *** denotes significance at the 1% confidence level. * denotes significance at the 10% confidence level. ** denotes significance at the 5% confidence level. *** denotes significance at the 1% confidence level.

contribution to the explained sum of squares, but relatively modestly. The ΔR^2 from adding the stock of pns to the regression falls by 8.3% for nes, and by 7.6% for divorce relative to the PSID estimate in column (1) once we include $\widetilde{n}$ as a regressor.

Columns (1) to (4) show that our model generates reduced form separation regression estimates that are quantitatively similar to those in the data. We can therefore use it additional insights into the relative importance of unobserved individual heterogeneity and state dependence in determining negative separations in the data. Columns (5) through (7) present these investigations.

Column (5) reports the results from the same regression as in column (4) on the model-generated data, but now using n rather than the $\widetilde{n}$ constructed from the simulated career histories. The inclusion of n further reduces the predictive power of pns for an impending nes or divorce, and also affects the coefficients on other explanatory variables that are correlated with n, though the direct lag of nes remains almost unchanged.[40] The ΔR^2 from the inclusion of the stock of pns now falls by 33% (37%) of the value from the PSID for nes (divorce) compared to column (3).[41] In column (6) we replace n with $\log k$ and in column (7) we include n, $\log k$, $\log k^2$ and $n \times \log k$ as predictors so as to capture the full range of (typically unobserved) individual characteristics. Focusing on the ΔR^2 due to pns, column (6) shows that pns does not mainly proxy a residual measure of $\log k$ (conditional on education and the current wage) as the ΔR^2 from pns falls modestly (in table 8) or not at all (in table 7) compared to column (3) when we include $\log k$ but not n. In column (7), by contrast, ΔR^2 from pns falls by 43% in the nes regression and 37% in the divorce regression, and the coefficients on pns itself fall in absolute value by 25% and 24% of their estimated values from the PSID respectively. For both divorce and nes, however, they remain significant.[42]

To summarize, the results in tables 7 and 8 show that after including individual heterogeneity n and k, and other current standard covariates in the reduced form regressions, the stocks of previous negative separations continue to predict current negative separations, even conditional on the immediate lag of nes. The model suggests that about 40% of "naive" state dependence in labor market instability and 35% of naive state dependence in marriage market instability can be attributed to persistent individual effects. In particular, the majority of it

[40] One discrepancy between the model and PSID estimates is that the lag of nes does not predict divorce in the model. In appendix D we show that this result holds for both men and women though it is sensitive to the estimated values of ℓ and χ_0.

[41] Specifically, the calculation is (column 4 - column 3)/column 1.

[42] In appendix tables A-5 − A-8 we show that the effects of controlling for individual heterogeneity are fairly consistent across gender, though larger for women, and that controlling for unobservable individual characteristics mainly reduces the impact of cross-market effects. When nes is the dependent variable, the coefficient on the woman's stock of previous divorces becomes insignificant once we control for n. Similarly, in the divorce regressions, the woman's stock of previous nes becomes insignificant once we control for n.

is attributable to n rather than k. Our proxy for n, $\widetilde{n}$, is a noisy but workable proxy for n much as education and wages are workable proxies for k.[43] In the model, the remaining real state dependence arises for straightforward reasons discussed in the literature: in the labor market, loss of job-specific human capital (achieved, for instance, through promotion) can make recently separated and rehired workers more vulnerable to further separations; a similar analysis applies the the marriage market in which recently separated individuals may quickly enter less suitable, hence unstable, unions.

7.2 Wage growth and relationship skill

In the PSID results, we see very little difference across gender in the effects of previous turnover on current turnover in either the labor or marriage market. However, we do observe a small gender difference in the reduced form effect of instability on wage growth in the PSID data in that the correlation of the stock of previous divorces with wage growth is larger and stronger for men than for women. Tables 9 and 10 repeat the wage growth regressions from table 3 and show corresponding results for the model, disaggregating previous separations into divorces and nes. As in the data, previous nes predict low current wage growth on average for both genders. However, the stock of previous divorces is once again a somewhat stronger predictor of low wage growth for men (though for neither gender is it robust to the inclusion of n). In the model, the difference arises mainly because women who experience wage growth early in the life cycle are more somewhat willing to leave a marginally efficient marriage in response to a bad ϵ_M shock, due to their lower valuation of marriage ($\ell_f < \ell_m$) and the fact that their earning power is relatively inefficient when paired with a low-k man ($\chi_0 = .33$).

8 Conclusion

In this paper, we have examined the role of relationship skill – measured in the O*NET and constructed for the 1980-2011 PSID – in determining life cycle outcomes in a structural setting across multiple markets. We find that several desirable personality traits, such as *persistence*, *cooperation*, *adaptability*, *dependability*, *attention to detail*, and *independence* map into stable marriages and careers in the PSID, conditional on observable human capital. Our structural model suggests that relationship skill is important: it directly explains about 7% of the variance in labor market earnings conditional on post-schooling human capital. Perhaps more important, it is also a strong predictor of divorce and has major implications for the

[43] In the model, the simple correlation of n and $\widetilde{n}$ is .51.

Table 9: Wage growth in the model and data: Men

	Data	Data $+\widetilde{n}$	Model	Model $+\widetilde{n}$	Model + n
	(1)	(2)	(3)	(4)	(5)
employer tenure	.0050 (.0008)***	.0050 (.0008)***	.0100 (.0007)***	.0099 (.0007)***	.0096 (.0007)***
tenure squared	-.00007 (.00003)**	-.00007 (.00003)**	-.0002 (.00003)***	-.0002 (.00003)***	-.0002 (.00003)***
log wage	-.3679 (.0147)***	-.3691 (.0147)***	-.2899 (.0066)***	-.2906 (.0066)***	-.3133 (.0072)***
stock of previous *nes*	-.0225 (.0023)***	-.0217 (.0023)***	-.0135 (.0021)***	-.0128 (.0021)***	-.0073 (.0021)***
stock of previous divorces	-.0125 (.0057)**	-.0124 (.0057)**	-.0180 (.0066)***	-.0168 (.0067)**	-.0089 (.0067)
n		.0193 (.0029)***		.0191 (.0056)***	.1380 (.0086)***
Obs.	54636	54636	61780	61780	61780

Table 10: Wage growth in the model and data: Women

	Data	Data $+\widetilde{n}$	Model	Model $+\widetilde{n}$	Model + n
	(1)	(2)	(3)	(4)	(5)
employer tenure	.0097 (.0012)***	.0099 (.0012)***	.0078 (.0007)***	.0078 (.0007)***	.0069 (.0007)***
tenure squared	-.0002 (.00005)***	-.0002 (.00005)***	-.0002 (.00003)***	-.0002 (.00003)***	-.0001 (.00003)***
log wage	-.4263 (.0173)***	-.4330 (.0174)***	-.3112 (.0055)***	-.3112 (.0055)***	-.3166 (.0057)***
stock of previous *nes*	-.0270 (.0038)***	-.0255 (.0038)***	-.0273 (.0023)***	-.0270 (.0023)***	-.0227 (.0023)***
stock of previous divorces	-.0114 (.0068)*	-.0106 (.0067)	-.0147 (.0064)**	-.0143 (.0064)**	-.0081 (.0065)
n		.0357 (.0038)***		.0048 (.0056)	.0675 (.0077)***
Obs.	43845	43845	56084	56084	56084

efficiency of marital sorting and household formation. Interestingly, relationship skill seems to have different impacts in different types of market. In the formal labor market, demand for and supply of relationship skill are strong complements, consistent with other recent papers that find a labor market return to certain desirable personality traits. In the household sector, relationship skill appears to be substitutable: the success of a marriage depends most strongly on *at least one* partner having good relationship skill.

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.

References

Ahituv, A. and R. I. Lerman (2011). Job turnover, wage rates, and marital stability: How are they related? *Review of Economics of the Household 9*(2), 221–249.

Almlund, M., A. L. Duckworth, J. Heckman, and T. Kautz (2011). Personality psychology and economics. *Handbook of the economics of education 4*(1).

Altonji, J. G., A. A. Smith, and I. Vidangos (2013). Modeling earnings dynamics. *Econometrica 81*(4), 1395–1454.

Amato, P. R. and S. J. Rogers (1997). A longitudinal study of marital problems and subsequent divorce. *Journal of Marriage and the Family*, 612–624.

Becker, G. S., E. M. Landes, and R. T. Michael (1977). An economic analysis of marital instability. *The Journal of Political Economy*, 1141–1187.

Borghans, L., B. Ter Weel, and B. A. Weinberg (2008). Interpersonal styles and labor market outcomes. *Journal of Human Resources 43*(4), 815–858.

Caspi, A., G. H. Elder Jr, and D. J. Bern (1987). Moving against the world: Life-course patterns of explosive children. *Developmental Psychology 23*(2), 308–313.

Cattan, S. (2013). Psychological traits and the gender wage gap. *The Institute for Fiscal Studies*.

Chiappori, P. A., M. C. Dias, and C. Meghir (2014). Human capital, matching and labor supply. *In progress*.

Cobb-Clark, D. A. and S. Schurer (2012). The stability of big-five personality traits. *Economics Letters 115*(1), 11–15.

Cunha, F., J. J. Heckman, and S. M. Schennach (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrica 78*(3), 883–931.

Fernández, R. and J. C. Wong (2014). Divorce risk, wages and working wives: A quantitative life-cycle analysis of female labour force participation. *The Economic Journal 124*(576), 319–358.

Flabbi, L., C. Flinn, and N. Guner (2013). Simultaneous search in the labor and marriage markets. Mimeo.

Greenwood, J., N. Guner, G. Kocharkov, and C. Santos (2012). Technology and the changing family: a unified model of marriage, divorce, educational attainment and married female labor-force participation. Technical report, National Bureau of Economic Research.

Heckman, J., R. Pinto, and P. Savelyev (2013). Understanding the mechanisms through which an influential early childhood program boosted adult outcomes. *American Economic Review 103*(6), 2052–86.

Heckman, J. J. and G. J. Borjas (1980). Does unemployment cause future unemployment? definitions, questions and answers from a continuous time model of heterogeneity and state dependence. *Economica*, 247–283.

Heckman, J. J., J. E. Humphries, S. Urzua, and G. Veramendi (2011). The effects of educational choices on labor market, health, and social outcomes. *Unpublished manuscript, University of Chicago, Department of Economics*.

Heckman, J. J. and T. Kautz (2012). Hard evidence on soft skills. *Labour economics 19*(4), 451–464.

Heckman, J. J., J. Stixrud, and S. Urzua (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics 24*(3), 411–482.

Jacquemet, N. and J.-M. Robin (2013). Assortative matching and search with labour supply and home production. Technical report, cemmap working paper, Centre for Microdata Methods and Practice.

Jencks, C., S. Bartlett, M. Corcoran, J. Crouse, D. Eaglesfield, G. Jackson, K. McClelland, P. Mueser, M. Olneck, J. Schwartz, S. Ward, and J. Williams (1979). *Who Gets Ahead? The Determinants of Economic Success in America.* Basic Books, New York.

Kambourov, G. and I. Manovskii (2009). Occupational specificity of human capital. *International Economic Review 50*(1), 63–115.

Knowles, J. A. (2013). Why are married men working so much? An aggregate analysis of intra-household bargaining and labour supply. *The Review of Economic Studies 80*(3), 1055–1085.

Light, A. and K. McGarry (1998). Job change patterns and the wages of young men. *Review of Economics and Statistics 80*(2), 276–286.

Lindqvist, E. and R. Vestman (2011). The labor market returns to cognitive and noncognitive ability: Evidence from the Swedish enlistment. *American Economic Journal: Applied Economics 3*(1), 101–128.

Lochner, L. and Y. Shin (2014). Understanding earnings dynamics: Identifying and estimating the changing roles of unobserved ability, permanent and transitory shocks. *University of Western Ontario Working Paper*.

Low, H., C. Meghir, and L. Pistaferri (2010). Wage risk and employment risk over the life cycle. *American Economic Review 100*(4), 1432–1467.

Lundberg, S. (2012). Personality and marital surplus. *IZA Journal of Labor Economics 1*(1), 1–21.

Lundberg, S. (2013). The college type: Personality and educational inequality. *Journal of Labor Economics 31*(3), 421–441.

Marinescu, I. (2012). Divorce: what does learning have to do with it? Technical report, University of Chicago Working Paper.

Mazzocco, M., C. Ruiz, and S. Yamaguchi (2014). Labor supply, wealth dynamics, and marriage decisions. American Economic Review: Papers and Proceedings.

Mincer, J. and B. Jovanovic (1981). Labor mobility and wages. In *Studies in Labor Markets*, pp. 21–64. University of Chicago Press.

Morgeson, F. P., M. A. Campion, R. L. Dipboye, J. R. Hollenbeck, K. Murphy, and N. Schmitt (2007a). Are we getting fooled again? coming to terms with limitations in the use of personality tests for personnel selection. *Personnel Psychology 60*(4), 1029–1049.

Morgeson, F. P., M. A. Campion, R. L. Dipboye, J. R. Hollenbeck, K. Murphy, and N. Schmitt (2007b). Reconsidering the use of personality tests in personnel selection contexts. *Personnel Psychology 60*(3), 683–729.

Mueller, G. and E. Plug (2006). Estimating the effect of personality on male and female earnings. *Industrial and Labor Relations Review*, 3–22.

Munasinghe, L. and K. Sigman (2004). A hobo syndrome? Mobility, wages, and job turnover. *Labour Economics 11*(2), 191–218.

Pistaferri, L., C. Meghir, A. Voena, and H. Low (2013). Marriage, social insurance and labor supply. In *2013 Meeting Papers*, Number 448. Society for Economic Dynamics.

Urzua, S. (2008). Racial labor market gaps the role of abilities and schooling choices. *Journal of Human Resources 43*(4), 919–971.

Weinberger, C. (2014). The increasing complementarity between cognitive and social skills. *Review of Economics and Statistics 14*(5).

Yamaguchi, S. (2012a). Changes in returns to task-specific skills and gender wage gap. *Available at SSRN 2035833*.

Yamaguchi, S. (2012b). Tasks and heterogeneous human capital. *Journal of Labor Economics 30*(1), 1–53.

APPENDIX

A Data Appendix

A.1 Identifying negative employer transitions in the PSID

In general, it is not straightforward to identify negative employer separations (*nes*) in the PSID. In particular, there is no single variable, or set of variables, that directly measures whether a job separation 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 change of jobs across employers or from employer to self-employment or vice-versa was desirable, economically, for the worker experiencing it.

In identifying negative separators, we exclude individuals who left an employer and report being out of the labor force due to disability, school, or homemaking since these may indicate voluntary separations. We also exclude individuals after 1997 who report having been unemployed for more than 53 weeks since we are using a definition of negative switching *in the previous year*. To identify negative separations based on wages, we examine if the worker's hourly wage in the year following the switch (typically time $t+1$ if a switch is indicated in the time t interview) is lower than the hourly wage reported in the last known year of the old job (at time $t-1$ or t if the wage at $t-1$ is not observed). For the post-1997 sample and for individuals for who the $t+1$ observation is not available, we compare the wage in period t of the switch with the wage in $t-1$.

It is important to note that divorce and *nes* are not treated fully symmetrically in the estimation. In particular, after 1997, we cannot identify divorces experienced between $t-1$ and t (where t indexes the PSID sample period) but not in the previous year. Thus the measured divorce rate is higher in years after 1996, which we control for with year dummies. By comparison, we do not use all negative employer separations after 1996 since some of these occurred more than a year before the interview date. Since *nes* is measured with error (both because it is based on self-reported employer tenure which is subject to noise and because some *nes* are likely to in fact be voluntary positive switches (i.e. transitioning to a lower wage job with a better working environment)) we do not consider this to be a major problem.

A.2 Summary statistics for the PSID sample

Table A-1 reports means and standard deviations of the main variables used in our PSID analysis. The first two columns report summary statistics for the sample of married men and women used in the main empirical analysis (tables 1-2). Columns 3-4 report the same statistics for the full unweighted PSID sample. Columns 5-6 report the same statistics for the full sample using the individual-level PSID weights. The only notable anomalies between the last two sets of columns are that (1) the marriage rate in the PSID population of women is lower than the corresponding rate for men and (2) the share of whites is much higher in the weighted samples. The first anomaly is due to the fact that single women are more likely than single men to head their own household and therefore to be included in the sample, especially among SEO respondents. The second reflects SEO oversampling of minorities and immigrant families. The divorce rate is also substantially higher in the unweighted sample of marrieds. To insure that we are not picking up cultural differences in separation rates, we include in all our regressions a dummy for race (white = 1) and also dummies for being in the SEO or immigrant subsamples. These controls are individually significant but have next to no effect on the main results.

A.3 Additional results on separations: PSID

Table A-2 reports results from several robustness checks testing the predictive power of stocks of *nes* and divorces in the presence of lagged dependent variables. All results in A-2 are based on the linear probability estimator but are robust to using the probit specification.

In table A-2, columns (1) and (2) examine the effects of a lagged divorce and a lagged *nes* (between sample periods $t-1$ and t), independently of the stocks of previous separations, on the likelihood of an impending *nes* in a sample of ever-married individuals. We see evidence of short-run state dependence in the labor market for *nes*, but no evidence that a lagged divorce increases the likelihood of a current *nes* conditional

Table A-1: Summary statistics: Men and women 20-55

	Married men unweighted	Married women unweighted	All men unweighted	All women unweighted	All men weighted	All women weighted
nes hazard	0.109	0.095	0.123	0.106	0.118	0.107
(wage earners)	(0.311)	(0.293)	(0.329)	(0.308)	(0.323)	(0.309)
divorce hazard	0.048	0.048	0.048	0.048	0.036	0.037
(marrieds)	(0.214)	(0.213)	(0.214)	(0.213)	(0.187)	(0.188)
total periods	18.5	19.1	17.9	19.0	21.1	22.0
observed	(9.9)	(9.9)	(9.8)	(9.8)	(9.9)	(9.8)
total periods of	14.8	10.9	14.3	11.2	16.6	12.9
wage work	(9.4)	(7.7)	(9.2)	(7.9)	(9.6)	(8.2)
age	37.5	36.1	36.6	36.1	37.9	37.8
	(8.8)	(9.1)	(9.1)	(9.4)	(9.4)	(9.6)
share white	0.66	0.60	0.69	0.69	0.85	0.81
	(0.47)	(0.49)	(0.46)	(0.46)	(0.36)	(0.40)
education	13.2	13.1	13.1	13.0	13.5	13.2
	(2.1)	(2.0)	(2.1)	(2.0)	(2.2)	(2.1)
log wage	2.97	2.59	2.90	2.56	3.00	2.64
	(0.72)	(0.76)	(0.76)	(0.75)	(0.77)	(0.76)
share married	1.0	1.0	0.79	0.70	0.73	0.67
			(0.41)	(0.46)	(0.44)	(0.47
current employer	8.3	6.2	7.7	6.1	8.2	6.5
tenure (wage earners)	(7.6)	(6.3)	(7.5)	(6.3)	(7.9)	(6.7)
current marriage	9.0	9.3	9.0	9.3	10.8	11.3
tenure (marrieds)	(7.5)	(7.8)	(7.5)	(7.8)	(8.1)	(8.3)

on the stock of previous *nes* and divorces. In both cases, the stocks of previous *nes* and divorces remain strongly significant and only slightly decrease in magnitude compared to the corresponding results in 1 and 2. Columns (3) and (4) report changes in the likelihood of experiencing a divorce among currently married men and women controlling for both the lag and stock of *nes*. The presence of an *nes* in the previous year increases the likelihood of divorce, consistent with Marinescu (2012), but the stocks of *nes* and divorces remain strongly significant conditional on the lags, though modestly smaller in magnitude. In columns (5) and (6) we repeat the estimates from columns (3) and (4) excluding all individuals who experience an *nes* between t and $t+1$, so as to check that timing effects (particularly after 1997 when the sample period is two years) are not biasing the estimated effect of the lag downward. The main results are robust, although the lag itself becomes much weaker. Finally, to test our concept of "negative" separations against a more standard pure "mobility" effect, columns (7)-(8) replace *nes* as the dependent variable with "positive employer switches" (*pes*): employer-to-employer transitions that result in higher observed wages and do not involve a spell of unemployment.[44] Like *nes*, positive employer switches are highly positively correlated over time, but the cross-market effects (the correlation of previous divorces with an impending *pes*) become completely insignificant. In columns (9) and (10) we add stocks of *pes* to the divorce regressions along with stocks of previous *nes* and previous divorces. Again, the cross-market correlation of previous *pes* with the likelihood of subsequent divorce are very weak while the correlation of the stock of *nes* with the likelihood of an impending divorce remains strong.

[44] Positive employer switches are again identified using the definition of employer switching from Kambourov and Manovskii (2009), subject to not meeting our definition of a negative switch.

Table A-2: Robustness checks: fixed factor vs. state dependence

	nes		Divorce		Divorce Excluding those with current *nes*		Positive employer separation		Divorce	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
tenure	-.010	-.012	-.004	-.003	-.001	-.0008	-.005	-.007	-.004	-.003
	(.0006)***	(.0006)***	(.0006)***	(.0006)***	(.0005)*	(.0006)	(.0003)***	(.0004)***	(.0006)***	(.0006)***
tenure^2	.0003	.0004	.0001	.00008	.00003	.00004	.0002	.0002	.0001	.00009
	(.00002)***	(.00002)***	(.00002)***	(.00002)***	(1.00e-05)***	(1.00e-05)***	(1.00e-05)***	(1.00e-05)***	(.00002)***	(.00002)***
yrs of educ	-.003	-.004	-.004	-.005	-.002	-.003	.005	.004	-.004	-.006
	(.0006)***	(.0007)***	(.0004)***	(.0005)***	(.0004)***	(.0005)***	(.0005)***	(.0005)***	(.0004)***	(.0005)***
dummy for white	.001	.012	-.017	-.034	-.012	-.018	.010	.008	-.017	-.034
	(.004)	(.003)***	(.003)***	(.003)***	(.002)***	(.003)***	(.002)***	(.003)***	(.003)***	(.003)***
log wage	.004	.008	-.007	-.0002	-.004	-.002	-.029	-.033	-.008	-.0002
	(.003)	(.002)***	(.001)***	(.001)	(.001)***	(.001)*	(.002)***	(.002)***	(.001)***	(.001)
stock of prev *nes*	.015	.013	.003	.005	.004	.004	.002	.005	.004	.005
	(.001)***	(.001)***	(.0007)***	(.001)***	(.0007)***	(.001)***	(.0009)*	(.001)***	(.0007)***	(.001)***
stock of prev divorces	.018	.017	.026	.036	.037	.043	-.0006	-.0005	.025	.035
	(.003)***	(.002)***	(.003)***	(.004)***	(.004)***	(.004)***	(.002)	(.002)	(.003)***	(.004)***
stock of prev *pes*							.008	.007	.0009	.002
							(.001)***	(.001)***	(.001)	(.001)*
nes last sample period	.103	.049	.010	.012	.005	.003				
	(.007)***	(.006)***	(.004)***	(.004)***	(.003)	(.004)				
divorce last sample period	.008	.005								
	(.009)	(.008)								
sample size	61134	56573	67334	58913	60116	53863	55268	46279	68439	60144
R^2	.054	.036	.034	.035	.026	.028	.033	.036	.035	.036

* denotes significance at the 10% confidence level. ** denotes significance at the 5% confidence level. *** denotes significance at the 1% confidence level. *nes* stands for 'negative employer separation.' *pes* stands for 'positive employer separation.' 'Divorce' denotes a spouse separation including from cohabiting relationships. All reported results are from the linear probability model. Corresponding probit results are available upon request.

A.4 Relationship skill and separations

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. This is a many-to-one match: there are roughly 500 three-digit census occupational codes compared to 800 O*NET-SOC codes. The O*NET-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 O*NET-SOC codes. We are able to match over 99.5% of PSID respondents who report a current occupation to the relevant O*NET code, but some O*NET occupations, in particular military occupations, lack the detailed information (e.g. in the Work Styles file) used in the analysis.

Table A-3 summarizes the results from the estimation described in section 3.2. Columns (1)-(8) list the eight $\widehat{n}$s that provide the greatest explanatory power of the separation fixed effect $\widehat{f_i}$ in decreasing order of R^2. The top panel lists the $\hat{n}^a$s included in each $\widehat{n}$. Each $\widehat{n}$ is normalized to lie between 0 and 1. The bottom panel reports the second stage regression results in which $\widehat{f_i}$ is regressed on the $\widehat{n}$, the other listed covariates, and controls for the age (as a cubic), year (as dummies), a dummy for female, and indicators for the PSID subsample (core sample, SEO or immigrant) from which the individual is drawn. The regressions are unweighted.

In each case, $\widehat{n}$ is a statistically and economically significant negative predictor of $\widehat{f_i}$. The effect of moving from the bottom to the top of the $\widehat{n}$ distribution reduces $\widehat{f_i}$ on average by about .075, approximately one fifth of a standard deviation. This effect is equivalent to an increase in life time hourly wages of 50% (relative to cohort and gender means), and about three times greater than the direct effect of identifying as white.

Two caveats should be kept in mind when interpreting the magnitude of the coefficients on the $\widehat{n}$s as measures of the true effect of n on $\widehat{f_i}$: first, under our assumptions the $\widehat{n}$ are at best noisy measures of n, and thus subject to attenuation bias toward zero. Second, since the wage itself captures some of the productive part of $\widehat{n}$ ($corr(\log w, \widetilde{n}) \approx .24$), the direct effect of $\widetilde{n}$ (or any of the $\widehat{n}$s) should be understood as net of its effect on earning ability.

At the bottom of the table we report the R^2s from the second-stage regressions on 14907 PSID individuals with occupation and marital histories who are observed for at least two periods. The R^2 for the top eight candidate $\widehat{n}$ are equal to within .0001. We therefore choose $\widehat{n}$ 3 which combines the six attributes $\hat{n}^a$ that show up most consistently. The Kaiser-Meyer-Olkin measure of these six attributes is .68 suggesting that they correlate relatively well in the sample. In appendix D we show that $\widetilde{n}$ turns out to be a significant negative predictor of individual-level separations for both genders in both the labor and marriage markets.

The first panel of table A-3 shows that the measured attributes that most consistently appear as predictors of negative separation are *persistence*, *cooperation*, *adaptability*, *dependability*, *attention to detail*, and *independence*. Analytical thinking also appears once. Taking the traits individually, (i.e. letting $\widehat{n} = \hat{n}^a$ for each $\hat{n}^a$), *integrity* is also significant at the 5% level, although it does not enter any of the $\widehat{n}$s in the table. The other eight $\hat{n}^a$ are all insignificant predictors of $\widehat{f_i}$ conditional on the other covariates. In general, we think these results are highly plausible. Relationship specific capital is, to a large extent, built on trust and reliability, whether in personal or professional relationships. Thus it is not surprising that persistence, dependability, and cooperation are important components of $\widetilde{n}$. Dependability, persistence, and attention to detail are also highly associated with the Big Five trait of conscientiousness, which has been shown in many studies to correlate with job and marital stability (see Lundberg (2012)), as well as with other positive life cycle outcomes (see Almlund et al. (2011)). Intuitively, such traits as adaptability and cooperation also contribute to maintaining long-term relationships since they suggest empathy or, in terms of the "Big Five" personality measures, agreeableness, though *concern for others*, another clear correlate of agreeableness, is not predictive.[45] We have less intuition about why independence figures strongly for relationship stability in the marriage market. One possibility is that independence is associated with Emotional Stability (the opposite of neuroticism), one of the "Big Five" personality traits, which Lundberg (2012) shows raises the likelihood of divorce for women in German

[45] While experimenting with different sample selection criteria, we note that concern for others does occasionally become conditionally significant at the 5% level but it is never sufficiently correlated with the other traits to appear in the principal factor, regardless of sampling criteria.

data. The non-predictiveness of Social Orientation (which in fact has a positive insignificant effect on $\widehat{f}$) is also consistent with Lundberg (2012)'s findings: extraversion raises both marriage rates and divorce hazards conditional on marrying among men in the German Socioeconomic Panel.

Table A-3: Conditional correlations of $\widehat{n}$ and the separation fixed effect

	First $\widehat{n}$	Second $\widehat{n}$	Third $\widehat{n}$	Fourth $\widehat{n}$	Fifth $\widehat{n}$	Sixth $\widehat{n}$	Seventh $\widehat{n}$	Eighth $\widehat{n}$
		Persistence	Persistence		Persistence	Persistence	Persistence	Persistence
	Cooperation	Cooperation	Cooperation	Cooperation	Cooperation			Cooperation
	Adaptability	Adaptability	Adaptability	Adaptability	Adaptability	Adaptability	Adaptability	Adaptability
			Dependability		Dependability		Dependability	
	Att. to Detail	Att. to Detail	Att. to Detail			Att. to Detail	Att. to Detail	
	Independence	Independence	Independence	Independence	Independence	Independence	Independence	Independence
				Analytical				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{n}$	-.0783	-.0752	-.0733	-.0820	-.0722	-.0756	-.0733	-.0675
	(.0234)***	(.0225)***	(.0222)***	(.0250)***	(.0222)***	(.0232)***	(.0225)***	(.0209)***
yrs of educ	-.0014	-.0011	-.0012	-.0012	-.0012	-.0011	-.0013	-.0011
	(.0016)	(.0016)	(.0016)	(.0016)	(.0016)	(.0016)	(.0016)	(.0016)
mean lifetime	-.1549	-.1543	-.1546	-.1538	-.1551	-.1536	-.1542	-.1550
log wage	(.0056)***	(.0056)***	(.0056)***	(.0056)***	(.0056)***	(.0056)***	(.0056)***	(.0056)***
dummy for white	-.0266	-.0262	-.0263	-.0261	-.0264	-.0258	-.0261	-.0263
	(.0066)***	(.0066)***	(.0066)***	(.0066)***	(.0066)***	(.0066)***	(.0066)***	(.0066)***
sample size	16419	16419	16419	16419	16419	16419	16419	16419
R^2	.2647	.2647	.2647	.2647	.2647	.2647	.2647	.2647

Dependent variable is $\widehat{f}_i$, the common cross-market separation fixed for married individuals in the PSID who are observed for at least two periods between 1980 and 2009. * denotes significance at the 10% confidence level. ** denotes significance at the 5% confidence level. *** denotes significance at the 1% confidence level.

B Bellman equations for household optimization in the computational model

In this appendix, we describe in detail the Bellman equations governing the optimization problems for married and single workers and non-workers in the model. The individual discount factor β is set to .985 per period or .913 annually.

Single non-employed. During the working life, a single non-employed individual i of gender g is characterized by state vector $x_g = \{j, k, n, \kappa, \nu, U\} = \{j, k, n, 0, 0, U\}$ where j indexes age in months and $U \in \{s, l\}$ indexes whether the individual is short- or long-term non-employed. His value function is given by:

$$\begin{aligned} V^S_{g,i}(j,k,n,0,0,U) = &\log(S^U_g) + \beta\Big(\big(1-\pi_i\big)\big((1-\tau_{0,i})V^S_{g,i}(j+2,k,n,0,0,l) \\ &+ \tau_{0,i}\sum_{\mathcal{J}} q(\hat{\kappa},\hat{\nu})\int_{\hat{\epsilon}'_W} V^S_{g,i}(j+2,k,n,\hat{\kappa}^*,\hat{\nu}^*,\hat{\epsilon}'_W)dF(\hat{\epsilon}_W)\big) \\ &+ \pi_i\big((1-\tau_{0,i})\sum_{X_{-g,i}} \varrho(x_{-g,i})\mathbb{E}_{\epsilon_{-W}} V^M_{g,i}(j+2,x'_g,x_{-g}) \\ &+ \tau_{0,i}\sum_{\mathcal{J}} q(\hat{\kappa},\hat{\nu})\sum_{X_{-g,i}} \varrho(x_{-g,i})\mathbb{E}_{\epsilon_W,\epsilon_{-W}} V^M_{g,i}(j+2,x'_g,x_{-g})\big)\Big) \end{aligned} \tag{A-1}$$

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

In (A-1), F is the conditional 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 *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 with associated density ϱ.

Similarly, $\mathcal{J}$ is the set of $\{\kappa, \nu\}$ job offers that the individual would accept if they were offered; $\tau_{i,0}$ is the individual-specific likelihood of receiving a job offer from this set, which is the product of exogenous probability of matching $\tau_{0,U}$ 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, and the resulting individual-specific conditional densities are given by q. Finally,

$$\{\hat{\kappa}^*, \hat{\nu}^*\} = \text{argmax}[V^S_{g,i}(j+2,k,n,\hat{\kappa},\hat{\nu},\hat{\epsilon}'_W), V^S_{g,i}(j+2,k,n,0,0,s)]$$

which says that $\hat{\kappa}^*, \hat{\nu}^*$ is the single individual's optimal employment choice for next period once match productivity $\hat{\epsilon}'_W$ has been realized in job $\{\hat{\kappa}, \hat{\nu}\}$. If the individual accepts a new job and then immediately quits, we assume he remains in short-term non-employment, though we will not observe the transition. If no offer is received, the individual moves into (or stays in) long-term non-employment.

Equation (A-1) incorporates a specific timing of events within the period. The individual enters the period with all uncertainty resolved and consumes S^U_g. At the end of the current period, three things happen. First, the non-employed individual receives and accepts an attractive job offer for next period with probability $\tau_{0,i}$. 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 match productivity shock ϵ'_W is realized, at which point the individual can choose to remain and produce in his new job during the next period or decline the offer and remain in non-employment. If the individual is single, he makes this last decision on his own. If he has married, the quit decision is a household-level decision which is defined in detail below. In this case, the decision and payoff depends both on own and spousal ϵ'_W.

Single employed. The value function for a single employed worker with a state vector $x_g = \{j, k, n, \kappa, \nu, \epsilon_W\}$

is given by:

$$
\begin{aligned}
V_{g,i}^{S}(j,k,n,\kappa,\nu,\epsilon_W) &= \log(S_g^E) \\
&+ \beta \sum_{k'=k}^{k+\iota_k} \Big[\tilde{p}(k,k')\Big(\big(1-\pi_i\big)\big((1-\tau_{1,i}) \int_{\epsilon'_W} V_g^S(j+2,k',n,\kappa^*,\nu^*,\epsilon'_W)dF(\epsilon'_W) \\
&+ \tau_{1,i} \sum_{\mathcal{J}} q(\hat{\kappa},\hat{\nu}) \int_{\hat{\epsilon}'_W} V_g^S(j+2,k',n,\hat{\kappa}^*,\hat{\nu}^*,\hat{\epsilon}'_W)dF(\hat{\epsilon}'_W)\big) \\
&+ \pi_i\big((1-\tau_{1,i}) \sum_{X_{-g}} \varrho(x_{-g,i}) \mathbb{E}_{\epsilon'_W,\epsilon_{-W}} V_{g,i}^M(j+2,x_g,x_{-g}) \\
&+ \tau_{1,i} \sum_{\mathcal{J}} q(\hat{\kappa},\hat{\nu}) \sum_{X_{-g}} \varrho(x_{-g,i}) \mathbb{E}_{\epsilon'_W,\epsilon_{-W}} V_{g,i}^M(j+2,x_g,x_{-g})\big)\Big)\Big]
\end{aligned} \tag{A-2}
$$

There are three differences between (A-2) and (A-1). First, 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.[46] This increment to capital is realized immediately after the wage is received and consumed, before any other decisions are made for the next period (see figure 1 in section 4). Second, following the realization of k', individual i faces job arrival probability $\tau_{1,i}$ rather than $\tau_{0,i}$, where τ_1 is the arrival rate of job offers among the employed and $\tau_{1,i}$ again is the product of τ_1 an the share of attractive job offers among all potential job offers. Third, once job change and marriage decisions are made, 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

$$\{\kappa^*,\nu^*\} = \text{argmax}\{V_{g,i}^S(j+2,k',n,\kappa,\nu,\epsilon'_W), V_{g,i}^S(j+2,k',n,0,0,s)\}$$

which again depends crucially on the realization of ϵ'_W, the distribution of which depends on n and ν (and so in general will be different from the distribution of $\hat{\epsilon}'_W$). 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.

Marrieds. We now turn to the value functions for married individuals. For simplicity, we focus on the case where both spouses are currently employed, but the cases in which one or both spouses are non-employed are very similar. A married household maximizes a household-level value function U_M:

$$U_M = V_f^M(x_M) + V_m^M(x_M) \tag{A-3}$$

[46] $\tilde{p}(k,k) = 1 - p_k$. $\tilde{p}$ is introduced here to make the notation in the value function more concise.

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,\epsilon_W,x_{-g},\epsilon_M) = \log(\ell_g 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}_g,\hat{\nu}_g) \\
&\quad \Big(\varphi'_g(x'_M) \max\Big[\int_{\hat{\epsilon}'_W}\int_{\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'_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}_g,\hat{\nu}_g)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{A-4}
$$

where

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

We make several notational innovations in order to simplify the above expressions. We introduce the likelihood that a married individual receives an attractive alternative job offer as $\mathcal{P} = \tau_{i,-i}$ where he i and $-i$ indicate that the set of job offers that the individual will accept is determined jointly (cooperatively) with his spouse and in general will differ for every couple in the economy. We omit the individual-level notation i throughout. Variables denoted with negative signs refer to the spouse.

The bellman equation (A-4), 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 utility $\log(\ell_g M)$. At the end of the period, each spouse experiences an increment to current human capital of ι_k with independent probabilities $\tilde{p}(k_g, k'_g)$, which have the same interpretation as for singles. The spouses then simultaneously receive their next-period alternative job offers and choose their jointly optimal response. Once employment decisions have been resolved, the couple first receives their next-period marriage shock ϵ'_M which determines the efficiency of the marriage in the next period.[47] 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. Lastly, after marital decisions have been taken, and assuming the couple stays together, the ϵ'_Ws are realized for both partners given their previous decision to move from or stay in their current jobs, at which point they jointly choose who (neither, one or both) will remain in their job and produce or quit to short-term non-employment. If they have separated, they take this last decision independently.

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 entering the next period is given by:

$$\begin{aligned}\{\kappa_f^{**},\nu_f^{**},\kappa_m^{**},\nu_m^{**}\} = \text{argmax}\{&U_M(k'_f,n_f,\kappa_f,\nu_f,\epsilon'_{W,f},k'_m,n_m,\kappa_m,\nu_m,\epsilon'_{W,m},\epsilon'_M),\\ &U_M(k'_f,n_f,0,0,s,k'_m,n_m,\kappa_m,\nu_m,\epsilon'_{W,m},\epsilon'_M),\\ &U_M(k'_f,n_f,\kappa_f,\nu_f,\epsilon'_{W,f},k'_m,n_m,0,0,s,\epsilon'_M),\\ &U_M(k'_f,n_f,0,0,s,k'_m,n_m,0,0,s,\epsilon'_M)\}\end{aligned}$$

where s denotes short-term non-employment. A similar set-up governs the continuation problem if either or both spouses receive job offers (corresponding to the remaining three continuation terms of (A-4)). If only the wife receives an acceptable offer (again assuming both spouses are working in the current period), $\{\hat{\kappa}_f,\hat{\nu}_f\}$, we have

$$\begin{aligned}\{\hat{\kappa}_f^{**},\hat{\nu}_f^{**},\kappa_m^{**},\nu_m^{**},\} = \text{argmax}\{&U_M(k'_f,n_f,\hat{\kappa}_f,\hat{\nu}_f,\hat{\epsilon}'_{W,f},k'_m,n_m,\kappa_m,\nu_m,\epsilon'_{W,m},\epsilon'_M),\\ &U_M(k'_f,n_f,0,0,s,k'_m,n_m,\kappa_m,\nu_m,\epsilon'_{W,m},\epsilon'_M),\\ &U_M(k'_f,n_f,\hat{\kappa}_f,\hat{\nu}_f,\hat{\epsilon}'_{W,f},k'_m,n_m,0,0,s,\epsilon'_M),\\ &U_M(k'_f,n_f,0,0,s,k'_m,n_m,0,0,s,\epsilon'_M)\}\end{aligned}$$

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 non-employment and the new jobs $\{\hat{\kappa},\hat{\nu}\}$ with initial productivity governed by $\hat{\epsilon}'_W$. One final implication of the timing of events as described here and displayed in figure 1 is worth noting: non-employed individuals will accept job offers that arrive to them at the end of a period in order to obtain the option value of working those jobs next period should they receive a high draw of ϵ'_W . Many of these individuals however will directly quit again once the wage shock is realized, before ever starting work, particularly if the job is a mis-match on n. In estimating the model, we assume that the econometrician does not observe these matches: the individual will appear to remain in non-employment from one period to the next. However, for computational ease, we assume these individuals return to short-term non-employment which means they receive the additional benefit of receiving offers at a higher rate in the subsequent period but lose the additional home productivity associated with long-term non-employment.

C Model identification and fit

In this appendix we present details on the identification process linking the 64 moments taken from the PSID to 51 estimated parameters of the model. The overall fit is summarized in table A-4 and in figures A-1 and A-2 showing, respectively, filled jobs by $\widetilde{n}$ and ν and the distribution of schooling by gender. Excluding the ζs from tables 1 and 2, there are 59 moments shown in Table A-4, figure A-1 and figure A-2, three of which − two education shares and one filled job share − are redundant.

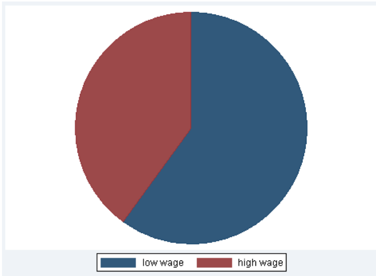
1. **Job shares and the job offer distribution.** We divide job-worker pairs in our PSID sample into nine bins corresponding to the top, bottom and middle terciles of the wage distribution (excluding the top .5% and bottom .5%) and a ν. "High" ($\nu = 3$), "medium" ($\nu = 2$) and "low" ($\nu = 1$) jobs

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

Table A-4: Model fit: Data and simulated moments

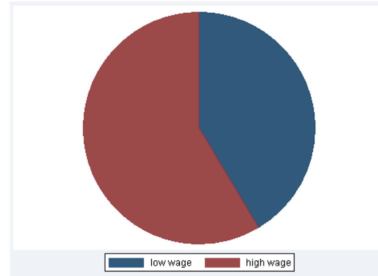
Target	Data value	Simulated value
Participation rate of single women	0.872	0.882
Participation rate of married women	0.798	0.900
Participation rate of single men	0.926	0.912
Participation rate of married men	0.967	0.946
Share of unemployment spells < 2 months	0.440	0.412
nes rate: low $\widetilde{n}$, low ν	0.100	0.089
nes rate: low $\widetilde{n}$, med ν	0.092	0.124
nes rate: low $\widetilde{n}$, high ν	0.108	0.176
nes rate: high $\widetilde{n}$, low ν	0.109	0.105
nes rate: high $\widetilde{n}$, med ν	0.076	0.060
nes rate: high $\widetilde{n}$, high ν	0.063	0.046
nes rate: women	0.075	0.087
nes rate: men	0.095	0.060
Correlation of nes and log wage	-0.041	-0.076
Positive employer separation rate	0.045	0.039
Wage return to age	-0.065	-0.007
Wage return to age^2:	0.00074	-0.00008
Wage return to education:	-0.089	0.047
Wage return to age $\times$ educ	0.010	0.003
Wage return to age$^2 \times$ educ	-0.00011	-0.00001
Conditional variance of log wage	0.369	0.388
Mean wage of single women, 2010 USD	16.9	16.1
Mean wage of married women, 2010 USD	17.8	18.0
Mean wage of single men, 2010 USD	20.1	18.2
Mean wage of married men, 2010 USD	26.1	22.8
Correlation of education and log wage	0.402	0.443
Correlation of $\widetilde{n}$ and log wage	0.242	0.217
Correlation of $\widetilde{n}$ and participation: women	0.083	0.067
Correlation of $\widetilde{n}$ and participation: men	0.030	0.046
Correlation of education and $\widetilde{n}$: women	0.372	0.341
Correlation of education and $\widetilde{n}$: men	0.446	0.387
Share of married	0.701	0.718
Correlation of nes and divorce among marrieds	0.046	0.017
Spousal correlation of education	0.612	0.331
Spousal correlation of $\widetilde{n}$	0.179	0.088
Spousal correlation of log wage	0.280	0.521
Divorce rate of low $\widetilde{n}$ spouses	0.042	0.042
Divorce rate of low $\widetilde{n}$ husband and high $\widetilde{n}$ wife	0.034	0.033
Divorce rate of high $\widetilde{n}$ husband and low $\widetilde{n}$ wife	0.032	0.033
Divorce rate of high $\widetilde{n}$ spouses	0.023	0.022
Correlation of divorce and log wage	-0.057	-0.184
Observed share of high $\widetilde{n}$ women	0.477	0.519
Observed share of high $\widetilde{n}$ men	0.514	0.551

Figure A-1: Filled jobs, by wages and ν, PSID 1980-2011 and simulation

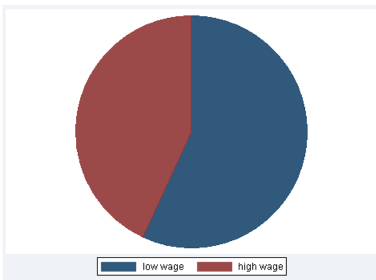


(a) filled jobs: $\nu = 1$, data

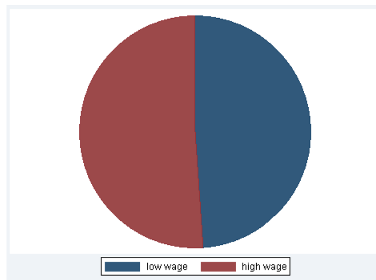
(b) filled jobs: $\nu = 2$, data



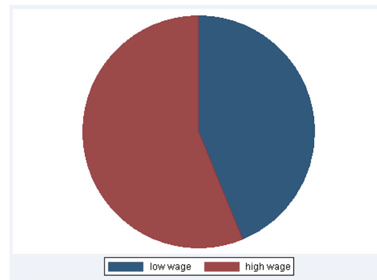
(c) filled jobs: $\nu = 3$, data



(d) filled jobs: $\nu = 1$, model



(e) filled jobs: $\nu = 2$, model



(f) filled jobs: $\nu = 3$, model

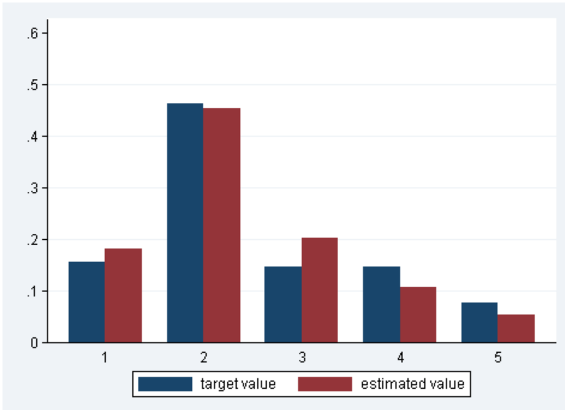
are determined according to their tercile of the reported importance of (or demand for) $\widetilde{n}$ among all (weighted) PSID worker-year observations between 1980 and 2011. Figure A-1 shows the real (top panel) and simulated (bottom panel) distributions of jobs across the ν and wage bins.[48] The figure shows that ν and log wages are positively but not strongly correlated; the raw correlation in the PSID is 0.145. Figure 2 in the main paper shows the offer distribution estimated in the model: that is, the joint distribution of κ and ν from which job offers are randomly drawn so as to generate the filled job distribution from the PSID.

2. **Participation rates and employment dynamics.** An individual is a "participant" in a given year if she supplies positive hours of work (in the model, works at least one two-month period out of the year). Among married and single individuals aged 20-55, the annual participation rates in our PSID sample are 97% and 93% for men and 80% and 87% for women, yielding four targets. To approximate the unemployment-re-employment process and the variation of participation with $\widetilde{n}$, we target gender-specific correlations between $\widetilde{n}$ and participation (.083 and .030 respectively); unconditional *nes* rates by gender (.075 and .093 respectively); and the aggregate two-month exit hazard out of non-employment (i.e. the share of non-employment spells among all participants that last ten weeks or less) which is 44%. These targets provide the primary identifying information for the parameters governing non-employment productivities B^{ne}; the job offer rates for short- and long-term non-employed τ_0^s and τ_0^l,; and the relative contribution of the wife's income to M, χ_0.

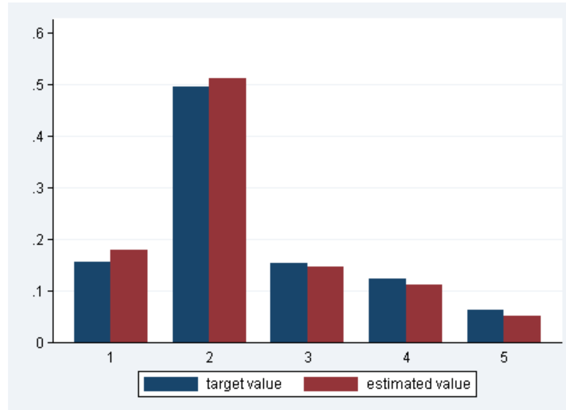
3. **Negative employer separation rates by n, ν, gender, and wages.** We calculate *nes* rates for high, medium, and low ν occupations by worker $\widetilde{n}$, which yield six targets, reported in table A-4. These targets (which are discussed at greater length in section 3.2.2) provide the main identifying information for the parameters governing the stochastic returns to job matches ϕ_0–ϕ_4 and for σ^2_ν, which should be interpreted as measurement error in the latent value of ν, which we then discretize into discreet levels

[48]Note that the calculations here and in table A-4 are made for *observed* wages and ν (i.e. $\widehat{W}$ and $\widehat{\nu}$ in the model), both of which are subject to measurement error. In the simulated data, the annual wage at age j is the average of $\widehat{W}$ over all the model periods during which the individual worked at age j and the occupation is taken to be the last occupation $\widehat{\nu}$ reported at j, assuming the individual is interviewed just before his birthday.

Figure A-2: Education shares



(a) men



(b) women

of observed relationship skill demand. We also calculate (1) the average nes rates in the population by gender (.075 for women and .095 for men), which provide important identifying information on the B^{ne} for each sex by short- and long-run unemployment status; (2) the correlation between nes and annual log wage (.041), which is important for distinguishing the effects of n on the mean and variance of the stochastic returns to job matches (through the ϕs); and (3) the annual correlation between nes and divorce among marrieds (.046), which has implications for cross-market state dependence and provides information on χ_1 and the parameters governing the stochastic returns to marriage.

4. **Promotions, positive employer separations, and wage returns to age and education.** Individuals may move up the career ladder either by internal promotion by their employer or successful on the job search. In the model workers are indifferent between these types of opportunities, which arrive at aggregate rate τ_1. We assume that a share μ are offers from external employers, so that offers from external employers arrive at rate $\mu\tau_1$ and internal promotions at rate $(1-\mu)\tau_1$. We identify μ by the share of "positive switches" in the population each period (see section 3), which is 4.5%.

   To capture wage variation over the life cycle, we regress workers' wages in logs on a quadratic in age, education, and interactions of age and education. The returns to age by education level provide identifying information on p_k, the stochastic rate of (general) human capital accumulation through learning by doing in the labor market, as well as the parameters governing returns to education: α_0, α_1, ψ_0 and ψ_1 and ψ_2. Matching the variance of the residual from this regression gives the conditional variance of wages of .37, which identifies the variance of measurement error in annual log wages, σ^2_{me}. We find σ^2_{me} to be relatively large, accounting for about 60% of the variance in wage growth at annual rates, substantially larger than the 35% found by Altonji et al. (2013). Measurement error in occupation is also substantial: at the annual level, occupation is observed correctly in the model 81% of the time.

5. **Wages by gender, education, and $\widetilde{n}$.** We take the mean wages of single and married men and women in our sample, scaled to 2010 USD, as four additional targets which play a major role in identifying $\phi_0 - \phi_4$, governing the mean and variance of wages, and the female wage penalty a_f. They also provide some additional identification for χ_0 and χ_1, governing the returns to spousal incomes in married household production, and the returns-to-schooling parameters. The degree of correlation between education and log wages among workers in the PSID is .40 and the correlation of $\widetilde{n}$ and log wages is .24.

6. **Education shares by gender and $\widetilde{n}$.** We target (i) the shares of PSID men and women obtaining less than high school, high school, college, undergraduate university, and post graduate education; and (ii) the correlation between $\widetilde{n}$ and educational attainment shares in the PSID by gender, which are quite

high at .37 for women and .45 for men. Variation in education shares across gender and $\widetilde{n}$ primarily helps to identify parameters governing the relative attractiveness of education as functions of innate skills and noise: b_0^s, b_1^s, ψ_1, and σ_B^2; and those governing the gender-specific distributions of k_0 and n for men and women: σ_{kn^f}, σ_{kn^m}, N_f and N_m. Figure A-2 shows the close fit of the simulated education shares to the PSID education shares by gender.

7. **Marriage, divorce rates, and spousal correlations.** In our PSID sample, 70% of individuals between 20 and 55 are married. As described in section 3, separation rates also vary with the $\widetilde{n}$s of the spouses: the incidence of divorce among high $\widetilde{n}$ pairs (including common-law separations) is .028 and among low n pairs is .039. Among mixed pairs, the incidence is .035 when the husband has high $\widetilde{n}$ and .029 when the wife has high $\widetilde{n}$. The individual-level correlation of divorce with log wages is -.057. The within-couple correlation of $\widetilde{n}$ is .18, of education (using our five categories) is .61, and of log wages is .28. Together, these nine marriage statistics provide the main identifying information for the single meet rate π and the parameters governing the productivity of marriage: ℓ_f, ℓ_m, χ_0, χ_1, and λ_0–λ_4.

8. **Reduced-form effects of stocks of previous separations on current separations.** The last eight moments are the PSID estimates of $\{\zeta^{11}, \zeta^{12}, \zeta^{21}, \zeta^{22}\}$ for men and women taken from the linear probability regressions reported in tables 1 and 2 respectively. These moments provide further information on the distributions of shocks to employment and marital output ($\phi_0 - \phi_4$ and $\lambda_0 - \lambda_4$), and on relative marriage valuations of men and women ℓ_f and ℓ_m. Specifically, the further help identify how much of separation is due to negative shocks resulting from mismatch on n and how much due to other factors. This is the main subject of section 7.1.

D Additional Tables

In this appendix, we report the reduced-form results from our separation regressions in section 7.1 disaggregated by gender and type of separation.

Table A-5: *nes* hazards in model and data (disaggregated splits): Men

	Data	Data $+\tilde{n}$	Model	Model $+\tilde{n}$	Model + n	Model + $\log k$	Model + $f(n, \log k)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
educ	-.0035	-.0025	-.0051	-.0038	.0001	-.0031	.0007
	(.0007)***	(.0007)***	(.0005)***	(.0005)***	(.0005)	(.0005)***	(.0005)
employer tenure	-.0092	-.0092	-.0113	-.0112	-.0109	-.0112	-.0109
	(.0006)***	(.0006)***	(.0005)***	(.0005)***	(.0005)***	(.0005)***	(.0005)***
tenure squared	.0003	.0003	.0003	.0003	.0003	.0003	.0003
	(.00002)***	(.00002)***	(.00002)***	(.00002)***	(.00002)***	(.00002)***	(.00002)***
log wage	.0034	.0037	-.0295	-.0295	-.0232	-.0195	-.0171
	(.0027)	(.0027)	(.0015)***	(.0015)***	(.0015)***	(.0018)***	(.0018)***
stock of previous *nes*	.0148	.0147	.0170	.0161	.0141	.0168	.0133
	(.0014)***	(.0014)***	(.0018)***	(.0018)***	(.0018)***	(.0018)***	(.0018)***
stock of previous divorces	.0192	.0193	.0109	.0102	.0072	.0105	.0071
	(.0038)***	(.0038)***	(.0029)***	(.0029)***	(.0029)**	(.0029)***	(.0030)**
nes last period	.0994	.0993	.0463	.0460	.0455	.0461	.0451
	(.0077)***	(.0077)***	(.0086)***	(.0086)***	(.0086)***	(.0086)***	(.0086)***
n		-.0051		-.0183	-.0471		-.1041
		(.0015)***		(.0021)***	(.0025)***		(.0097)***
$\log k$						-.0138	-.0665
						(.0018)***	(.0100)***
$\log k^2$							.0043
							(.0016)***
$n \times \log k$							.0226
							(.0035)***
Obs.	53273	53273	60994	60994	60994	60994	60994
R^2	.0483	.0485	.0683	.0695	.0734	.0691	.075
ΔR^2	.00407	.00399	.00348	.00310	.00226	.00339	.00201

Dependent variable is an indicator for experiencing an *nes* between t and $t+1$ at time t. Columns 1-2 report estimates based on married male wage workers from the 1980-2011 PSID. Columns 3-6 report estimates based on married male workers in the benchmark simulation. All regressions control for a cubic in age, number of periods the individual has previously been married, and number of periods the individual has previously been working for wages. The regressions in columns 1-2 also include a dummy for race (1=white), number of children in the household, and year and sample dummies. * denotes significance at the 10% confidence level. ** denotes significance at the 5% confidence level. ΔR^2 reports the joint contribution of the stocks of previous *nes* and of previous divorces to the R^2 in each regression specification. *** denotes significance at the 1% confidence level.

Table A-6: nes hazards in model and data (disaggregated splits): Women

	Data	Data $+\widetilde{n}$	Model	Model $+\widetilde{n}$	Model + n	Model + $\log k$	Model + $f(n, \log k)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
educ	-.0039	-.0031	-.0054	-.0044	.0001	-.0050	-.0002
	(.0007)***	(.0008)***	(.0007)***	(.0007)***	(.0008)	(.0008)***	(.0008)
employer tenure	-.0110	-.0110	-.0174	-.0173	-.0168	-.0174	-.0163
	(.0007)***	(.0007)***	(.0006)***	(.0006)***	(.0006)***	(.0006)***	(.0006)***
tenure squared	.0004	.0004	.0005	.0005	.0004	.0005	.0004
	(.00003)***	(.00003)***	(.00002)***	(.00002)***	(.00002)***	(.00002)***	(.00002)***
log wage	.0120	.0127	-.0379	-.0376	-.0311	-.0356	-.0308
	(.0027)***	(.0027)***	(.0019)***	(.0019)***	(.0020)***	(.0026)***	(.0027)***
stock of previous nes	.0137	.0135	.0150	.0143	.0121	.0150	.0100
	(.0020)***	(.0020)***	(.0016)***	(.0016)***	(.0017)***	(.0016)***	(.0017)***
stock of previous divorces	.0174	.0174	.0080	.0075	.0036	.0079	.0051
	(.0035)***	(.0035)***	(.0035)**	(.0035)**	(.0036)	(.0035)**	(.0036)
nes last period	.0490	.0490	.0458	.0461	.0463	.0459	.0456
	(.0071)***	(.0071)***	(.0080)***	(.0080)***	(.0080)***	(.0080)***	(.0080)***
n		-.0039		-.0154	-.0485		-.1263
		(.0016)**		(.0026)***	(.0032)***		(.0123)***
$\log k$						-.0032	-.1281
						(.0028)	(.0128)***
$\log k^2$							.0159
							(.0023)***
$n \times \log k$							.0286
							(.0044)***
Obs.	44515	44515	55656	55656	55656	55656	55656
R^2	.0312	.0314	.0904	.0910	.0941	.0905	.0976
ΔR^2	.00408	.00403	.00266	.00239	.00159	.00266	.00113

Dependent variable is an indicator for experiencing an nes between t and $t+1$ at time t. Columns 1-2 report estimates based on married female wage workers from the 1980-2011 PSID. Columns 3-6 report estimates based on married female workers in the benchmark simulation. All regressions control for a cubic in age, number of periods the individual has previously been married, and number of periods the individual has previously been working for wages. The regressions in columns 1-2 also include a dummy for race (1=white), number of children in the household, and year and sample dummies. * denotes significance at the 10% confidence level. ** denotes significance at the 5% confidence level. ΔR^2 reports the joint contribution of the stocks of previous nes and of previous divorces to the R^2 in each regression specification. *** denotes significance at the 1% confidence level.

Table A-7: Divorce hazards in model and data (disaggregated splits): Men

	Data	Data $+\widetilde{n}$	Model	Model $+\widetilde{n}$	Model + n	Model + $\log k$	Model + $f(n, \log k)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
educ	-.0035	-.0030	-.0020	-.0015	.0007	-.0006	.0009
	(.0004)***	(.0005)***	(.0004)***	(.0004)***	(.0004)*	(.0004)	(.0004)**
marriage tenure	-.0034	-.0034	-.0061	-.0060	-.0061	-.0061	-.0060
	(.0006)***	(.0006)***	(.0009)***	(.0009)***	(.0009)***	(.0009)***	(.0009)***
tenure squared	.00009	.00009	.0002	.0002	.0002	.0002	.0002
	(.00002)***	(.00002)***	(1.00e-05)***	(1.00e-05)***	(1.00e-05)***	(1.00e-05)***	(1.00e-05)***
log wage	-.0067	-.0065	-.0058	-.0057	-.0025	.0010	-.0003
	(.0013)***	(.0013)***	(.0011)***	(.0011)***	(.0011)**	(.0014)	(.0014)
stock of previous nes	.0032	.0031	.0037	.0034	.0022	.0035	.0023
	(.0007)***	(.0007)***	(.0008)***	(.0008)***	(.0008)***	(.0008)***	(.0008)***
stock of previous divorces	.0272	.0273	.0115	.0113	.0093	.0111	.0091
	(.0034)***	(.0034)***	(.0025)***	(.0025)***	(.0025)***	(.0025)***	(.0026)***
nes last period	.0120	.0120	.0053	.0051	.0042	.0052	.0042
	(.0037)***	(.0037)***	(.0036)	(.0036)	(.0036)	(.0036)	(.0036)
n		-.0028		-.0070	-.0233		-.0369
		(.0012)**		(.0014)***	(.0019)***		(.0065)***
$\log k$						-.0092	.0131
						(.0012)***	(.0066)**
$\log k^2$							-.0043
							(.0012)***
$n \times \log k$							.0052
							(.0023)**
Obs.	66666	66666	63197	63197	63197	63197	63197
R^2	.0326	.0327	.0248	.0252	.0276	.0256	.0279
ΔR^2	.00231	.00229	.00106	.00095	.00053	.00098	.00052

Dependent variable is an indicator for experiencing a divorce between t and $t+1$ at time t. Columns 1-2 report estimates based on married men from the 1980-2011 PSID. Columns 3-6 report estimates based on married men in the benchmark simulation. All regressions control for a cubic in age, number of periods the individual has previously been married, and number of periods the individual has previously been working for wages. The regressions in columns 1-2 also include a dummy for race (1=white), number of children in the household, and year and sample dummies. ΔR^2 reports the joint contribution of the stocks of previous nes and of previous divorces to the R^2 in each regression specification. * denotes significance at the 10% confidence level. ** denotes significance at the 5% confidence level. *** denotes significance at the 1% confidence level.

Table A-8: Divorce hazards in model and data (disaggregated splits): Women

	Data	Data $+\widetilde{n}$	Model	Model $+\widetilde{n}$	Model $+ n$	Model $+ \log k$	Model + $f(n, \log k)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
educ	-.0052	-.0041	-.0029	-.0024	.0004	-.0011	.0007
	(.0005)***	(.0006)***	(.0004)***	(.0004)***	(.0004)	(.0004)***	(.0004)
marriage tenure	-.0022	-.0022	-.0072	-.0072	-.0071	-.0071	-.0070
	(.0006)***	(.0006)***	(.0010)***	(.0010)***	(.0010)***	(.0010)***	(.0010)***
tenure squared	.00007	.00007	.0002	.0002	.0002	.0002	.0002
	(1.00e-05)***	(.00002)***	(1.00e-05)***	(1.00e-05)***	(1.00e-05)***	(1.00e-05)***	(1.00e-05)***
log wage	-.0003	.0001	-.0097	-.0095	-.0055	.00006	-.0011
	(.0013)	(.0013)	(.0011)***	(.0011)***	(.0011)***	(.0014)	(.0015)
stock of previous nes	.0044	.0042	.0021	.0019	.0005	.0022	.0005
	(.0012)***	(.0012)***	(.0006)***	(.0006)***	(.0006)	(.0006)***	(.0006)
stock of previous divorces	.0373	.0373	.0122	.0120	.0097	.0120	.0098
	(.0039)***	(.0039)***	(.0024)***	(.0024)***	(.0024)***	(.0024)***	(.0024)***
nes last period	.0134	.0134	-.0021	-.0021	-.0026	-.0019	-.0027
	(.0044)***	(.0044)***	(.0027)	(.0027)	(.0027)	(.0027)	(.0027)
n		-.0052		-.0073	-.0279		-.0713
		(.0013)***		(.0014)***	(.0018)***		(.0055)***
$\log k$						-.0125	-.0024
						(.0012)***	(.0064)
$\log k^2$							-.0051
							(.0011)***
$n \times \log k$							.0168
							(.0019)***
Obs.	58584	58584	60142	60142	60142	60142	60142
R^2	.0329	.0332	.0233	.0237	.0273	.0247	.0282
ΔR^2	.004082	.00403	.00101	.00091	.00046	.00100	.00047

Dependent variable is an indicator for experiencing a divorce between t and $t+1$ at time t. Columns 1-2 report estimates based on married women from the 1980-2011 PSID. Columns 3-6 report estimates based on married women in the benchmark simulation. All regressions control for a cubic in age, number of periods the individual has previously been married, and number of periods the individual has previously been working for wages. The regressions in columns 1-2 also include a dummy for race (1=white), number of children in the household, and year and sample dummies. ΔR^2 reports the joint contribution of the stocks of previous nes and of previous divorces to the R^2 in each regression specification. * denotes significance at the 10% confidence level. ** denotes significance at the 5% confidence level. *** denotes significance at the 1% confidence level.