The Changing Impact of Fathers on Women's Occupational Choices[1]

Judith K. Hellerstein
Melinda Sandler

Preliminary: Comments Welcome

February 2006

[1]Hellerstein is an associate professor in the Department of Economics at the University of Maryland, a faculty associate of the Maryland Population Research Center, and a research associate of the NBER. Sandler is a Ph.D. candidate in Economics at the University of Maryland, and acknowledges the support of the Training Program at the Maryland Population Research Center. We are grateful for the comments provided by Seth Sanders, as well as Suzanne Bianchi, Bill Evans, Jonah Gelbach, and seminar participants at the University of Maryland and the University of Wisconsin. We are especially grateful for the efforts of Megan Brooks early in this project.

1 Introduction

Over the last century, the labor force participation of women has risen threefold.[1] In addition, there has been a tremendous increase in the amount of integration of women in the labor market, so that women are far more likely now to work with men than in previous generations. Although the exact mechanisms for these changes remain somewhat elusive,[2] the fact that more women enter the labor market now and work in the same occupations as men has profound implications for many dimensions of the economy.

This paper focuses on one of these implications. Because women have become more likely to enter the labor market and to enter more traditionally male occupations, the incentives for fathers to invest in daughters have changed both in terms of quantity and in terms of composition. In particular, the return to a father's investment in transmitting to his daughter the specific human capital embodied in his occupation has increased because his daughter is much more likely than in previous generations to consider entering her father's occupation.

Because a woman born in a recent cohort is more likely to enter traditionally male-dominated occupations generally, however, she is more likely than a woman born in an earlier cohort to enter her father's occupation even absent any changes in investment her father makes. As a result, if one wants to provide evidence that intergenerational transmission of occupation-specific human capital between fathers and daughters has increased, one must demonstrate empirically that the positive trend in the probability that a woman works in her father's occupation is larger than that which would be predicted just from changes in the marginal distribution of women's occupations.

We develop a simple model that combines features of intergenerational job-specific human capital transmission with an occupational choice model. The model, though static in nature, motivates the use of information on a woman's father-in-law to generate an empirical test of

[1]See, for example, Goldin (1991).

[2]See, for example, Acemoglu, Autor, and Lyle (2004) and Goldin and Katz (2002).

whether daughters have become increasingly more likely to enter their fathers' occupations, conditional on the general economic forces that have led women to enter men's occupations more generally. The basic idea is that because of assortative mating, a woman's father-in-law is likely to be working in the set of occupations that a woman might choose to work in, given her preferences and her general human capital. Therefore, changes in the probability over time that women work in their fathers'-in-law occupations can account for the occupational upgrading of women more generally. As we explain in detail, the father-in-law is not a perfect "counterfactual father," but as long as assortative mating by occupation has not decreased over time (which we argue is likely), we can still identify whether the increase in the probability that a woman works in her father's occupation is at least partially due to an increase in occupation-specific investments that fathers make in daughters.

We use data from the General Social Survey (GSS), the Survey of Income and Program Participation (SIPP), and the Occupational Changes in a Generation (OCG) to document changes in occupation-specific human capital transmission between fathers and daughters spanning birth cohorts from 1909 to 1977. We present an empirical analysis of whether the increase in the probability that a woman works in her father's occupation can be attributed at least partially to increased transmission of occupation-specific skills between fathers and daughters, or whether it arises solely as a result of the changing composition of women's occupations. Our results suggest that there was indeed an increase in the transmission of occupation-specific human capital between fathers and daughters. The shift in women's occupations toward their fathers' occupations is around 20% of the total increase in the probability a woman enters her father's occupation over our sample period, an estimate that is likely a lower bound. Robustness checks, including those adding controls for each survey, sensitivity to inclusion of women who are out of the labor force, sensitivity to age restrictions, and controls for fathers and fathers-in-law occupations, confirm the main findings. In contrast, we find no increase over time in the fraction of sons working in their fathers' occupations, nor any evidence that there has been an increased amount of specific human capital transmission over time between fathers and sons.

2 Background and Related Literature

2.1 Estimates of Intergenerational Transmission

Research on intergenerational transmission between parents and children has a long and rich history across multiple disciplines, going all the way back to Galton's work (1889) on the heritability of height. Becker and Tomes (1979, 1986) present an economic model where the utility of parents is a function of current consumption and the utility of a child, which itself is a function of the child's general human capital, so that parents optimize by choosing between consumption and investments in children. The model in its simplest form generates a straightforward, empirically testable relationship that specifies that the log of the income of the child will be a linear function of the log income of the parent. Actually testing the model empirically, however, is harder than it first appears given measurement error in income, (Solon, 1992), with perhaps the best current estimate of a stable intergenerational income parameter in the United States between fathers and sons standing at 0.6 (Mazumder, 2005). Because these estimates just measure a correlation across generations, they cannot distinguish between a simple model of genetic heritability of traits associated with income and an economic model of investments parents make in children. This point has been made and examined in detail by Mulligan (1999) and Grawe and Mulligan (2002), who derive tests aiming to distinguish between economic models and models of heritability and find some evidence weakly consistent with investments.

In sociology, the tradition has been to estimate intergenerational measures of "occupational prestige" and "occupational mobility." Sons may enter their fathers' occupations because of investments that fathers make in sons, because of heritable aspects of occupation-specific skills that lead sons to have comparative advantages in their fathers' occupations, or because of barriers to movement out of a father's occupation. Contingency tables (transition matrices) can be utilized to measure the extent of occupational mobility, where the cells of the contingency table are determined by fathers' occupations and sons' occupations. Occupational mobility can then calculated as the probability or odds of a son not entering his father's occupation (see, e.g., Ferrie, 2005 and Mosteller, 1968).

Measurements of the intergenerational transmission of occupational prestige involve rankings of occupations along some index, usually determined as functions of average income in occupations, and estimating the correlation in occupational prestige across generations. While the exact specification of the occupational prestige index may be subject to criticism, using average incomes in an occupation may mitigate some of the problems associated with noisy measures of permanent income that have plauged some of the estimates of intergenerational income transmission in the economics literature.

There has been much less research devoted to intergenerational transmission between pairs other than father-son.[3] This is not surprising given that transmission parameters based on income or occupation conditional on labor force participation are not very meaningful when large fractions of women are not labor force participants.

2.2 Changes in Intergenerational Transmission

Sociologists have long been interested in changes in intergenerational transmission across generations, as seen in work discussed by Hauser and Featherman (1978). Economists have only recently begun to examine this issue, partially as a result of the availability of panel data such as the PSID with long enough time series to estimate changes in the transmission parameter over time. Evidence on the extent of change in intergenerational transmission of income between fathers and sons is mixed (see Fertig, 2003, Lee and Solon, 2006, and the references therein) and depends to a large extent on the data sets used, how income is measured, and the time span considered. Partially as a result of this, we are careful in

[3] One notable exception is Solon and Chadwick (2002). Fernandez et al (2004) discuss preference formation in an intergenerational transmission framework between mothers and sons.

this paper to combine data from three different data sets collected over a time span of 29 years to ensure the robustness of our results across data sets that differ in the timing of data collection, the wording of questions, and sampling schemes.

When estimating changes in occupational mobility over (at least) two different generations, researchers distinguish between changes in "prevalence" and changes in "association." Changes in prevalence refer to changes across generations in the marginal distributions of the rows and columns of the contingency tables, whereas changes in association refer to changes that are left over once marginal distributions of contingency tables have been adjusted to be equal. It is changes in association that are generally referred to as changes in occupational mobility over time.[4]

What is absent from much of the empirical investigation into changes in intergenerational transmission is an investigation of underlying changes in behavior. For example, when contingency tables are adjusted for prevalence so that only changes in association are used to quantify changes in occupational mobility over generations, there is no consideration given for why it may be that the marginal distributions of occupations have changed across the generations. In the case of women and their fathers, the fact that women have become more likely over time to be in male-dominated occupations may be a function of changes in investments made by their fathers. Adjusting contingency tables so that the marginal distribution of women's occupations for recent cohorts looks like that of much older cohorts may adjust away the important changes in the impact of fathers on the occupation choices of their daughters.

In this paper we take a different approach. Our empirical strategy to detect whether a woman is more likely to be in her father's occupation, absent changes in the marginal

[4]For a summary of statistical methods to adjust for differences in prevalence across contingency tables, see Little and Wu (1991). For a recent study of changes in occupational mobility, see Ferrie (2005) who concludes that occupation mobility in the United States has fallen over the 20th century. For an analogy between these methods and estimation techniques more commonly used by economists, see Hellerstein and Imbens (1999).

distribution of women's occupations, is to compare changes in the probability that a woman is in her father's occupation over time to changes in the probability that she is in a counterfactual man's occupation. We choose this counterfactual man so that, given our identifying assumptions, changes in the probability that a woman is in this man's occupation account for changes in the marginal distribution of women's occupations. We motivate this counterfactual man more formally in the next section.

3 The Illustrative Model

The purpose of developing a simple illustrative model of intergenerational transmission between fathers and daughters in combination with a model of occupation choice is to motivate how fathers' incentives to invest in daughters change as women's labor market opportunities change and to suggest how daughters' fathers-in-law can be used to control for changes in the marginal distribution of occupations, absent changes in transmission of occupation-specific human capital between fathers and daughters. The model consists of an occupational choice decision nested within a model of human capital investments in children. First, the father chooses the amount of consumption good to purchase and the amount of investment to make in his daughter's general human capital H and job-specific human capital S, given his income I. The father can only invest in job-specific human capital for his own occupation. The daughter then chooses her occupation conditional on paternal investments that have been made and may decide to remain out of the labor force.[5] We begin with the daughter's occupation decision.

3.1 The Daughter's Problem

The daughter gains utility from working or not working, given the investment made by her father. Let y_{dad} be an indicator function for the daughter choosing the occupation of her

[5]We explicitly consider the father as the individual decision-maker in this context, given that we are considering transmission of human capital embodied in the occupation of the father.

father. We think of the daughter's choice of occupation choice as from the maximization of her latent utility y^*. The latent utility of the daughter, y^*, varies over four "occupations." The first is her father's occupation (occupation 1), where her father earns an income I. The second occupation (occupation 2) is an occupation where men in her father's cohort also make income I. Occupation 3 represents remaining out of the labor force. Occupation 4 is an occupation that the woman will never choose, either due to preferences or societal constraints on her ability to enter it. The woman's utility in each of the four occupations is represented as:

$$y^*_{dad} = \beta H + \gamma S + \epsilon_d$$

$$y^*_{other} = \beta H + \epsilon_j$$

$$y^*_{OLF} = \beta_o H + \epsilon_o$$

$$y^*_{never} = \kappa \; y^*_{OLF}$$

where $\kappa < 0$.

In this formulation, general human capital pays the same return to a woman in the labor market, but a different return (β_o) if she is out of the labor market. Specific human capital only has a payoff if the woman enters her father's occupation. Without loss of generality, y^*_{OLF} could represent the latent utility in an entirely female occupation, and where the other occupations represent occupations in which men do work.

The daughter chooses the occupation j which yields the maximum value of y^*:

$$y^*_j = \max\{y^*_{dad}, y^*_{other}, y^*_{OLF}\}. \tag{1}$$

Conditional on the H and S with which she has been endowed, the probability that a woman enters her father's occupation is:

$$\Pr(y_{dad} = 1) = \Pr(y^*_{dad} > y^*_{other}) \Pr(y^*_{dad} > y^*_{OLF}) \tag{2}$$

$$= \Pr(\gamma S > \epsilon_j - \epsilon_d) \Pr((\beta - \beta_o)H + \gamma S > \epsilon_o - \epsilon_d).$$

We assume the ϵ's are i.i.d from a Type I Extreme Value Distribution[6] so that:

$$\Pr(y_{dad} = 1) = \frac{e^{\beta H + \gamma S}}{e^{\beta H + \gamma S} + e^{\beta H} + e^{\beta_o H}}. \tag{3}$$

Similarly, the probability that a woman enters occupation 2 is

$$\Pr(y_{other} = 1) = \frac{e^{\beta H}}{e^{\beta H + \gamma S} + e^{\beta H} + e^{\beta_o H}}. \tag{4}$$

Note that if $S = 0$, so that the father has not made any investments in the daughter, then $Pr(y_{dad} = 1) = Pr(y_{other} = 1)$. Therefore, if one does not have data on the the investments of fathers, and in particular no data on S, an empirical test of whether fathers are making any specific human capital investments in their daughters can instead involve testing whether $Pr(y_{dad} = 1) = Pr(y_{other} = 1)$. This test presumes no knowledge of S, but it does presume that one can distinguish occupation 2 from both occupation 1 and occupation 4.

Now consider the population of men of her father's cohort who are either in occupation 1 or occupation 2. The probability that a woman is in the occupation of a randomly selected man from this population is:

$$\Pr(y_{man} = 1) = \Pr(y_{dad} = 1)\alpha + \Pr(y_{other} = 1)(1 - \alpha), \tag{5}$$

where α is the fraction of men in this population in Occupation 1, and $(1-\alpha)$ is therefore the fraction of men in this population in the Occupation 2. Note again that if $S = 0$ then $Pr(y_{dad} = 1) = Pr(y_{man} = 1)$.

That is, with no investments in specific human capital, the probability that the woman is in her father's occupation is equal to the probability that she is in this randomly selected man's occupation. So another possible empirical test of whether $S = 0$ would involve testing whether $Pr(y_{dad} = 1) = Pr(y_{man} = 1)$. This involves identifying the set of men in the father's cohort who are in occupation 1 and 2 and randomly selecting one of them. We follow an empirical strategy similar to this, as explained further in Section 3.4.

[6] This is a formalization of the idea that occupation 4 is never chosen. It is the "irrelevant alternative."

3.2 The Father's Problem

We assume that the father gains utility from his own consumption and from the utility of his daughter.[7] The father has a finite level of income I earned in occupation 1 to allocate between his own consumption, general human capital investment (e.g., schooling), and job specific human capital investment (e.g., time spent with daughter). The father can only invest in job specific human capital S for his occupation. The problem takes the following form:

$$\max_{H,S} \left\{ E[u^P(C, y^*(H,S))] \right\} \tag{6}$$

$$s.t.\ I = C + p_H H + p_S S. \tag{7}$$

where $u^P(C, y^*(H,S))$ represents the father's utility, a function of own consumption, C, and daughter's utility, y^*, given optimal levels of H and S, and where p_H is the cost of general human capital and p_S is the cost of occupation-specific human capital.

In this example, the daughter's choice of occupation is given from $y^* = \max\{y^*_{dad}, y^*_{other}, y^*_{OLF}\}$. The father calculates expected utility knowing β, γ, and only the distribution of the ϵ's in the daughter's optimization problem. One could make functional form assumptions about the form of the father's utility function, but this is unnecessary for our purposes.[8]

3.3 Comparative Statics and Empirical Strategy

In the model, a father must make predictions about the actions of his daughter and decide on a level of investment to make in order to maximize his daughter's (and hence his own) utility. A father's investment decision changes with exogenous changes in the parameters of

[7] We assume that fathers maximize household utility and that there is no specific human capital transmission between mothers and daughters. This is not unreasonable in our context because the female labor force participation rates for mothers of many of the cohorts in our sample were very small.

[8] An obvious functional form assumption to make is that $u^P(C, y^*(H,S)) = \phi \ln(C) + (1-\phi)E[\max_j\{y^*_j\}]$. This, coupled with the assumption that $\beta_0 = 0$ would lead to a closed form solution of $u^P(C, y^*(H,S)) = \phi \ln(C) + (1-\phi)\ln[e^{\beta H + \gamma S} + e^{\beta H} + 1] + E$, where E is Euler's constant (see, e.g. McFadden, 1981).

the model. We focus on changes in β, the return to general human capital, which can be thought of as representing an overall rise in the return to female labor market participation. Because we have no direct data on investments of H or S that fathers make in daughters, we focus on a comparative static that show that if a father's investment in S increases with β, then the probability that a woman will enter her father's occupation increases relative to the probability a woman enters a randomly chosen man's occupation.[9]

From the daughter's problem, we derive the following comparative static from considering how the probability a woman enters her father's occupation changes with respect to β:

$$\frac{\partial \ln[Pr(y_{dad}=1)]}{\partial\beta} = \gamma\frac{\partial S}{\partial\beta} + \frac{\partial \ln[Pr(y_{other}=1)]}{\partial\beta}, \tag{8}$$

This shows that if $\frac{\partial S}{\partial\beta} > 0$, the rate of change at which the daughter enters her father's occupation, occupation 1, due to a rise in β is larger than the rate of change at which she enters occupation 2.[10]

Additionally,

$$\frac{\partial \ln[Pr(y_{man}=1)]}{\partial\beta} = \frac{\alpha\gamma\frac{\partial S}{\partial\beta}e^{\gamma S}}{(\alpha e^{\gamma S}+(1-\alpha))} + \frac{\partial \ln[Pr(y_{other}=1)]}{\partial\beta}, \tag{9}$$

so that the rate of change at which she enters a randomly chosen man's occupation is also positive if $\frac{\partial S}{\partial\beta} > 0$. The difference between these two comparative statics is:

$$\gamma\frac{\partial S}{\partial\beta}(1 - \frac{\alpha e^{\gamma S}}{(\alpha e^{\gamma S}+(1-\alpha))}), \tag{10}$$

which is positive as long as $\frac{\partial S}{\partial\beta}$ is positive, and zero otherwise. Therefore, an empirical test of whether fathers specific human capital investments in daughters have increased over

[9] While this discussion focuses specifically on the effects of changes in β, our empirical strategy looks at changes over time. Given the extensive empirical evidence in the literature, we assume that $\frac{\partial\beta}{\partial t} > 0$. These cases are identical as long as $\frac{\partial\gamma}{\partial t} = 0$. It is theoretically possible that $\frac{\partial\gamma}{\partial t} > 0$, and our empirical results cannot actually distinguish between a rise in S and a rise in γ. We find increases in investment to be a more compelling interpretation of the observed phenomena than simply increasing returns.

[10] Given the functional form of the utility function suggested in footnote 8, an interior solution for the optimal level of specific human capital S is $S = \frac{\ln[p_S\beta]-\ln[p_H\gamma-p_S\beta]}{\gamma}$, which happens when $\frac{2p_S}{p_H} > \frac{\gamma}{\beta} > \frac{p_S}{p_H}$. The relevant comparative static is $\frac{\partial S}{\partial\beta} = \frac{\gamma p_H}{\beta(\gamma p_H - \beta p_S)}$ which must be greater than zero.

time can be cast as a comparison of Equation 8 and Equation 9. Moreover, because the last term in parentheses in Equation 10 is positive, the difference between Equation 8 and Equation 9 provides a lower bound estimate for the rate at which changes in S increase the probability that a women works in her father's occupation, above and beyond changes in the probability that she works in an occupation where only her general human capital pays a return.[11]

3.4 The Counterfactual Man and Assortative Mating

Recall that our randomly chosen man in Equation 9 must be chosen from occupation 1 or occupation 2 and not from occupation 4, the occupation that the daughter will never enter. Since empirically we can never distinguish what occupation 4 actually is for any given woman, we therefore need a mechanism to identify the set of men who are employed in occupations 1 or 2. That is, we need to constrain ourselves to considering the men in occupations that a woman might enter, given her father's income I, his preferences, and her preferences. The daughter's preferences are represented by the parameter κ (a parameter she may inherit from her father), which constrains her from entering occupation 4, leaving her to choose only between occupation 1, her father's occupation, and occupation 2. Once we can identify a man like this, we can test empirically whether S has increased over time.

We assume that all fathers are identical and that perfect positive assortative mating occurs on κ, where by assortative mating on κ we mean that the woman's father-in-law will never come from occupation 4. Therefore, a woman will have a father-in-law who with probability α works in occupation 1, and with probability $(1-\alpha)$ works in occupation 2. If assortative mating occurs in this way, a woman's father-in-law can serve as the counterfactual,

[11] We recognize that this model is simple in many ways and potentially could be extended along a number of interesting dimensions. For example, it incorporates no dynamics of the form of increasing β leading to increasing H and S which lead to further changes in the returns to H and S (similar in spirit to Fernandez et al., 2004). It would also be interesting to expand our model to incorporate a search model of marriage with the intergenerational transmission of human capital framework. Ermisch and Francesconi (forthcoming) contains a model of general human capital investment and marriage.

randomly chosen, man in the model above. This means that comparing the rates of change in the probabilities that a woman is in her father's occupation versus her father-in-law's occupation serves as an estimate of the extent to which fathers' increased occupation-specific human capital investment in their daughters caused a shift towards women working in their fathers' occupations. One way to think about the father-in-law, then, is that if he were to have had a daughter, she would be identical to his daughter-in-law except that his daughter would have specific human capital useful in his own occupation.

Of course, in reality assortative mating is not perfect along the dimensions of sets of occupations and preferences. One obvious way in which this could occur is if there is some probability that the woman will marry a man whose father is in occupation 4. If this probability is unchanging over time, this will simply lead to an intercept shift down in the probability that the woman is in her father-in-law's occupation, and more specifically will not affect the rate of change over time as β rises. Alternatively, the woman may be more likely to marry a man whose father is in her father's occupation. Her father-in-law then is not the counterfactual man as described above, but instead will be more likely than a randomly chosen man to be in occupation 1. To the extent that this is true, the changing rate at which a woman is in her father-in-law's occupation will bias upward the estimate of Equation 9, and therefore will lead us to further underestimate the extent to which increased specific human capital investments have induced women to enter their fathers' occupations. Finally, it is possible that, in reality, assortative mating patterns themselves have changed over time. To the extent that women are more likely than previously to marry a man whose father is in her own father's occupation, this again will cause us to underestimate the extent to which father's specific human capital investments have increased.

There is a long literature on the extent of assortative mating and its change over time (see, e.g., Mare, 1991, and the references therein, and Rose, 2001). Most of these studies simply compare correlations in observables between husbands and wives. There is indeed evidence of positive assortative mating by many observables of husbands and wives. Determining how assortative mating has changed over time is more difficult and the evidence appears inconclusive. One problem with estimating the rate at which assorative mating has changed is that this rate will be spuriously affected by changes in marginal distributions of observables such as education, similar to the issues we discuss above respect to relationships between fathers and daughters over time. That said, our strong sense is that if assortative mating by occupation of husbands and wives has changed, it has increased. As women's education and labor force participation rates have risen, there is more contact between women and men in the same occupation, which likely leads to increased assortative mating on husbands' and wives' occupation, and hence by the occupations of fathers-in-law and wives. In total, we find it hard to imagine that we will over-estimate the extent to which increased human capital investments of fathers have induced women to enter their fathers' occupations, and in fact we think it likely that we will underestimate its extent.[12]

4 Data and Summary Statistics

4.1 The Data Sets

As mentioned in Section 2, we combined data from three sources: the 1973 Occupational Changes in a Generation (OCG), the General Social Survey (using years 1975-2002), and the Survey of Income and Program Participation (1986-1988, Wave II). In the Data Appendix we provide an explanation of how the main variables of interest, labor force participation and occupation, were defined.

[12] We know of one other paper that utilizes information on the relationship between fathers and children relative to fathers-in-law and children. Lam and Schoeni (1995) compares the intergenerational income correlation between fathers and sons and fathers-in-law and sons-in-law in the United States and Brazil. The father-son correlation is higher than the father-in-law-son-in-law correlation in the United States, but the opposite is true in Brazil. They argue that in Brazil assortative mating is so strong as to match husbands to fathers-in-laws who are more similar to them than the husband's own fathers, but that this is not true in the United States. In our results below, we find results for the United States similar to these; the probability that a man works in his father's occupation is higher than that for a man and his father-in-law. Rose (2001) also utilizes information on fathers and fathers-in-law to measure changes in assortative mating patterns, in her case by education.

We chose to focus on more than one survey, and on these three surveys in particular, for a few reasons. First, these surveys are similar in that they are cross-sectional in nature and all ask information about a respondent's occupation and the occupation of at least one respondent's father at a point in time. Second, combining data sets allow us to separate age from cohorts effects with large enough sample sizes to get precise estimates. Third, because we use data spanning the years 1973 to 2002 and focus on individuals between the ages of 25 and 64, we are able to estimate effects for birth cohorts spanning a long time period–1909 to 1977. Finally, using multiple data sets allow us to examine the robustness of our estimates. This is important given the heterogeneous findings in research on intergenerational income transmission for men. That said, we can only compare results across data sets to the extent that the cross-sectional data sets do not confound age and cohort effects, something we return to below.

The GSS has the distinct advantage of being drawn from a series of nationally representative cross-sectional data sets over a long period of years. Because of this, when a series of GSS's are linked together, there are observations on individuals at different ages who were born in the same birth cohort, allowing analyses that separately identify age and cohort effects. This is vital in our context because our aim is to identify how fathers' occupations affect daughters' occupations over birth cohorts, conditional on the age of the women in the sample. This analysis obviously cannot be done with cross-sectional data alone. The GSS does have a few shortcomings, however. First, it is a small data set, even when surveys are pooled over multiple years. Second, the unit of observation in the GSS is an individual and not a household, so while information is collected on the occupation of the respondent, the respondent's father, and the respondent's spouse, when applicable, there is no information on the occupation of the respondent's father-in-law. As a result, one cannot explore relationships between in-law pairs of married couples.[13] We utilize data from the GSS surveys

[13]This shortcoming was noted as well in Fernandez et al. (2004), who therefore rely on an even smaller data set to generate the critical results in their paper.

of 1975-2002. 1975 was the first year that the GSS employed standard probability sampling.

The 1973 OCG is an obvious candidate survey for this paper because it was a large survey that was designed specifically to capture intergenerational relationships (see Featherman and Hauser, 1978, for more information). Because we combine data from the OCG with later surveys, we concorded the 1970 occupation codes that are used in the OCG to 1980 so that the occupations would be comparable. More details on this are given in the Data Appendix.[14] The SIPP Personal History Topical Modules in 1986, 1987, and 1988 were designed to mimic the OCG and are therefore complements to the OCG, as they contain similar information on cohorts of individuals 13-15 years after the OCG. Because these SIPP topical modules were all conducted in Wave II, there is very little of the attrition that sometimes plagues studies that use the SIPP.

The OCG was conducted as a supplement to the CPS in March 1973. Questionnaires were mailed out to male CPS respondents, specifically asking information about their family and their background, including the occupation of their father when they were 16 and, for married respondents, the occupation of their wife's father when their wife was 16. These responses, combined with the occupation responses and other background variables given as part of regular CPS survey, allow us to have for our sample of white, married households the occupations of the husband and wife, the occupations of their fathers, the ages of the husband and wife, and other demographic variables such as education, children in the household, and number of siblings. The SIPP data that we use naturally contains similar information.

Because our analysis relies on using information on the occupation of fathers-in-law, we necessarily restrict the data to contain only married respondents. Because the age at first marriage has risen over time and the age of retirement has declined over time, we examine the robustness of our results to limiting the age range to those between the ages of 35 and 55. We further restrict the sample to only whites, so as not to confound occupational changes

[14] There was a 1962 OCG survey as well, but we have chosen not to use it because it would have required yet another concordance, of 1960 occupations to 1980 occupations.

that are unique to women with those that are due to changing opportunities for blacks.

4.2 Female Labor Force Participation

In order to get some sense of how comparable the data are across surveys and how they reflect general trends, we first examine female labor force participation by birth cohort in each data set. We provide a graph in Figure 1 that shows the fraction of women who were employed in each year for each survey. Because we treat "out of the labor force" as an occupation in itself (one that daughters do not, by our definition, ever share with their fathers), it is important to examine female labor force participation rates in the context of occupation transmission between fathers and daughters.

We do not expect our data sets to provide identical female labor force participation rates for each birth cohort because of age effects. We therefore also graph female labor force participation rates by birth cohort for the 1970-2000 Decennial Census Public Use Micro Samples (PUMS), four nationally representative data sets drawn from years similar to our three data sets. Our samples consist of married, white women between the ages of 25 and 64 who report that they are not in school and are either working or out of the labor force (we exclude "unemployed" women and women in school).[15] We also restrict our attention to women who are either the head of household or the spouse of the head of household.

It is useful to begin by comparing data from the PUMS samples. For the birth cohorts that overlap between the samples, it is clear that overall female labor force participation increased over time, but not across all birth cohorts. For earlier birth cohorts, there is exit out of the labor force as women age, presumably due to early retirement, while for later birth cohorts female labor force participation clearly increased over the decade. For all four data sets, a dip in female labor force participation exists for women in their 30's, presumably as a result of child-rearing. The changing labor force participation rates of women through their

[15]Note that the PUMS definition of labor force participation is closest to that of the SIPP. See the Data Appendix for exact definitions of female labor force participation across data sets.

lifetimes foreshadows the importance of controlling for age in our analysis of intergenerational occupation between fathers and daughters.

Data from the GSS surveys of 1975-2002 provide the longest time period over which to examine labor force participation by birth cohort. The GSS spans the data from the SIPP and OCG, and nearly spans our Census years as well. As the graph in Figure 1 indicates, the GSS labor force participation rates do cut through those of the other data sets and rise from well below 20 percent for the birth cohorts early in the 20th century to well above 60 percent for women born in the 1960s and thereafter.

The OCG contains information on the labor force participation in 1973 of women born between 1909 and 1948. Average labor force participation of women in the OCG lies between the 1970 and 1980 PUMS graphs, as it should. Similarly, the SIPP profile of female labor force participation, derived from data collected between 1986 and 1988, is between the two PUMS profiles from 1980 and 1990, albeit closer to 1990, as would be expected. In total, female labor force participation in our data reflects that seen in PUMS data, and across our three data sets the trends in female labor force participation over time by birth cohort are consistent with age effects of retirement and child-rearing.

4.3 The Definition of Occupations

Until this point we have been vague as to what we mean by an occupation and how to operationalize it. Following standard practice, we define occupation using Census definitions. In our baseline results, the six major occupation groups as defined by the 1980 codes: Managerial and Professional Specialty; Technical, Sales, and Administrative Support; Service; Farming, Forestry, and Fishing; Precision Production, Craft, and Repair; and Operators, Fabricators, and Laborers. As in our model, for women we also include a seventh occupation group, Out of the Labor Force, which basically includes women who are not working, are not in school full time, and are not unemployed or looking for work. As part of our robustness checks we disaggregate the list of occupations further, to 13 occupations listed as subheadings of three-digit 1980 Occupation Codes.[16] Clearly, the more we disaggregate, the less power we have to detect changes in father-daughter occupation transmission because the occupations become extremely narrow. We are therefore not optimistic that we can refine occupation much more without incorporating other data sets. Perhaps more importantly, as mentioned above, the theoretical notion of occupation-specific human capital does not map directly to Census occupation classifications. For example, just as the literature on job-specific human capital can be recast to be about industry-specific human capital (see e.g. Neal, 1995), so our definition of occupation can be recast to map into industries, or into industries crossed with broad occupation definitions. We therefore also present our main results using an indicator of a woman being in the same industry as her father or father-in-law.

Table 1 contains summary statistics for our pooled sample, as well as for each data set. The statistics cover the occupational breakdown of women, fathers, and fathers-in-law, as well as age and birth year of women in our sample. The pooled data set is our estimation sample, so that for all women we have information on the occupation of her father or her father-in-law.[17] In our pooled data set, almost half (46.2%) of women are out of the labor force, with the next most populated occupation being Technical, Sales, and Administrative Support, comprising 22.8% of the sample. By comparing the proportions in each occupation across data sets, and particularly by comparing women in the OCG and women in the SIPP, one can clearly see how the occupational distribution of women has changed over time. In the OCG, 57.0% of women are coded as out of the labor force, whereas only 37.3% of women are in the SIPP. Moreover, conditional on labor force participation, women in the SIPP are more likely than their earlier counterparts to be either managerial and professional occupations or in technical, sales, and administrative support (46.1% in the SIPP versus 27.7% in the OCG).

[16] See Appendix Section A.3 for a mapping between the six and thirteen occupation category groupings.

[17] The distribution of occupation for women is very similar when women for whom we have no information on fathers or fathers-in-law are included.

The occupation distributions of fathers and fathers-in-law are extremely similar within each data set, as they should be absent non-random sampling or response by occupation of parents and in-laws. Over time for these fathers and fathers-in-law there are also changes in the occupational distribution; for example, these men are less likely to be in farming in the SIPP relative to the OCG. Because of this, and because fathers in different occupations may invest differently in children, we show results below with and without occupation controls for fathers and fathers-in-law.

Below the distributions of occupations in Table 1 we present summary statistics on the fraction of women who are in their father's and father-in-law's occupations in each data set. Overall, 10.7% of women in the data work in their father's occupation, and 9.9% work in their father-in-law's occupation. While these differences are not large in absolute terms, they are in percentage terms. Moreover, across data sets, it becomes clear that the differences grow over the birth cohorts in our sample: in the OCG, where the mean birth year of women is 1931, the difference between the two means in is 0.2 percentage points, whereas in the GSS, where the mean birth year is 1946, the difference is 1.8 percentage points.

5 Empirical Implementation and Results

Our basic empirical strategy is to compare the trends over birth cohorts in the probability that a woman is in her father's occupation relative to the probability that a woman is in her father-in-law's occupation. We formulate this as a single regression equation, pooling observations where we observe a woman and her father and observations where we observe a woman and her father-in-law:

$$Prob(same = 1)_i = \delta_0 + \delta_1 * DIL_i + \delta_2 * D_i * Y_i + \delta_3 * DIL_i * Y_i + \delta_4 * D_i * A_i + \delta_5 * DIL_i * A_i + \varepsilon_i. \quad (11)$$

In this specification, *same* is an indicator which equals one if a woman is in the same occupation as her father or father-in-law, DIL is a dummy variable that equals one if the observation contains information on a woman (daughter-in-law) and her father-in-law, D is

(1-DIL), Y is the birth year of the woman, and A is the age of the woman. The empirical prediction of the theoretical model suggests that we should be comparing rates of change in the probabilities over time, rather than absolute changes. But, as we show below, the estimate of δ_1 is small, and, when statistically significant, is positive. This indicates that the baseline probability for fathers and daughters to be in the same occupation is the same or lower as that for fathers-in-law and daughters-in-law, so that a statistically significant differences in the absolute change (a difference between δ_2 and δ_3) alone implies that fathers have increased investments over time in occupation-specific human capital of daughters.

Controlling for age (when possible) is important because women may transition into their "final" occupations as they gain experience in the labor market and, more importantly, as women move in and out of the labor force as they have children. Theoretically, it is quite possible for the coefficients on age, δ_4 and δ_5, to be different if, for example, a woman whose father has transmitted to her occupation specific human capital moves into her father's occupation as she gains experience in the labor market.

For two of our data sets, the OCG and the SIPP, we often observe information on the occupation of a woman and those of her father *and* her father-in-law, contributing two observations to the regression, so we always calculate robust standard errors clustering on observations where the same woman is observed. We present results for linear probability models. Marginal effects from logit models are extremely similar.

In Table 2 we show basic results for this regression specification for all three data sets together and then the three data sets separately. Because we cannot separately identify age and cohort effects in the OCG and SIPP, we do not include separate controls for age in this table. Column 1 contains results for the full sample. The estimated coefficient on the daughter's birth year, δ_2, is 0.2675 percentage points and is statistically significant, implying that the probability that a woman enters her father's occupation increases by 2.7 percentage points per decade. To put this in perspective, the fraction of women in their father's occupation born over the first decade of our sample (1909-1919) is only 5.8 percent, so that we estimate each decade thereafter leads to a very large 46.1 percent increase in the probability that a woman works in her father's occupation.

The coefficient estimate on the daughter-in-law's birth year is 0.2128 and is also statistically significant.[18] The fact that this point estimate is also large in magnitude, a finding repeated throughout the empirical results to follow, highlights the importance of controlling for overall trends in women's labor market entry in teasing out the distinct impact of the change in the extent of occupation-specific human capital transmission between fathers and daughters. We estimate nonetheless that $\delta_2 - \delta_3$, the annual change in the probability of a daughter being in her father's occupation *relative* to the equivalent change for a daughter-in-law/father-in-law pair, is a statistically significant 0.0548 percentage points. This difference, a measure of the impact of increased investment in specific human capital on the shift toward women working in their fathers' occupations, represents 20.4% of the overall change in the probability that a woman works in her father's occupation.

Figure 2 is the graphical representation of Table 2, column (1), except that instead of using linear regression, we generate these results using locally weighted least squares. There are two important things to take away from this figure. First, the probability that a woman is in her father's occupation is very slightly below that of fathers-in-law and daughters-in-law early in the period, but grows over the period of our sample to be above that of fathers-in-law and daughters-in-law. Second, the time trends in both of these probabilities are indeed close to linear, as we model them in equation 5.

Column 2 of Table 2 shows results for only the OCG sample of women who were born between 1909 and 1948. Of the women in this sample, 57.0% are recorded as being out of the labor force in 1973. The gradient of the probability of a woman working in her father's occupation is relatively flat over this period, with a precisely estimated increase of 0.0876

[18] The fraction of women in their father-in-law's occupation born over the first decade of our sample (1909-1919) is 6.3 percent which is actually statistically indistinguishable from the fraction of daughters in their fathers' occupations.

percentage points every year. The estimated increase in the fraction of women entering their father-in-law's occupation is lower, 0.0645 percentage points. The difference between these two is not statistically significant. This is not surprising given that women born in these years largely remained out of the labor force.

Column 3 shows the baseline results for the GSS for women in birth cohorts spanning 1911 to 1977 (although with very few observations for women at the tails of this distribution). The point estimate on the increased probability of father-daughter occupation transmission over ten years is 0.3281 percentage points. Relative to the baseline over the 1909-1919 period, this represents almost a 60 percent increase in this probability per decade of the sample. The increase in the probability that a woman works in her father-in-law's occupation is smaller, at 2.7 percentage points per decade. Finally, the relative difference between these two is 0.0582 percentage points per year, which while not statistically significant, is 17.8% of the overall increase in the probability that a woman works in her father's occupation. In column 4 we report results for the SIPP sample, representing women born 1921-1963. These results are similar to those for the GSS.

In Table 3 we examine results for various specifications of the model in the full sample of pooled data. Column 1 replicates the baseline results of Table 2 but includes controls for the survey from which the observation comes. If survey questions differ in a way that might affect the baseline probability of a woman being in a man's occupation, the inclusion of these controls should pick that up.[19] The point estimates of the father-daughter and father-in-law-daughter-in-law trends are somewhat smaller than in the previous table, but still are large and statistically significant. Moreover, the difference in the trends between fathers and daughters and fathers-in-law and daughters-in-law again is 0.0582 percentage points per year and is statistically significant. There are a few other things to note in this specification. First, there are statistically significant differences in the constant terms across data sets,

[19]For example, the GSS asks the respondent to report the occupation of her father while she was growing up, while the SIPP and OCG ask for the occupation of her father when she was 16 years old.

with the dummy variable for the OCG having a negative and significant coefficient. It turns out that this result does not hold up in other specifications. Second, the dummy variable for the daughter-in-law equation constant, δ_1 in the regression equation, has a coefficient of 0.0152 and is statistically significant. This result is also not robust.

In column 2 of Table 3 we include variables for age separately for daughters and daughters-in-law, as in equation 5. The estimates of the coefficients of the age variables are highly significant, almost identical (0.2467 and 0.2264 percentage points), and statistically indistinguishable from one another. They imply that every 10 years the probability that a woman enters her father or father-in-law's occupation increases by a healthy 2 percentage points. Given this result, and given that birth year and age are negatively correlated in these data, the inclusion of age into the model should cause the coefficients on the birth year trend variables to go up. Indeed, the estimates more than double, indicating large changes between birth cohorts in the probability that a woman works in both the occupations of her father and her father-in-law. The coefficient on the birth year of a daughter rises to 0.441 percentage points (from 0.2181), while the coefficient on the birth year of a daughter-in-law rises to 0.3709 percentage points. The former result can be interpreted as a 7.6 percent increase per year relative to the baseline probability, while the latter yields a 5.9 percent increase. The estimate of the relative difference in the two trend variables is 0.0703 percentage points and again is statistically significant. This difference is 15.9% of the overall change in the probability that a woman works in her father's occupation.

The fact that the dummy variables for the survey of origin and the dummy variable for the daughter-in-law are all statistically significant in column 2 leads to the specification in column 3, where we interact the survey of origin dummy variables with the daughter-in-law dummy variable. The point estimates on birth year are slightly closer together and slightly less precise, so while the estimate of the relative difference between the two is very close to the previous specifications (0.0546 percentage points), it is not statistically significant. The full set of interactions between the survey dummies and the daughter-in-law constant leads to small and insignificant differences across the board in these coefficients. Because they are small and statistically insignificant, we drop the interaction terms in the columns that follow, in order to gain more power in estimating the difference in the trends between daughters and daughters-in-law. Similarly, we constrain the coefficient on daughter's age, δ_4, to equal that on daughter-in-law's age, δ_5. These results are presented in column 4, where the point estimates on the birth year coefficients are virtually unchanged, but more precise, so that the estimated difference of 0.0546 percentage points between the two coefficients is statistically significant (standard error of 0.0170). Finally, because the distribution of the occupations of fathers and fathers-in-law has changed over time as well (see Table 1) in ways that may affect the probability that a woman is in one of these men's occupations, and because we can only estimate the impact of average investments may be made by men in different occupations, in column 5 we include a full set of controls for the occupations of fathers and fathers-in-law. To the extent that it is fathers making investments rather than fathers-in-law, there is no reason to expect the coefficients on these dummy variables to be the same for these two groups, and indeed (in results not shown) they are not. Including these dummy variables reduces the point estimates on the birth year variables and the variable for women's age. The coefficient on the birth year of daughters is 0.2793 percentage points, a 48 percent increase per decade over the baseline father-daughter probability, while that of the daughter-in-law is 0.2340 percentage points. Both remain highly statistically significant. The difference between these two is 0.0454 and is again statistically significant (standard error of 0.0161). This represents 16% of the overall increase in the probability that a woman works in her father's occupation and, once again, implies that fathers have increased their occupation-specific investments in their daughters.

The different specifications reported across columns in Table 3 vary the specification and set of covariates included in the model. In the first four columns of Table 4 we vary the samples over which we estimate the model, and in the last two columns we modify the definition of occupation, using specifications that parallel those in columns 4 and 5 of Table

3. Recall that the age range of women in our baseline sample is 25 to 64. By necessity, all these women are married. Because the age at first marriage has been rising over time and because the age of retirement has been falling, there may be compositional changes over time in who is included in our this sample. To test whether this has an affect on our results, in columns 1 and 2 of Table 4 we restrict the age range of our sample to 35 to 55, an age range where the vast majority of people (particularly whites) have gotten married, and where early retirement is not yet a major factor. This reduces our sample size considerably, from 63,076 to 34,544. The specification in column 1 mimics that of Table 3, column 4, where we include separate controls for survey and constrain the effect of age to be the same for daughters and daughters-in-law. The coefficient on the birth year variables in this column (0.4551 percentage points for daughters and 0.3988 percentage points for daughters-in-law) are very similar to those in the previous table and are again statistically significant. The estimate of the difference between the two, 0.0563 is also statistically significant (standard error of 0.0318). Column 2 adds controls for the occupations of fathers and fathers-in-law, paralleling the specification of Table 3, column 5. Here, the point estimates are again similar to those of Table 3, column 5, but the difference between the two of 0.0374 has a larger standard error than in Table 3, presumably because the sample size has been cut almost in half. In total, we interpret these specifications as providing evidence that our results are robust to these sample selection issues.

The theoretical model in Section 3 differentiates between women who are out of the labor force and women who are in a set of occupations in which men work. As mentioned above, we could recast the occupation of women who are out of the labor force in our model to be traditionally female occupations where men never (or almost never) work, such as nursing. The model would yield the same implications. Moreover, our model suggests that if investments in specific human capital S increases as the return to general human capital in the labor market increases, we should see an increase in the probability that a woman works in her father's occupation, relative to that of her father-in-law, even conditional on labor market participation. In columns 3 and 4 we therefore explore this empirically by including in the sample only women who are in the labor force. This again causes the sample to fall by almost one half. Column 3 replicates the specification of column 4, Table 3. Because so much of the change over time in the probability a woman enters the occupation of her father or father-in-law is due to labor force entry, the coefficients on the birth year trend are lower when we restrict the sample. The coefficient on birth year of daughters is 0.3326 percentage points and that of daughters-in-law is 0.2546. Both are statistically significant and, importantly, the difference between the two is 0.0779 and is statistically significant.

In column 4 we add controls for father and father-in-law occupations. While the birth year coefficients themselves become small and statistically insignificant, the relative difference between the two remains of the same magnitude as the full sample result at 0.0490. This estimate is only marginally significant, due to the much lower sample size. In summary, the results in columns 3 and 4 show that our full sample results are not being driven solely by entry into the labor market, and, as our model suggests, that occupational changes over time by women in the labor market are affected by the transmission of specific human capital between fathers and daughters.

In the last two columns of Table 4 we refine the definition of occupation to consist of 13 occupations (rather than 6).[20] Perhaps the most important distinction between the categorizations is that the two broad occupations in which most women work conditional on labor market participation, "Managerial and Professional Specialty" and "Technical, Sales, and Admin. Support," are each broken up. In column 5, the estimate on the coefficient on birth year for daughters is 0.1908 percentage points and is statistically significant. The estimate on the father-in-law trend coefficient is smaller, at 0.1498 percentage points, and the difference between the two is 0.0410 and statistically significant. Column 6 includes occupation controls, and while the coefficients on the trends fall and the difference between the two falls to 0.0300, it is still statistically significant, and again implies that fathers have

[20]For a list of the 6 and 13 occupation groupings see Appendix Table A3.

increased their occupation-specific human capital investments in their daughters.

Finally, as mentioned previously, while our results thus far have used Census occupation codes, this may not correspond to our theoretical notion of occupation-specific human capital. Therefore, in Appendix Table A1, we report results from various specifications using industry to classify the notion of specific human capital.[21] The magnitudes of the estimates are different than those using occupation codes, not surprisingly, and they are less robust across specifications, but across all specifications we find evidence consistent with increased specific-human capital investments of fathers.

In total, the results are remarkably robust across specifications and samples. There has been a large increase over time in the probability that a woman enters her father's occupation. Moreover, this increase is not due simply to changes in the marginal distribution of women's occupation, but is due at least partially to increased investments that fathers have made in the occupation-specific human capital of their daughters. Our results imply that the increase in the probability a woman is in her father's occupation is about 20% larger than the increased probability that a woman will enter an occupation where her father does not work, and this estimate is likely a lower bound.

Our final check on the link between our empirical results and the main motivation for this paper is performed in Table 5. We have claimed that something special changed in the relationship between fathers and daughters as a result of the increased entry of women into the labor market and into traditionally male occupations, and we framed our model to be changing incentives for fathers to invest in the specific human capital of their daughters. To the extent that this is true, we should not see the same trends in the probability that sons work in their fathers' occupations. We therefore repeat our empirical analysis, but on the

[21]We collapse the 15 major industries categories from the 1980 Census into 13 categories: (1) Agriculture, Forestry, and Fishing, (2) Mining, (3) Construction, (4-5) Manufacturing (combined Nondurable and Durable Goods), (6) Transportation, Communications, and Other Public Utilities, (7-8) Wholesale Trade (combined Durable and Nondurable Goods), (9) Retail Trade, (10) Finance, Insurance, and Real Estate, (11) Business and Repair Services, (12) Personal Services, (13) Entertainment and Recreational Services, (14) Professional and Related Services, and (15) Public Administration.

sample of sons and their fathers and fathers-in-law.[22]

The specification in column 1 of Table 5 includes trends for birth year of sons, birth year of sons-in-law, and separate age controls for both sons and sons-in-law.[23] Once again, we do not want to constrain the coefficients on the age controls to be the same a-priori because the impact of age on father-son probabilities may be quite different than that of father-in-law and son-in-law. For this sample of men, about 30 percent of men are in their father's occupation, and 27 percent are in their father-in-law's occupation, a much higher fraction in each case than for women. To the extent that we care about rates of change, this is important to keep in mind. The estimate on the birth year for sons is 0.0798 percentage points and statistically insignificant, almost 5 times lower than the parallel point estimate for women (in Table 3, column 2)! That is, unlike for women, there is no trend over time in the probability that a son enters his father's occupation. The coefficient for birth year of son-in-law is actually negative, but it is also small (-0.0411 percentage points) and statistically insignificant. It is the case, however, that the relative difference between these two is 0.1208 and statistically significant. Column 2 includes controls for the occupations of fathers and fathers-in-law. Again, the birth year trends are small and the father-son probabilities is statistically insignificant, but

[22]There is one caveat to using men as a falsification test of our results. Until this point, our model and discussion have focused on one-child families. If human capital transmission within the family is a purely private good, and if fathers over time invest more in their daughters, they may invest less in their sons. This will itself affect the results in Table 5, rendering it a flawed falsification test of our model and results for women. Moreover, if fathers invest less in sons, and if there is assortative mating in marriage by occupation, this could lead over time to fathers-in-law becoming a poorer control for fathers in our analysis of women. The OCG and SIPP do contain data on the number and sex mix of siblings which could potentially be used to examine whether the impact on boys of having sisters has changed over time, but of course family size and sex mix are endogenous.

[23]The sample sizes for men are smaller than for women. One reason for this is that the data force us to restrict the sample to only married couples where both the man and woman are older than 25, but allow people who are themselves younger than 65 who are married to people older than 65. Since men marry younger women, restricting on both partners being older than 25 differentially reduces the sample of men. For a more complete discussion of this, see the Data Appendix. We also exclude from our sample men who are not working. We think it unlikely that most of these men are actively engaged in home production, but instead that they are temporarily out of the labor force, so that the fact that they are not in their father's occupation at the time of the survey is transitory. This eliminates very few men in practice and including a separate out-of-labor force category for these men does not affect the results.

the father-in-law/son-in-law trend is negative and statistically significant and the difference between the two is large and statistically significant. The significant result on the birth year of the son-in-law is not found in any other specification.

Unlike in the sample of women, the coefficients on the survey dummies in this specification are large and highly significant, implying that there are indeed differences in baseline probabilities across data sets, even after controlling for age and birth year. Therefore, in column 3 we expand the specification to include interactions between the son-in-law dummy and each of the survey dummies. The results again suggest important differences across surveys. The coefficients on the dummy variables for the surveys are each statistically significant, as is the dummy variable for the interaction between the son-in-law dummy and the OCG dummy. The magnitudes of these coefficients are also large; for example, the coefficient estimate on the OCG dummy implies that, on average, men in the OCG are 4.3 percentage points less likely to be in the occupation of their fathers relative to men in the GSS, even conditional on birth cohort and age. Including these interactions also has a large impact on the coefficients on age and leads to a large difference in the estimated coefficient on son's age (-0.2159 percentage points) relative to son-in-law's age (-0.0746 percentage points). One possible interpretation of the negative coefficient on son's age is that there is selection into marriage, with sons who marry early also being more likely to be in their father's occupations. With the addition of these statistically significant controls to the model, the point estimate on the coefficient on birth year for son becomes negative (whereas in column 1 it is positive) and the coefficient on birth year for sons-in-law becomes positive, although both remain statistically insignificantly different from zero. The difference between these two is therefore actually negative (-0.1343) and statistically insignificant. This specification therefore yields absolutely no evidence whatsoever that the transmission of specific human capital from fathers to sons has changed over time.

Finally, in the last two columns we repeat the specifications in columns 1 and 2 for the sample of men aged 35-55. Just as with the female sample, this eliminates most problems of changing selection into marriage and changing selection into retirement. In column 4 we repeat the specification in column 2. We do this rather than reporting results using the specification in column 3 because that specification on this sample leads to small and imprecisely estimated coefficients on every variable (and a small, negative, and insignificant difference in the birth year trends). For that reason, we present results constraining the father-in-law dummy to be the same across surveys, recognizing that doing this gives the regression some extra power to find differences in the coefficient on birth year. With this specification, the estimate on the birth year for sons is 0.1349 percentage points, smaller again than for women and once again it is statistically insignificant (standard error is 0.0849). The birth year trend for sons-in-law is also small, positive, and statistically insignificant. The difference between these two (0.0688), while as large in magnitude as that for women, is also statistically insignificant (standard error is 0.0600). These results are robust to the inclusion of occupation controls, as seen in column 5.

In sum, looking across the columns of Table 5, we find no evidence suggesting that the probability that men work in their fathers' occupations has grown over time, no evidence suggesting that there has been a change in the equivalent probability for men and their fathers-in-law, and no robust evidence of a difference between these two trends. The results for men are therefore very different than that for women, and lead us to conclude that the impact of fathers on daughters' occupational choice has clearly changed in ways that are unique to that relationship, and are consistent with increased investments by fathers in the specific-human capital of their daughters.

6 Conclusion

The labor market in the 20th century was profoundly affected by the increase in female labor force participation. One potential implication of increased female labor force participation is that it changes the incentives for fathers to invest in their daughters. In particular, it can increase the incentive to invest in human capital that is specific to a father's occupation, increasing the probability that a woman enters her father's occupation.

Simply documenting that there has been an increased probability over time in the propensity of a woman to enter her father's occupation is not enough to determine whether there has been increased occupation-specific human capital transmission between fathers and daughters. A women will be more likely to enter her father's occupation even absent such an increase, because she will be more likely to enter any traditionally male-dominated occupation, including her father's.

We demonstrate that under the assumption that assortative mating by fathers' occupation, income, and preferences have not decreased over time, an assumption we argue is very plausible, a comparison of the rates of change over time in the probability that a woman enters her father's occupation and her father-in-law's occupation can be used to determine whether fathers have increased investments in the occupation-specific human capital of their daughters.

We combine three data sets spanning information collected between 1973 and 2002 and containing information on birth cohorts born between 1909 and 1977. We show that over time the probability that a woman enters her father's occupation has increased significantly and substantially. For the full sample of women that includes those out of the labor force, we estimate that with each successive year, the probability that a woman born in a particular year would enter her father's occupation increased by somewhere between 2.2 and 4.4 percent. The fraction of women entering their father-in-law's occupation increased anywhere from 1.6 percent to 3.8 percent. Across our many specification checks, the increase in the probability that a woman enters her father's occupation is larger than the probability that a woman enters her father-in-law's occupation, a finding that we interpret as evidence of increased transmission of occupation-specific human capital between fathers and daughters. For the full sample of women, our results imply that the increase in the probability that a woman enters her father's occupation is around 20 percent higher than the increased probability that she enters another occupation in her choice set, an estimate that is likely a lower bound.

It is natural to speculate as to the form that these specific human capital investments take. Unfortunately, there is no evidence that we know of that would help in this regard. For example, perhaps the most obvious form of specific human capital investment is investments in time. While there is some information in time-use surveys on how much time parents spend with children (see the review in Raley and Bianchi, 2005), there is no systematic evidence over time in how this time is allocated across daughters and sons. Dahl and Moretti (2005) present evidence that the ways in which fathers are part of the lives of sons and daughters have changed over time (e.g., via divorce, custody, single parenthood), but these various ways all indicate that fathers have preferences for sons and do not suggest how this manifests itself in terms of changing investments in daughters over time.

We have focused on investments between fathers and daughters in this paper because for many of the birth cohorts in our sample, the vast majority of their mothers were out of the labor force, so that maternal investments that affected labor market outcomes of daughters seem second-order and difficult to formalize. However, as recent cohorts of women with high levels of labor force attachment themselves become mothers, there should be changing incentives for these women to make investments of occupation-specific human capital in their own daughters (and sons). It will be quite interesting to examine for future cohorts how potentially "competing" investments made by fathers and mothers affect the occupation choices of children, and in particular how they affect the occupation decisions of daughters relative to sons.

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A Data Appendix

A.1 Core Sample Description

In each data set we restrict to white, married men and women. We exclude respondents who are younger than 25 years old or who report being married to someone under age 25. While we exclude women who are older than 64 years in the regressions (and make similar restrictions for men in the male sample regressions), we do allow women who are married to men older than 65. One reason for this asymmetric treatment is that restricting to men and women older than 25 helps control for data quality, since occasionally children are incorrectly coded as spouses. The results are insensitive to restricting to *couples* that are between 25-64 years old, but relaxing the upper bound restriction allows for a larger sample. One effect of this asymmetric treatment is that the male sample is slightly smaller than the female sample, since men tend to marry women who are younger. All of our results are for married, white individuals who report being either the head of household or the spouse of the head of household.

A.2 Labor Force Participation and Occupations

Table A2 describes how we define who participates in the labor force and who is dropped from the sample across each data set. As described in the text of the paper, we consider women who have decided not to work as a separate occupation "Out of Labor Force" (OLF). This category includes women who are "keeping house," as the OCG and GSS categorize them. The OLF category should not include women who are unemployed, looking for work, in school, or doing something else that is distinct from choosing to remain out of the labor force. We run sensitivity tests restricting regressions to include only women who report working and to include an OLF category for men and our results are qualitatively consistent across these samples. Note that we never include OLF for fathers or fathers-in-law, since we do not have an employment status code for fathers and therefore can not distinguish between item non-response and a non-working father.

The SIPP is distinct from the OCG and GSS in how employment status is coded. In the SIPP, work status is asked separate of school enrollment or other activities. A respondent could be coded as having a job and being enrolled in school, while the GSS and OCG only report one employment status per individual. We feel someone enrolled in school, either part-time or full-time, is likely to not be in their final occupation, even if a valid occupation code is given. Because of this, we restrict the SIPP sample to include only individuals who are not currently enrolled in school. While we were not able to make an identical restriction in the OCG and GSS, sensitivity tests including only individuals who reported working full-time provide similar results.

A.3 Occupation Coding and Concordances

Because our three surveys contain different occupation codings, we had to find a way to get a consistent definition of "occupation" for our analyses. For each decennial census a new set of occupation codes are defined. Though these tend to be similar, they are not identical across years. The 1973 OCG reports 1970 (and 1960) Census Occupation Codes, while the SIPP reports 1980 Occupation Codes. The GSS, on the other hand, uses 1970 codes for some years, 1980 codes for later years, and both for the middle years. To get a consistent definition of occupation we created a concordance from the 1970 to 1980 Census Occupation Codes. In the GSS survey years 1975-1990 the 1970 occupation codes are reported, while 1980 codes are provided for survey years 1988-2002. This provides us with 3 survey years (1988, 1989, and 1990) for which both 1970 and 1980 occupation codes are given to create a concordance.

To create the concordance we take the 1980 occupation code that is most frequently matched to each 1970 occupation code, choosing the smallest code by default in a tie. Once we have this mapping from 1970 to 1980, we merge the 1980 occupation codes onto the early years of the GSS with only 1970 occupation codes and onto the OCG. Tests of the sensitivity to using categorizations of the 1970 and of the 1960 codes provided consistent results.

Appendix Table A3 lists the occupation groupings used in our analysis.

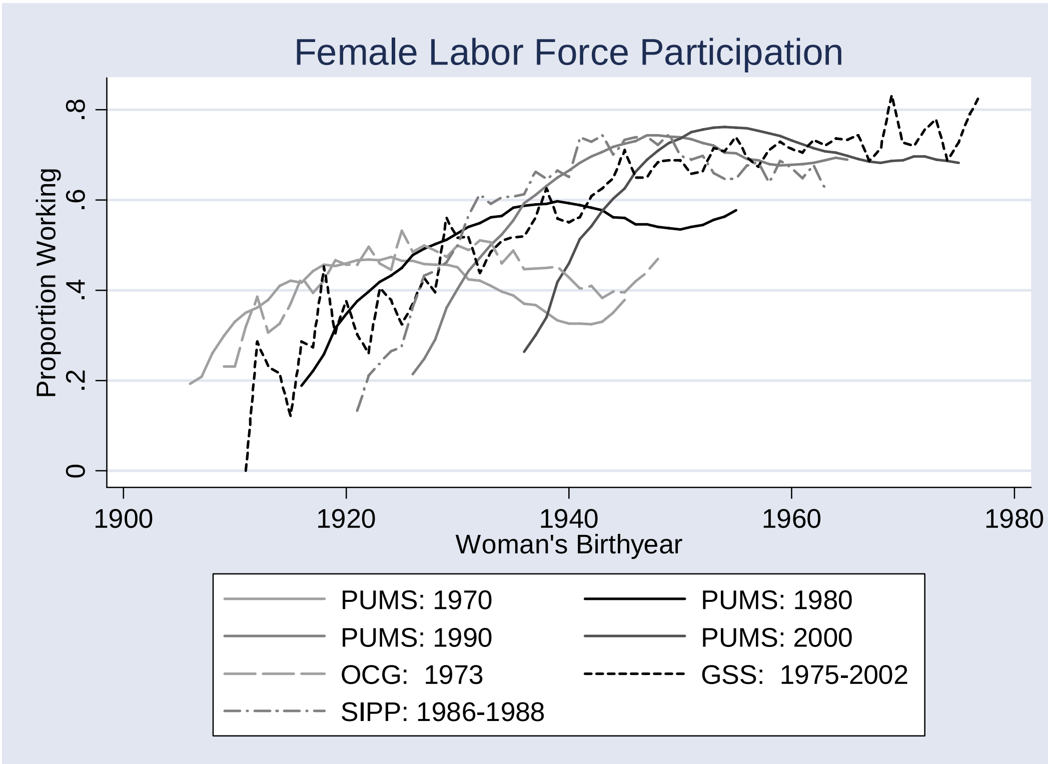

Figure 1: Female Labor Force Participation by Birth Cohort

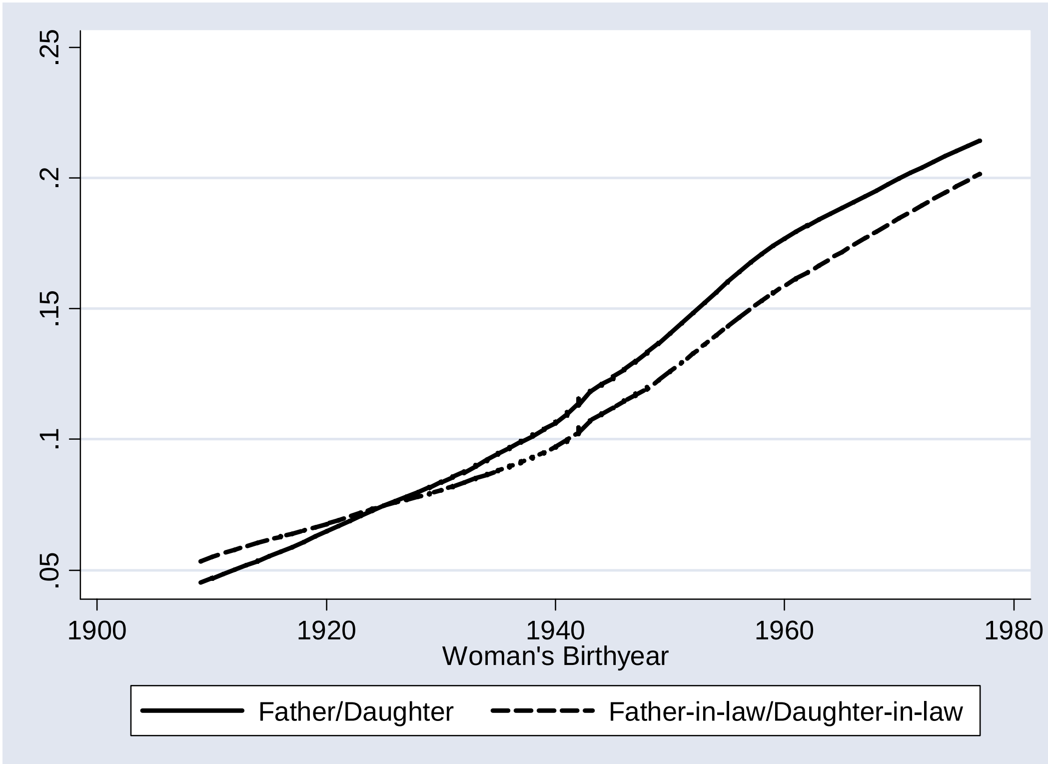

Figure 2: The fraction of women in the same occupation of their father and their father-in-law

Table 1: Summary Statistics for Women

	ALL	OCG	GSS	SIPP
WOMEN				
(1) Managerial and Professional Specialty	.155	.103	.215	.178
(2) Technical, Sales, and Admin. Support	.228	.174	.254	.283
(3) Service	.078	.068	.082	.088
(4) Farming, Forestry, and Fishing	.009	.010	.006	.010
(5) Precision Production, Craft, and Repair	.011	.008	.012	.015
(6) Operators, Fabricators, and Laborers	.058	.067	.050	.052
(7) Not in Labor Force	.462	.570	.381	.373
FATHERS				
(1) Managerial and Professional Specialty	.191	.180	.223	.190
(2) Technical, Sales, and Admin. Support	.119	.096	.131	.147
(3) Service	.050	.055	.040	.048
(4) Farming, Forestry, and Fishing	.195	.232	.156	.157
(5) Precision Production, Craft, and Repair	.230	.224	.240	.235
(6) Operators, Fabricators, and Laborers	.216	.213	.210	.224
FATHERS-IN-LAW				
(1) Managerial and Professional Specialty	.184	.172	.225	.185
(2) Technical, Sales, and Admin. Support	.111	.090	.117	.145
(3) Service	.048	.050	.040	.048
(4) Farming, Forestry, and Fishing	.222	.263	.174	.174
(5) Precision Production, Craft, and Repair	.223	.214	.242	.228
(6) Operators, Fabricators, and Laborers	.213	.212	.202	.221
Fraction of Women in Father's Occupation	.107	.079	.138	.134
Fraction of Women in Father-in-Law's Occupation	.099	.077	.120	.128
Woman's Age	42.1	41.8	42.3	42.3
	(10.9)	(10.7)	(11.0)	(11.2)
Woman's Birthyear	1939.1	1931.2	1946.2	1944.4
	(13.6)	(10.7)	(13.3)	(11.2)
Obs.	40,360	17,617	11,006	11,737

Table 2: Baseline Results for Probability of Daughter in Same Occupation as Father

Dependent variable: In same occupation as father or father-in-law

	Pooled	OCG	GSS	SIPP
	(1)	(2)	(3)	(4)
Birthyear Daughter	.2675	.0876	.3281	.3051
	(.0132)	(.0192)	(.0313)	(.0277)
Birthyear Daughter-in-law	.2128	.0645	.2698	.2498
	(.0130)	(.0189)	(.0323)	(.0306)
Const.	.0052	.0513	-.0135	-.0008
	(.0048)	(.0061)	(.0138)	(.0119)
Daughter-in-law Equation Dummy	.0131	.0052	.0085	.0149
	(.0062)	(.0074)	(.0199)	(.0162)
(BirthyearD - BirthyearDIL)	.0548	.0231	.0582	.0553
	(.0170)	(.0231)	(.0450)	(.0368)
Obs.	63,076	32,700	11,006	19,370

Notes: Standard errors are in parentheses. Coefficients on the birth years variables, the relative difference in slopes, and the age variables are in percent terms. Samples include married women ages 25-64. Occupations are defined at the 1-digit occupation level as in Table 1. Results are from linear probability models. Standard errors are robust and account for correlation across observations that arise from a daughter and daughter-in-law representing the same woman. Baseline (cohorts 1909-1919) fraction of women in the same occupation as their father (father-in-law) is 0.058 (0.063).

Table 3: Full Specification for Women

Dependent variable: In same occupation as father or father-in-law

	(1)	(2)	(3)	(4)	(5)
Birthyear Daughter	.2181	.4412	.4336	.4350	.2793
	(.0140)	(.0423)	(.0551)	(.0404)	(.0377)
Birthyear Daughter-in-law	.1599	.3709	.3790	.3779	.2340
	(.0140)	(.0424)	(.0564)	(.0405)	(.0378)
Const.	.0341	-.1728	-.1635	-.1665	
	(.0064)	(.0368)	(.0484)	(.0349)	
SIPP	.0045	.0086	.0044	.0086	.0074
	(.0041)	(.0041)	(.0055)	(.0041)	(.0038)
OCG	-.0231	.0107	.0069	.0107	.0030
	(.0038)	(.0065)	(.0090)	(.0065)	(.0061)
Daughter-in-law Equation Dummy	.0152	.0285	.0090	.0149	
	(.0062)	(.0246)	(.0689)	(.0062)	
DIL Dummy*SIPP			.0089		
			(.0076)		
DIL Dummy*OCG			.0079		
			(.0127)		
Daughter's Age		.2467	.2392		
		(.0444)	(.0570)		
Daughter-in-law's Age		.2264	.2349		
		(.0446)	(.0580)		
Constrained Daughter/DIL's Age				.2372	.1896
				(.0410)	(.0383)
F/FIL Occupation Controls	No	No	No	No	Yes
(BirthyearD - BirthyearDIL)	.0582	.0703	.0546	.0571	.0454
	(.0170)	(.0306)	(.0786)	(.0170)	(.0161)
Obs.	63076	63076	63076	63076	63076

Notes: See Table 2.

Table 4: Robustness checks

Dependent variable: In same occupation as father or father-in-law

	Prime Age		Labor Force		13 Occs	
	(1)	(2)	(3)	(4)	(5)	(6)
Birthyear Daughter	.4551	.2558	.3326	.0793	.1908	.1223
	(.0560)	(.0520)	(.0649)	(.0573)	(.0286)	(.0275)
Birthyear Daughter-in-law	.3988	.2184	.2546	.0303	.1498	.0923
	(.0566)	(.0525)	(.0648)	(.0572)	(.0285)	(.0274)
Const.	-.1703		.0146		-.0671	
	(.0495)		(.0572)		(.0247)	
SIPP	.0037	.0039	.0043	.0025	.0050	.0049
	(.0057)	(.0053)	(.0064)	(.0057)	(.0029)	(.0028)
OCG	.0116	-.0007	.0218	.0204	.0043	-.0008
	(.0092)	(.0085)	(.0118)	(.0104)	(.0046)	(.0044)
Daughter-in-law Equation Dummy	.0134		.0164		.0108	
	(.0107)		(.0128)		(.0045)	
Constrained Daughter/DIL's Age	.2482	.1664	.1048	.0743	.1061	.0870
	(.0616)	(.0574)	(.0664)	(.0586)	(.0291)	(.0281)
F/FIL Occupation Controls	No	Yes	No	Yes	No	Yes
(BirthyearD - BirthyearDIL)	.0563	.0374	.0779	.0490	.0410	.0300
	(.0318)	(.0297)	(.0313)	(.0292)	(.0124)	(.0120)
Obs.	34,544	34,544	33,242	33,242	63,076	63,076

Notes: See Table 2.

Table 5: Results for Men

Dependent variable: In same occupation as father or father-in-law

	Baseline Sample			Prime Age	
	(1)	(2)	(3)	(4)	(5)
Birthyear Son	.0798	-.0280	-.0542	.1349	-.0069
	(.0653)	(.0621)	(.0891)	(.0849)	(.0800)
Birthyear Son-in-law	-.0411	-.1475	.0801	.0661	-.0811
	(.0639)	(.0605)	(.0813)	(.0830)	(.0775)
Const.	.3258		.4465	.2845	
	(.0584)		(.0800)	(.0799)	
SIPP	-.0207	-.0076	-.0243	-.0273	-.0101
	(.0061)	(.0059)	(.0088)	(.0080)	(.0076)
OCG	-.0174	-.0069	-.0426	-.0132	-.0031
	(.0109)	(.0103)	(.0161)	(.0145)	(.0135)
Son-in-law Equation Dummy	.0218		-.2081	.0082	
	(.0407)		(.1080)	(.0618)	
SIL Dummy*SIPP			.0066		
			(.0118)		
SIL Dummy*OCG			.0482		
			(.0216)		
Son's Age	-.0832	-.0465	-.2159	-.0439	-.0113
	(.0706)	(.0670)	(.0927)	(.1051)	(.0987)
Son-in-law's Age	-.1055	-.0746	.0144	-.0602	-.0240
	(.0688)	(.0650)	(.0849)	(.1025)	(.0956)
F/FIL Occupation Controls	No	Yes	No	No	Yes
(BirthyearS - BirthyearSIL)	.1208	.1195	-.1343	.0688	.0743
	(.0465)	(.0446)	(.1204)	(.0600)	(.0570)
Obs.	56,254	56,254	56,254	33,377	33,377

Notes: Standard errors are in parentheses. Results are from linear probability models. Coefficients on birth year, age, and the relative difference in slopes are in percent terms. Standard errors are robust and account for correlation across observations that arise from a son and son-in-law representing the same man.

Table A1: Results for Women Using Industry

Dependent variable: In the same *industry* as father or father-in-law

	(1)	(2)	(3)	(4)	(5)	(6)
Birthyear Daughter	.1011	.2266	.2661	.2238	.1499	.1920
	(.0119)	(.0355)	(.0452)	(.0336)	(.0323)	(.0435)
Birthyear Daughter-in-law	.0585	.1788	.1337	.1819	.1104	.0622
	(.0120)	(.0353)	(.0476)	(.0337)	(.0323)	(.0453)
Const.	.0307	-.0852	-.1171	-.0824		
	(.0053)	(.0308)	(.0395)	(.0289)		
SIPP	.0015	.0032	-.0029	.0032	.0079	.0005
	(.0036)	(.0036)	(.0047)	(.0036)	(.0035)	(.0046)
OCG	-.0057	.0128	.0166	.0128	.0084	.0117
	(.0031)	(.0053)	(.0071)	(.0053)	(.0052)	(.0069)
Daughter-in-law Equation Dummy	.0161	.0219	.0898	.0159		
	(.0053)	(.0213)	(.0572)	(.0053)		
DIL Dummy*SIPP			.0129			.0157
			(.0064)			(.0063)
DIL Dummy*OCG			-.0081			-.0071
			(.0105)			(.0101)
Daughter's Age		.1388	.1782			.1469
		(.0374)	(.0469)			(.0453)
Daughter-in-law's Age		.1297	.0857			.0549
		(.0372)	(.0489)			(.0466)
Constrained Daughter/DIL's Age				.1345	.1034	
				(.0341)	(.0328)	
F/FIL Occupation Controls	No	No	No	No	Yes	Yes
(BirthyearD - BirthyearDIL)	.0426	.0478	.1323	.0419	.0395	.1298
	(.0146)	(.0265)	(.0654)	(.0146)	(.0143)	(.0626)
Obs.	58,039	58,039	58,039	58,039	58,039	58,039

Notes: Standard errors are in parentheses. Results are from linear probability models. Coefficients on birth year, age, and the relative difference in slopes are in percent terms. Standard errors are robust and account for correlation across observations that arise from a daughter and daughter-in-law representing the same woman.

	OCG	GSS	SIPP	PUMS
Question wording	"What was _ doing most of LAST WEEK?"	"Last week were you working full time, part time, going to school, keeping house, or what?"	Work status: Month 4 School: During any of the past 4 months	Employment Status Recode (empstatg): Previous week School attendance: During the past 2 months
Possible Responses	(1) Working (2) With a job, but not at work (3) Looking (4) Housework (5) School (6) Unable (7) Other	(1) Working full time (2) Working part time (3) With a job, but not at work b/c of temp illness, vacation, or strike (4) Unemployed (5) Retired (6) In School (7) Keeping house (8) Other (9) No answer	With a job entire month… (1) worked all weeks (2) missed one or more weeks, no time on layoff (3) missed one or more weeks, spent time on layoff With a job one or more weeks… (4) no time spent looking or on layoff (5) spent one or more weeks looking or on layoff No job during month… (6) spent entire month looking or on layoff (7) spent one or more weeks looking or on layoff (8) no time spent looking or on layoff	Employment Status Codes: (1) Employed (2) Not Employed (3) Not in Labor Force
Women	Working: (1) or (2) Out of Labor Force: (4) or (7) Dropped: (3), (5), or (6)	Working: (1), (2) or (3) Out of Labor Force: (5), (7), or (8) Dropped: (4), (6), or (9)	If respondent not enrolled in school: Working: (1) – (5) Out of Labor Force: (8) Dropped: (6) or (7)	If respondent not enrolled in school: Working: (1) Out of Labor Force: (3) Dropped: (2)
Men	Working: (1) or (2) Dropped: (3) – (7)	Working: (1), (2), or (3) Dropped: (4) – (9)	Working: (1) – (5) Dropped: (6) – (8)	N/A

Table A.2: Description of Labor Force Definitions

1980 Census Occupation Codes	
Six Occupation Categories	**13 Occupation Categories**
(1) Managerial and Professional Specialty	(1) Executive, Administrative, and Managerial Occupations and Management Related Occupations
	(2) Professional Specialty Occupations
(2) Technical, Sales, and Administrative Support	(3) Technologists, Technicians and Related Support Occupations
	(4) Sales Occupations
	(5) Administrative Support Occupations, Including Clerical
(3) Service	(6) Service Occupations, Private Household Occupations
	(7) Protective Service Occupations
	(8) Service Occupations, Except Protective and Household
(4) Farming, Forestry, and Fishing	(9) Farming, Forestry, and Fishing Occupations
(5) Precision Production, Craft, and Repair	(10) Precision Production, Craft, and Repair Occupations
(6) Operators, Fabricators, and Laborers	(11) Machine Operators, Assemblers and Inspectors
	(12) Transportation and Material Moving Occupations
	(13) Handlers, Equipment cleaners, Helpers, and Laborers

Table A.3: 1980 Census Occupation Code Groupings