THREE ESSAYS
IN
HOUSEHOLD ECONOMICS

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Chapter 1

Introduction

Household economics dates back to pioneering work by Gary Becker, but it is no less relevant today. Household economics describes how individuals organize themselves, how they make consumption decisions, how they determine labor supply and other time use, how they form new households and dissolve others, and how they create and invest in the next generation. Broadly speaking, if we lopped off the roofs of every house, household economics could tell us who was in each house, and what factors likely led them to be there.

The organization of households has important implications for both microeconomics and macroeconomics. On an individual level, household organization determines access to credit and informal insurance, which impacts investments in human capital and labor force participation. On a macro level, household organization determines investment in real estate, associated consumption, and labor force productivity.

This dissertation addresses household formation and composition through three avenues. First, I document trends in parental coresidence among young adults in multiple cohorts, contextualizing these decision with demographic shifts and local economic characteristics. Second, I investigate a relationship between coresidence by young adults and coresidence by those young adults' parents later in life. Third, I analyze divorce decisions within first marriages to determine if divorce's perceived association with economic success can be attributed to more behavioral factors. These essays jointly document transitions into and out of households, generating new insights into the micro processes of household formation.

Essay 1: Parental Coresidence Among Young Adults: A Cross-Generational Analysis

This paper examines the factors influencing exits from and returns to a young adult's parental home. Using three cohorts from the National Longitudinal Surveys of Youth, I investigate generational differences, incorporating local economic characteristics to contextualize the coresidence decision. Additionally, I use matched mother-child data to determine how locational economic differences may impact the coresidence decision. Finally, I investigate each cohort's experience during the recent housing crisis and economic downturn. I find that the relationship between most household covariates and living independently has changed little over time; the majority of the observed increase in per-period coresidence is driven by increased coresidence at older ages, mainly in the form of delayed exits. Delayed exits are correlated with a rising age at first marriage. While local economic characteristics have little relationship to coresidence decisions, the relative difference in conditions between the parent and child's current location does play a significant role. The Great Recession additionally delayed exits from the parental home, with potential long-term implications for household formation.

Essay 2: Intergenerational Altruistic Links: A Model of Family Coresidence

This analysis uses linked sibling data from the 1979 National Longitudinal Survey of Youth (NLSY) to investigate the presence of a relationship between young adult and elderly coresidence within families. I find that children who departed late or returned to the parental home are more likely to have coresident parents later in life, such that even within a given family, parents requiring coresidence live with the child who exited later or returned. I present both linear and non-parametric models of this effect, and contextualize it with a mixed motivation behavioral model of intra-family generosity which exhibits preferences consistent with these new facts. The model suggests that an increase in public aid to emerging young adults may decrease intra-family assistance to elderly individuals due to reduced signaling capacity, an important implication amid current policy discussions.

Essay 3: Learning by "I Do"ing: A Model of Marital Stability

When couples say "I do" at the altar, they pledge to a lifelong marriage, but many couples part before death. This paper investigates the process that leads some couples to divorce, focusing on a potentially important factor: learning. Spouses learn about one another over the course of the marriage, and this information can lead to a reassessment of the marriage. A model of Bayesian learning provides several distinctive predictions, which are tested using data from the 1979 cohort of the National Longitudinal Survey of Youth (NLSY79). Specifically, individuals are assumed to learn about a spouse's "capability," which is modeled using item responses on the AFQT, a test of cognitive skills. Findings consistent with the model include (a) the divorce hazard is higher for low-capability individuals, especially a few years into marriage; (b) in terms of predicting divorce, the role of capability (which is not easily observed) increases over time relative to schooling (which is easily observed); and (c) an adverse shock to the capability assessment (in the form of a job layoff or firing) has a greater impact on divorce for high-capability individuals. These findings provide insight into the inequality in marriage stability observed in the U.S. across income, education, and cognitive ability.

Chapter 2

Parental Coresidence Among Young Adults: A Cross-Generational Analysis

Abstract

This paper examines the factors influencing exits from and returns to a young adult's parental home using three cohorts from the National Longitudinal Surveys of Youth to investigate generational differences, incorporating local economic characteristics to contextualize the decision. Additionally, I use matched mother-child data to determine how locational economic differences may impact the coresidence decision. Finally, I investigate each cohort's experience during the recent housing crisis and economic downturn. I find that the relationship between most household covariates and living independently has changed little over time; the majority of the observed increase in per-period coresidence is driven by increased coresidence at older ages, mainly in the form of delayed exits. Delayed exits are correlated with a rising age at first marriage. While local economic characteristics have little relationship to coresidence decisions, the relative difference in conditions between the parent and child's current location does play a significant role. The Great Recession additionally delayed exits from the parental home, with potential long-term implications for household formation.

2.1 Introduction

After a long decline in American multigenerational coresidence (Ruggles, 2007), research (along with the popular press) suggests that the empty nest phenomenon is being offset by the boomerang phenomenon, in which adult children return home to live with their parents (Mitchell, 1998). Delays in marriage and child-bearing, rising educational attainment, and new economic challenges have delayed the formation of independent households by young adults.

Furthermore, young adults were disproportionately affected by the tightening labor market accompanying the Great Recession. (2). More than a third of young adults (ages 18-31) coresided with parents in 2012 (Fry, 2013). Thus, documenting the generational trends in coresidence behavior in light of recent economic challenges will contextualize these figures, and lend insight into the longer-term implications of these new trends.

2.1.1 Importance of the question

Parental support in a multitude of forms–emotional, physical, financial–can assist in launching a child to adulthood. Settersten, Jr. and Ray find that these channels have become increasingly important in the path to adulthood, supporting the newly lengthened process of launching. They observe that new institutions are necessary to aid young adults from lower- and middle-class backgrounds in navigating the extended process without as much familial financial support (Settersten, Jr. and Ray, 2010).

Coresidence is a form of indirect parental transfer, and when coresidence and direct parental transfers are used to smooth a youth's consumption, they take the place of government aid programs that are also intended to serve as a supplement in times of transition. As Kaplan found significant detrimental long-term labor effects for males electing not to move home after a job loss (Kaplan, 2012), young adults without open parental homes may suffer steeper consequences from economic downturn. Kaplan additionally found that this effect is particularly strong among males from low-income backgrounds (whose families may be unable to substitute direct financial transfers for coresidence) (Kaplan, 2012). The option to coreside is especially important for teen mothers enrolled in the Temporary Aid to Needy Families (TANF) program, who must live in an adult-supervised setting to maintain eligibility if they are unmarried minors. Work by Deleire and Kalil (2002) suggests that multigenerational living arrangements can mitigate some of the negative behavioral outcomes associated with being raised by a single mother.

However, there are a variety of existing government programs designed to help transitioning young adults and their families cope with a change in family or labor circumstances without relying on familial resources–Temporary Assistance for Needy Families (TANF), Women, Infants, and Children (WIC), and Unemployment Insurance (UI). Settersten and Ray (2010) also suggest the expansion of institutions like learning service programs, military opportunities, and community college, which provide simulated independence in a lower risk environment, as the option to coreside is not available to all.

Additionally, coresidence may not be preferable to temporary financial support from parents or government. An extensive literature (e.g. Booth and Johnson (1974), Krieger and Higgens (2002)) establishes that a more crowded household is less desirable, all else equal. Beyond the impact on transmission of communicable disease, parents have less control over childrearing when other adults are present, and children raised in crowded households have worsened economic and behavioral outcomes as adults. Moreover, a trend toward shared living arrangements means less demand for housing, and less demand for any goods associated with a newly formed household. Thus, understanding the uptick in coresidence in the context of generational trends and the Great Recession is of crucial importance for forecasting economic growth and demand for public support.

2.1.2 Research questions and previous work

Glick and Lin (1986) find that young adult children move back in due to school enrollment or labor market changes, and older adult children move in with their parents due to changes in Marital status (divorce or separation), or to care for parents in times of medical need. Jacob and Kleinert (2008) find significant effects of substitution of a partner's resources (spouse or long-term relationship partner) for a young adult's own resources (and to some extent, parental resources), causing an earlier transition from the parental home than if the youth had no partner. Thus, the rising age at first marriage may be limiting young adults' access to additional resources, contributing to the current rate of coresidence. A number of media outlets (e.g. *The New York Times*) have commented on a perceived increase in "doubling up," with many citing the recent economic downturn as a potential accelerator of this phenomenon.

The Great Recession brought on dramatic changes in both housing and labor markets, and likely influenced young adults' decisions about where and with whom to live. Work by Brown and Matsa (2016) suggests that a sharp decline in housing prices can limit geographic mobility for homeowners due to a loss in equity. Rogers and Winkler (2014) find that local rent prices did correlate with coresidence patterns, but foreclosure rates, home prices, and unemployment rates appear to not have played a significant role. However, the analysis by Rogers and Winkler is limited in that it only considers characteristics local to the young adult's MSA, rather than the young adult's MSA in comparison to that of his or her parent(s). Using data from the American Community Survey, Elliott, Young, and Dye (2011) find that the U.S. proportion of "complex" family households (multigenerational households with adults of separate generations) increased by one percentage point from an 18 percent base. They find that local unemployment rates are less important than the unemployment of individual household members in determining complex household composition. Consistent with previous work by Keene and Batson (2010), they find that families of Hispanic origin comprise a significant proportion of such households.

This paper will add to the coresidence literature by examining how the incidence of coresidence has varied over generations, how economic conditions local to the young adult and to the parental residence may relate to the coresidence decision, and how each of three cohorts from the National Longitudinal Survey of Youth fared in maintaining independent living during the increased financial stresses of the Great Recession.

Empirical facts

As shown in Figure 2.1, NLSY respondents from the 1979 cohort have higher rates of living away from parents for ages 20 and older. However, the coresidence decision is likely influenced by the resources of both the young adult and the parents. One factor influencing the respondent's household resources is his or her Marital status. Thus, in Figures 2.2 and 2.3, the rate of independent living is conditioned on Marital status. A striking finding emerges–younger cohorts are equally or more likely to live independently if they are unmarried, a trend primarily driven by differences in the age-specific coresidence rate of unmarried women. Furthermore, while married respondents in the 1979 cohort are more likely to live independently than those of more recent cohorts, the differences are not as profound as in Figure 2.1. Thus, it is likely that the increasing age at first marriage among more recent cohorts plays a role in this phenomenon, as the rate of living independently is much greater for married respondents than for unmarried respondents.

2.2 Empirical Strategy

Suppose Jen Smith is struggling financially, and she thinks a move might ameliorate her situation. Jen could move in with her parents, allowing us to model her decision as:

$$\begin{aligned} Pr(\text{Live independently next year}) &= \beta_0 + \beta_1 \text{Ln(income)} + \beta_2 B_i + \beta_3 H_i + \beta_4 F_i \\ &+\beta_5 \text{Education} + f(\text{Marital status}) + g(\text{Age}) + h(\text{Childbearing}) + \epsilon \end{aligned} \tag{2.1}$$

However, if Jen's parents live several hundred miles away, her relocation only makes sense if the labor market where they live is as good as or better than Jen's local market. If we don't know anything about Jen's parents, we can model her decision as a function of her current local variables:

$$\begin{aligned} Pr(\text{Live independently next year}) &= \beta_0 + \beta_1 \text{Ln(income)} + \beta_2 B_i + \beta_3 H_i + \beta_4 F_i + \beta_5 \text{Education} \\ &+\beta_6 \text{House price index} + \beta_7 \text{Median rent} + \beta_8 \text{Unemployment rate} \\ &+f(\text{Marital status}) + g(\text{Age}) + h(\text{Childbearing}) + \epsilon \end{aligned} \tag{2.2}$$

Preferably, we'd consider the difference in local economies:

$$\begin{aligned} Pr(\text{Live independently next year}) &= \beta_0 + \beta_1 \text{Ln(income)} + \beta_2 B_i + \beta_3 H_i + \beta_4 F_i + \beta_5 \text{Education} \\ &+\beta_6 \text{Child's rent-mother's rent} + \beta_7 \text{Child's unemployment rate-mother's unemployment rate} \\ &+f(\text{Marital status}) + g(\text{Age}) + h(\text{Childbearing}) + \epsilon \end{aligned} \tag{2.3}$$

Each of these models (2.1, 2.2, and 2.3) can also be used to reflect entries and exits, by conditioning on the set of young adults already living independently (in the case of entries) or still coresidence (in the case of exits).

Jen's parents have heard that Jen's generation is full of indolent young people content to live in their parents' basements, but they also remember that many members of their generation stayed with parents until ready to start their own families. Equations 2.1 and 2.3 can be estimated for all three cohorts, allowing for a comparison of the correlates of coresidence over time.

Finally, perhaps Jen's need for coresidence was driven by the Great Recession. The reappraisal of home prices could conceivably impact homeowners and children of homeowners by threatening their primary residence, which inspires the final model:

$$\begin{aligned} Pr(\text{Live independently next year}) = \beta_0 + \beta_1 \text{Ln(income)} + \beta_2 B_i + \beta_3 H_i + \beta_4 F_i + \beta_5 \text{Education} \\ + \beta_6 \text{Homeowner} + \beta_7 \text{Homeowner} \times \text{Crisis} + \beta_8 \text{Crisis} \\ + f(\text{Marital status}) + g(\text{Age}) + h(\text{Childbearing}) + \epsilon \end{aligned} \tag{2.4}$$

where "Crisis" represents the period between 2006 and 2010.

2.2.1 Identification challenges

The data used (described in the next section) are primarily annual observations, which presents a few challenges to analysis. First, there is a risk of missing short spans of coresidence or independent living. While the primary objective is to compare across cohorts, this analysis would be unable to detect an increase in short spurts of coresidence unless the interview happened to coincide with such instances. Second, potential moves during the year pose a challenge for linking to the "correct" local economic conditions, as the month of moves cannot be identified. Finally, this is a non-causal analysis, as behavioral regression components like marital status, education, and childbearing are certainly endogenous.

2.3 Data

The data come from two cohorts of the National Longitudinal Survey of Youth, which consists a panel of almost 9,000 individuals born between 1980 and 1984 who have been surveyed approximately annually since 1997 (NLSY97), and a panel of almost 12,700 individuals born between 1957 and 1964 who have been surveyed since 1979 (NLSY79). Both data sets consist of a cross-section and at least one oversample; descriptive statistics presented will be for the cross-section only to maintain representativeness but the full sample is used in regression analysis where the dimensions of oversample can be accounted for (e.g. race/ethnicity, income).

I use an additional cohort, the Children of the 1979, which consists of all children born to women in the NLSY79 (and thus is not nationally representative), and birth years range between 1970 and 2011. Coverage varies across the cohorts–data have been released through 2014 for the NLSY79 and the Children sample, and through 2013 for the NLSY97.

Questions range from basic demographics to financial practices, job history to sexual behavior, and drug use to political participation. For some categories of questions, participants are asked to recall monthly or weekly characteristics of their life over the last year. The interviews take less than 90 minutes, and participants (in early years, both the parent and the youth) are paid ten dollars for their participation.

Sample selection

Because of the recent nature of the 1997 cohort, the ages of sample members are limited to a younger range (oldest is 33) than the 1979 cohort (oldest is 57). In contrast, the Children of the 1979 cohort are included in the survey since birth, and coresidence decisions before age 18 are likely decisions of the parent, not the youth. Unless otherwise specified, the 1979 and Children of the 1979 cohorts will be limited to individuals aged 18-30 to increase comparability (birth years 1970-1996). The sample characteristics that follow are for the age-restricted sample of each cohort.

Key dependent variables

This analysis will examine both the "stock" of coresidence (how many young adults live with parents in a given period) and "flows" of coresidence–movements into and out of the parental home.

Living away from parents

This "stock" measure is drawn from two data sources. First, the residence type is reported for most individuals, and "living in parental home" is one of several options. However, household composition is additionally measured by the household roster, in which the young adult reports every individual living in his/her (potentially) shared household. Parent and parent-figures can be identified from the relationship codes, but this study only codes coresidence if parents are present and the young adult does not report "owns/rents" as residence type. If the young adult is the primary owner/lessee and parents are present, that is considered to be a case of parents coresiding with children, a phenomenon beyond the scope of this analysis.

Returning to the parental home

A young adult is "eligible" for a return next year if he is currently living away from parents. Young adults already coresiding are coded as missing for returns. A young adult returns to the parental home if he is observed living independently in one year and observed to coreside in the following year.

Exiting the parental home

A young adult is "eligible" for an exit next year if he is currently living with parents. Young adults already living independently are coded as missing for exits. A young adult exits the parental home if he is observed living with parents in one year and observed to live independently in the following year.

Key independent variables

House price index (HPI)

The house price index data are reported by the Federal Housing Finance Agency. HPI is a measure of the change in housing costs in an area, measured by repeated transactions on the same properties. Note that since the underlying source of HPI data is Fannie Mae and Freddie Mac, only mortgage types issued, bought, or guaranteed by these agencies are included; i.e. jumbo loans are not considered.

Homeownership

Homeownership is directly reported in the NLSY. Respondents are asked if they or their spouses own or make any payments on their primary residence. An affirmative answer in a given year is coded as owning a home in that same year.

Unemployment rate

The unemployment rate used is the county-level annual unemployment rate reported by the Bureau of Labor Statistics in the Local Area Unemployment Statistics. As the figures are annual averages, they are not seasonally adjusted.

Median rent

The median rent figures used are for the county level, and are only available from the Department of Housing and Urban Development starting in 1995. Therefore this analysis cannot incorporate rental prices into the analysis of the NLSY79 cohort's launch.

Sample characteristics

Table 2.1 presents descriptive statistics for the (cross-sectional sample of the) three cohorts used in this analysis. The rate of completing high school varies little by cohort. However, educational attainment is increasing on the upper end–respondents in the 1997 cohort complete, on average, slightly less than one more year of schooling than those in the 1979 cohort. However, respondents from the 1997 cohort are far less likely to be married by age 30–a difference of roughly twenty-five percentage points! Respondents from the 1997 cohort that do exit do so at younger ages, and are only marginally more likely to return to the parental home, a surprising contrast to the "boomerang" phenomenon depicted in popular culture. The higher rate of per-period coresidence in the 1997 cohort is driven by a minority of respondents–those that do return in the 1997 cohort do so for longer periods, and are slightly less likely to exit the parental home again.

It is worthwhile to note why the statistics portrayed here differ from those reported by the Census Bureau. The Census Bureau counts young adults enrolled in college and living in dormitories as coresident, while this analysis does not. The rising rate of college enrollment over the past two decades likely amplifies the impact of this reporting difference. Furthermore, the Census definition of "young adult" usually includes individuals through age 34, while this analysis must truncate at age 30.

2.4 Results

2.4.1 Coresidence in three cohorts

Table 2.2 compares the correlates of living independently between ages 18 and 30 across the three cohorts from the NLSY. Additional income reduces the probability of coresiding for all three cohorts, but particularly for the children of the 1979 cohort. Being currently married or previously married is also associated with a reduction in coresidence, though previous marriages have no significant relationship for the most recent cohort. In all three cohorts, racial and ethnic minorities are more likely to coreside, and those with children and with more education are less likely to coreside.

However, current-period living arrangements give little indication of the flows into and out of the parental home. Table 2.3 presents the probability of exiting the parental home conditional on coresiding in the previous year. The oldest cohort suggest that income assists with exits, although there is no significant correlation for the more recent cohorts. Similar to the results in the previous table, married and previously married individuals are generally more likely to exit to an independent living situation than their never married counterparts. It appears that at least part of racial and ethnic minorities' increased odds of coresidence is due to a lack of exit, as across all three cohorts, these individuals are less likely to leave the parental home. Having children increases the odds of exiting for the two more recent cohorts, but not for the oldest cohort.

As for flows back to the parental home, table 2.4 presents the probability of returning, conditional on having previously exited and having lived independently in the previous year. Education and income reduces the odds of a return for all cohorts, though less profoundly for the most recent cohort. Married and previously married individuals are significantly less likely to return, with some significance in each of the three cohorts. Additionally, black members of the most recent cohort are no more likely to return than white members, suggesting that the higher rate of per-period coresidence is driven entirely by delayed exits. The presence of children generally reduces returns, although this varies across cohorts.

While factors inside the home likely influence the resources to which a young adult has access, local housing and economic conditions likely also play a role. The next series of tables maintains the controls used in the previous analysis, but add controls for the house price index (HPI), unemployment rate, and rent. In determining leaving the parental home, median rent and unemployment rate play a significant role only for the Children of the 1979 cohort. The other measures of local economic conditions are insignificant, perhaps because an exit from the parental home might likely involve a relocation. Results from the Children cohort suggest that young adults leave the parental home when the local unemployment rate is high, likely in pursuit of better economic opportunities.

In determining where the young adult resides in any given year, rent does play a significant role (along with the unemployment rate), suggesting that young adults do not exit parental homes due to high local rent, but do avoid high rent areas when choosing where to live independently. The 1997 and 1979 cohorts suggest that living in an area with a high unemployment rate currently decreases the probability of continuing to live independently. However, results for the Children cohort are insignificant, and in the model for returns, members of the Children cohort with high local unemployment rates are *less* likely to return to the parental household in the next year.

The results presented so far are consistent with the previous literature in that a partner's resources as well as one's own income and education can help prevent coresidence, but the difference in the strength of these associations across cohorts is intriguing. The 1997 cohort was uniquely exposed to the Great Recession–respondents were between 22 and 30 during 2006-2010, prime ages for launching from the parental home and forming one's own family. The Children of the 1979 cohort features a wider range of ages, but the mean respondent was 22 during the Great Recession, and the data give an advantageous view into the resources of not only the young adult and his/her family, but also the young adult's parents. Thus, the second part of this analysis will focus on familial resources, and the third part will examine coresidence during the Great Recession across all three cohorts.

2.4.2 Parental economic conditions

Table 2.8 presents the probability that a child previously living independently returns to live in the parental home. While the local economic conditions of the mother's county do not appear to play an individually significant role, they are significant in each "paired" specification, suggesting that young adults do indeed consider the relative merits of their two options.

Table 2.9 shows that the local unemployment rate in both locations plays a role in determining coresidence–the higher the unemployment rate where the young adult lives, the more likely he/she is to coreside, while the reverse is true for the mother's local unemployment rate. After accounting for unemployment rate and HPI, rent does not play a significant role, but HPI may capture local housing costs in aggregate.

While the previous specifications allow for some comparison, table 2.10 models independent living and returns to the parental home as functions of the *difference* in the two county HPIs and unemployment rates. The differences are significant–respondents move away from high unemployment rates, returning home when the mother's unemployment rate is lower, and children. Respondents also appear to remain in more expensive areas, but this could reflect preferences over geography, as few own homes.

2.4.3 The Great Recession

The Great Recession and associated housing crisis had drastic impacts for the labor market and overall economy. The recession was the longest-lasting since the Great Depression (NBER 2012). The Great Recession also saw a near-doubling of the unemployment rate and of the count of the long-term unemployed (BLS 2012). Although educational achievement has increased over the last few decades, unemployed individuals with bachelor's degrees were just as likely to experience long-term unemployment during the recession as those with only a high school diploma (Kosanovich and Sherman, 2015). However, the recession impact did vary by region–nearly half of the unemployed in Washington, D.C. were unemployed for 27 weeks or more, whereas in non-coastal states, this proportion was generally less than one quarter.

Accompanying the Great Recession were new stresses on living arrangements. More than nine million homeowners faced foreclosure, and the National Association of Realtors expects fewer than a third of those homeowners to own again (*The Wall Street Journal*, 2012). Many switched to renting, but others turned to friends and family for assistance, leading to a drastic increase in multigenerational living. Thus, the year of 2006-2010 present a unique context in which to examine multigenerational living, particularly with cohorts at different ages and stages of homeownership.

While most of the 1997 cohort did not own significant real estate by this time, almost three-quarters of the 1979 cohort had become homeowners.[1] As shown in Table 2.11, those who owned a home in the previous period were much less likely to coreside with parents, but the crisis significantly decreased that relationship. A comparable analysis for the 1997 cohort yields generally consistent results–those who owned homes in the previous year are less likely to live with their parents, but there is no significant difference during the crisis. This may be due to the smaller fraction of the 1997 cohort observed to become homeowners (roughly one quarter own a home at some point in the sample).

Table 2.12 reports the probability of living independently for the Children of the 1979 women, again stratifying on the period of the economic and housing crisis. Income played a stronger role in determining independent living during the crisis than before or after. Outside of the housing crisis, a respondent's parents owning a home in the previous year significantly reduced the probability of living independently; however, during the crisis, that relationship lessened considerably. Age became a weaker deterrent to coresidence during the crisis, consistent with a period of shifting priorities. A parent's home foreclosure or late payments did not significantly impact the probability of their child living independently, although foreclosure is a low-frequency event in this data.

Table 2.13 offers a different perspective–the experience of emerging young adults before and during The Great Recession. Those coming of age before the crisis did not have their date of exit significantly influenced by local economic conditions, but for those who were still coresident between ages 18 and 30 during the crisis, high local rents and high unemployment discouraged their exit. The story is less strong for returns–Table 2.14 suggests that local conditions only played a role in determining returns for the most recent cohort. Due to the age restrictions imposed, the pre-crisis samples are notably smaller, so it is possible that the lack of significance stems from larger standard errors.

Table 2.15 shows that homeownership is associated with an increased rate of living independently and a decrease in returns to the parental home. The economic and housing crisis featured more returns for the Children cohort, and fewer exits for the 1997 cohort. Like the 1979 cohort, homeowners in the Children cohort were less likely to continue to live independently during the crisis than before or after the crisis.

2.5 Conclusions

This paper uses nationally representative data across generations to document changes in coresidence correlates and trends. These have two additional advantages. First, they span the period of the Great Recession, allowing insight into conditions before, during, and after the housing crisis and economic downturn. Second, the data are linkable with local economic conditions, not just of the young adult, but also of the parent, allowing a comparative analysis.

[1] The 1979 cohort members were in their 40s when the crisis began.

This paper presents evidence that the elevated rates of coresidence observed in the most recent generation are likely responses to changes in marriage and educational attainment (associated with delayed exits from the parental home). Curiously, those who do exit "on-time" do so at *younger* ages than previous cohorts (particularly among women)–the increase is concentrated at older ages.

Furthermore, the recent economic downturn appears to have accelerated the rate of return and delayed the exiting of many young adults. Previous cohorts' experiences suggest that home-leaving requires a good deal of inertia–older young adults are more likely to stay independent if independent, and stay coresident if coresident. The long-term effects of this phenomenon are less clear, but impact on real estate markets is of great importance. A number of individuals who lost their homes during 2006-2010 are unlikely to buy again due to damaged credit and increasing borrowing restrictions,[2] and with the delayed family and independent household formation of recent cohorts, there may be a permanent decrease in home-buying. Coupled with this decrease in collateralized credit would be declines in the purchasing of insurance, furniture, and home services, suggesting that the Great Recession's impact on economic markets may persist for several years.

However, this study is not without limitations. The incidence of factors influencing coresidence is not exogenous, and so this study is purely descriptive. Furthermore, parent geographic data is only available for the Children cohort, whose experiences are not nationally representative. Finally, while the NLSY contains sporadic data on financial transfers, the data do not reflect in-kind forms of support, which may have important geographic interactions. The substitution of such support measures is an important avenue for future research.

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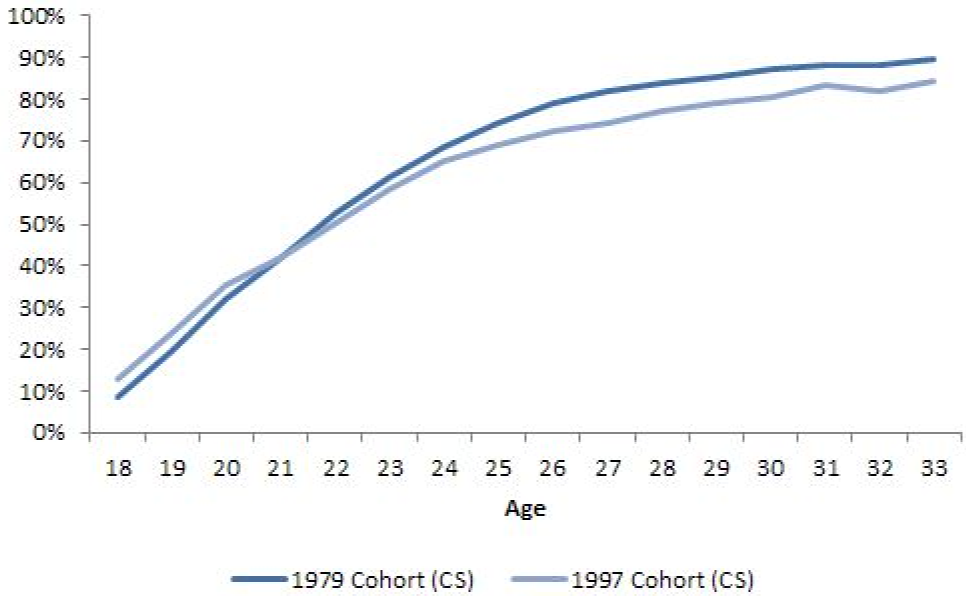
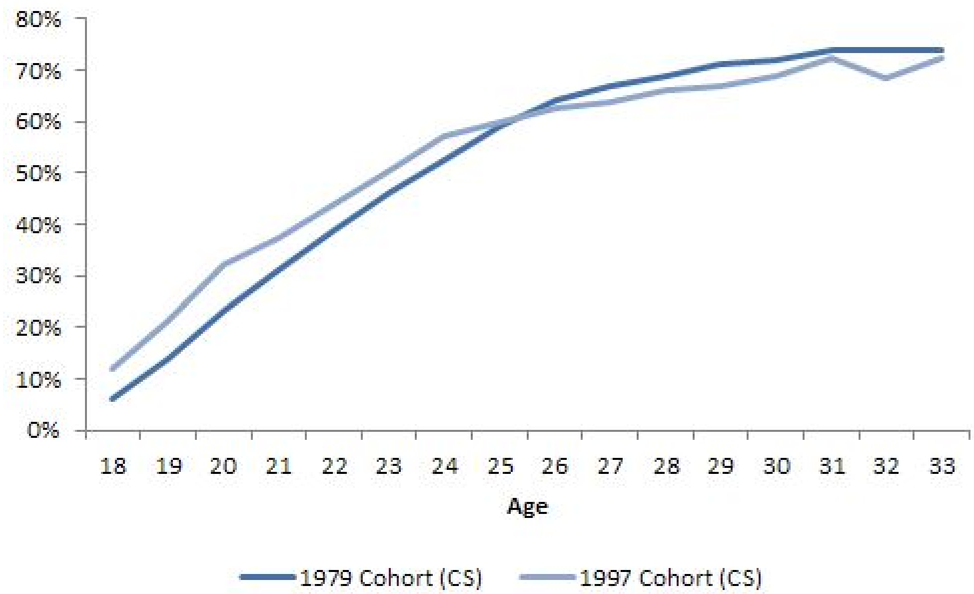
2.6 Tables and Figures

Figure 2.1: Young adults living away from parental home, all respondents



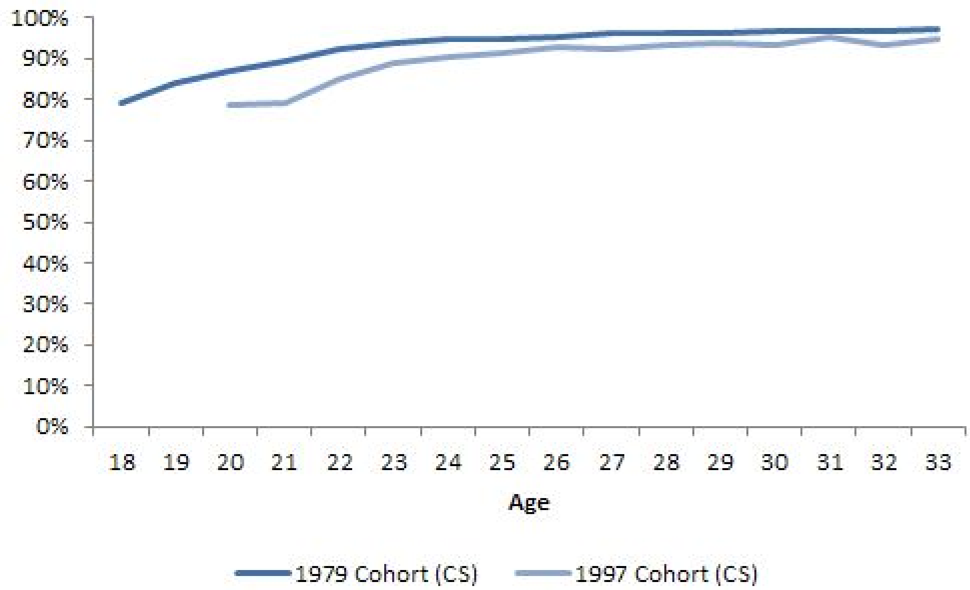
Note: CS denotes cross-sectional sample (oversample excluded)

Figure 2.2: Young adults living away from parental home, unmarried respondents



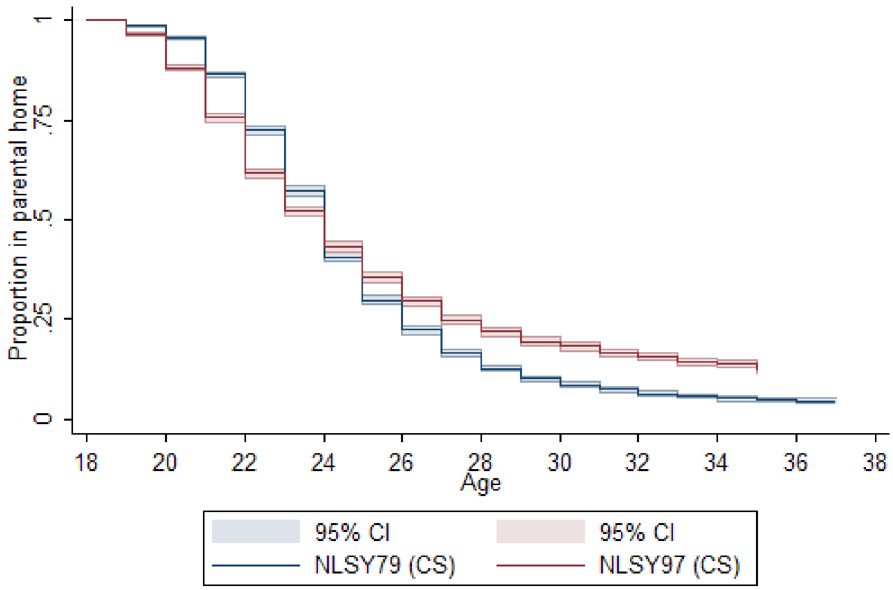
Note: CS denotes cross-sectional sample (oversample excluded)

Figure 2.3: Young adults living away from parental home, married respondents



Note: CS denotes cross-sectional sample (oversample excluded)

Figure 2.4: Survival curve for remaining in parental home



Note: CS denotes cross-sectional sample (oversample excluded)

Table 2.1: Sample Characteristics

	NLSY97	Children of the NLSY79	NLSY79
White	0.69	0.51	0.81
Black	0.16	0.31	0.12
Hispanic	0.14	0.19	0.07
Female	0.49	0.49	0.51
High school graduate	0.82	0.80	0.82
Years of education	14.0	13.3	13.3
Ever married	0.46	0.42	0.71
Age of first marriage	24.4	24.3	24.6
Away (age 18-30)	0.54	0.51	0.63
Ever exited	0.72	0.47	0.78
Age of first exit	21.5	22.7	22.6
Ever returned	0.33	0.15	0.29
N	6,748	6,438	6,060

Notes: "Ever" measures are by age 30. The observation for "Away" is a person-year. "Age of" measures are conditional on having reached that milestone. The Children of the NLSY79 sample is restricted to having been observed to at least age 28 (the minimum age observed in the NLSY97), due to its non-cohort nature. The NLSY79 and NLSY97 are limited to the cross-sectional samples.

Table 2.2: Logit model for living apart from parents next year
(Sample is respondents ages 18-30)

	(1) 1979	(2) Children of the NLSY79	(3) 1997
Ln(income)	0.0187***	0.0278***	0.0188***
	(0.00211)	(0.00373)	(0.00385)
Currently married	0.221***	0.130***	0.116***
	(0.00971)	(0.0332)	(0.0171)
Ever married	0.0835***	0.0772**	0.0246
	(0.00947)	(0.0311)	(0.0159)
Age	0.0545***	0.130***	0.0316*
	(0.00978)	(0.0213)	(0.0173)
Age^2	-0.000823***	-0.00219***	-0.000462
	(0.000197)	(0.000455)	(0.000349)
Observations	53,996	14,236	16,460
N	10,194	5,362	3,903

Specification is logistic regression; coefficients are partial effects. Clustered standard errors in parentheses. All columns contain controls for gender, race/ethnicity, enrollment status, childbearing, and education.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 2.3: Logit model for exiting parental home next year
(Sample is respondents ages 18-30 coresiding)

	(1) 1979	(2) Children of the NLSY79	(3) 1997
Ln(income)	0.00817**	0.00684	0.00359
	(0.00324)	(0.00471)	(0.00768)
Currently married	0.0688***	0.0710	0.0268
	(0.0178)	(0.0453)	(0.0295)
Ever married	0.121***	0.0282	0.0610**
	(0.0136)	(0.0363)	(0.0254)
Age	0.102***	0.321***	-0.0480
	(0.0180)	(0.0295)	(0.0345)
Age^2	-0.00227***	-0.00683***	0.000809
	(0.000369)	(0.000620)	(0.000708)
Observations	17,904	8,286	3,941
N	6,398	4,536	1,678

Specification is logistic regression; coefficients are partial effects. Clustered standard errors in parentheses. All columns contain controls for gender, race/ethnicity, enrollment status, childbearing, and education.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 2.4: Logit model for returning to parental home next year
(Sample is respondents ages 18-30 living independently)

	(1) 1979	(2) Children of the NLSY79	(3) 1997
Ln(income)	-0.00366***	-0.00791***	-0.00687***
	(0.00102)	(0.00270)	(0.00210)
Currently married	-0.0447***	-0.00154	-0.0250***
	(0.00411)	(0.0206)	(0.00846)
Ever married	-0.000466	-0.0354*	-0.00415
	(0.00419)	(0.0198)	(0.00791)
Age	-0.0118**	0.0837***	0.00504
	(0.00595)	(0.0159)	(0.0112)
Age^2	0.000127	-0.00200***	-0.000187
	(0.000120)	(0.000337)	(0.000226)
Observations	38,683	8,342	12,425
N	9,118	3,685	3,446

Specification is logistic regression; coefficients are partial effects. Clustered standard errors in parentheses. All columns contain controls for gender, race/ethnicity, enrollment status, childbearing, and education.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 2.5: Logit model for exiting the parental home next year

	(1)	(2)	(3)	(4)
Panel A: NLSY79				
HPI	-0.000127***			3.90e-05
	(4.02e-05)			(7.22e-05)
County unemployment rate			-0.00183	-0.00152
			(0.00213)	(0.00245)
Observations	24,154	29,338	2,442	2,195
N	7540	8791	1614	1456
Panel B: Children of the NLSY79				
Child's HPI	-0.000114***			-5.78e-08
	(2.15e-05)			(3.65e-05)
Child's median county rent		-0.000143***		-0.000142***
		(3.17e-05)		(4.24e-05)
Child's county unemployment rate			0.00284*	0.00524**
			(0.00160)	(0.00208)
Observations	8,648	4,382	8,840	4,380
N	4578	2946	4669	2946
Panel C: NLSY97				
HPI	7.73e-07			2.47e-05
	(1.93e-05)			(3.20e-05)
Median county rent		1.15e-05		-1.15e-05
		(3.15e-05)		(4.40e-05)
County unemployment rate			0.00249	0.00253
			(0.00199)	(0.00261)
Observations	6,209	3,714	6,287	3,709
N	2,429	1,713	2,451	1,712

Specification is logistic regression; coefficients are partial effects. Clustered standard errors in parentheses. All columns contain controls for gender, race/ethnicity, childbearing, marital status, income, age, and education.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 2.6: Logit model for living away from the parental home next year

	(1)	(2)	(3)	(4)
Panel A: NLSY79				
HPI	-0.000136***			-7.78e-05
	(4.39e-05)			(5.41e-05)
County unemployment rate			-0.00781***	-0.00710***
			(0.00146)	(0.00156)
Observations	56,374	68,266	7,697	7,102
N	9627	10833	3606	3358
Panel B: Children of the NLSY79				
Child's HPI	-0.000146***			3.71e-05
	(2.26e-05)			(3.54e-05)
Child's median county rent		-0.000132***		-0.000162***
		(3.40e-05)		(4.32e-05)
Child's county unemployment rate			-0.00461***	8.96e-05
			(0.00164)	(0.00201)
Observations	11,951	6,078	12,175	6,072
N	4840	3519	4915	3517
Panel C: NLSY97				
HPI	-7.12e-05***			-1.40e-05
	(1.92e-05)			(2.98e-05)
Median county rent		-0.000109***		-9.74e-05**
		(2.92e-05)		(4.03e-05)
County unemployment rate			-0.00718***	-0.00681***
			(0.00167)	(0.00205)
Observations	16,283	10,724	16,416	10,710
N	3,877	3,180	3,898	3,180

Specification is logistic regression; coefficients are partial effects. Clustered standard errors in parentheses. All columns contain controls for gender, race/ethnicity, childbearing, marital status, income, age, and education.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 2.7: Logit model for returning to the parental home next year

	(1)	(2)	(3)	(4)
Panel A: NLSY79				
HPI	7.97e-05***			3.27e-05
	(1.48e-05)			(2.22e-05)
County unemployment rate			0.000200	0.000322
			(0.000700)	(0.000792)
Observations	44,771	54,181	7,550	6,939
N	9179	10367	3775	3479
Panel B: Children of the NLSY79				
Child's HPI	1.73e-05*			-1.55e-05
	(9.39e-06)			(1.87e-05)
Child's median county rent		-7.21e-06		7.15e-06
		(1.76e-05)		(2.33e-05)
Child's county unemployment rate			-0.000441	-0.00290**
			(0.000833)	(0.00123)
Observations	9,754	5,084	9,929	5,079
N	4205	3022	4265	3021
Panel C: NLSY97				
HPI	1.82e-05**			-6.69e-06
	(7.17e-06)			(1.20e-05)
Median county rent		1.83e-05		2.45e-05
		(1.15e-05)		(1.57e-05)
County unemployment rate			0.000142	0.000485
			(0.000748)	(0.000915)
Observations	14,997	10,022	15,097	10,011
N	3,805	3,135	3,823	3,135

Specification is logistic regression; coefficients are partial effects. Clustered standard errors in parentheses. All columns contain controls for gender, race/ethnicity, childbearing, marital status, income, age, and education.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 2.8: Logit marginal effects for returning to the parental home, Children of the NLSY79

	(1)	(2)	(3)	(4)
Child's HPI	-2.36e-05**			-4.19e-05*
	(1.14e-05)			(2.37e-05)
Mother's HPI	4.47e-05***			7.21e-06
	(1.10e-05)			(2.45e-05)
Child's rent		-2.62e-05		1.55e-05
		(2.17e-05)		(2.86e-05)
Mother's rent		4.75e-05**		3.34e-05
		(2.05e-05)		(2.67e-05)
Child's county unemployment rate			0.00497***	0.00378*
			(0.00108)	(0.00217)
Mother's county unemployment rate			-0.00214**	-0.00271
			(0.000990)	(0.00200)
Observations	6,612	3,354	6,628	3,348
N	2,918	1,979	2,927	1,978

Specification is logistic regression; coefficients are partial effects. Clustered standard errors in parentheses. All columns contain controls for gender, race/ethnicity, childbearing, marital status, income, age, and education.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 2.9: Logit marginal effects for living away from the parental home, Children of the NLSY79

	(1)	(2)	(3)	(4)
Child's HPI	0.000221***			0.000237***
	(4.48e-05)			(6.89e-05)
Mother's HPI	-0.000339***			-0.000183**
	(4.67e-05)			(7.18e-05)
Child's rent		0.000176***		-6.75e-05
		(6.34e-05)		(8.04e-05)
Mother's rent		-0.000310***		-0.000106
		(6.49e-05)		(8.15e-05)
Child's county unemployment rate			-0.0314***	-0.0263***
			(0.00447)	(0.00647)
Mother's county unemployment rate			0.0202***	0.0172***
			(0.00444)	(0.00643)
Observations	12,732	6,186	12,754	6,178
N	4,975	3,411	4,984	3,410

Specification is logistic regression; coefficients are partial effects. Clustered standard errors in parentheses. All columns contain controls for gender, race/ethnicity, childbearing, marital status, income, age, and education.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 2.10: Importance of familial resources, Children of the NLSY79

Panel A: Logit marginal effects for living away from parents

	(1)	(2)	(3)
Child-mother HPI difference	0.000276***		0.000235***
	(4.34e-05)		(4.38e-05)
Child-mother unemployment rate difference		-0.0256***	-0.0236***
		(0.00439)	(0.00447)
Observations	12,732	12,754	12,724
N	4975	4984	4975

Panel B: Logit marginal effects for returning to parental home

	(1)	(2)	(3)
Child-mother HPI difference	-3.43e-05***		-3.02e-05***
	(9.30e-06)		(9.27e-06)
Child-mother unemployment rate difference		0.00351***	0.00316***
		(0.000948)	(0.000938)
Observations	6,612	6,628	6,606
N	2,918	2,927	2,918

Specification is logistic regression; coefficients are partial effects. Clustered standard errors in parentheses. All columns contain controls for gender, race/ethnicity, childbearing, marital status, income, age, and education.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 2.11: Correlates of living away from parents next year
(Sample is NLSY79 (all ages))

	(1) 2000-2005	(2) 2006-2010
Ln(income)	0.00919***	-0.00300
	(0.00301)	(0.00377)
Age	-0.0250	0.114
	(0.0223)	(0.0870)
Age^2	0.000282	-0.00121
	(0.000269)	(0.000916)
Own a home	0.0818***	0.0600***
	(0.00773)	(0.0103)
Observations	6,848	3,283
N	4,116	3,126

Specification is logistic regression; coefficients are partial effects. Clustered standard errors in parentheses. Additional controls include gender, race/ethnicity, Marital status, childbearing, and education. Note that this sample is not age-restricted due to the focus on the 2006-2010 (crisis) period.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 2.12: Correlates of living away from parents
(Sample is children of the NLSY79 ages 18-30)

	(1) Pre-2006	(2) 2006-2010
Ln(income)	0.0360***	0.0551***
	(0.00884)	(0.00718)
Age	0.0638***	0.0358***
	(0.00544)	(0.00303)
Mother's county house price index	-0.000335***	-0.000136***
	(8.53e-05)	(3.58e-05)
Mother's change in county home prices	0.00392	0.00415***
	(0.00282)	(0.00104)
Mother owned house last year	-0.0707***	-0.0349*
	(0.0198)	(0.0181)
Observations	2,614	2,830

Specification is logistic regression; coefficients are partial effects. Clustered standard errors in parentheses. Additional controls include gender, race/ethnicity, Marital status, childbearing, and education.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 2.13: Logit marginal effects for exiting the parental home

	(1)	(2)	(3)	(4)
	Children of the NLSY79		NLSY97	
	Pre-2006	2006-2010	Pre-2006	2006-2010
HPI	7.30e-06	1.97e-05	-4.42e-05	1.69e-05
	(6.82e-05)	(3.36e-05)	(8.32e-05)	(4.00e-05)
Median county rent	-0.000153	-0.000134***	2.16e-05	-8.21e-05
	(0.000117)	(4.10e-05)	(0.000162)	(5.87e-05)
County unemployment rate	-0.00912	-0.00667***	0.000802	-0.00703**
	(0.00861)	(0.00228)	(0.0132)	(0.00348)
Observations	1,252	4,246	855	2,623
N	1,252	2,602	648	1,285

Specification is logistic regression; coefficients are partial effects. Clustered standard errors in parentheses. All columns contain controls for gender, race/ethnicity, childbearing, marital status, income, age, and education.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 2.14: Logit marginal effects for returning to the parental home

	(1)	(2)	(3)	(4)
	Children of the NLSY79		NLSY97	
	Pre-2006	2006-2010	Pre-2006	2006-2010
HPI	-3.42e-07	-2.95e-05	1.46e-05	-3.89e-06
	(3.71e-05)	(2.30e-05)	(3.26e-05)	(1.47e-05)
Median county rent	-4.99e-06	3.42e-05	-3.27e-05	4.43e-05**
	(6.93e-05)	(2.87e-05)	(5.93e-05)	(1.81e-05)
County unemployment rate	-0.00576	0.000477	-0.000563	0.00165*
	(0.00603)	(0.00135)	(0.00439)	(0.000965)
Observations	1,128	4,075	1,931	7,440
N	1,128	2,385	1,354	2,756

Specification is logistic regression; coefficients are partial effects. Clustered standard errors in parentheses. All columns contain controls for gender, race/ethnicity, childbearing, marital status, income, age, and education.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 2.15: Logit model for flows into and out of the parental home

	(1)	(2)	(3)	(4)	(5)	(6)
	Children of the 1979 Women			NLSY 1997		
	Away	Return	Exit	Away	Return	Exit
Ln(income)	0.0210***	-0.00133	0.00782	0.0197***	-0.00704***	0.00415
	(0.00381)	(0.00281)	(0.00536)	(0.00379)	(0.00199)	(0.00744)
High school graduate	0.00200	-0.0200**	-0.0251	0.00405	-0.00940*	-0.0194
	(0.0126)	(0.00840)	(0.0170)	(0.0116)	(0.00523)	(0.0182)
Age	0.177***	0.0358**	0.319***	0.0558***	0.00220	0.0102
	(0.0135)	(0.0141)	(0.0231)	(0.0170)	(0.0107)	(0.0319)
Age^2	-0.00313***	-0.000955***	-0.00658***	-0.000920***	-0.000136	-0.000295
	(0.000289)	(0.000300)	(0.000511)	(0.000339)	(0.000213)	(0.000643)
Crisis (2006-2010)	-0.0238**	0.0216***	0.00835	-0.0113	-0.000537	-0.0537***
	(0.00933)	(0.00678)	(0.0133)	(0.00758)	(0.00519)	(0.0183)
Own a home	0.221***	-0.0678***	-0.0336	0.102***	-0.00632	-0.0715
	(0.0355)	(0.0186)	(0.0940)	(0.0312)	(0.0159)	(0.117)
Crisis $\times$ own home	-0.0710*	0.0268	0.0328	0.0166	-0.0302	0.0983
	(0.0430)	(0.0226)	(0.110)	(0.0411)	(0.0233)	(0.148)
Observations	10,360	6,711	5,587	16,970	12,826	4,046

Specification is logistic regression; coefficients are partial effects. Clustered standard errors in parentheses. Sample is restricted to young adults ages 18-30. All columns contain controls for gender, race/ethnicity, childbearing, and marital status.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Chapter 3

Intergenerational Altruistic Links: A Model of Family Coresidence

Abstract

This analysis uses linked sibling data from the 1979 National Longitudinal Survey of Youth (NLSY) to investigate the presence of a relationship between young adult and elderly coresidence within families. I find that children who departed late or returned to the parental home are more likely to have coresident parents later in life, such that even within a given family, parents requiring coresidence live with the child who exited later or returned. I present both linear and non-parametric models of this effect, and contextualize it with a mixed motivation behavioral model of intra-family generosity which exhibits preferences consistent with these new facts. The model suggests that an increase in public aid to emerging young adults may decrease intra-family assistance to elderly individuals due to reduced signaling capacity, an important implication amid current policy discussions.

3.1 Introduction

There are many forms of support parents can provide to their children as they develop–for example, prenatal care, childhood health care, primary and secondary education involvement, and college financing. During the recent economic downturn, media outlets such as the *Chicago Tribune*, CNN, and the *New York Times* have highlighted an additional dimension to parents' support of children–prolonged coresidence and the "boomerang" phenomenon, in which adult children either continue to live with or move back in with their parents past the typical age of launching.

Over the last few decades, researchers have observed a delay in marriage, an increase in the frequency of parental coresidence, and an increase in financial transfers from parent to child (Glick, 1986; Furstenberg, 2010; Aquilino, 1990). No matter the cause, the traditional path to independence–school completion, full-time employment, independent housing, marriage, children–has lengthened and shifted over the last 30 years, resulting in a lower rate of marriage, a higher rate of extramarital childbearing, and longer and more frequent occurrence of adult children living with their parents (Settersten and Ray, 2010), suggesting that today's young people need more support from their parents than ever before.

Simultaneously, the public has seen the rise of the "sandwich" generation–the parents of the boomerang generation who face supporting not only their own children but also their parents, who may require transfers of time, money, or coresidence. While the literature has commented on the existence of these phenomena, it has not yet posited a relationship between the two suggesting any benefit to those "sandwiched". This paper will present empirical evidence of a link between these two forms of coresidence and will contextualize this finding with three competing models of coresidence behavior from the family transfers literature, with preliminary support for a mixed motivation behavioral model.

Motivation and Previous Work

When coresidence is used to smooth consumption, it takes the place of government aid programs that are also intended to serve as a supplement in times of transition (e.g. Temporary Assistance for Needy Families). Coresidence can be an efficient way for family members to help each other, as joint residence permits consumption of an array of "public" goods, including housing, electricity, water, and potentially food and transportation. Identifying factors influencing coresidence among a broader cohort can help policymakers understand how government aid interacts with parental transfers (as suggested by Rosenzweig and Wolpin, 1994).

It is also important to consider the effect of children's coresidence on the parent generation. Financial support results in a direct loss of disposable income, but coresidence may take a similar toll on parental happiness. Rosenzweig and Wolpin (1994) find that parents value privacy and prefer for their adult children to live independently, and parents with empty nests report higher marital satisfaction (White and Edwards, 1990). Bures (2009) finds that families with children (adult or otherwise) living at home are less likely to move than those with empty nests. Extending the launching process in this manner may delay the parent generation from being able to "downsize" or relocate for other reasons. The substitution of parental resources for governmental ones, therefore, is not without cost.

Furthermore, these costs may not be entirely private. Each coresident young adult is one not forming a new household, causing consequences in the rental and real estate markets. Figure 1 shows the fraction of young adults living with parents, and the homeownership rate among young adults. It is clear that these two factors are inversely correlated (see Figure 1), as the homeownership rate drops as coresidence increases. Thus, understanding the factors influencing coresidence will aid in real estate market analysis.

Finally, one must consider the longer-term impacts of prolonged coresidence on those late to leave the parental home and on the parents housing them. Leopold (2012) finds that late home leavers maintain closer relationships with their parents, although it is unclear whether this is because of continued dependence or strengthened family ties. If parents receive future benefits in exchange for permitting extended coresidence, a comprehensive evaluation must include these components to accurately portray the intertemporal tradeoffs of coresidence. In addition, if children who "owe" their parents these future benefits (after leaving late or returning to the parental home) resist moving in order to pay their parents back in kind, there may exist mutually beneficial opportuntities to improve efficiency.

This paper contributes to the existing coresidence literature by shedding light on the longer-term consequences of coresidence and highlighting intra-family support networks as an important form of transfer. This paper proposes a model consistent with observed empirical facts which has significant implications for governmental policy.

3.2 Data and Sample Characteristics

The full cohort of the 1979 National Longitudinal Survey of Youth (NLSY) is used for the analysis of sibling[1] departure ages as well as the analysis of young adult coresidence's correlation with elderly parent coresidence. The 1979 NLSY is a panel of almost 13,000 men and women born between 1957 and 1964 who have been surveyed annually from 1979 to 1994, and biennially after that.

Questions range from basic demographics to financial practices, job history to sexual behavior, and drug use to political participation. For some categories of questions, participants are asked to recall monthly or weekly characteristics of their life over the last year. The interviews take less than 90 minutes, and participants (in early years, both the parent and the youth) were paid for their time.

Sample Characteristics

As seen in the descriptive statistics presented in Table 2, of the 6,413 individuals in the sample, approximately a quarter are observed to have ever had coresident parents. This proportion increases if we limit the sample to those observed through later ages (e.g. 40). The average individual in the sample has completed high school and some college, scores slightly below the 50th percentile on the AFQT, and earns an average of 50,000 dollars between ages 30 and 45. The sample is equally divided between men and women, and about 30% are black, 20% are Hispanic, with the rest being white or Asian. The average respondent has 3.8

[1] Many thanks to Joe Rodgers for creating and maintaining the NLSY sibling linkages.

siblings, exits the parental household just before age 22, and returns to the parental household, with a final exit at age 27. More than eighty percent of the sample has been married, with about half of those having been separated or divorced. About a quarter of the sample had a child before age 20, and just less than three quarters of the sample have biological children. The slightly lower fertility rates in the sample may be due to truncation during childbearing years, as these rates increase if we limit the sample to those observed through age 40.

Sample Selection

Due to the longitudinal nature of the NLSY, there is a large amount of attrition and missing information for the later waves. While the Bureau of Labor Statistics attempts to survey every member of the original cohort, many original respondents have migrated or are otherwise out of contact, and two large oversamples–the military oversample and the poverty oversample–were dropped from active fielding in 1985 and 1991, respectively. Furthermore, the wave-like nature of the survey means that the respondents were at different life stages when first contacted in 1979. Consequently, approximately 5,000 of the respondents must be excluded from this analysis because they were born before 1960, as many of the members of this cohort would have already exited in 1979 and including only those respondents still coresident in 1979 would bias the sample. Restricting the sample to individuals observed until age 30 or older (in order to have a chance of observing parents coresiding) drops another 1,000 respondents from the sample, and another 300 must be excluded because they are coresident for the duration of NLSY observations (thus no age of exit can be recorded). This leaves a sample of 6,413 men and women, although in some regression specifications the sample will drop to 5,649 due to missing birth order or fertility information.

3.3 Econometric Model

In order to test the prediction that coresidence by children is related to future coresidence by parents, I take advantage of the longitudinal parent-child data in the NLSY. I model the incidence of elderly parents living with adult children as a function of those same children's coresidence behaviors that would have burdened parents during emerging adulthood:

$$\begin{aligned} Pr\{\text{Parents Coreside with } i\} = \beta_0 + \beta_1 \text{Child}_i \text{ Exited Late} + \beta_2 \text{Child}_i \text{ Returned} \\ + \beta_3 \text{Child}_i \text{ Demographics} + \beta_4 \text{Family Resources}_i + \epsilon_i \end{aligned} \tag{3.1}$$

Here, child demographics include gender, race, marital status, fertility, education, and Armed Services Vocational Aptitude Battery (ASVAB) percentile (a measure of intellectual ability). Family resources consist of the number of siblings of the child, the number of children of the child, and income quartile. In this way I approximate the support network available to the child's parents–children with more children of their own (for a given income) have fewer resources to share with parents, and parents with more children have more opportunities to draw resources. If either β_1 or β_2 is positive and significant in equation (4), we have preliminary evidence that coresidence by children is correlated with future coresidence by parents.

3.4 Empirical Results

In Table 2, I investigate the possibility of an exchange relationship through which parents permit inconvenient behaviors by the youth during emerging adulthood (delayed launches or returns) in exchange for future coresidence by the parent. In column 1, I present the correlation between late exits while controlling for a number of family background characteristics. Results suggest exiting at 24 or older raises the probability of having future coresident parents by about 12 percentage points. In column 2, I present the correlation between returns and future coresidence, and find that returns to the parental home raise the probability of having coresident parents by about 20 percentage points. In column 3, we include both explanatory variables and find that they remain high significant, each raising the probability of coresident parents by about 14 percentage points.

In Table 3, I model this relationship non-parametrically. There is an progressively increasing trend in the likelihood of having coresident parents, suggesting that the linear approach is merited. In Table 4, I model these correlations separately for each income quintile, and find that these results are significant separately for each income group, although the effects of returns are concentrated in the lower half of incomes, and the effects of late exits are concentrated in the upper half of incomes.

In Table 5, I present how these results differ by race. We find the strongest effects of returns are concentrated among non-white individuals, and the strongest effects of late exits are concentrated among Hispanic and white individuals. In Table 6, I replace first exits with last exits in the non-parametric model from table 3. Although early values are insignificant, we see the same generally progressive trend, although it does become less significant as we add more controls. However, together, last exits have significant explanatory power in predicting parental coresidence.

In Table 7, I restrict my sample to families where we observe multiple children with at least one parent who eventually coresides with one or more children. Column 1 shows the general effect in this sample, column 2 adds controls and family clustered standard errors, and column 3 includes a family fixed effect. The family fixed effect allows us to compare between siblings–given different ages at exit, what is the probability that the parent chooses to live with the later exiting child? Parents are 22 percentage points more likely to live with a child who exited after age 23, and 42 percentage points more likely to live with a child who returned.

3.5 Models of Coresidence

In order to interpret this correlation, we will set forth two theoretical frameworks from the intra-family transfers literature, and discuss how the findings are contextualized by such models. We will also present a new "mixed motivation" signaling model, consistent with the emerging tendency to model intra-family support in this way.

To ease interpretation across the three models (altruism, exchange, and mixed motivations) in this section, we will adapt all models to a generic framework. All models will represent these decisions as the behavior of the members of a 2-generation, 2-period game, where the child generation members are emerging adults (support from parents during childhood is taken as given), and their parents comprise the other generation. We elect to use a two-period game in order to reflect the distinct timings involved in coresidence exchange.

We observe the education, income, residence, and fertility of the young generation, and the family linkages (siblings, parents, etc.) of these individuals. The young receive a stochastic wage offer, low or high, and can choose whether to try to continue coresiding with their parents or move out. In the second period, elderly parents receive an unobserved stochastic income, low or high, which is their only source of financial support (excluding in-kind services). The middle generation in each period (parents of young adults in the first period, children of elderly parents in the second) can choose to block or permit coresidence by either generation.

There is no opportunity for borrowing or saving in this model. While T will be treated as continuous in all models, we can imagine that T as a continuous measure of parental generosity (perhaps through time transfers), which has some threshold parameter $\bar{T}$ past which the generosity level is sufficient to permit coresidence.

In this model, parents pay a utility cost c for making transfers, they earn a benefit r which is a function of the transfer to children, T_c, and they have some expectation of a transfer in the future which is partly determined by the transfer they make to their children. Children also pay a utility cost c for transfers T_p made to parents, and earn a utility benefit θ for making transfers to parents, which depend on transfers made by parents in the first period.

The parent determines what transfer T_c to make to children in the first period in order to maximize his utility, U:

$$max(T_c)U = -cT_c + r(T_c) + E[T_p|T_c] \tag{3.2}$$

And in the second period, children determine what transfer T_p to make to parents to maximize their own utility:

$$max(T_p)U = -c(T_p) + \theta T_p(T_c) \tag{3.3}$$

Altruism

In the classical model of intra-family altruism proposed by Becker (1981), a benevolent wage-earner (usually the patriarch of a household) maximizes not just his own utility but also some weighted measure of another household member's utility. Adapted to the coresidence framework, we have a parent maximizing his utility from consumption and some function of his child's utility, $\psi(U_c)$, wherein the parent chooses t to transfer to the child as well as consumption Z and coresidence (d=1) is jointly determined:

under coresidence, (d=1) and

$$U_p = U(Z_p, d, \psi(U_c)) \tag{3.4}$$

under independent housing (d=0),

$$U_p = U(Z_p, \psi(U_c)) \tag{3.5}$$

- $\frac{\delta U_p}{\delta \psi(U_c)} > 0$ (parent is altruistic and gets utility from the child's consumption) all else equal (transfers and income),
- $U_p|(d=0) > U_p|(d=1)$ (parents prefer independent living) all else equal (transfers and income),
- $U_c|(d=0) > U_c|(d=1)$ (children prefer independent living)
- $\psi(U_c)$ is a monotonically non-decreasing function of U_c
- the parent's budget constraint is Z_p+t=Y_p
- the child's budget constraint is Z_c=Y_c+t-h*(1-d)

Given that coresident children do not need to pay rent, if child's income is low enough, it is more efficient for the parent and child to live together than have the parent subsidize the child through transfers, as this indirectly increases consumption for the child (by allowing the child to spend h housing cost on consumption instead of rent) and directly increases consumption for the parent (who no longer needs to transfer t out of his consumption budget).

Empirically, income potential tends to rise over time and peak between age 45 and 55, before dropping off rather sharply around retirement age. We can imagine that families with lower degrees of altruism will shift toward independent living at a lower threshold income than those with higher degrees of altruism, but generally, assuming the child's income potential (and thus consumption potential) is monotonically non-decreasing over time for the first 40 years of life, it is easy to see that coresidence is optimal early in life (e.g. during childhood and emerging adulthood when the child's income potential is low) and non-optimal later in life.

If we assume children are altruistic toward their parents, we also have a prediction for parents moving in with children during later adulthood, should parent income (and thus consumption) fall below a certain threshold. Further, should economic circumstances (e.g. job loss during a recession) jeopardize the consumption of either party, we may observe coresidence outside of these typical life cycle timings (as described in Kaplan, 2012).

We could reconcile the phenomenon of these two coresidence behaviors (children residing with parents at older ages and then parents residing with children in old age) with a pure altruism model, but this would require several assumptions on the distribution and selective inheritance of altruistic tendencies to match what we observe in the data. Therefore, I will propose an alternative model which features characteristics of both altruism and exchange, requiring fewer assumptions about heterogeneity and gaining commitment on the part of the child generation.

Exchange

On the opposite end of the spectrum, the exchange hypothesis suggests that observed generosity is due to a "tit-for-tat" arrangement between parents and children, and not maximization of joint utility. While the decision to have children itself is often viewed as an exchange to provide old-age security (Leibenstein, 1957;

Nugent, 1985), this is perhaps less the case in developed nations with extensive savings and support networks for the elderly. Instead, we will take the decision to have children as exogenous to our problem and focus instead on the parental decision to support children during emerging adulthood.

In their review of the intra-family transfer literature, Arrondel and Masson (2006) define exchange as "the implicit contract where (e.g.) parents trade prior education, or the promise of future inheritance, for children's support in their old age, is expected to be mutually advantageous–if enforceable." Indeed, enforceability of this contract is the challenge, due to the distinct timings of each generation's need. If the link between children's late departures and parents' future coresidence were exchange, we would need an additional mechanism to cause children to hold up their end of the bargain when it was their turn to provide housing, due to the distinctly separate timing of these events. Alternatively, we could be observing two sets of exchanges, where parents trade coresidence to children for simultaneous time transfers early in life, and then the children do the same with the parents later in life, but there is nothing to suggest that those two behaviors would be exhibited by the same individuals, so we cannot explain why child coresidence correlates with parental coresidence via exchange alone.

Mixed Motivation/Behavioral

The transfers literature has proposed several mixed models. Indirect reciprocity, also called retrospective altruism, describes the familial cycle of every parent generation providing goods/services to every child or elderly grandparent generation (Bevan & Stiglitz, 1980; Cox & Stark, 1996). This is not an exchange transaction, as there is not necessarily a two-way trade occurring, but the behavior also differs from altruism, and instead functions as a habituation or self-enforcing altruism mechanism. Cox and Stark refer to this as a demonstration effect that causes generations to repeat their parents' seemingly altruistic (or lack thereof) behavior.

In order to adapt these mixed motivation models to the distinct timing challenges of coresidence, I will adopt some enforcement mechanisms from the behavioral literature. It is generally accepted that parents care to some degree about their children, and it is not unreasonable to extend this to parents caring about what their children think of them. Rabin (1993) pioneered the approach of incorporating of social goals in economic modeling, following empirical work by Weisbrod (1988) and Train (1987). Rabin presents a model of fairness where in which agents are willing to sacrifice their own utility to punish or reward individuals for being unfair or fair, respectively. Benabou and Tirole (2005) expand on this framework to analyze whether the existence of rewards and punishments diminishes the potential for signaling generosity, and demonstrate that under certain conditions, it is difficult to arrive at a separating equilibrium due to the signaling "noise" created by rewards and punishments, whether those rewards are tangible (e.g. money) or intangible (e.g. praise/shame). If even ungenerous individuals behave generously (given large enough rewards), this casts doubt on the "true" generosity of those seen exhibiting generous behavior, and can in fact reduce the payoff from generous behavior.

This tendency to care about others' opinions has also been documented empirically (Arai et. al, 2000), such as when individuals do not take advantage of welfare or other publically available support due to concern about "public face." In short, there is a long behavioral literature establishing that the way we behave toward other people is in part determined by what we think they think of us–their esteem for us.

Ellingsen and Johanneson (2007, 2008) propose a model of worker-employer relations in which worker effort is affected by employer generosity, as this perceived employer generosity determines how much the worker cares about the employer's opinion of his effort level. In their model, beliefs about generosity and respect are determined in one period. For the purposes of my analysis, I adapt this framework of generosity and esteem to a two-period model where a child's esteem for his parent is not just generated by chance, but instead determined by that parent's previous generosity toward the child–in particular, by the parent's generosity in permitting extended coresidence. In other words, how I (the child) behave toward my parents is a function of what I think of them, because I only care about their opinion of me if I think highly of them.

Contributed Model

I model the behavior of the members of a 2-generation, 2-period game, where the child generation members are emerging adults (support from parents during childhood is taken as given), and their parents comprise the other generation. This model is a two-period signaling game in order to reflect the distinct timings involved in coresidence exchange. I will present a very simple model in which there are two types of parents and children–generous and ungenerous–who decide whether or not to provide residence to each other during two periods. I observe the education, residence, and fertility of the young generation, the income and family characteristics of the parent generation, and the family linkages (siblings, parents, etc.) among these individuals.

The young receive a stochastic wage offer, low or high, and can choose whether to continue coresiding with their parents or move out. In the second period, elderly parents receive an unobserved stochastic income, low or high, which is their only source of financial support (excluding in-kind services). The middle generation (parents in the first period, children in the second) can choose to block or permit coresidence by each generation.

In this model, I prohibit access to credit markets, which is logical for the young generation who are unattractive to lenders, and potentially plausible as well for the middle generation if the intra-family interest rate on the exchange of in-kind goods such as residence exceeds that of the market. As a consequence, there is no borrowing or saving.

The model is parameterized as follows:

- T_c represents the amount (of time or some other service) parents transfer to children, and T_p represents current valuation of future transfers from children to parents
- θ_c is child's type, θ_p is parent's type (private information at the start of the game)
  - For both generations, type 1 is "generous" and type 2 is "ungenerous"
  - $\theta_{c1} >\_ \theta_{c2} > 0$ (generous children get more utility from generosity)

- c_1T_c is the total cost of transfers for generous parents; c_2T_c is the total cost of transfers for ungenerous parents; $c_2>c_1$
- c(T_p) is the cost function for children;
- p(T_c) is the probability the child holds the parent in esteem given T_c
- r is the parent's valuation of child's esteem

Parents maximize total utility where transfers are costly but they increase the probability of being held in high esteem this period, which both types value, and transfers also affect the likelihood of future transfers from children (which depend on both child type and the child's esteem for the parent); that is:

$$\max_{T_c} U = -c_1T_c + rp(T_c) + E[T_p|p(T_c), \theta] \tag{3.6}$$

$$\max_{T_c} U = -c_2T_c + rp(T_c) + E[T_p|p(T_c), \theta_c] \qquad \text{if type 2 (ungenerous).} \tag{3.7}$$

The child gets utility from transfers to the parent according to her type, but pays a cost c(T_p) for that transfer, with her problem being:

$$\max_{T_p} U = -c(T_p) + \theta_1 T_p p(T_c) \qquad \text{if type 1 (generous);} \tag{3.8}$$

$$\max_{T_p} U = -c(T_p) + \theta_2 T_p p(T_c) \qquad \text{if type 2 (ungenerous).} \tag{3.9}$$

Proposition 1: *There exists a separating equilibrium satisfying the Intuitive Criterion in which parent type is fully revealed by amount transferred to children, wherein ungenerous parents give T_c=0 and generous parents give T_c^*>0.*

Proof The Intuitive Criterion (Cho and Kreps, 1987) tells us that because transfers are costly, ungenerous parents must select T_c=0, and thus p(T_c) must also be 0. Therefore, transfers from the generous parents must be just high enough that ungenerous parents are indifferent between faking generosity and choosing T_c=0.

Suppose we had a pooling equilibrium where ungenerous parents chose T_c such that they were believed to be generous, that is, such that p(T_c)=1:

$$\max_{T_c} U = Y_c - c_2T_c + r*1 + E[T_p|1, \theta_c] \qquad \text{if type 2 (ungenerous).} \tag{3.10}$$

Then $T_c^2 \leq \frac{r+E[T_p|1,\theta_c]}{c_2}$, and so generous parents will choose $T_c^{1*} = \frac{r+E[T_p|1,\theta_c]}{c_2}$ (as utility is decreasing in transfer amount once esteem is established), and we gain separation on types (assuming that indifferent ungenerous parents choose to give nothing rather than fake generosity). However, this must mean that ungenerous parents will choose $T_c^{2*} = 0$.

Solving for the child's decision, because transfers are costly without esteem (remember if $T_c = 0$, $p(T_c) = 0$, ungenerous parents must then receive T_p= 0. Generous parents' transfer receipt depends on child type–

$$\max_{T_p} U = -c(T_p) + \theta_1 * 1 \qquad \text{if type 1 (generous);} \tag{3.11}$$

$$\max_{T_p} U = -c(T_p) + \theta_2 * 1 \qquad \text{if type 2 (ungenerous).} \tag{3.12}$$

Generous children will give T_p such that c'(T_p)=θ_1, and ungenerous children will give T_p such that c'(T_p)=θ_2.

For the parents, the motivation to give is forward-looking, akin to Cox and Stark's demonstration effect. For the children, the motivation to give is backward-looking (as it depends on parent generosity), often called "retrospective" or "golden rule" generosity (Arrondel & Masson, 2001). This model features both esteem and exchange and most closely resembles a serial reciprocity model, in which good behavior is enforced through the family network (members care about other members' opinions as well as how that affects the likelihood of future transfers). It can be directly adapted to the coresidence framework by viewing T as a continuous measure of generosity (perhaps through time transfers), which has some threshold parameter $\bar{T}$ past which the generosity level is sufficient to permit coresidence.

This model also easily adapts to one in which T is offered and observed but not necessarily taken up, perhaps due to stochastic income draws. Individuals would still gain esteem for the offer of T, and future offers of T from children would depend on what the parental offer would be (regardless of use). Furthermore, this model can be adapted to allow the possibility of type inheritance, which would affect the expected value of R in the parent's utility function. For this model to be an accurate depiction of behavior, it requires that the incidence of generosity from parents (in this case, coresidence) is correlated with generosity from children, regardless of child's type. Furthermore, this model also provides a framework in which Cox and Stark's demonstration effect could enforce a family cycle of generosity, causing correlation in coresidence behavior across generations.

3.6 Conclusions

This paper presents evidence that behaviors by youth that inconvenience parents during emerging adulthood are correlated with future youth generosity (permitting parent coresidence in old age). These results are robust to including controls for family size (of both the parent and the child) and regional relocation. The strong results for the family size of both generations suggests that the support network available to the parents plays a role in determining their residence (both the need for coresidence instead of direct financial transfers and the offer of coresidence from various children).

Modeling these behaviors is important for policy in that there is significant potential for government action to crowd out family support networks. According to the mixed motivations model presented, an increase in government support to emerging adults decreases the need for parental transfers at that age, and thus adds noise to the signaling game, preventing parents from precisely communicating their types. This communication breakdown could have repercussions for parental support in old age, as children would be unable to determine which parents were generous and which were ungenerous. Thus we might expect an expansion of aid programs for emerging young adults to cause in increase in need for public aid among elderly individuals 20 years later, a non-intuitive result.

Limitations

Threats to interpretation

Coresidence is a two-part decision (for both types)–observing it requires both that the householder offers it to the potential coresider (either parent or child), and that the coresider needs it. It is reasonably plausible that the family members have a prior on each other's generosity; that is, they know what the offer would be whether or not they need or take up the coresidence. This is a problem for this analysis, as we only observe "used" offers. We are almost certainly underestimating the generosity from both generations, but one could argue that "making good" on the offer is a higher level of generosity, and that is what we are able to measure.

Omitted variable bias

In observing the young person's coresidence decisions (late exits/returns), we should be concerned about systematic differences in the need of coresidence that correlate with parental demonstrated willingness/generosity. However, we attempt to account for these systematic differences by approximating the individual's support network. To do this, we control for marriage and household income (two earners are less likely to need parental support), age at first birth (potentially a disruption to employment/education), and number of biological children (tighter budget constraint for a given income).

We do not observe residential location specifically enough to incorporate local labor market characteristics, and so we would be concerned about the situation where a youth needs coresidence because of an economy-driven job loss, but the parents are unable to provide coresidence due to foreclosure on their house (though they are willing). This correlation between need and take-up could cause us to be under-observing generosity, which could potentially bias our estimate in the main regression specification. This would cause us to underestimate the magnitude on "returns," because there is generosity in this family which is unobserved, and the cause blocking the visibility of generosity (bad economy) could also cause the parent to need coresidence later in life. However, that would mean that what we observe is an underestimate of the true effect, and our results support a positive finding even with this potential bias.

For us to overestimate the magnitude of the correlation, there would need to be an unobserved variable that is positively correlated with both parental coresidence and youth coresidence. Potential causes of this could be a disabled family member (observationally quite rare–see tables B2 and B3 in the Appendix), or other systematic hindrance to earning income (e.g. personality not conducive to employment that is common to both generations). However, controlling for income should account for the majority of a family correlation in "need."

Mismeasurement

We have imputed exits for those who are observed to coreside and then are missing in the data, and then show up as not coresident. This is a small number of exits (214 of more than 6,000) and their exclusion does not significantly affect the estimates. As the data are self-reported, there are also concerns about misrepresentation. For example, some 17-year-olds claim to be living in a household independent of their parents in which they are the primary householder. We have recoded any occurrence of a respondent younger than 25 claiming to be head of household but reporting coresident parents as independent housing for both; that is, we have not recorded this as parents living with children (dependent parents), but have not recorded this as children living with parents (dependent children). In the tables presented, the only parental figures coded as coresident are biological or step-parents (not in-laws), but inclusion of mothers-in-law, fathers-in-law, step-mothers-in-law, and step-fathers-in-law does not significantly change the estimates.

Observing the wrong relationship (omitted variables, no bias)

There may be inherent characteristics that cause people to be dependent or simply prefer coresidence and these are genetically or behaviorally transmitted between parents and children. One would expect, then, that children who themselves left late would be more likely to coreside with their children when older. Unfortunately the cohorts in the NLSY are not yet old enough to measure this effect, but this will be testable as the 1979 cohort ages. We also present in Appendix Table B4 a comparison among those in the 10th percentile of exits, those in the 90th percentile of exits, and those at the mean. We show that while white individuals are more likely to leave early, and black individuals are more likely to leave late, exiters at all ages look fairly similar in terms of education, birth order, and self-esteem (although early exiters are slightly more educated). Furthermore, just as with altruism, we would need these characteristics to be selectively transmitted along certain parent-child dyads and not others in order to find the between-sibling effect.

In any case, while we may be putting the wrong label on the observed relationship, it is concretely observed. We would need exogenous variation in the intended age of departure (and thus in capacity to signal generosity) in order to disentangle our empirical findings from a simple model of tastes, and future work should incorporate local labor market characteristics.

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Figure 3.1: Homeownership and Coresidence among Young Adults

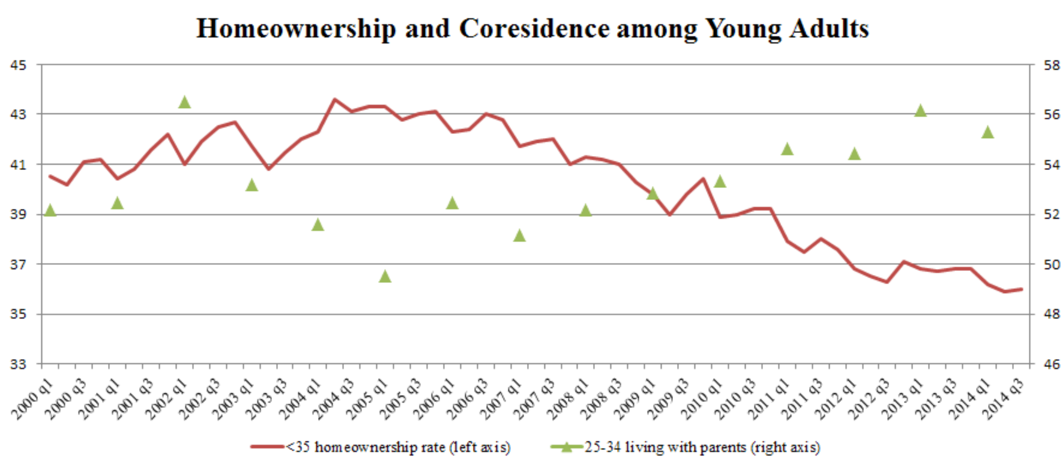

Table 3.1: Descriptive Statistics of Sample

	Count(N)	Mean	Std. Dev.
Dependent Variable			
Parents ever live with respondent	6,413	0.24	0.43
Education/Income			
AFQT percentile	6,144	41.08	28.80
Highest grade completed	6,413	13.2	2.5
Average income from 30 to 45	6,272	49,988	51,981
Assets	5,850	6,048	12,003
Demographics			
Female	6,413	0.50	0.50
Hispanic	6,413	0.19	0.39
Black	6,413	0.30	0.46
First born	6,405	0.20	0.40
Last born	6,405	0.25	0.43
Total siblings	6,405	3.8	2.6
Exit variables			
Exited parental household prior to 1979	6,413	0.07	0.26
Age at first exit from parental household (of those not already out in 1979)	6,199	21.6	3.0
Age at last observed exit from parental household	6,199	27.0	7.5
First exited at 24 or older	6,413	0.20	0.40
Ever returned to parental household	6,413	0.61	0.49
Family formation			
Never married	6,413	0.18	0.39
Ever separated or divorced	6,413	0.41	0.49
Biologically parented child before age 20	5,089	0.24	0.42
Age at first birth	5,089	24.4	5.9
Any biological children	6,019	0.72	0.45
Biological children	6,019	1.6	1.4

Table 3.2: Probability of Parents Living with Adult Children (LPM)

	(1)	(2)	(3)
Exited past 23	0.119***		0.135***
	(0.0191)		(0.0183)
Separated or divorced	0.0778***	0.0491***	0.0551***
	(0.0155)	(0.0153)	(0.0152)
Highest grade completed	0.00180	0.000458	0.000843
	(0.00378)	(0.00369)	(0.00367)
Female	-0.0479***	-0.0339**	-0.0339**
	(0.0148)	(0.0145)	(0.0144)
Married	-0.210***	-0.191***	-0.184***
	(0.0254)	(0.0248)	(0.0246)
Black	0.0542***	0.0454**	0.0391**
	(0.0195)	(0.0190)	(0.0189)
Hispanic	0.110***	0.0953***	0.0897***
	(0.0214)	(0.0211)	(0.0209)
Total siblings	-0.00776***	-0.00707**	-0.00686**
	(0.00291)	(0.00287)	(0.00286)
Own children	0.0336***	0.0367***	0.0414***
	(0.00633)	(0.00620)	(0.00619)
AFQT	-0.000668*	-0.000724**	-0.000567*
	(0.000343)	(0.000337)	(0.000334)
Youngest	0.0533***	0.0469***	0.0496***
	(0.0178)	(0.0174)	(0.0172)
Live where raised	0.0714***	0.0687***	0.0572***
	(0.0200)	(0.0197)	(0.0199)
Ever returned		0.198***	0.206***
		(0.0129)	(0.0128)
Constant	0.308***	0.211***	0.143**
	(0.0595)	(0.0577)	(0.0580)
Observations	3,595	3,595	3,595
R-squared	0.103	0.138	0.153

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Also includes controls for income quintile and birth year.

Table 3.3: Probability of Parents Living with Adult Children (Nonparametric)

	(1)	(2)	(3)
Exited at 20	0.0467**	0.0225	0.0261
	(0.0192)	(0.0201)	(0.0204)
Exited at 21	0.0733***	0.0594***	0.0540**
	(0.0206)	(0.0216)	(0.0217)
Exited at 22	0.0726***	0.0525**	0.0508**
	(0.0219)	(0.0229)	(0.0231)
Exited at 23	0.132***	0.117***	0.113***
	(0.0241)	(0.0254)	(0.0257)
Exited at 24	0.121***	0.0934***	0.0949***
	(0.0292)	(0.0308)	(0.0308)
Exited at 25	0.162***	0.142***	0.144***
	(0.0324)	(0.0341)	(0.0345)
Exited at 26	0.210***	0.192***	0.195***
	(0.0404)	(0.0418)	(0.0418)
Exited at 27	0.182***	0.160**	0.160**
	(0.0552)	(0.0627)	(0.0640)
Exited at 28	0.321***	0.288***	0.287***
	(0.0588)	(0.0595)	(0.0594)
Exited 29+	0.377***	0.336***	0.335***
	(0.0463)	(0.0467)	(0.0468)
Ever returned	0.235***	0.212***	0.210***
	(0.0123)	(0.0130)	(0.0131)
Separated or divorced		0.0614***	0.0593***
		(0.0149)	(0.0151)
Female		-0.0312**	-0.0332**
		(0.0142)	(0.0143)
Married		-0.187***	-0.182***
		(0.0241)	(0.0244)
Black		0.0310*	0.0332*
		(0.0187)	(0.0189)
Hispanic		0.0892***	0.0897***
		(0.0205)	(0.0207)
Total siblings		-0.00810***	-0.00650**
		(0.00276)	(0.00283)
Own children		0.0409***	0.0433***
		(0.00618)	(0.00624)
Youngest			0.0523***
			(0.0169)
Lives where raised			0.0511***
			(0.0198)
Constant	0.0187	0.174***	0.0996*
	(0.0141)	(0.0531)	(0.0583)
Observations	4,098	3,676	3,595
R-squared	0.102	0.158	0.164

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.4: Probability of Parents Living with Adult Children by Income (LPM)

	(1) Low	(2) Lower Middle	(3) Middle	(4) Upper Middle	(5) Upper
Exited past 23	0.120***	0.101**	0.111***	0.172***	0.183***
	(0.0430)	(0.0417)	(0.0394)	(0.0401)	(0.0398)
Ever returned	0.245***	0.237***	0.267***	0.167***	0.136***
	(0.0389)	(0.0334)	(0.0311)	(0.0248)	(0.0227)
Separated or divorced	0.0735	0.0723*	0.0223	0.0456*	0.0445
	(0.0553)	(0.0411)	(0.0337)	(0.0275)	(0.0286)
Female	-0.0563	-0.0823**	0.0417	-0.0435	-0.0530**
	(0.0407)	(0.0358)	(0.0336)	(0.0267)	(0.0265)
Married	-0.0862	-0.211***	-0.226***	-0.354***	-0.245***
	(0.0551)	(0.0503)	(0.0565)	(0.0765)	(0.0783)
Total siblings	0.00521	-0.0180***	-0.00794	-0.00348	-0.00643
	(0.00700)	(0.00559)	(0.00579)	(0.00622)	(0.00682)
Own children	0.0444***	0.0565***	0.0267*	0.0454***	0.0461***
	(0.0132)	(0.0151)	(0.0160)	(0.0125)	(0.0131)
Youngest	0.185***	0.0171	0.0430	0.0683**	0.00603
	(0.0524)	(0.0445)	(0.0423)	(0.0345)	(0.0276)
Black	0.0238	0.00461	0.0729*	0.0445	0.0626
	(0.0505)	(0.0426)	(0.0430)	(0.0360)	(0.0425)
Hispanic	0.0394	0.156***	0.101**	0.137***	-0.00377
	(0.0608)	(0.0511)	(0.0454)	(0.0426)	(0.0394)
Lives where raised	0.0835	0.0963*	0.0252	0.0547	0.0264
	(0.0847)	(0.0562)	(0.0457)	(0.0343)	(0.0318)
Constant	-0.0199	-0.0748	0.223	0.128	0.417***
	(0.171)	(0.145)	(0.137)	(0.140)	(0.128)
Observations	670	663	705	721	836
R-squared	0.109	0.154	0.160	0.181	0.126

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Also includes controls for birth year.

Table 3.5: Probability of Parents Living with Adult Children

	(1) White	(2) Black	(3) Hispanic
Exited past 23	0.148***	0.113***	0.145***
	(0.0267)	(0.0303)	(0.0431)
Ever returned	0.167***	0.267***	0.218***
	(0.0161)	(0.0251)	(0.0359)
Separated or divorced	0.0478**	0.0626**	0.0586
	(0.0186)	(0.0309)	(0.0392)
Female	-0.0513***	0.00482	-0.0544
	(0.0186)	(0.0273)	(0.0368)
Married	-0.236***	-0.158***	-0.160***
	(0.0412)	(0.0380)	(0.0600)
Total siblings	-0.0129***	-0.00390	-0.00553
	(0.00460)	(0.00453)	(0.00585)
Own children	0.0546***	0.0391***	0.0332**
	(0.00896)	(0.0102)	(0.0149)
Youngest	0.0304	0.106***	0.00981
	(0.0207)	(0.0355)	(0.0524)
Live where raised	0.00592	0.114***	0.117**
	(0.0242)	(0.0439)	(0.0537)
Constant	0.347***	0.0682	0.0156
	(0.0827)	(0.113)	(0.143)
Observations	1,737	1,184	674
R-squared	0.143	0.143	0.132

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: Also includes controls for income quintile and birth year.

Table 3.6: Probability of Parents Living with Adult Children (Nonparametric)

	(1)	(2)	(3)
Last exit at 20	-0.0151	-0.0284	-0.0615
	(0.0222)	(0.0464)	(0.0650)
Last exit at 21	-0.0141	-0.0170	-0.0594
	(0.0232)	(0.0433)	(0.0707)
Last exit at 22	-0.0107	-0.0136	-0.0850
	(0.0233)	(0.0440)	(0.0643)
Last exit at 23	0.0168	-0.00870	-0.109*
	(0.0272)	(0.0449)	(0.0584)
Last exit at 24	0.0168	0.0178	-0.0191
	(0.0272)	(0.0503)	(0.0659)
Last exit at 25	0.0249	0.00734	0.132
	(0.0289)	(0.0514)	(0.0813)
Last exit at 26	0.117***	0.127**	0.0536
	(0.0442)	(0.0643)	(0.0937)
Last exit at 27	0.155***	0.299***	0.0278
	(0.0526)	(0.0739)	(0.0809)
Last exit at 28	0.203***	0.206***	0.138
	(0.0650)	(0.0746)	(0.106)
Last exit at 29	0.294***	0.288***	0.370***
	(0.0672)	(0.0829)	(0.104)
Last exit 30+	0.430***	0.439***	0.410***
	(0.0307)	(0.0380)	(0.0542)
Constant	0.0766***	0.127***	0.222***
	(0.0130)	(0.0298)	(0.0421)
Observations	1,949	1,277	748
R-squared	0.185	0.194	0.183

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Columns 2 and 3 also contain controls for birth year, income quintile, AFQT, and education, and column 3 also controls for birth order.

Table 3.7: Probability of Needy Parents Coresiding with a Given Child

	(1)	(2)	(3)
Exited past 23	0.122***	0.142***	0.218***
	(0.0289)	(0.0315)	(0.0722)
Ever returned	0.316***	0.298***	0.417***
	(0.0279)	(0.0292)	(0.0634)
Ever separated or divorced		0.0995***	0.136*
		(0.0329)	(0.0766)
Education		0.00241	-0.00684
		(0.00692)	(0.0209)
Female		-0.0563*	-0.0803
		(0.0297)	(0.0699)
Black		-0.0813***	
		(0.0261)	
Hispanic		-0.0459*	
		(0.0243)	
Total siblings		-0.00579*	
		(0.00338)	
Biological children		0.0539***	0.0796***
		(0.0102)	(0.0227)
AFQT		0.000342	0.000220
		(0.000637)	(0.00201)
Married		-0.223***	-0.312***
		(0.0423)	(0.0914)
Constant	0.230***	0.357***	1.379***
	(0.0219)	(0.0971)	(0.280)
Observations	1,250	1,164	1,164
R-squared	0.095	0.160	0.316

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Column 2 SEs are clustered by family. Column 3 contains a family fixed effect. Columns 2 and 3 include controls for income and birth year.

Chapter 4

Learning by “I Do”ing: A Model of Marital Stability

Abstract

When couples say “I do” at the altar, they pledge to a lifelong marriage, but many couples part before death. This paper investigates the process that leads some couples to divorce, focusing on a potentially important factor: learning. Spouses learn about one another over the course of the marriage, and this information can lead to a reassessment of the marriage. A model of Bayesian learning provides several distinctive predictions, which are tested using data from the 1979 cohort of the National Longitudinal Survey of Youth (NLSY79). Specifically, individuals are assumed to learn about a spouse's “capability,” which is modeled using item responses on the AFQT, a test of cognitive skills. Findings consistent with the model include (a) the divorce hazard is higher for low-capability individuals, especially a few years into marriage; (b) in terms of predicting divorce, the role of capability (which is not easily observed) increases over time relative to schooling (which is easily observed); and (c) an adverse shock to the capability assessment (in the form of a job layoff or firing) has a greater impact on divorce for high-capability individuals. These findings provide insight into the inequality in marriage stability observed in the U.S. across income, education, and cognitive ability.

JEL Keywords: J12, J63, D83

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The day two people say "I do," they anticipate spending their lives together, but this is not always the case. Over time spouses learn about one another, and this progression of character revelations can lead to divorce. Individuals marry with particular expectations about each other and their shared future, and these expectations are revised over time as new information arrives. In this paper I study how this learning process affects the decision to divorce.

Marital stability is of broad societal concern and has garnered a great deal of attention among social scientists, as it affects a wide range of behaviors and outcomes, including location decisions, labor supply, fertility, home-buying, and consumer spending. However, the traditional "'til death do us part" marriage may not be desirable by all—important work by Geronimus (2003) illustrates the validity of many models of family and fertility. Still, divorce plausibly has important effects on both the couple divorcing and any children involved. Amato (2010) notes that spouses who divorce experience a decline in mental health and an increase in mortality. There may be additional long-lasting effects on children: Amato (2010) points to evidence that, as adults, those whose parents divorced obtain less education, feel less close with their parents, and face a greater risk of their own marriages ending in divorce. On the other hand, high-conflict marriages that do not end in divorce are also costly. Morrison and Coiro (1999) found that in high-conflict marriages that do not dissolve, behavioral problems among children are even more frequent than among children whose parents do divorce. Insight into the complex issues surrounding marriage requires conceptual clarity about the forces that determine marital stability, highlighting the value of research that helps us understand these forces.

My contribution is to set out a model of learning in marriage and to test the model's implications. The key assumption in my theoretical setup is that among the many factors determining an individual's satisfaction with a spouse, one is the assessment of a characteristic I will term "capability." Prior to marriage, a wife will judge her future husband's capability and marry him only if he is deemed to be sufficiently capable.[1] After marriage she will likely update that assessment over time. This process entails Bayesian updating, through which she evaluates her existing assessment in comparison to new information, and forms a new belief that is a precision-weighted combination of the two. I embed this learning within a utility framework: individuals divorce if utility falls to a sufficiently low level, which happens if the current capability assessment is sufficiently low.

The learning model of marriage has several predictions. First, individuals who actually do have high capability are less likely to divorce. Second, very early in marriages, divorce rates will be low, as little relevant news has accumulated since the day of marriage. The divorce rate is then expected to rise over time as learning occurs. Eventually, most spouses will have formed reasonably precise assessments of their spouse, so divorce late in marriages will be rare; there is thus a decline in the divorce rate among remaining marriages. Third, new information about the husband's capability may arrive in the form of labor market shocks, and the effect of such a shock will depend on the resulting correction to the previously-held belief. Thus, a sharply negative shock will be particularly divorce-inducing for those who were previously assessed to be highly capable.

[1] In my empirical work, I can only study opposite-sex couples, so in describing marriage I use nouns and pronouns accordingly. Often I will refer to a *wife* forming assessments of her *husband;* the logic is symmetric so readers can mentally swap the genders if they like.

Of course, the process I am describing can never be directly observed. However, I can make headway studying the logic of the model using data from the National Longitudinal Survey of Youth (NLSY79). These data record life outcomes for more than 12,000 individuals born between 1957 and 1964. The data include records of cohabitation and marriage; a large majority of individuals in the data married at least once. Importantly for my work, the data include item responses to an assessment tool, the Armed Forces Qualification Test (AFQT), which is a broad measure of aptitude and ability. Performance on the AFQT is indicative of native cognitive ability, along with many factors that matter for future success, including cognitive skills, ability to focus and persist, work habits, and interest in learning. In important studies documenting employer learning in the labor market, Farber and Gibbons (1996) and Altonji and Pierret (2001) show that performance on the AFQT is an important predictor of labor market success that is not fully observable to employers. I am making an analogous argument for marriage—suggesting that the AFQT measures traits that are valuable in life generally, and within marriage specifically, but that these traits are (initially) not observable to spouses.

Many papers use the AFQT score as an independent variable in regression models (e.g., Farber and Gibbons, 1996; Altonji and Pierret, 2001; Neal and Johnson, 1996). As Bollinger (2003) and others have noted, there is a methodological issue with this standard practice. At best, the AFQT measures a *latent* trait, and does so imperfectly; it is problematic to treat a summary measure (the AFQT "score") as if it were an ordinary explanatory variable. I therefore take an alternative approach, relying on recent advances in statistics developed in Junker et al. (2012) and formalized in Schofield et al. (2015), which treats latent traits in terms of a posterior distribution. The posterior is estimated using the full array of item responses from the original AFQT, which are available in recent releases of the NLSY79. I estimate a series of models that provide evidence in support of propositions developed in my theory.

I find, first of all, that the divorce hazard is higher for low-capability individuals than for high-capability individuals, especially a few years into the marriage. Second, in terms of predicting divorce, the role of the unobservable latent characteristic (capability) increases over time relative to observed characteristics like schooling. Third, I conduct a series of investigations examining the impact of a job market shock on divorce. I find that, in general, job losses hamper marital stability. Importantly, when an individual has a job loss "for cause," i.e., is laid off or fired (as opposed to losing a job because of a business closure), this serves as a highly pertinent piece of information about capability. Such a shock is particularly likely to be followed by a divorce among individuals for whom the shock is most informative, i.e., for those who would previously have been assessed as having high capability.

My work is the first to explicitly demonstrate how an unobserved latent trait like capability can be learned through a sequence of public and private signals, which then translate to heterogeneous divorce risks. My work is also unusual in terms of its focus on learning *after* marriage has taken place.[2] Much of the literature focuses on learning in premarital search and matching (e.g., Becker, 1974; Shimer and Smith, 2000; Smith, 2006; Choo and Siow, 2006; Chiappori, Oreffice, and Quintana-Domeque, 2012), which may impact overall match quality, but not the timing of divorce. Furthermore, this learning provides a compelling explanation for the hetergeneous divorce risks by capability already documented in the literature (Herrnstein and Murray, 1994; Dronkers, 2002; Holley et al., 2006; Blazys, 2009; Black, Taylor, and Zaber,

[2]Brien, Lillard, and Stern (2006) and Marinescu (2016) are notable exceptions.

2014). Previous work has established that capability matters to a number of life outcomes (e.g., for labor market outcomes, Lindqvist and Vestman, 2011 and Heineck and Anger, 2008; for risky behaviors, Heckman, Stixrud, and Urzua, 2006; for early childbearing, Shearer et al., 2002), and this paper adds to the literature the notion that it is *demonstrable* cognitive ability that matters to marriage outcomes. Finally, my work contributes to a growing literature on the importance of non-observables to matching (e.g., Dupuy and Galichon's 2014 work on personality traits).

4.1 Previous Work

Informational asymmetry has been featured in many models of marriage and cohabitation. Oppenheimer (1988) applies logic from the theory of job search to marriage timing to show how changes in wages and labor force participation ratios between men and women and the subsequent decrease in household specialization could explain the delay in first marriages. With less household specialization, gains from marriage will come from coordination and matching on other components of marital utility. Oppenheimer suggests that the associated rising importance of matching could explain the increase in premarital cohabitation. In agreement, Cherlin (2004) refers to modern premarital cohabitations as "trial marriages." Brien, Lillard, and Stern (2006) create a structural model of cohabitation, marriage, and divorce, and conclude that a primary motivation for cohabitation is the need to learn about one's partner. While they discuss intra-marital learning, they do not explicitly measure any unobservable spousal characteristics.

My work is also connected to papers by Weiss and Willis (1997) and Charles and Stephens (2004), who present empirical results that can be contextualized by a model in which spouses learn about each other after they marry. Using the Panel Study of Income Dynamics (PSID), Charles and Stephens show that layoffs and firings increase the probability of subsequent divorce, but plant closures and disability do not, despite having an impact on both short- and long-term wages. These results suggest that marriage-relevant information conveyed by a job loss is not simply that the spouse has lower earnings potential. Weiss and Willis also find that an unexpected increase in the husband's earnings stabilizes the marriage.[3] In contrast, Hankins and Hoekstra's (2011) analysis of lottery winners finds that winning the lottery (both large and small amounts) does not change divorce rates, but it does change the probability that a single woman gets married. These results are consistent with a model in which only "merited" income shocks affect divorce.

Marinescu (2016) formalizes a test among several models of marriage, using the shape of hazard curves and the response to labor market shocks as differentiating predictions. She finds that a model where marriage quality changes over time, rather than being initially unknown and then learned, fits the Survey of Income and Program Participation (SIPP) data best. However, she finds contradictory results with the National Longitudinal Survey of Youth (NLSY) 1979 cohort that is used in this paper. I supplement Marinescu's hazard test with a proxy for what is unknown, a measure of the amount of initial uncertainty, and a second data set, the Panel Study of Income Dynamics (PSID). Finally, I simulate the model, comparing the resulting

[3] They also find that an unexpected increase in the wife's earnings actually destabilizes the marriage, perhaps suggesting that wages could be a useful signal of a husband's quality for a wife, but a wife's wages may perhaps play a more important role in determining the value of her outside options.

hazard curves to those observed in the NLSY, and conclude that learning is the most likely explanation for the patterns observed.

4.1.1 Empirical Regularities

Before proceeding to my theoretical and empirical contributions, it is worthwhile to review a number of empirical regularities about marriage and divorce established in the existing literature:

1. The probability of marriage is not related to capability (measured by AFQT score). Black, Taylor, and Zaber (2015) establish (using the NLSY79) that there are few significant differences in rates of ever being married within a race-gender combination: AFQT scores seem to play little role in determining who gets married.[4] I show this fact again in Figure 4.1: within a race-gender combination, there is little relationship in the rates of ever being married (by age 55) and AFQT score.

2. There is substantial heterogeneity in divorce rates and capability. Herrnstein and Murray (1994) and Black, Taylor, and Zaber (2015) establish that who *stays* married is correlated with capability: those of higher capability are significantly less likely to get divorced than their low-capability counterparts. Figure 4.2 shows that the probability of getting divorced does vary by capability within race and gender.

3. Few marriages dissolve in the first year. Clarke (1995) uses divorce registrations to plot the proportion of divorces at different marriage durations. She shows that the divorce rate in the first year is half of that in years two and three. Figure 4.3 demonstrates that the initial hazard is low (around 1.5 percent of NLSY79 first marriages dissolve within the first year), peaking around year seven.

4. Marriages face a decreasing divorce risk over time. Clarke's (1995) data show that a much smaller fraction of divorces occur late in the marriage. Brien, Lillard, and Stern (2006) also document the decline in hazard for both marriage and cohabitation as relationship duration increases. Figure 4.3 also shows that after about seven years of marriage, the risk of divorce monotonically decreases.

In the following section, I develop a model consistent with these existing facts, generating distinctive predictions that I subsequently test empirically.

4.2 Theoretical and Empirical Framework

Standard marriage models (e.g., Becker, 1974) posit that individuals marry when joint surplus under marriage is believed to exceed some threshold, where the threshold is a function of what each spouse expects if he or she is single or is married to someone other than the spouse. Of course, all relevant surplus calculations are

[4] In the cohort used in this paper, marriage markets are generally segregated by race.

subjective evaluations that are based on public and private signals. Clearly, learning will be relevant both to the marriage decision and subsequently for any decision to divorce.

I work with the familiar "normal learning" model. To simplify matters I focus only on capability. There are many other traits that matter to marital surplus, and there may be insights from models that have learning along multiple dimensions.[5] However, the central ideas are most clearly conveyed with a simple setup.

4.2.1 Learning model

Let θ denote a husband's *capability*, and let $\hat{\theta}$ be the wife's assessment of that capability. Assume that $\hat{\theta}$ is a direct argument in the utility function; wives value having a husband whom they consider to be capable, $\frac{\partial U}{\partial \hat{\theta}} > 0$.

The characteristic θ is not observed at the time of marriage. Instead, the wife has a judgment based on objective characteristics and on other subjective information she has collected prior to the marriage. For example, suppose she observes schooling (s), which is informative about capability, and also some additional information, x_0, which is known to be drawn from a normal distribution, $x_0 \sim N(\theta, \sigma_0^2)$. The wife then forms an initial assessment, given by

$$\widehat{\theta_0} = E[\theta | s, x_0]. \tag{4.1}$$

There are two key properties of this time-0 assessment:

First, if the wife knows the joint distribution of θ, s, and x_0, then in expectation her assessment $\widehat{\theta_0}$ lies between her husband's true (unobserved) capability θ and the mean value of θ among men with his schooling level s. So, for example, if she marries an exceptionally capable man, she will typically underestimate his capability, as $\theta > E[\widehat{\theta_0}] > E[\theta|s]$. Let the variance of this initial belief be τ_0^2, and note that this τ_0^2 depends on the precision of s and x_0 as predictors of θ.

Second, in my model, a divorce will occur if the wife's utility level falls to a sufficiently low level, which happens if the assessment of θ falls below some threshold, denoted θ_D.[6] Given that there are substantial fixed costs to a divorce (e.g., Bougheas and Georgellis, 1999), forward-looking behavior means that the wife will marry in the first place only if $\widehat{\theta_0} - \theta_D > c$, where c is a positive constant related to the anticipated cost of any future divorce.

Now suppose that after marriage, the wife gains a new piece of information in the form of a draw, $x_1 \sim N(\theta, \sigma^2)$. She updates her assessment accordingly:

$$\widehat{\theta_1} = \widehat{\theta_0} + \left[\frac{\tau_0^2}{\tau_0^2 + \sigma^2} \right] (x_1 - \widehat{\theta_0}). \tag{4.2}$$

[5] Assortative mating is known to play a role in matching (e.g., Kalmijn, 1994; Mare, 1991), and the empirical work will allow for matching on education. However, the data used in this analysis do not allow me to observe assortative mating on the unobservable characteristic, so the model that follows will only allow one spouse's characteristic to matter to divorce.

[6] The value of θ_D could evolve over time as outside options change, but for simplicity I treat it as a constant.

After n such draws (assumed for the moment to be i.i.d.), her updated assessment takes the following form:

$$\widehat{\theta_n} = \left[\frac{\sigma^2}{n\tau_0^2 + \sigma^2}\right]\widehat{\theta}_0 + \left[\frac{n\tau_0^2}{n\tau_0^2 + \sigma^2}\right]\bar{x}. \tag{4.3}$$

Notice that as n increases, the weight placed on the initial assessment declines and the weight on the post-marriage information increases. Because $E[\bar{x}] = \theta$, the wife's assessments of her husband's capability are converging to the true value.[7]

New information may sometimes arrive in an idiosyncratic fashion; for instance, suppose that in period t a highly-relevant piece of information arrives. Let that information be $x_t \sim N(\theta, \sigma_t^2)$. Then, as in (2), the assessment update is

$$\widehat{\theta}_t = \widehat{\theta}_{t-1} + \left[\frac{\tau_{t-1}^2}{\tau_{t-1}^2 + \sigma_t^2}\right](x_t - \widehat{\theta}_{t-1}), \tag{4.4}$$

where τ_{t-1}^2 is the variance of the previous $(t-1)$ assessment of θ. The new information is "highly relevant" if σ_t^2 is small, in which case the coefficient on $(x_t - \widehat{\theta}_{t-1})$ is relatively large, *and* the new information x_t differs substantially from the previously-held assessment $\widehat{\theta}_{t-1}$.

4.2.2 Implications

The model has several implications, which I discuss here. Additional details on more formal proofs are available in Appendix II.

Proposition 1. *In expectation, individuals with high values of θ are less likely to divorce than those with low values of θ.*

This results immediately from the fact that high-θ people on average have capability that is underestimated at marriage, while low-θ individuals tend to have capability that is initially overestimated. Intuitively, news after marriages will tend to be "good news" for individuals who are genuinely high-capability, but the opposite is true for low-capability individuals.

Proposition 2. *Suppose information arrives as in (4.3). Then if the anticipated cost of divorce is sufficiently high: (a) the probability of divorce will initially be rising over time among individuals who will eventually divorce, and (b) as the number of signals increases (n becomes large), marriages that have survived become increasingly likely to never end in divorce.*

Part (b) of the proposition is straightforward. The marriages that survive will be ones for which θ is well above θ_D, and so signals x_t are increasingly less likely to induce divorce. As for part (a), notice that $\hat{\theta}_0 - \theta_D > c$, so the divorce threshold on the right-hand of (5) is decreasing in c, particularly when n is small. Even when a marriage is destined to end because $\theta < \theta_D$, as in the example, the divorce will virtually never happen for $n = 1$, i.e., immediately after marriage. Note that these two properties will tend to lead to a hump-shaped divorce hazard. A similar argument is outlined in Jovanovic (1979). Note further that if τ_0^2

[7] Also, the variance of $\widehat{\theta_n}$ is $\tau_n^2 = \frac{\tau_{n-1}^2\sigma_{xn}^2}{\tau_{n-1}^2+\sigma_{xn}^2} = \frac{\tau_0^2\sigma_x^2}{\sigma_x^2+n\tau_0^2}$; thus, the precision in assessment is increasing over time.

is close to 0 (i.e., if the initial prior is extremely reliable relative to signals), signals will play little role in updating $\widehat{\theta}$, so the learning shape will be less pronounced.

Proposition 3. *As signals accumulate over time, an observable component of the initial prior such as schooling* (s) *will have progressively less weight in the assessment of capability, and thus be less predictive of divorce. The converse is true of* θ *itself.*

This proposition parallels the learning results of Farber and Gibbons (1996) and Altonji and Pierret (2001). It follows from (4.3). Notice that the weight on the initial prior $\hat{\theta_0}(s)$ is decreasing in n, while the corresponding weight on $\bar{x}$ is increasing. As $E[\bar{x}] = \theta$, θ is thus more predictive of divorce over time.

Proposition 4. *A low-variance signal* x_t *will increase the probability of divorce if it is substantially lower than the currently-held capability assessment* $\widehat{\theta}_{t-1}$.

This follows from (4); the weight on x_t is greatest when a signal is precise and is a strong corrections to previous beliefs. Examples might include an arrest or infidelity.

Proposition 5. *Given identical* $\bar{x}_n$ *and* $\widehat{\theta_0}$*, a signal occurring early in the marriage (e.g., at* $n = t$*) will have a greater impact on divorce risk than an identical signal occurring later in the marriage (at* $n = t + 1$*).*

Note that the derivative of $\hat{\theta_n}$ with respect to a single x_n can be written as $\frac{\tau_0^2}{\tau_0^2 n + \sigma_x^2}$. This is clearly decreasing in the number of signals n, so an identical x_n occurring after $t-1$ signals would have a stronger effect than that same x_n occurring after t signals, all else constant.

4.2.3 Characteristics of θ

Thus far, I have discussed a single θ that matters to marital stability. There are many possible candidates for θ—unobservable or imperfectly observed characteristics that affect utility from marriage. However, most characteristics that are unobservable to a spouse are also unobservable to the econometrician. I take advantage of the rich set of variables in the National Longitudinal Survey of Youth 1979 cohort (NLSY79), and use a measure of capability (as measured by a cognitive ability test) as θ. The capacity to demonstrate cognitive ability on a test depends on actual cognitive ability, but also on diligence, respect for authority, ability to focus, etc. Furthermore, those with high cognitive ability may have other marriage-valuable attributes such as openness or creative problem-solving, indistinguishable from cognitive ability in the data.

Thus, I will refer to this unobserved characteristic as "capability," reflecting the rich set of desirable qualities potentially correlated with cognitive ability. Still, there is empirical basis for cognitive ability contributing to marital satisfaction. Christensen (1947) created a mate selection survey that has been administered to various samples of single Americans over the past several decades, asking participants to rank various potential mate attributes in order of importance. While "love" has consistently ranked first since 1977, dependable character falls second, and education and intelligence have been in the top five since the 1980s. In contrast, ambitiousness is ranked eighth, and good financial prospects are ranked tenth (Boxer, Noonan, and Whelan, 2015), suggesting that, at least in theory, cognitive ability may matter to spouses more than what that ability buys in the labor market.

4.2.4 Assessing θ

Cognitive ability is a latent construct, entering into regression models as "measured" cognitive ability from some test, denoted $\tilde{\theta}$. Any test score is imperfect in capturing cognitive ability: in particular, it depends on the individual's ability to demonstrate his or her ability on a test (a function of that individual's characteristics), and the validity of the test as a means of separating individuals of different abilities. This "errors-in-variable" problem is explored at length in work by Griliches (1977; 1985) and more specifically with regard to the Armed Forces Qualifications Test (AFQT) score by Bollinger (2003).

The AFQT score has been used as a traditional explanatory variable in a number of important works, including the work of Farber and Gibbons (1996) and Altonji and Pierret (2001) on employer learning and Neal and Johnson's (1996) work on black-white wage differences. While accounting for inherent skill can shed light on important phenomena in labor economics, the direct use of AFQT score as an explanatory variable neglects to account for the inherent measurement error. This raises a unique variant of the "errors-in-variable" problem—not only is there measurement error, but this measurement error is also heteroskedastic and non-normal (Schofield, 2014). This stems from the difficulty in constructing test questions separating the tails of the distribution—the error in AFQT score will be U-shaped. Thus, the coefficient on an AFQT score is inherently biased, and the coefficients on any other explanatory variables X_i correlated with AFQT would also be biased.

I take advantage of new statistical techniques developed in Junker et al. (2012) and formalized in Schofield et al. (2015), conditioning the prior distribution for θ on the X_i from the equation of interest. Following this literature, I construct a system of equations, Mixed Effects Structural Equations (MESE), to simultaneously account for this conditioning and estimate the relationship between θ and divorce:

$$\text{divorce}_i \sim \text{Bernoulli}(q_i), \qquad \ln\left[\frac{q_i}{1-q_i}\right] = \beta_0 + \beta_1\theta_i + \beta_2 X_i + \epsilon_i \tag{4.5}$$

$$p_{ij}|\theta_i \sim IRT(p_{ij}|\theta_i, a_j, b_j, c_j) \tag{4.6}$$

$$\theta_i|X_i \sim N(\theta_i|\alpha_0 + \alpha_1 X_i, \delta^2) \tag{4.7}$$

where individuals are indexed by i, test items are indexed by j, X_i represents other covariates in the divorce model that may be correlated with θ (e.g., education, fertility, gender, etc.), p_{ij} is the probability that individual i answers question j correctly, and IRT represent the three parameter logistic (3PL) distribution described in Appendix II. Note that the formulation in (4.5) implies a type I error distribution; i.e., the various βs are logit coefficients. Here, equation (4.5) is the equation of interest, and equations (4.6) and (4.7) construct the posterior and prior distributions of θ, respectively.[8]

I use the 3PL parameters (a_j, b_j, c_j) from Schofield (2014) to construct the ability distribution from the item responses as shown in (4.6). I use Markov Chain Monte Carlo (MCMC) simulations implemented with the JAGS package in R (Plummer, 2003) to estimate the MESE coefficients of (4.5), and use the conditioning model in (4.7) as the prior for ability. I opt for simulation rather than explicit calculation of likelihoods due to the size and complexity of the estimation.

[8]This approach is similar in philosophy to estimating θ using 105 instruments—each of the 105 responses to the AFQT items is a binary measure correlated with capability.

In a few specifications (i.e., those involving restricted data), I am unable to use MESE coefficient estimation due to the substantial computational demand. While there is implicit heteroskedasticity in measured cognitive ability, the measurement error should be at its minimum at the middle of the distribution—it is easier to separate "high" ability from "low" ability than to separate "high" from "higher" ability. I confirm that the direction of the results presented is consistent with what I obtain when I simply split capability into above average and below average.

4.3 Empirical Strategy

The model presented in the previous section set out several empirically testable predictions in the form of propositions. Proposition 1 states that those of higher θ should experience less divorce after enough learning has occurred. In Section 3, I showed evidence in the raw data that those of higher measured capability are less likely to divorce over their lifetime. However, to reflect the per-period risk, I estimate the following divorce hazard as a function of capability θ_i for each sex ($F_i = 1$ if the respondent is female), conditioning on several observable characteristics (schooling, s_i; an indicator for being black, B_i; and an indicator for being Hispanic, H_i):

$$\lambda_{it} = f(\theta_i, F_i | s_i, B_i, H_i) \tag{4.8}$$

I additionally estimate regression coefficients of the following logistic regression using the MESE framework. Here, each time period t represents a two-year span.[9]

$$\tilde{\lambda_{it}} = \beta_0 + \beta_1\theta_i + \beta_2 F_i + \beta_3 B_i + \beta_4 H_i + \beta_5 a_i + \beta_6 k_{it} + \beta_7 t + \beta_8 t^2 + \beta_9 t^3 + \beta_{10} E_i + \epsilon_{it} \tag{4.9}$$

where θ represents the respondent's measured capability, and there are indicators for female (F_i), black (B_i), and Hispanic (H_i). I also control for the respondent's age at first marriage (a_i), the current number of children (k_{it}), a cubic in years married, and a set of indicators for spousal education matching (E_i) with vector coefficient β_{10}. Variables k_{it} and E_i function to capture variation in divorce costs (e.g., if divorce costs increase with the number of children) and marital quality (if assortative matching on education enhances marital quality), a relaxation of the simplifying assumptions in the model.

The second proposition states that if learning is happening, the divorce hazard should be initially rising and then falling, and that the sharpness of the "learning peak" will be proportional to the variance in the initial prior, τ_0^2. The plot of the hazard function in (4.9) can also be used to reflect this rising and falling shape. However, I do not have an explicit measurement of τ_0^2. It is plausible that some individuals have more reliable priors on their spouse's characteristics due to a longer courtship or to greater access to premarital signals. Living with a future spouse before marriage may be indicative of lower earnings, but it would also give such couples greater opportunity to learn about each other's habits, personality, and capability. With c_i indicating premarital cohabitation with the first spouse, I assume $[\tau_0^2 | c_i = 1] \leq [t_0^2 | c_i = 0]$, such that premarital cohabitors have (weakly) more precise priors.

[9] I use $\tilde{\lambda_{it}}$ to denote hazard models where this is the case. While year of divorce can be imputed, other time-variant variables such as job separation cannot, so models using these variables will define a two-year hazard.

I estimate eight separate hazard curves, stratifying on sex, premarital cohabitation (c_i), and capability (above/below average):

$$\lambda_{it} = f(\theta_i, F_i, c_i | s_i, B_i, H_i) \tag{4.10}$$

to determine if premarital cohabitors have a reduced divorce risk and a less peaked hazard curve.

If premarital cohabitation reduces τ_0^2, more premarital cohabitation should (weakly) reduce τ_0^2 more. Thus, I estimate MESE regression coefficients of a smoothed hazard to determine if there is a "dosage" effect to cohabitation:

$$\begin{aligned} \tilde{\lambda_{it}} = \beta_0 + \beta_1\theta_i + \beta_2 F_i + \beta_3 B_i + \beta_4 H_i + \beta_5 a_i \\ + \beta_6 k_{it} + \beta_7 t + \beta_8 t^2 + \beta_9 c_i^t + \beta_{10}(C_i^t \times \theta_i) + \epsilon_{it} \end{aligned} \tag{4.11}$$

where C_i^t is a set of dummies for length of cohabitation.

The model predicts that the elements of α_1 should be negative and increasingly so (as cohabitation duration increases, presumably τ_0^2 decreases).

In their paper on on employer learning, Altonji and Pierret (1997) showed that employers shift weight from observable factors to unobservable factors as job tenure increases. I employ a similar strategy, as Proposition 3 predicts that the protective effect of capability will be increasing in marriage tenure, and the protective effect of schooling, an observable characteristic, will be decreasing in marriage tenure.

I estimate MESE logistic regression coefficients of the following model:

$$\begin{aligned} \tilde{\lambda_{it}} = \beta_0 + \beta_1\theta_i + \beta_2 F_i + \beta_3 B_i + \beta_4 H_i + \beta_5 t + \beta_6 t^2 + \beta_7(\theta_i \times t) \\ + \beta_8 s_i + \beta_9(s_i \times t) + \epsilon_{it} \end{aligned} \tag{4.12}$$

where s_i represents schooling. I allow for potential nonlinearities in this model by estimating it both with linear θ_i and s_i and with indicator versions of these variables (above-average θ_i and college attendance). Additionally, I plot the resulting hazard to visualize the "turning point" past which the relationship with θ_i overtakes the relationship with s.

Proposition 4 suggests that signals very indicative of θ (e.g., with low σ_x^2) should affect the hazard more than those that are less precise. While spouses obtain signals from many venues, one set of signals observable to both the econometrician and the spouse is the set arriving from the labor market. While individual wage observations are noisy, job losses are well-documented in the NLSY and varied in their precision. For example, getting fired from a job is an extremely negative, precise signal. In contrast, losing a job because the business closed is much noisier—the closure could have been related to a particular individual's lack of productivity, but it is far more likely related to administrative decisions and macroeconomic conditions. Thus, I can compare the impact of low σ_x^2 and high σ_x^2 signals:

$$\begin{aligned} \tilde{\lambda_{it}} = \beta_0 + \beta_1\theta_i + \beta_2 F_i + \beta_3 B_i + \beta_4 H_i + \beta_5 t + \beta_6 t^2 + \beta_7 t^3 \\ + \beta_8 a_i + \beta_9 k_{it} + \beta_{10}\gamma_{it} + \beta_{11}(\gamma_{it} \times \theta_i) + \beta_{12} E_i + \epsilon_{it}. \end{aligned} \tag{4.13}$$

Here, γ_{it} is an indicator for the first job loss of a particular type observed within the marriage. I will compare the β_{10} obtained using a layoff or firing and a business closure as the job loss type. Using a geocoded subsample of the NLSY, I will also estimate (4.13) with an additional $\beta_{12}u_{it}$ term, controlling for the respondent's county's current unemployment rate. This will allow me to identify the effect of a job loss on divorce net of any wider macroeconomic conditions.

Note also the interaction between θ and γ_{it} captured by β_{11}. Proposition 4 also states that negative signals should increase the hazard more for those of high θ, predicting that when the γ indicator represents a layoff or firing, β_{11} should be positive and significant, but when γ represents a business closure, β_{11} should be insignificant.

Furthermore, the value of a more reliable prior should differ by true θ as θ determines the stream of signals received (as $E[x_t] = \theta$). Equation (4.11) also interacts θ with cohabitation duration, and Proposition 4 suggests that this interaction should be positive: higher θ individuals gain less from cohabitation. This property can also be viewed in the plots of the eight hazard curves referenced in the discussion of Proposition 2.

Proposition 5 states that it is not only σ_x^2 and the magnitude of x that matters—the timing of x_t determines how much of an impact the signal will have. Thus, I estimate approximate hazard curves by marriage tenure, splitting on the seventh year of marriage. Proposition 5 predicts that λ_t will rise more for those laid off or fired early in their marriage compared to those with the same shock later in marriage, as it is a precise and negative signal being weighted against a less precise prior.

I estimate equation (4.13) again, with four specifications: a layoff or firing early in marriage, a layoff or firing late in marriage, a business closure early in marriage, and a business closure late in marriage. The model predicts that β_{10} early in marriage should be less than β_{10} later in marriage with a layoff, but in the case of business closures, β_{10} should not change, as timing matters only for learned information.

4.3.1 Identification

Causal identification is a perennial challenge in marriage research, as researchers cannot randomize couples to different quality marriages, nor to marriages with different amounts of information about that quality. While I observe a measure of capability, I do not observe the spouse's current-period belief about capability, the information set of the spouse, some of the informative signals, nor the amount of error in the distribution of both beliefs and signals. Furthermore, error in measured capability biases coefficients on variables related to test performance in the standard reduced-form framework.

Although I do not claim to identify the causal effect of capability on divorce, I do amass substantial evidence consistent with the predictions of the learning model. The first prediction suggests that higher-capability individuals will experience less divorce, and that this occurs because this capability is a gradually learned utility-relevant factor in marriage. It could also be the case that capability is perfectly known at the altar, and high-capability individuals face higher costs of dissolution or that low-capability individuals gain less utility from marriage overall. Alternatively, low-capability marriages may be more exposed to utility-disruptive shocks like layoffs and firings. While I do not directly observe divorce costs, I can compare marital satisfaction and subsequent divorce using the rich set of variables in the NLSY, conditioning on happiness to see if differential divorce rates persist. If low-capability individuals gained less utility from marriage, first marriage rates would have to be comparably smaller. Finally, I control for utility-disruptive shocks so that differential exposure alone cannot account for my results.

The second prediction involves a rising and falling hazard. While learning requires this shape, this shape could also be obtained by a model with evolving divorce costs. I control for the number of children as an approximation of divorce costs. In addition, a pure cost model does not predict the distinctive separation by capability present in the raw data, nor does it predict any variation in divorce risk by the reliability of the initial prior. Premarital cohabitation, my approximation of τ_0^2, is endogenous and known to be correlated with marital quality. However, this correlation is generally inverse—premarital cohabitation is generally associated with an increased risk of divorce, meaning tests of this prediction will have conservative bias. I also employ a "dosage response" model, which measures the protective benefit of an additional year of cohabitation, conditioned on already cohabiting. If the effect of cohabitation on divorce is pure selection, the length of the cohabitation would be irrelevant.

The third prediction suggests that observable factors should give way to initially unobservable factors in predicting divorce as time progresses. Suppose high-capability individuals are better at addressing marital conflict, and little marital conflict shows up until the honeymoon period is over. This situation would also lead to capability becoming increasingly protective. However, this would not explain a corresponding decline in schooling's importance. Furthermore, if high-capability individuals were better at dealing with marital conflict, they would presumably be better at dealing with utility-disruptive shocks like layoffs and firings. The learning model predicts the opposite relationship, so this prediction helps distinguish the learning model from one where capability is purely correlated with marriage skill.

The fourth prediction indicates that precise, strongly corrective signals will have the greatest impact on the divorce hazard. The first challenge lies in identifying which shocks are perceived to be precise. I view job losses "for cause" as precise, and those due to economic circumstance or chance as imprecise. However, the spouse has access to an additional source of learning—private signals—which is unobserved by the econometrician. Fortunately, this would cause me to underestimate the amount of learning, as I am able to measure only the learning correlated with informative shocks. While ever experiencing a shock is almost certainly correlated with marital quality, I hold with Charles and Stephens (2004) that the arrival of a shock in a given period is likely to be exogenous. Violation of this exogeneity would require a respondent to watch his marriage quality decline, and then allow his job performance to suffer so much that he was fired before the divorce was finalized. While this is possible, this situation is unlikely to comprise a significant portion of sample divorces.

I cannot observe the error in beliefs directly, but I can use the predictability of the shocks to determine how pronounced the learning process is. According to the fifth prediction, later first shocks are less likely to impact beliefs (and therefore divorce risk) than those early in the marriage, as private learning will have conveyed a large amount of information already. While marriages generally become more stable as time passes, I allow the slopes of all the variables to differ between the "early" and "late" specifications, and additionally include a time trend.

4.4 Data

I use data from the 1979 National Longitudinal Survey of Youth (NLSY79), a representative sample of individuals born between 1957 and 1964. The NLSY79 presents several distinct advantages. First, the NLSY contains information on a unique variable: performance on the Armed Forces Qualifications Test (AFQT). While this test was created to measure aptitude for various forms of military service, it can also be interpreted as a measure of general intelligence. Second, the longitudinal nature of the NLSY79 allows us to precisely distinguish a first layoff from a second layoff, rather than generalize about the effect of layoffs. Third, in some years, wives were asked about their degree of happiness with their marriages, as well as how frequently they argue with their spouses about certain topics. Thus, although inferring marital quality from divorce/marriage continuation is possible, I can also infer marital quality from marital happiness, a more disparate and thus preferable measure. Additionally, the restricted geocoded data from the NLSY is used to incorporate local labor market characteristics that may affect marital quality or opportunities for learning about capability.

The disadvantage of using the NLSY is its relatively low frequency in surveying. The NLSY started out as an annual survey in 1979, and then switched to biennial surveying in 1994. However, respondents are still asked to "fill in" important events that happen between response dates. It is possible that using recall data may introduce some error to my analysis, but it is unlikely to be systematic. The primary concern would be the censoring of extremely short-duration marriages. However, Loftus and Marburger (1983) show that recall data is fairly reliable when landmark events are involved. Mitchell (2010) focuses specifically on the accuracy of reporting divorce dates, matching self-reports in the Life Events and Satisfaction Study to administrative records, and finds that 90 percent of reported divorce dates are within a year of the filed divorce certificate. Mitchell also finds that failing to report a divorce is rare, and finds no cases of individuals reporting a divorce that did not occur. Thus, I expect measurement error in year of divorce to be quite limited.

Survival time analysis techniques allow me to include individuals who disappear from the sample before divorcing. However, I do impose several restrictions on the main sample. I drop those who are never observed to marry, those who have no valid AFQT score, and those for whom education and/or spouse's education are unrecorded. The effect on sample size can be seen in Table 4.1.

I drop observations of second or later marriages (as well as individuals who marry previously married spouses), as available information and learning processes in subsequent marriages may differ. For specifications involving local labor market conditions, I will limit to those living in counties for which I have Current Population Survey (CPS) estimates of the local unemployment rate. For specifications involving marital quality, I will limit to women married by age 26, as these questions were only asked of women, and only in later rounds of the survey. The age limitation serves to reduce the effect from "late bloomers" and to constrain the estimates to those who marry at more standard times.

Additionally, I compare divorce hazard curves generated using two samples from the Panel Study of Income Dynamics (PSID). While the NLSY79 is an incredibly rich dataset, the sampling frame is smaller than that of the PSID. However, the PSID contains no measure of capability unobservable to the spouse at marriage, so these data will be used only to estimate hazard curves to supplement the test of Proposition 2.

I select two subsamples: one of individuals born between 1940 and 1979, and one of individuals born in the NLSY79 cohort (1957-1964).

Finally, for the specifications that include local labor market characteristics, I use the Current Population Survey (CPS). Neither the NLSY nor the PSID contains enough individuals to accurately estimate local labor market characteristics. Thus, I use the CPS data on annual county-level unemployment rates where married NLSY79 respondents reside to contextualize labor market shocks.

4.4.1 Key dependent variables

Divorce

Timing of divorce is identified using two key variables. First, the NLSY constructs a marital history for each respondent containing the most up-to-date information (including corrections across survey years), and the dates of marriage and divorce are primarily pulled from this history. However, in some cases, these constructed variables are missing, so I infer dates of marriage and divorce by isolating changes in marital status (reported every survey year).

Divorce within two years

As many other variables in the NLSY are not restrospectively coded, I use "divorce within two years" as a smoothed version of the divorce variable. This variable has a valid value for any currently still-married person, and is coded as 0 if there is no divorce within two years, and 1 if there is a divorce in either the following year or the year after.

Marital quality

A marital quality supplement was given to married women in the NLSY79 starting in 1992 (and every other year since then). This supplement asked for the rating of the happiness of the marriage ("Very happy," "Fairly happy," or "Not too happy") as well as how often they argued about topics such as religion, children, money, and family. Unfortunately, this supplement was not filled in retrospectively, so I have data only for women who were still in their first marriage in 1992.

4.4.2 Key independent variables

Cohabitation

Cohabitation is indicated both by the report of marital status and by the spousal history. Where the cohabitation occurred with an eventual spouse, I can identify the month cohabitation began and thus determine the length of premarital cohabitation. Due to the rarity of casual cohabitation (cohabitation with partners other than the eventual spouse) in this cohort, I do not use information on other forms of premarital cohabitation.

Layoff/firing

Respondents who report a job ending are asked the reason for the job's end. I consider an individual to have been laid off or fired if he reports “Layoff, job eliminated” or “Discharged or fired.” This information is recorded both annually and by job, and I code a layoff or firing as any layoff or firing from any job in a given year. I also construct an indicator to see if a particular layoff or firing was the first one observed within the marriage, as subsequent layoffs or firings may have a different impact on divorce risk. I combine layoffs and firings, as they are not distinguished in all years of the NLSY79, and because approximately a quarter of layoffs are “for cause” (Barron and Loewenstein, 1985).

Plant/business closure

This variable is also constructed from the job-end question. I code responses of “Company, Office closed,” “Plant closed,” and “Closed business down” as closures—labor shocks stemming from information about the company rather than about the worker individually. Note that only some individuals work in industries likely to be exposed to plant or business closures.

Education matching

In some specifications, a set of controls for “education matching” is used to difference out baseline differences in marital quality. Following Charles and Stephens (2004), I construct a nine-category index of education level and similarity. Each spouse is coded to one of the following educational groups: “less than or exactly high school,” “some college,” “exactly (four-year) college or beyond college.” An index for the couple combines the set of three for each spouse, yielding nine possibilities. While the NLSY respondent may be male or female, I do not impose symmetry on these coefficients, and I consistently code the husband’s education as the first set and the wife’s education as the second.

Family structure

In some specifications, I also control for time-specific marital investments through the fertility measures in the NLSY. I include the number of children in the household, an indicator for the presence of children younger than five, and the age of the youngest child in the household. Most specifications will control only for the number of children in order to not drop childless couples.

4.4.3 Sample characteristics

I use three samples from the NLSY79 in this analysis.[10] As seen in Table 4.2, the main and unemployment samples are gender-balanced, but the marital quality supplement was only issued to women. The NLSY79 contains an oversample of black and Hispanic individuals, as do each of the samples. On average, individuals in the NLSY79 have slightly lower measured capability than the national average. Many individuals in the sample experience some form of job loss, with roughly a quarter having been laid off or fired at least once, and a fifth having experienced a plant or business closure. About a quarter of the sample cohabited before marriage, and a vast plurality of the marriages are composed of individuals with a high school education or

[10]For brevity, sample characteristics from the PSID and CPS samples are not presented, but are available from the author upon request.

less. The average individual's first marriage is observed for 13.4 years, but this falls to 7.4 if I condition on having been divorced (i.e., the average marriage among those who are observed to divorce lasts 7.4 years). Figure 4.4 shows the distribution of the length of first marriages conditional on an observed divorce in the sample. The upper part of the distribution does not appear to be truncated; thus, I am confident that I have a long enough marital history to pick up the majority of eventual divorces.

4.5 Empirical results

4.5.1 Do spouses learn?

Figures 4.5 and 4.6 show how the differential rates of divorce by capability are reconciled over marriage tenure—divorce risk is initially very similar, and then high-capability couples gains an advantage from years two to twelve, with divorce risks identical for later years. While I am splitting at the part of the capability distribution with the most precision, I confirm these results by plotting a hazard estimated with MESE. I model the probability of divorce within two years as a function of capability, a cubic in years married, as well as controls for age first married, number of children, education matching, gender, and race/ethnicity.

These figures present evidence that the separation of divorce risk by capability cannot be attributed to education alone. Even after accounting for education, race, and gender, the same rising and falling divorce hazard persists, with clear separation by capability. For men, the log-rank and Wilcoxon-Breslow-Gehan tests for differences in the adjusted survival curves (years 0-15) have p-values of 0.04 and 0.004, respectively. For women, the log-rank test has a p-value of 0.06, and the Wilcoxon-Breslow-Gehan test has a p-value of 0.01. Thus, consistent with Proposition 1, I conclude that the differences by capability for both men and women remain significant after accounting for education and race. Furthermore, the hazard curves follow the pattern predicted in Proposition 2.

Proposition 2 also predicts that those with more precise priors are less likely to divorce. In Figures 4.7 and 4.8, the "learning peak" for non-cohabitors is much steeper than for cohabitors, suggesting that less learning occurs during marriage for those who lived together before marriage. I additionally confirm that more cohabitation is increasingly protective against divorce: Table 4.7 shows that cohabitation of less than one year significantly reduces divorce risk compared to no cohabitation, and cohabitation of one or more years additionally significantly reduces the divorce risk. While there may eventually be decreasing returns to cohabitation, this "dosage" effect is consistent with the model predictions (so long as more years of cohabitation continue to reduce τ_0^2). This result also suggests that cohabitation's protective impact is not purely due to the selection of positive cohabitations into marriage after some fixed trial period.

Table 4.3 tests the predictions of Proposition 3, comparing the relative trajectories of schooling and capability coefficients on divorce risk. The learning model predicts that capability should have little effect in early years, but should become more protective (reducing divorce risk) as time goes on. In contrast, the model predicts that observables like schooling will be protective early in the marriage, but that these effects would fade over time, leading to a positive coefficient on the duration interaction term. The results are consistent with the learning model—ability is protective and becomes more protective over time; college is initially protective but this effect fades over time. These results are robust to linear specifications in capability and education.

Proposition 4 implies that negative and reliable signals will not only increase the risk of divorce, but also that they will do so especially when the prior suggested the spouse was high θ. In Table 4.4, I demonstrate that while job losses universally increase the risk of divorce, this effect is most pronounced among job losses "for cause"—namely, layoffs and firings. Furthermore, the interaction between the job loss and capability is significant only for layoffs and firings, suggesting that business closures' effect on divorce risk stems from something other than a revised belief of capability.

In Table 4.5, I run this same model on a subsample of the NLSY79 for whom I can match locations. The effects and significance are similar to that of Table 4.4, so Table 4.6 uses the same sample to separate out layoffs or firings that may be due to local economic conditions rather than an individual's capability by including a control for the county's average annual unemployment. The unemployment rate has a modest, but insignificant, effect in increasing the divorce risk, but importantly, the effect of job loss remains significant. By including the unemployment rate, the variation captured by the job loss is the variation independent of local economic conditions, and thus reflective of either the individual or the company. As in Table 4.4, job loss interacted with capability remains significant and positive for the types of shocks that I expect to communicate capability.

Proposition 4 also implies that a more reliable prior is more valuable for those of low capability, as their spouses would otherwise be learning "bad news" compared to those who married high capability spouses. Presumably, spouses who knowingly married a low-capability partner are not surprised to learn that their partner is low capability, and so there should be less change in the divorce hazard. In Figures 4.7 and 4.8, cohabitation associates with a greater reduction in divorce (larger vertical difference in the hazard) for low-capability individuals (the chi-square statistic for equality is three times as large). In fact, low- and high-capability couples who have cohabited prior to marriage face no significant difference in divorce risk (p $\approx$ 0.13 for males, p $\approx$ 0.60 for females). In Table 4.7, the benefit from cohabitation noted previously is far greater for those of low capability than those of high capability.

In Table 4.8, I estimate the job loss model by timing of the job loss. I find that the increase in divorce from a layoff or firing is almost entirely due to the effect in the first seven years of marriage. The coefficient for later years of marriage is insignificant and a third of the magnitude. In contrast, the effect of a business closure early in the marriage is not significantly different from the effect of a business closure later in the marriage. While the standard error is large relative to the magnitude of the coefficient, I find an additional positive and marginally significant relationship between layoffs or firings and divorce for higher-capability individuals. This is consistent with the prediction that high-capability individuals face steeper consequences from negative signals, as they have a higher period-specific belief of capability.

4.5.2 Interpretation of θ

While firings are negative signals of both future earnings and actual capability, plant closures are negative signals only of future earnings. Thus, if the main driver of capability's impact on divorce rates were purely pecuniary, plant closures should have an effect equal to that of firings and layoffs. I have already shown that this is not the case, as layoffs have an additional effect in the form of an interaction with capability. The results of this interaction also suggest that the heterogeneity in divorce by capability does not stem solely from high-capability individuals being better at handling marital stress.

I provide further evidence by considering a sample of married women who are never observed to participate in the labor market. Figure 4.9 shows that divorce rates among nonworking females are generally higher among low-capability women than among high-capability women. However, this explanation is indistinguishable from strong assortative mating by capability, allowing women's capability to proxy for that of their spouse.

I also interact my measures of labor market shocks with an indicator for receipt of unemployment insurance. If the effect of shocks is due only to a reduction in current wages, receipt of unemployment insurance should mitigate that reduction. I find no evidence that this is the case, and the effect from shocks remains significant after controlling for unemployment insurance.

4.5.3 Extensions on marital quality

Next, I take advantage of the rich set of variables in the NLSY79 to shed light on the reasons for differential divorce rates. Women in the NLSY79 were asked questions about their marital quality, rating their happiness on a scale of one to three, and describing the frequency of their arguments about various topics. Previous work using this supplement has found that while premarital cohabitors have lower initial marital quality than non-cohabitors, this is entirely attributable to premarital conception, and after accounting for this factor, cohabitors and non-cohabitors face equally declining marital quality over time (Tach and Halpern-Meekin, 2009). Mizell and Steelman (2000) also find that while more children generally decrease marital quality, this relationship subsides if all of the children are male.

The model suggests that couples divorce when beliefs about current and future marital quality fall short of what was expected at the time of marriage. While I have no direct measure of marital quality, I can use the marital quality supplement to assess marital happiness. Table 4.9 shows that high-capability females *do* start out with happier marriages, but this happiness gap disappears after approximately 15 years of marriage. The learning model suggests that the happiness gap is due to differences in revealed quality, and after 15 years of marriage, sorting on this new information is complete.

In Table 4.10, high- and low-capability females are shown to leave unhappy marriages at roughly the same rates, so it is unlikely that differential divorce rates are due to different thresholds for marriage quality—I find no evidence that high-capability women stay in unhappy marriages at higher rates than low-capability women. Thus, the differences in divorce rates are unlikely to be driven by different costs of divorce.

Using the data on arguments in the marital quality supplement, I can also investigate differences in the household dynamic. High-capability women are less likely to argue with their husbands about money, other women, drinking, children, chores, and the husband's family. However, most of these differences arise over time. In the first seven years of marriage, the only significant differences in arguing are about other women and drinking. Furthermore, there's no significant difference in the amount of arguing about affection, leisure time, and the wife's family. While arguing increases the risk of divorce, conditional on arguing, high- and low-capability women are equally likely to get divorced.

4.5.4 Robustness and sensitivity

The findings of this paper differ greatly from those of Marinescu (2016), obtained using SIPP data. To verify that the hazard shape estimated is not a quirk of the NLSY79 data or its comparably lower frequency in surveying, I construct a divorce hazard using married PSID respondents of the same birth cohort as the NLSY79. Figure 4.10 shows that the rising and falling shape to the hazard curves found in the NLSY79 is not unique to that sample. Marinescu combines marital separations and divorces in her measure of marriage dissolution. If many divorces are preceded by a separation, and separations are a lower-cost option than divorce, this could explain the differing results. However, I additionally combine reported separations and divorces in the NLSY and find the same significantly rising and falling hazard.

While the cohort sampling frame of the NLSY gives an excellent view into the behavior of that cohort, it is possible that their choices are anomalous. Furthermore, there were many legislative changes to both divorce and fertility legislation[11] in the decades before members of the NLSY79 cohort were marrying, and these may affect the usefulness of learning. Given the differing cohort ages of the NLSY79 and the SIPP, I additionally use a larger sample from the PSID, including married individuals born between 1940 and 1979. Figure 4.11 shows that whether I limit to the same cohort or examine any of four decades, the PSID sample gives the same canonical learning shape of a rising and falling hazard.

Additionally, I confirm that the main specifications are robust to both linear and dummy specifications. If the relationship between capability and divorce were concentrated in a particular portion of the capability distribution, the local effect averaged over the whole sample would result in a coefficient biased toward zero in a linear specification. I find the same sign and general significance whether I split at the 50th percentile or use a linear specification.

4.6 Simulation

As an additional check of the sensibility of this model, I simulate the model for 10,000 married white males of similar characteristics to the NLSY79, drawing capability from a standard normal distribution. I condition education distributions on being below- or above-average capability, using a bimodal distribution for above-average capability individuals to capture the dual peaks at exactly high school and college educations observed in the NLSY79. I allow the spouse to form a conditional expectation of capability based on education, and set each marriage's threshold for divorce θ_D equal to the time-0 belief less divorce costs (parametrized to be 1.15 standard deviations of capability to fit observed average divorce rates).

[11] Throughout the 1970s, many states passed "no-fault" divorce legislation. *Roe v. Wade* was decided in 1973. The average year of first marriage for NLSY79 respondents is 1984, and the earliest is 1971, so I have little heterogeneity in exposure to different legislation in the NLSY79.

In Figure 4.12, I calculate the time-specific divorce hazard for all individuals in the simulated sample. The simulation features the canonical rising and falling hazard consistent with the model, though I do over-predict divorce in later years of marriage. Relaxing the assumption of signals being drawn from a stationary distribution (i.e., allowing σ_x^2 to decline with t) improves the fit considerably.

In Figure 4.13, I calculate hazards for individuals simulated to have above- and below-average capability. The model easily generates the separation by capability featured in the NLSY, although the learning process for high-capability individuals is underestimated in simulation. If divorce costs were not uniform, but rather a proportion of the initial belief, the simulation generates more learning for high-capability individuals. However, even the simple case pictured here generates a rising and falling hazard, and reflects that the differential divorce rates also rise and fall with learning.

These results suggest that a learning model where marital expectations are formed based on a limited set of information (here, schooling, race, and gender) is enough to generate differential divorce rates by capability and the general timing of those divorces. In Figure 4.14, I show how beliefs could evolve for simulated individuals of various true capability and educational levels. One can think of the difference between the red and green lines as the amount of discoverable surplus (where green is above red)—the amount of "good news" that will be received later. Similarly, where the red line is above the green, the difference indicates the amount of "bad news" conveyed to the spouse. Thus, where education distributions are condensed, low-capability individuals are particularly disadvantaged: the mix of low and high-capability individuals at a particular education level sets the expectation, and the more high-capability individuals present, the higher the expectation that the low-capability individual needs to meet. Therefore, the premarital provision of reliable information is key for appropriately setting expectations for the marriage. This simulation provides a basis for future structural work.

4.7 Conclusion

This paper provides compelling evidence in favor of marital learning, and the model provided accounts for the previously unexplained inequality in divorce rates by capability. Policy and marital status are inextricably linked: benefits for programs such as Veteran's disability, Supplemental Security Income, and Medicaid as well as tax exemptions are dependent on current marital status. This paper demonstrates that learning both at and during marriage plays a significant role in determining the ultimate stability of a match, with implications for future analyses of policies affecting marriage. There is an extensive literature examining the effects of legislation about unilateral divorce (e.g., Wolfers, 2006), marriage penalties (e.g., Alm, and Whittington, 1999), and paternity obligations (e.g., Stevenson and Wolfers, 2007). My model suggests that future policy analyses should also regard implications for learning when modeling the effect of legislative changes.

My model also has positive implications for policy. While the timing of marriage may not seem to be something policymakers can control, policies regarding cohabitation and fertility likely impact individuals' decisions on when to wed. Cohabitation serves as a valuable opportunity for forming reliable priors, and a rushed marriage would curtail such opportunity. The current versions of the Earned Income Tax Credit

(EITC) and Temporary Assistance to Needy Families (TANF) do not discourage cohabitation, and critics have pointed to the "marriage penalty" paid by some recipients who transition from cohabitation to marriage. This "marriage penalty" may actually be providing a very important function: increasing the opportunity for pre-marital learning among a population generally predisposed to higher divorce rates (Amato, 2010).

Social norms and laws about contraceptives and fertility can also impact marriage timing. Goldin and Katz (2002) show that access to oral contraceptives increased the age at first marriage among women, and provided there was no impact on at what age these women encountered their eventual partners, opportunities for forming a reliable prior were likely similarly increased. In contrast, if unexpected pregnancy induced some women to marry earlier than intended, opportunities for forming reliable priors would be decreased.

Finally, my results suggest that firings and layoffs destabilize not only income streams, but also marriages. There is an economic literature examining employers' motivations for firing and laying off workers, finding that some job losses occur without "just cause" (Levine, 1989). Some job losses may occur due to bad luck and employer misinformation, and this paper suggests that such losses may increase the risk of divorce among individuals who are likely to be highly capable.

Ultimately, many factors contribute to the decision to divorce. This paper provides compelling evidence that learning plays a significant role, and that some of what is learned is spousal capability. Models that neglect to take into account learning may underestimate the importance of initial matching or factors affecting how informed the matching process is. The model is agnostic on whether the learning process is identical for marriages after the first. Given the higher rate of divorce among higher order marriages, it would be valuable to extend the model to this context.

4.8 References

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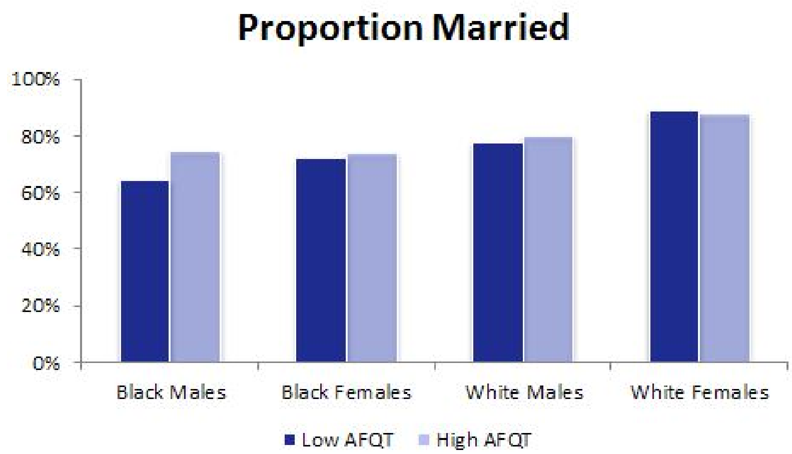
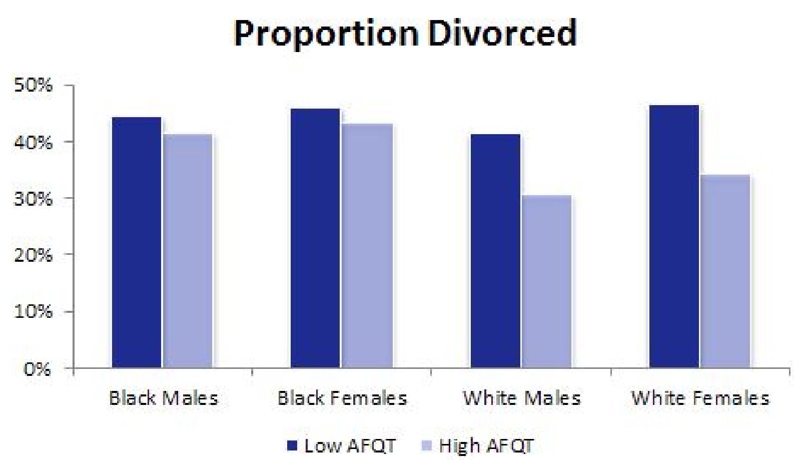
4.9 Figures

Figure 4.1: Marriage rates by race, gender, and capability, NLSY79.



The p-values for $H_0 : P(\text{Marry}|\text{Low AFQT}) < P(\text{Marry}|\text{High AFQT})$ are: 0.005, 0.592, 0.083, 0.340.

Figure 4.2: Divorce rates by race, gender, and capability, NLSY79.



The p-values for $H_0 : P(\text{Divorce}|\text{Low AFQT}) < P(\text{Divorce}|\text{High AFQT})$ are: 0.262, 0.284, 0.000, 0.000.

Figure 4.3: Divorce rates, NLSY79.

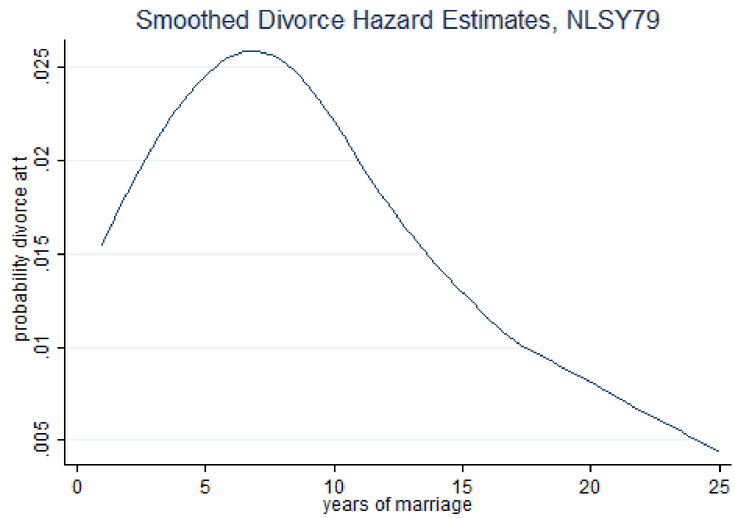


Figure 4.4: Length of first marriage conditional on observed divorce, NLSY79.

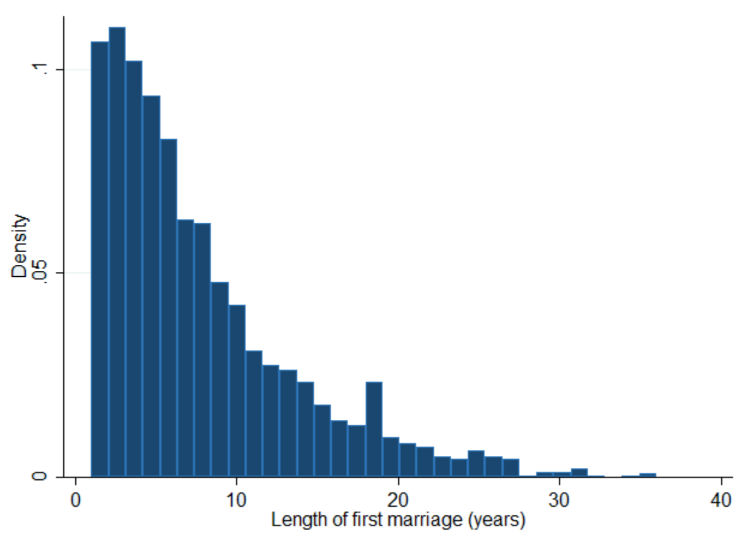
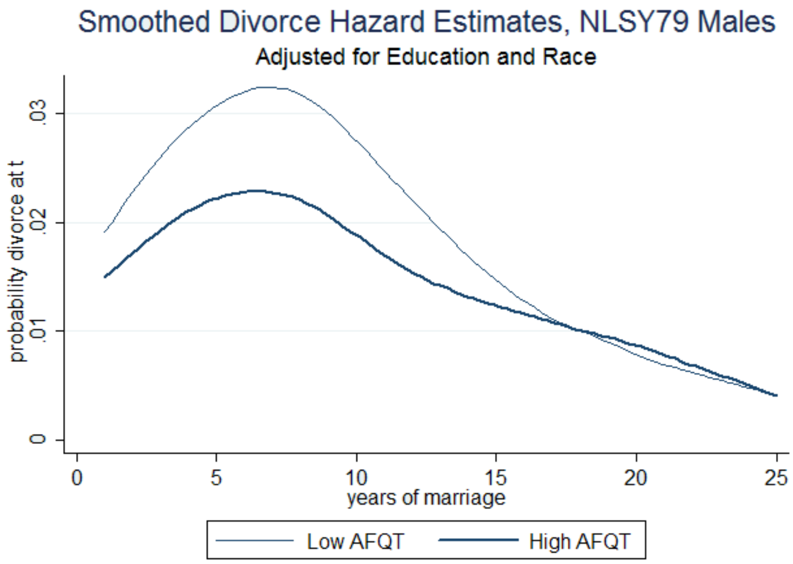
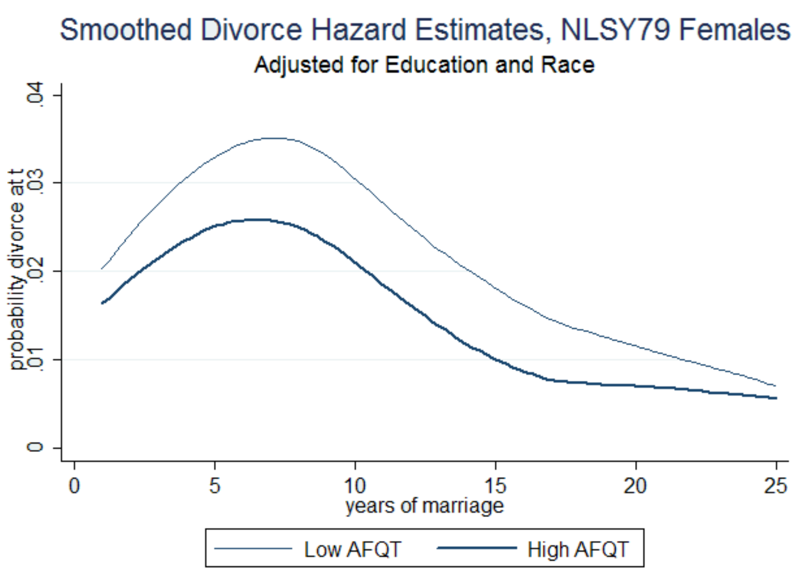


Figure 4.5: Divorce rates adjusted for education and race, NLSY79 males.



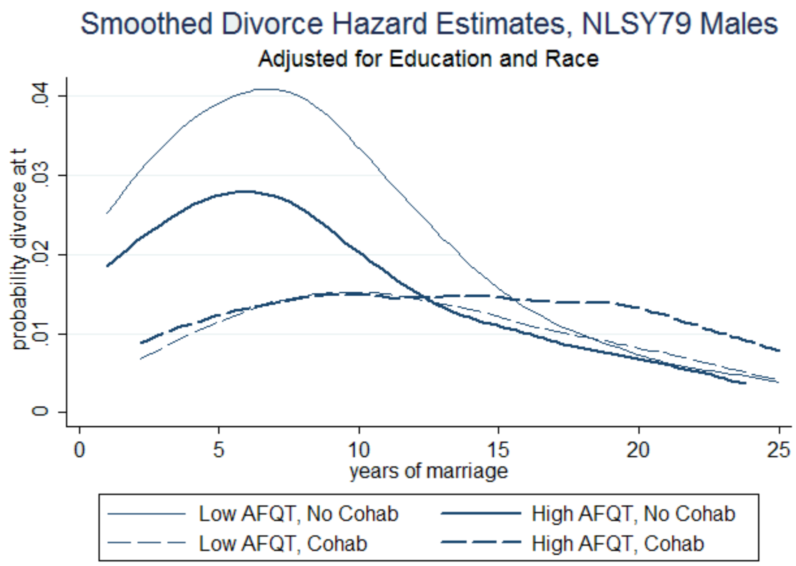
The p-value for H_0 : Survive|Low AFQT = Survive|High AFQT is 0.040 for the first 15 years of marriage.

Figure 4.6: Divorce rates adjusted for education and race, NLSY79 females.



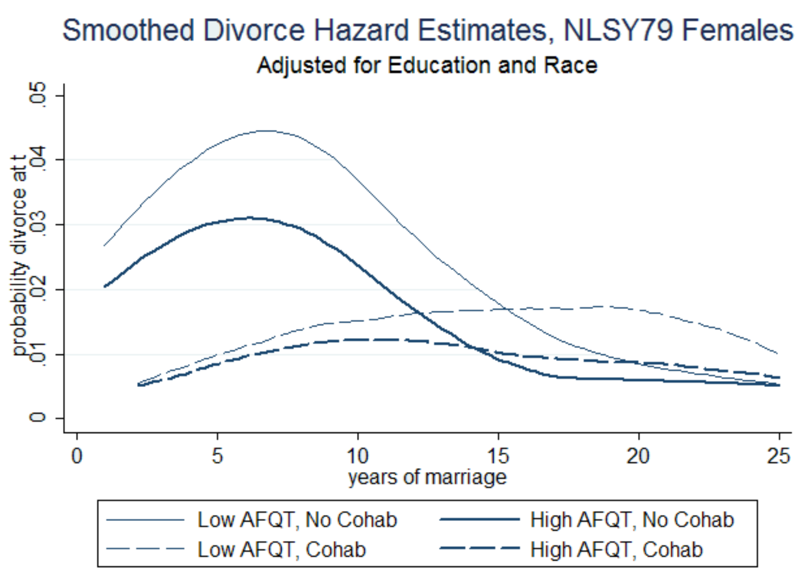
The p-value for H_0 : Survive|Low AFQT = Survive|High AFQT is 0.060 for the first 15 years of marriage.

Figure 4.7: Divorce rates by cohabitation and capability, NLSY79 males.



For the first 15 years of marriage:
The p-value for H_0 : Survive|[High AFQT, Cohabitation] = Survive|[High AFQT, No Cohabitation] is 0.001
The p-value for H_0 : Survive|[Low AFQT, Cohabitation] = Survive|[Low AFQT, No Cohabitation] is 0.000
The p-value for H_0 : Survive|[High AFQT, Cohabitation] = Survive|[Low AFQT, Cohabitation] is 0.131

Figure 4.8: Divorce rates by cohabitation and capability, NLSY79 females.



For the first 15 years of marriage:
The p-value for H_0 : Survive|[High AFQT, Cohabitation] = Survive|[High AFQT, No Cohabitation] is 0.000
The p-value for H_0 : Survive|[Low AFQT, Cohabitation] = Survive|[Low AFQT, No Cohabitation] is 0.000
The p-value for H_0 : Survive|[High AFQT, Cohabitation] = Survive|[Low AFQT, Cohabitation] is 0.594

4.10 Tables

Table 4.1: Sample Selection, NLSY79

	N
Full NLSY sample	12,686
Valid AFQT score	11,911
Ever married	9,502
Non-missing education & fertility measures	7,618
Sample 1: Valid job history	7,258
Sample 2: Marital quality supplement*	1,365
Sample 3: Matched locations**	5,354

*Females, married ages 18-26, still married in 1992+ **Currently living in a county for which the CPS provides unemployment rates

Table 4.2: Sample Means, NLSY79

	Main	Marital Quality	Matched Locations
Observed divorce	0.25	0.09	0.19
Female	0.51	1.00	0.51
Black	0.22	0.24	0.23
Hispanic	0.15	0.20	0.17
AFQT (standardized)	0.02	0.09	-0.03
AFQT percentile	44.84	46.60	44.76
Wife age at marriage	23.31	25.59	23.93
Husband age at marriage	25.24	26.74	25.91
Job loss (ever occurred)			
workplace closed	0.21	0.08	0.11
laid off	0.18	0.06	0.11
fired	0.11	0.02	0.04
laid off or fired	0.24	0.07	0.14
Premarital cohabitation	0.26	0.34	0.34
Number of children	1.64	2.09	1.94
Education*			
HS/HS	0.44	0.34	0.40
HS/SC	0.08	0.10	0.07
HS/C	0.03	0.03	0.03
SC/SC	0.07	0.08	0.05
SC/HS	0.08	0.07	0.06
SC/C	0.03	0.04	0.02
C/HS	0.02	0.03	0.02
C/SC	0.05	0.07	0.03
C/C	0.09	0.13	0.11
Years married	13.39	20.33	16.55
if divorce observed	7.41	13.27	10.95
N	7,618	1,883	5,791

*Husband's education/wife's education. HS indicates up to high school (less than or equal to 12 years of education), SC indicates some college (13 to 15 years of education), and C indicates four-year college or beyond (16 or more years of education).

Table 4.3: Probability of Divorce within 2 Years, Logit Specification

	(1) Coefficient	(2) Partial Effect
High AFQT Indicator	-0.109*	-0.024*
	(0.067)	
High AFQT × Years Married	-0.019***	-0.004***
	(0.007)	
College Indicator	-0.772***	-0.153***
	(0.095)	
College × Years Married	0.018**	0.004**
	(0.011)	
Years Married	0.004	0.001
	(0.010)	
Square of Years Married	-0.002***	0.000***
	(0.000)	
N	7,396	7,396
Observations	77,538	77,538

Notes: Bootstrapped standard errors in parentheses. The regression includes controls for gender, race, and ethnicity. The estimation procedure is MESE, as described in the text.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 4.4: Probability of Divorce within 2 Years, Logit Specification

	Type of Job Loss			
	(1) Layoff or Firing		(2) Closure	
	Coefficient	Partial Effect	Coefficient	Partial Effect
AFQT (Standardized)	-0.053**	-0.001**	-0.046**	-0.001**
	(0.026)		(0.025)	
AFQT × Job Loss	0.238**	0.007**	-0.040	-0.001
	(0.122)		(0.126)	
Job Loss	0.231**	0.007**	0.269***	0.010***
	(0.109)		(0.106)	
Age First Married	-0.034***	-0.001***	-0.033***	-0.002***
	(0.004)		(0.004)	
Number of Kids	-0.090***	-0.002***	-0.092***	-0.003***
	(0.020)		(0.020)	
Years Married	0.079***	0.002***	0.085***	0.001***
	(0.013)		(0.016)	
Square of Years Married	-0.009***	0.000***	-0.01***	-0.002***
	(0.001)		(0.001)	
Cube of Years Married	0.000***	0.000***	0.000***	0.000***
	(0.000)		(0.000)	
N	7,396		7,396	
Observations	77,538		77,538	

Notes: Bootstrapped standard errors in parentheses. This regression includes controls for race/ethnicity, gender, and education matching. Partial effects for dummy variables reflect a change from 0 to 1. The estimation procedure is MESE, as described in the text.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 4.5: Probability of Divorce within 2 years, Logit Specification

	Type of Job Loss			
	(1) Layoff or Firing		(2) Closure	
	Coefficient	Partial Effect	Coefficient	Partial Effect
First Job Loss	0.402**	0.008**	0.378*	0.007*
	(0.185)	(0.004)	(0.202)	(0.004)
AFQT (Standardized)	-0.021	-0.000	-0.003	-0.000
	(0.053)	(0.001)	(0.053)	(0.001)
AFQT $\times$ Job Loss	0.608***	0.012***	-0.120	-0.002
	(0.176)	(0.003)	(0.186)	(0.004)
Age Married	-0.086***	-0.002***	-0.086***	-0.002***
	(0.011)	(0.000)	(0.011)	(0.000)
Number of Kids	-0.100***	-0.002***	-0.100***	-0.002***
	(0.035)	(0.001)	(0.035)	(0.001)
N	5,354	5,354	5,354	5,354
Observations	40,170	40,170	40,170	40,170

Notes: Clustered standard errors in parentheses. Sample is NLSY79 respondents with matched locations. This regression also controls for race/ethnicity, gender, education matching, and a cubic in years married. Preliminary table—MESE results forthcoming.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 4.6: Probability of Divorce within 2 years, Logit Specification

	Type of Job Loss			
	(1) Layoff or Firing		(2) Closure	
	Coefficient	Partial Effect	Coefficient	Partial Effect
Unemployment Rate	0.006	0.000	0.007	0.000
	(0.012)	(0.000)	(0.012)	(0.000)
First Job Loss	0.400**	0.008**	0.378*	0.007*
	(0.185)	(0.004)	(0.202)	(0.004)
AFQT (Standardized)	-0.019	-0.000	-0.001	-0.000
	(0.053)	(0.001)	(0.053)	(0.001)
AFQT $\times$ Job Loss	0.607***	0.012***	-0.121	-0.002
	(0.176)	(0.003)	(0.186)	(0.004)
Age Married	-0.086***	-0.002***	-0.086***	-0.002***
	(0.011)	(0.000)	(0.011)	(0.000)
Number of Kids	-0.100***	-0.002***	-0.1000***	-0.002***
	(0.035)	(0.001)	(0.035)	(0.001)
N	5,354	5,354	5,354	5,354
Observations	40,170	40,170	40,170	40,170

Notes: Clustered standard errors in parentheses. Sample is NLSY79 respondents with matched locations. This regression also controls for race/ethnicity, gender, education matching, and a cubic in years married. Preliminary table—MESE results forthcoming.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 4.7: Probability of Divorce within 2 Years, Logit Specification

	(1) Coefficient	(2) Partial Effect
AFQT (Standardized)	-0.265***	-0.007***
	(0.024)	
Cohabited <1 Year	-0.621***	-0.017***
	(0.046)	
Cohabited 1-2 Years	-2.200**	-0.028**
	(1.147)	
Cohabited 2+ Years	-1.865**	-0.027**
	(0.979)	
Years Married	0.003	0.000
	(0.007)	
Square of Years Married	-0.002***	0.000***
	(0.000)	
Cohabited <1 year × AFQT	0.181***	0.006***
	(0.049)	
Cohabited 1-2 years × AFQT	1.424	0.088
	(1.154)	
Cohabited 2+ years × AFQT	1.376*	0.083*
	(1.000)	
N	3,961	3,961
Observations	39,057	39,057

Notes: Clustered standard errors in parentheses. This regression also controls for race/ethnicity and gender. The estimation procedure is MESE, as described in the text.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

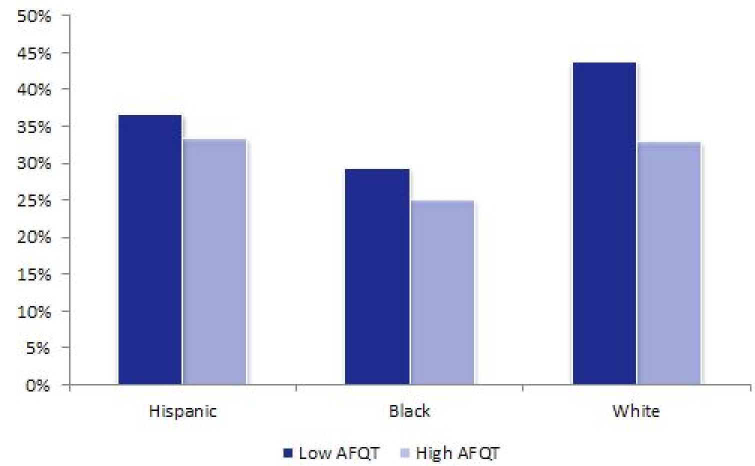
Table 4.8: Probability of Divorce within 2 years, Partial Effect from Logit Specification

	Type of Job Loss			
	(1) Layoff or Firing		(2) Closure	
	First 7 Years	Year 8+	First 7 Years	Year 8+
Years Married	0.015***	-0.002***	0.015***	-0.002***
	(0.002)	(0.001)	(0.002)	(0.001)
Square of Years Married	-0.002***	0.000	-0.002***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
First Job Loss	0.017***	0.006	0.012**	0.008**
	(0.005)	(0.004)	(0.006)	(0.004)
AFQT (Standardized)	-0.002	0.001	-0.001	0.001
	(0.002)	(0.001)	(0.002)	(0.001)
AFQT $\times$ Job Loss	0.007	0.006*	-0.005	0.001
	(0.005)	(0.004)	(0.006)	(0.004)
Number of Kids	-0.004**	-0.002***	-0.004**	-0.002***
	(0.002)	(0.001)	(0.002)	(0.001)
Age at Marriage	-0.003***	-0.001***	-0.003***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	44,389	33,149	44,389	33,149

Notes: Clustered standard errors in parentheses. Also includes controls for race/ethnicity, gender, and education matching. Preliminary table—MESE results forthcoming.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Appendix I: Additional Tables and Figures

Figure 4.9: Lifetime divorce rates, NLSY79 females who never work



The p-values for $H_0 : P(\text{Divorce}|\text{Low AFQT}) \leq P(\text{Divorce}|\text{High AFQT})$ are: 0.456, 0.431, 0.062.

Table 4.9: Probability of Reporting Marital Happiness, Ordered Probit Specification

	(1)	(2)	(3)
High AFQT Indicator	0.0316	0.281**	0.284**
	(0.062)	(0.113)	(0.128)
Years Married	-0.009***	-0.004	-0.0183*
	(0.003)	(0.003)	(0.007)
High AFQT $\times$ Years Married		-0.012**	-0.013**
		(0.005)	(0.006)
Black	-0.273***	-0.270***	-0.232***
	(0.076)	(0.076)	(0.082)
Hispanic	-0.156**	-0.157**	-0.190**
	(0.074)	(0.074)	(0.081)
Observations	7,651	7,651	6,315

Notes: Clustered standard errors in parentheses. Marital happiness questions were asked only of women still married in 1992 and later. Column 3 contains controls for family structure, ages at marriage, and education matching. Marital happiness has 3 categories.

*** Significant at the 0.01 level.

** Significant at the 0.05 level.

* Significant at the 0.10 level.

Table 4.10: Probability of Divorce within 2 Years, Linear Probability Model Specification

	(1)	(2)	(3)
Years Married	-0.001**	-0.001**	-0.001
	(0.001)	(0.001)	(0.001)
Square of Years Married	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Black	-0.009***	-0.009***	-0.005*
	(0.003)	(0.003)	(0.003)
Hispanic	-0.003	-0.003	-0.001
	(0.003)	(0.003)	(0.003)
High AFQT Indicator	-0.004	-0.006	-0.004
	(0.002)	(0.007)	(0.007)
Marital Happiness	-0.016***	-0.015***	-0.012***
	(0.003)	(0.004)	(0.004)
High AFQT $\times$ Happiness		-0.002	-0.003
		(0.006)	(0.006)
Observations	10,424	10,424	8,371

Notes: Clustered standard errors in parentheses. Marital happiness questions were asked only of women still married in 1992 and beyond. Column 3 contains controls for family structure, ages at marriage, and education matching. Marital happiness has 3 categories. Preliminary table—MESE results forthcoming.

*** Significant at the 0.01 level.

** Significant at the 0.05 level.

* Significant at the 0.10 level.

Figure 4.10: Smoothed hazard estimates for divorce, PSID born 1957-1964

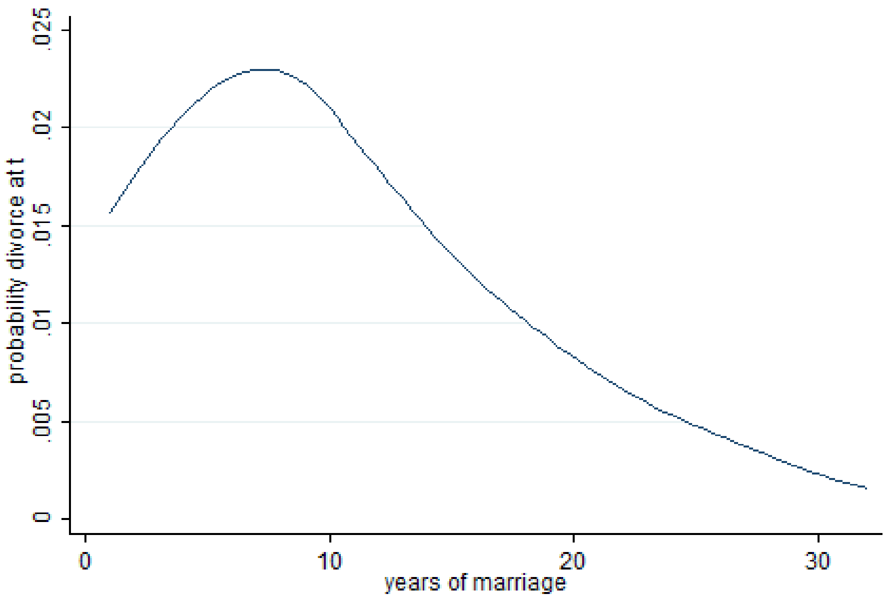


Figure 4.11: Smoothed hazard estimates for divorce, PSID first marriages

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Figure 4.12: Divorce hazard, simulated sample

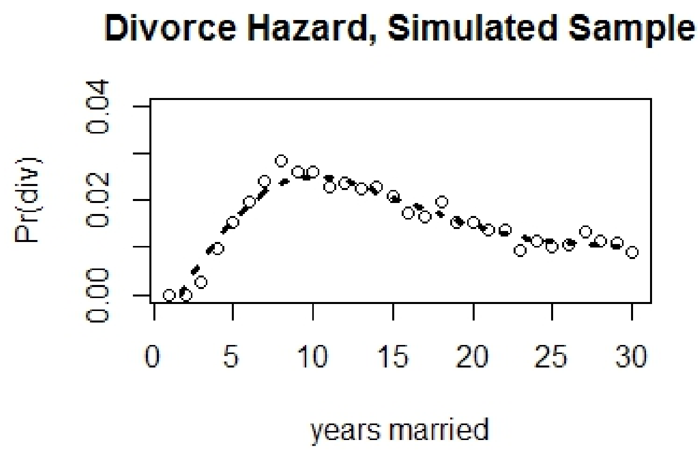

Figure 4.13: Divorce hazard by capability, simulated sample

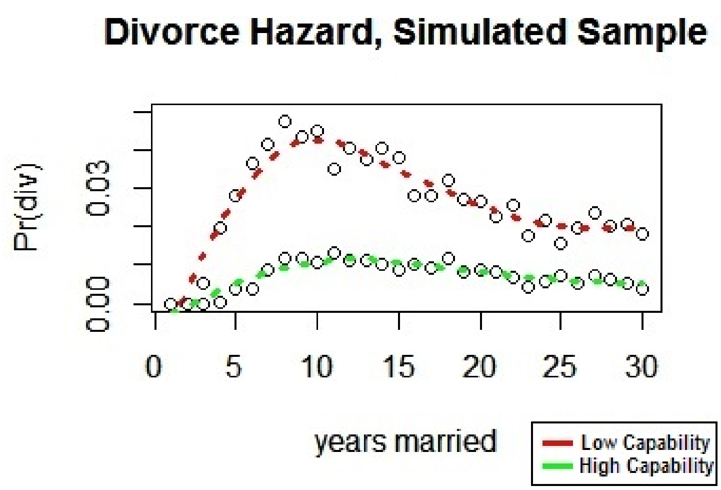

Figure 4.14: Evolution of beliefs by education and true ability, simulated sample

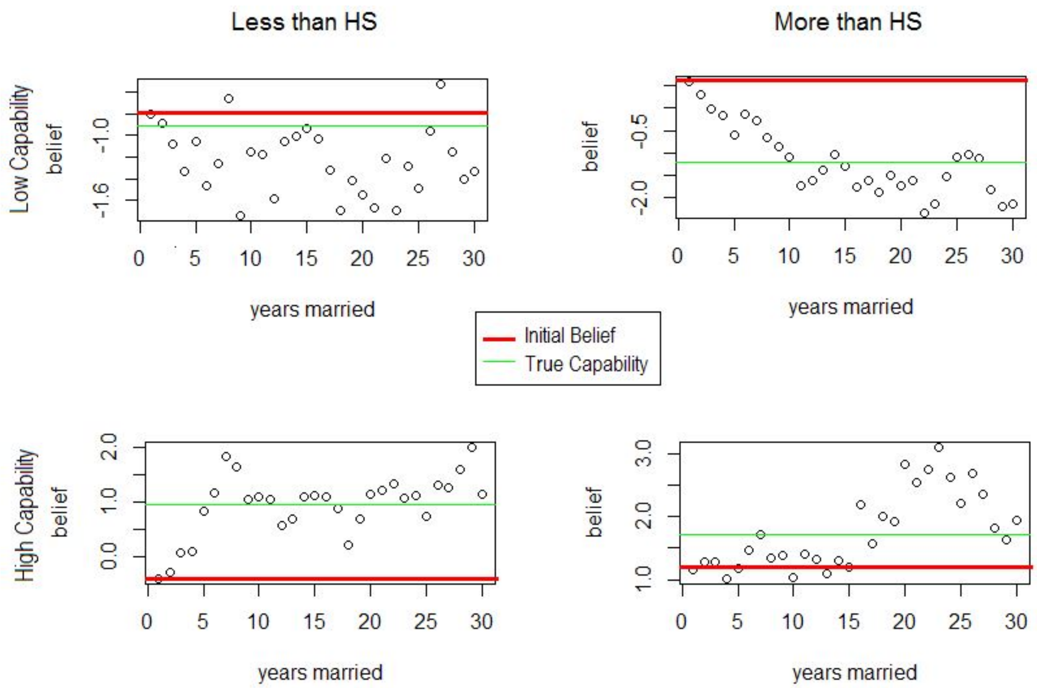

Table 4.11: Probability of Divorce within 2 Years, Partial Effect from Logit Specification

	Type of Job Loss		
	(1) Layoff or Firing	(2) Firing	(3) Closure
Years Married	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)
Square of Years Married	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
First Job Loss†	0.010***	0.017***	0.009***
	(0.003)	(0.004)	(0.003)
AFQT (Standardized)	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
Job Loss × AFQT†	0.005*	0.007*	-0.002
	(0.003)	(0.004)	(0.003)
Number of Kids	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)
Age First Married	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)
N	7,396	7,396	7,396
Observations	77,538	77,538	77,538

Notes: Clustered standard errors in parentheses. Sample is NLSY79 respondents. This regression also controls for race/ethnicity, gender, and education matching. AFQT measure is a standard normal transformation of AFQT percentile.

† A χ^2-test of joint significance of job loss and job loss × ability yields p-values of (1) 0.0012, (2) 0.0001, and (3) 0.0073.

*** Significant at the 0.01 level.

** Significant at the 0.05 level.

* Significant at the 0.10 level.

Table 4.12: Probability of Divorce within 2 Years, Linear Probability Model Specification

	(1)	(2)
Years Married	-0.002***	-0.002***
	(0.000)	(0.000)
Square of Years Married	-0.000	-0.000
	(0.000)	(0.000)
High AFQT Indicator	-0.013***	-0.020***
	(0.003)	(0.004)
Cohabited <1 year	-0.028***	-0.038***
	(0.002)	(0.003)
Cohabited 1-2 years	-0.042***	-0.060***
	(0.009)	(0.003)
Cohabited 3+ years	-0.053***	-0.060***
	(0.003)	(0.003)
High AFQT × Cohabited <1 year		0.024***
		(0.005)
High AFQT × Cohabited 1-2 years		0.033**
		(0.015)
High AFQT × Cohabited 3+ years		0.018***
		(0.004)
Observations	39,057	39,057

Clustered standard errors in parentheses. Sample is NLSY79 males. High ability denotes an AFQT percentile ≥ 50. This regression additionally controls for race and ethnicity.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Table 4.13: Probability of Divorce within 2 Years, Logit Specification

Panel A: Coefficients estimated using standardized AFQT score

	Type of Job Loss			
	(1) Layoff or Firing		(2) Closure	
	Coefficient	Partial Effect	Coefficient	Partial Effect
AFQT (Standardized)	-0.012	-0.000	-0.006	-0.000
	(0.032)	(0.001)	(0.032)	(0.001)
AFQT × Job Loss	0.180*	0.005*	-0.063	-0.002
	(0.097)	(0.003)	(0.105)	(0.003)
Job Loss	0.360***	0.011***	0.297***	0.009***
	(0.100)	(0.003)	(0.107)	(0.003)

Panel B: Coefficients estimated using MESE

	Type of Job Loss			
	(1) Layoff or Firing		(2) Closure	
	Coefficient	Partial Effect	Coefficient	Partial Effect
AFQT (Standardized)	-0.053**	-0.001**	-0.046**	-0.001**
	(0.026)		(0.025)	
AFQT × Job Loss	0.238**	0.007**	-0.040	-0.001
	(0.122)		(0.126)	
Job Loss	0.231**	0.007**	0.269***	0.010***
	(0.109)		(0.106)	
N	7,396		7,396	
Observations	77,538		77,538	

Notes to Panel A: Clustered standard errors in parentheses. This regression includes controls for race/ethnicity, gender, number of children, age at first marriage, a cubic in years married, and education matching. Partial effects for dummy variables reflect a change from 0 to 1.
Notes to Panel B: Bootstrapped standard errors in parentheses. This regression includes controls for race/ethnicity, gender, number of children, age at first marriage, a cubic in years married, and education matching. Partial effects for dummy variables reflect a change from 0 to 1. The estimation procedure is MESE, as described in the text.
*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

Appendix II: Theory Appendix

Proposition 1. *In expectation, individuals with high values of θ are less likely to divorce than those with low values of θ.*

Proof. As divorce occurs when $\widehat{\theta_t} < \theta_D$, this proposition requires that for two individuals i, j with the same θ_D but where $\theta_i > \theta_j$, $E[\widehat{\theta_i}] > E[\widehat{\theta_j}]$. Proceed by contradiction. Suppose for some $t > 0$, $E[\widehat{\theta_i}] < E[\widehat{\theta_i}]$. By the definition of $\hat{\theta_n}$ in (4.3), $E[\frac{\widehat{\theta_{0_i}}\sigma^2+\tau_0^2(n\bar{x_i})}{\tau_0^2 n+\sigma_x^2}] < E[\frac{\widehat{\theta_{0_j}}\sigma^2+\tau_0^2(n\bar{x_j})}{\tau_0^2 n+\sigma^2}]$ if (at least one of) $\widehat{\theta_{0_i}} < \widehat{\theta_{0_j}}$ or $E[\bar{x_i}] < E[\bar{x_j}]$.

However, for identical θ_D, $\widehat{\theta_{0_i}} = \widehat{\theta_{0_j}}$. As x is drawn from a mean θ distribution, $E[\bar{x_i}] < E[\bar{x_j}]$ requires $\theta_i < \theta_j$. Thus, we have a contradiction.

As this holds for any number of signals n, individuals with higher θ have both a lower baseline risk of a divorce, and a lower per-period (expected) risk of divorce. □

Proposition 2. *Suppose information arrives as in (4.3). Then if the anticipated cost of divorce is sufficiently high: (a) the probability of divorce will initially be rising over time among individuals who will eventually divorce, and (b) as the number of signals increases (n becomes large), marriages that have survived become increasingly likely to never end in divorce.*

Let $\sigma = 1$.[12] Then after n signals, $\hat{\theta}_n < \theta_D$ if and only if

$$\bar{x}_n < \theta_D - \left[\frac{\hat{\theta_0} - \theta_D}{n\tau_0^2}\right]. \tag{4.14}$$

Proof. Part (b) of the proposition is straightforward. The left-hand side of (5), $\bar{x}_n$, converges to the true value of θ. If that value is greater than θ_D, as n increases, the probability of divorce declines to 0.

For part (a), proceed by inspection. As divorce is costly, $\theta_D < \widehat{\theta_0}$. Substituting in from (4.3), after one signal, $\widehat{\theta_1} = \frac{\widehat{\theta_0}\sigma^2+\tau_0^2 x_1}{\tau_0^2 n+\sigma^2}$. Divorce would occur iff $\theta_D > \frac{\widehat{\theta_0}\sigma^2+\tau_0^2 x_1}{\tau_0^2 n+\sigma^2}$.

This requires both very small x_1 and small σ^2—the signal would have to be extremely negative and also precise. This will be comparatively rare, so the initial hazard will be low. However, at least some individuals have initial overestimates ($\widehat{\theta_0} > \theta$) due to the noisiness of time-0 signals. If $\theta < \widehat{\theta_0}$, $E[x] < \widehat{\theta_0}$ as it has mean θ. Thus, future signals for such individuals will be negative, and amassing such signals will pull future $\widehat{\theta_t}$ down toward θ, and below θ_D, triggering divorce. Thus, the hazard will be initially increasing.

Note that as τ_0^2 grows relative to σ^2, the prior is more imprecise, and new signals play a larger role in determining future $\widehat{\theta_t}$ and, consequently, in determining divorce. □

Proposition 3. *As signals accumulate over time, an observable component of the initial prior, such as schooling (s), will have progressively less weight in the assessment of capability, and thus be less predictive of divorce. The converse is true of θ itself.*

[12]This saves on notation, but causes no loss in generality.

Proof. Proceed by inspection. Note that in equation (4.3), new signals x are given non-zero weight (provided initial priors are imperfect forecasts: $\tau_0^2 > 0$). Simultaneously, the weight on the initial prior declines—it is multiplied by $\frac{\sigma^2}{\tau_0^2 n}$, which is declining in n—while the weight on new information x_t increases at the rate of $\frac{\tau_0^2 n}{\tau_0^2 n + \sigma_t^2}$. As $E[x] = \theta$, increasing weight on x implies (in expectation) increasing weight on θ. □

Proposition 4. *A low-variance signal x_t will increase the probability of divorce if it is substantially lower than the currently-held capability assessment $\widehat{\theta}_{t-1}$.*

Proof. Proceed by examining the definition of $\widehat{\theta}_t$ given in (4.4). The magnitude of the change in $\widehat{\theta}$ from $t-1$ to t is clearly decreasing in σ_x^2 and is proportional to $|x_t - \widehat{\theta}_{t-1}|$. Thus, a signal that differs greatly from previous beliefs or an extremely precise signal will have the greatest impact on $\widehat{\theta}_t$, and for a given $\widehat{\theta}_0$ or θ_D, the divorce hazard is monotonically decreasing in $\widehat{\theta}_t$.

Now consider the differential impact of a signal x_t. Suppose we have two individuals, i and j, with identical x_t, but $\theta_i > \theta_j$. In expectation[13], $\widehat{\theta}_{t-1,i} > \widehat{\theta}_{t-1,j}$. Thus, the downward revision of belief in constructing $\widehat{\theta}_t$ will be larger for individual i. As θ_D is increasing in true θ, the divorce risk is increased more for individual i than j; i.e., for the higher ability individual. □

Proposition 5. *Given identical $\bar{x}_n$ and $\widehat{\theta}_0$, a signal occurring early in the marriage (e.g., at $n = t$) will have a greater impact on divorce risk than an identical signal occurring later in the marriage (at $n = t+1$).*

Proof. Consider equation (4.3). Suppose $n-1$ signals have accumulated, and the average of these signals is m. Then equation (4.3) can be rewritten as
$\widehat{\theta_n} = \frac{\widehat{\theta}_0\sigma^2 + \tau_0^2(n(\frac{m(n-1)+x_n}{n}))}{\tau_0^2 n + \sigma^2} = \frac{\widehat{\theta}_0\sigma^2 + \tau_0^2(m(n-1)+x_n)}{\tau_0^2 n + \sigma^2}$.
The impact of x_n is thus proportional to $\frac{\tau_0^2}{\tau_0^2 n + \sigma^2}$; i.e., it is decreasing in n. Reducing the effect on $\widehat{\theta}_t$ will correspondingly reduce the impact on the divorce hazard, given identical thresholds θ_D (implicit in identical $\widehat{\theta}_0$).

□

Item Response Theory

Suppose an IQ test consists of one item,[14] with no heterogeneity in how wrong a wrong answer can be. It's possible that the question is very easy, in which case low-capability individuals can be identified, but some low- to moderate- capability individuals may be misclassified as high capability. It's possible that the question is a poor discriminator, with roughly equal probability of a correct answer for high and low ability individuals, creating misclassification throughout the spectrum. It's also possible that the question has an answer that is easy to guess, which will mediate any heterogeneity generated by difficult or discriminating questions. These situations are each reflected in a parameter of the three parameter logistic (3PL) model, mapping an individual's actual cognitive ability into the probability of a correct answer on a given question.

[13] This expectation is formed by integration over the distribution of x

[14] Fortunately, the Armed Forces Qualification Test used in this analysis consists of 105 items.

In the 3PL model, the probability that respondent i answers question j correctly given ability θ_i is given by:

$$p_j(\theta_i) = c_j + \frac{1 - c_j}{1 + exp[-a_j(\theta_j - b_j)]} \tag{4.15}$$

However, as noted previously, identifying these a_j, b_j, c_j parameters for each question is insufficient. If an additional explanatory variable in the main regression is correlated with the error in measured cognitive ability, the measurement error will bias the coefficients on capability and on the correlated variable. Thus, I use the Mixed Effects Structural Equations (MESE) model described in the text to directly model the measurement error and condition on observable factors, mitigating this bias.