Women and Careers: Skill-Specific Atrophy and Repair*

Andrew Rendall† and Michelle Rendall‡

The University of Zurich

January 14, 2015

Abstract

We present and test the theory that women rationally select occupational paths through preferences for skills that are both resilient and repairable when faced with work gaps. Using the NLSY and O*net, we show that college educated women avoid occupations requiring significant math skills due to the costly skill atrophy experienced during a career break. In contrast, verbal skills are very robust to career interruptions. The results support the broadly observed female preference for occupations primarily requiring verbal skills - even though these occupations exhibit lower average wages. Thus, skill-specific atrophy during employment leave and the speed of skill repair upon returning to the labor market are shown to be important factors underpinning women's occupational outcomes. This research suggests that a substantial portion of female occupational sorting could be determined by skill-specific atrophy-repair characteristics.

JEL classification: I20, J16, J22, J24, J31

Keywords: gender differences, human capital depreciation, occupations, mathematics abilities

*Michelle Rendall gratefully acknowledges financial support from the ZUNIV FAN Research Talent Development Fund.

†University of Zurich, Graduate School of Business, Plattenstrasse 14, CH-8032 Zurich. Email: andrew.rendall@uzh.ch.

‡University of Zurich, Department of Economics, Schoenberggasse 1, CH-8001 Zurich. Corresponding Email: michelle.rendall@econ.uzh.ch. We are solely responsible for errors and omissions.

1 Introduction

The gender wage gap is a persistent characteristic of the US labor market. Although it has narrowed significantly between 1970 and 2010, research suggests that it will not disappear for a number of reasons. Favored explanations generally focus on female-male differences in bargaining, fertility, and preferences across occupations (see Goldin, 2014, and references therein). In this paper, we focus on the idea that women and men have different economic valuations (preferences) over human capital types, which is underpinned by their employment expectations. The subsequent specific capital accumulation leads to an occupation gap between men and women that is surprisingly robust.[1]

The precise mechanism underpinning the differences between female and male occupational choices is still under debate. The traditional model (Roy, 1951) suggests that individuals choose occupations that maximize their skill returns. However, this model cannot explain the large labor market gender differences observed, including occupational choices over the life-cycle. Thus, the basic question is: How do women (men) choose occupations?

Hsieh et al. (2013) provides detailed statistics underlining the observed female-male occupational differences, along with the closing (but still existing) gender gap in occupational choice. The authors argue that the misallocation of talent from 1960 to today has shrunk, as frictions in both the labor market and schooling choices have decreased. They model both frictions as taxes that diminish over time based on changes in occupational barriers, the distribution of talent and occupation-specific technical change. However, even with a decrease in these frictions, the occupational gender gap is still significant today. More specifically, the occupation similarity index (see Table 1 in Hsieh et al., 2013), where zero denotes no overlap and one denotes a perfect overlap with the occupational distribution of white men, increases from 0.38 to 0.59 from 1980 to 2008 for higher educated white

[1] Although occupational differences across gender have diminished rapidly, the pace of convergence has slowed recently.

women and from 0.40 to 0.46 for lower educated women. Thus, while men and women have similar *ex ante* abilities (Goldin et al., 2006), women self-select into vastly different occupations compared to men. Goldin (2014) suggests that the penalty attributed to part time work or the inflexibility of work schedules of certain occupations is a primary driver of occupational differences. In the context of Hsieh et al. (2013), rigid work schedules are a friction that has yet to be overcome.

We propose a mechanism that is complimentary to Hsieh et al. (2013) and Goldin (2014), and consistent with the large skill-biased technical change literature. Technological innovation in the last few decades has been exceptionally fast by historical standards, especially within the ICT sector. Some skills may be more exposed to this innovation than others. That is, as technology moves forward, certain skills may become obsolete more quickly. If women are more likely to take career breaks, e.g., for child bearing/rearing, they may optimally choose occupations that exhibit less skill-obsolescences if they experience work gaps. Therefore, we explore if certain types of skills are more likely to become obsolete in the labor market after career breaks.

This idea follows from the large literature explaining occupational choices through human capital characteristics. The gender dimension is first explored by Mincer & Polachek (1974) who theorize that women acquire human capital taking into account their expectations regarding family formation and future labor market attachment. The authors estimate human capital depreciation rates for women from the National Longitudinal Survey of Mature and Young Women (NLS). Polachek (1981) takes the generalized depreciating human capital concept and allows for occupation-specific skill depreciation, with the author concluding that occupational choice is related to the period of time spent out of the labor force. McDowell (1982) similarly notes that women tend to avoid fields where knowledge depreciates quickly (is non-durable) and this selection bias is correlated with aggregate fertility patterns. Mincer & Ofek (1982) find evidence of wage "rebound" when estimating income losses from labor market withdrawal and re-entry. They hypothesize that this wage rebound is actually a form of "repairing" or relearning previously depreciated human capital, based on the assumption that relearning skills is less costly than learning a task for the first time. Additional support comes from Lazear & Rosen (1990), who suggest women are passed up for promotions within the same "narrow" jobs due to a lack of firm-specific human capital, possibly due to career interruptions.

The previous literature, due to a lack of data availability, used occupation labels (e.g., lawyer, nurse) or the share of women within an occupation to differentiate between male and female human capital types.[2] Given new data sources, this study focuses on gender differences in the demand and supply of specific skills such as mathematics and language. That is, we expand on the literature by analyzing whether women choose certain occupations because of skill-specific atrophy and repair rates. Although *ex ante* women possess similar abilities to males, women will potentially prefer lower paying occupations when maximizing expected lifetime income because the skills required in these occupations have small absolute depreciation rates.[3] Depreciation rates are especially important for women who expect employment gaps (e.g., child-rearing). For example, Adda et al. (2012) build a model where fertility affects career paths through initial occupational decisions. The authors study how German women make career choices within the apprenticeship system, given that these women will make fertility choices during their working years. The difference between our work and Adda et al. (2012) is two-fold. First, we focus on occupation decisions related to certain skills (i.e., math, verbal, science, technical skills), both for college graduates and non-college workers. Second, we consider occupational choices throughout an individual's life-cycle. Therefore, the goal of this paper is to quantitatively assess whether there is a gender bias in occupational choices based on skill requirements and to what extent varying skill-specific atrophy-repair rates exist.

Section 2 starts with a short summary of the data and the basic facts concerning

[2] An occupation is classified to have female human capital if the share of female workers within that occupation surpasses a certain threshold.

[3] In this study, absolute depreciation rates are defined as the depreciation of skill taking into account potential repair rates when reentering the labor market.

occupational gender differences in the National Longitudinal Survey of Youth 1979 (NLSY) sample. Section 3 provides a simple model of individual occupational choice. We use the model to derive a monetized mismatch of skill measure, based on occupation requirements by gender-education groups and absolute depreciation rates. The data analysis, Section 4, has two main objectives. First, we detail the gender-specific relationships between *ex ante* ability and *ex post* occupation outcomes. We compute the mismatch of men and women by skill type from the NLSY. Second, we document skill-specific atrophy-repair functions from the NLSY. The NLSY is ideally suited to compute mismatch and atrophy-repair rates, as it provides individual ability measures (e.g., math) through the Armed Services Vocational Aptitude Battery (ASVAB), along with detailed work histories. In conjunction with the NLSY, the Occupational Information Network (O*net) provides the necessary occupation-specific skill measures. Section 5 concludes.

2 Skills and Occupations

We make use of two data sources, the NLSY (National Longitudinal Survey of Youth 1979) and the O*net (Occupational Information Network) versions 4.0-9.0. These datasets provide two unique descriptive dimensions for occupations: (1) individual skills and wage returns to various skills in each occupation; and (2) O*net descriptors, where occupations are differentiated by the tasks and skills they require, rather than the *ex ante* abilities of individuals within those occupations.

To assess the *ex ante* abilities of individuals, we use the NLSY, which records skill-specific test scores for math, verbal, science and technical skills from the ASVAB administered in 1980 (see Appendices A and B for details on the data). These tests are based on a set of standardized tests created in WWII by the US military, which were further refined in the mid-1970s by psychometricians who created the first computerized, adaptive tests. The ASVAB tests multiple skill dimensions, turned into composite scores, for career placement purposes. These tests are commonly used by high schools to assist career counselors.

The NLSY cohort was tested using the 1980 version of these exams, with results for each individual providing relative skill measures. In addition, 26 occupational descriptors from O*net have been mapped into seven ASVAB test types by the *ASVAB Career Exploration Program*.[4]

Table 1 summarizes the data used in the analysis using broad education groups.[5] Although individuals were interviewed from 1979 to 2010, the sample here only includes observations after individuals graduated from their highest degree (i.e., all students are dropped). The empirical analysis differentiates wages observations of part-time and full-time workers., where part-time workers are individuals that worked at least 500 hours but no more than 1,400 hours in a calendar year.

In the empirical analysis we use two samples. One including all individuals with valid occupational observations and wages, the other only including workers with substantial labor force attachment. The labor force attachment variable in Table 1 computes the share of individuals that spend at least 75 percent of their life-cycle (after graduating) working. Not surprisingly, this share is considerably higher for men than women, and also larger for college graduates compared to non-college graduates. Consistently, summary statistics on the total time spent at home (either as unemployed or not in the labor force) are generally higher for women than men and for non-college than college-graduates. Moreover, women not only have a higher mean number of week gaps, but also a larger standard deviation, especially when comparing weeks out of the labor force within the last year.

Given the *ASVAB Career Exploration Program* mapping between O*net descriptors and ASVAB test scores, the difference between the occupational skills of men and women can be studied. Original ASVAB test scores and O*net occupational task requirements are converted into percentile ranks within each year using the NLSY cross-sectional weights.

[4] The *ASVAB Career Exploration Program* is sponsored by the Department of Defense; more details on the mapping procedure can be found at www.asvabprogram.com/downloads/Technical_Chapter_2010.pdf.

[5] "LTC" denotes individuals without a college degree, and "C+" denotes individuals that have completed at least a four-year college degree.

Table 1: Sample Summary Statistics

	Male				Female			
VARIABLES	LTC (1)		C+ (2)		LTC (3)		C+ (4)	
Year	1,992	(8)	1,995	(8)	1,992	(9)	1,995	(8)
Age	31	(9)	35	(8)	32	(9)	35	(8)
Married	46	(50)	60	(49)	52	(50)	59	(49)
Graduation Year	1,979	(4)	1,985	(4)	1,980	(4)	1,985	(5)
Part-time Worker	12	(33)	8	(28)	21	(41)	17	(38)
Full-time Worker	80	(40)	87	(34)	66	(47)	74	(44)
Labor Force Attachment	75	(43)	94	(24)	56	(50)	75	(43)
Total Weeks at Home	164	(166)	207	(155)	237	(227)	226	(176)
Weeks at Home Last Year	6	(12)	3	(9)	9	(15)	5	(11)
O*net M Rank	46	(29)	65	(27)	46	(26)	62	(28)
O*net V Rank	43	(30)	65	(26)	48	(26)	66	(25)
O*net S Rank	50	(30)	61	(27)	44	(27)	58	(29)
O*net T Rank	57	(29)	58	(28)	40	(26)	52	(28)
Pre-ASVAB M Rank	43	(26)	76	(20)	43	(25)	75	(21)
Pre-ASVAB V Rank	43	(27)	74	(21)	44	(26)	72	(21)
Pre-ASVAB S Rank	45	(26)	72	(22)	44	(27)	71	(24)
Pre-ASVAB T Rank	48	(28)	67	(23)	44	(27)	67	(25)
ASVAB M Rank	45	(26)	78	(20)	41	(25)	73	(21)
ASVAB V Rank	42	(27)	72	(21)	46	(26)	73	(20)
ASVAB S Rank	49	(28)	77	(21)	40	(24)	65	(23)
ASVAB T Rank	58	(29)	77	(21)	35	(22)	54	(22)
Observations	32,839		9,444		30,720		9,147	
Individuals	2,123		661		2,176		694	

Notes: Standard errors are in parentheses.

Math (M), verbal (V), science (S) and technical (T) variables are denoted by their respective first letter.

Source: NLSY. Females and males aged 14-22 in 1979. For detailed definitions see text.

Since the NLSY is a representative sample of the US population and workforce each survey year this percentile ranking will be consistent.[6] Two measures of ASVAB ranks are

[6]Alternatively, we can also rank individuals according to their test score in 1980 (one-time ranking). However, this does not change the results, as only a biased drop-out from the interview survey would do so. Therefore, assuming the same ranking strategy for individual skills and occupations is our preferred benchmark.

Table 2: Gender Gap in Occupational Skill

Time	Skill Requirements Math (1)	Verbal (2)	Science (3)	Technical (4)
Non-College				
1985	2.63***	7.25***	-4.51***	-14.91***
1990	0.34	4.55***	-5.47***	-15.94***
1995	-0.67	3.17***	-6.19***	-17.02***
2000	-2.32***	1.63***	-7.34***	-18.20***
2005	-3.04***	0.70	-7.87***	-19.47***
College				
1990	-0.50	2.22***	-0.70	-4.19***
1995	-2.60***	0.86	-2.59***	-5.41***
2000	-4.10***	-0.57	-4.11***	-6.80***
2005	-4.99***	-0.34	-3.83***	-6.57***

Statistical significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Reporting 5-year averages. For detailed see text.

reported. Following Cawley et al. (1998) we standardize test scores using two methods: (1) by age alone (labeled "ASVAB"); and (2) by gender and age (labeled "Pre-ASVAB"). The age adjustment is done as all individuals took the test in 1980 and are, therefore, of different age. The gender adjustment is done under the assumption that *ex-ante* men and women are born with the potential to develop the same skill distribution. However, due to economic incentives/preferences/stereotypes men and women choose to specialize in different skills starting at a young age (see Bordalo et al., 2014, and references therein). Specifically, at first glance, women seem to work in higher verbal task occupations and also score higher in verbal tests compared to both men and relative to other skill types.

To broadly summarize the occupation-skill gaps between men and women, Table 2 reports the percentile differences across four skill categories by education and gender. This summary converts skills to a percentile rank for each year and then averages over five year intervals by gender. A negative value indicates that women work in occupations requiring less of a given skill then men. Despite convergence along a number of important dimensions (e.g., wages), it appears that the NLSY cohort gender differences actually grew across all skill categories except verbal. These results point to strong occupation preferences across gender, as the table summarizes occupational skill requirements rather than *ex ante* ability. This last point is especially important given *ex ante* ability is shown to be virtually identical between gender (Goldin et al., 2006). Thus, women with a college degree work in occupations with similar verbal requirements as men, but lower math, science and technical skills. This pattern is repeated for uneducated women, but more skewed toward technical skills.

3 Model of Occupational Choice

Beginning with an occupational choice model based on Roy (1951), we model both individuals' skills and their occupational choices. Individuals have n skill types θ^k, $k = 1, , n$, which are drawn from a given distribution at the beginning of their working life. We are agnostic concerning how these skill distributions are initially set, but they may arise from educational choices earlier in life.[7] We account for the potential educational investment in the empirical section. Individuals can choose from a continuum of occupations in period 0 that differ by their skill requirements, Θ_k for all $k = 1, , n$, where $\Theta_k > 0$. That is, all occupations require some skill level of skill type k.

Individuals receive shocks during their lifetime that will force them to temporarily leave the workforce. This is modeled by a simple two-stage Markov process (below) which differs by gender. Individuals are aware of these labor force transition probabilities. The transition probability subscripts denote sequential period status. Specifically, π_{ee} is the conditional probability of being employed today and tomorrow and π_{eh} is the conditional probability of being employed today and staying home tomorrow, where $\pi_{ee} + \pi_{eh} = 1$. As women are more likely to dropout of the labor force (i.e., childbirth) and less likely to return (i.e., child rearing), we set $\pi^m_{ee} > \pi^f_{ee}$ and $\pi^m_{he} > \pi^f_{he}$ to cover these respective

[7] There are many other possible inputs forming these skill distributions.

observations. Additionally, $\nu_e^f < \nu_e^m$ and $\nu_h^f > \nu_e^m$ match the observed gender-specific employment and, by definition, home probabilities.

$$\Pi^g = \begin{bmatrix} \pi_{ee}\nu_e^g & 1-\pi_{ee}\nu_e^g \\ 1-\pi_{hh}\nu_h^g & \pi_{hh}\nu_h^g \end{bmatrix} \text{ for } g = f, m$$

When out of the labor force, skills depreciate by $\delta_{k,h} < 0$. However, when returning to the labor force some skills are recovered $\delta_{k,he} > 0$, but $|\delta_{k,he}| \leq |\delta_{k,h}|$. The atrophy and repair rates are skill-type specific. For most of the theoretical analysis we set learning-by-doing to zero, $\delta_{k,e} = 0$. However, the empirical analysis does account for returns to experience. Assume that $(1+\delta_j) = (1+\delta_{j,he})(1+\delta_{j,h}) < (1+\delta_{i,he})(1+\delta_{i,h}) = (1+\delta_i)$ for $j > i$. That is, skills are sorted according to their absolute atrophy/repair, $\delta_k \leq 0$, where a higher skill has relatively higher destruction of skill. The heterogeneity of skill depreciation suggests that some skills are more insulated against technological innovations.

3.1 Agents' Problem

For simplicity, assume a three period model. Individuals work in period 0 for certain and, if they do not drop out of the labor market in period 1, they also work for certain in period 2. Transition probabilities govern if individuals who drops out of work in the middle of their lives will return to work. Individuals draw utility from consumption,

$$U(c) = E\left\{\sum_{t=0}^{2} \beta^t \log(c_t)\right\}. \tag{1}$$

There is no savings mechanism and individuals simply consume their income each period, $\log(c_t) = \log(W_t^i) = \omega_t^i$. Individuals that do not work derive utility $b = \log(c_t)$, the value of their home production.[8]

Rather then employ shocks to working or not working, we could have drawn b from a

[8] Alternatively, assume the economy has complete markets so income maximization yields the same results as utility maximization.

distribution each period, with women having a higher mean then men. However, this will not affect the qualitative results. Therefore, we keep a fixed (gender equal) utility from staying home and allow for differing transition probabilities.

3.2 Wages

Assume all possible skill type occupations exist, i.e., there is a continuum of occupations using different skill mixes. The wage an individual receives in the labor market is,

$$\omega_t^i = \sum_{k=1}^{n} \left[\alpha_k \Theta_k^i + \gamma_k \left(\theta_{k,t}^i - \Theta_k^i \right) \Theta_k^i \right]. \tag{2}$$

Wages are a function of the returns to each skill type α_k, such that the higher the skill content an occupation requires the higher the wage as long as $\alpha_k > 0$. Agents are potentially penalized if they choose an occupation that requires more skill then they have, $\gamma_k \geq 0$. The interaction between occupation requirement Θ_k^i and skill mismatch $\left(\theta_{k,t}^i - \Theta_k^i \right)$ suggests the penalty (or reward) of mismatch is larger the greater the skill content. This second term will ensure that not all individuals try to match with the highest possible skill content given increasing returns. The second term can also be written as, $\gamma_k \theta_{k,t}^i \Theta_k^i - \gamma_k \left(\Theta_k^i \right)^2$, where the first part is the complementarity between individual skills and occupation requirements, and the second term is the general decreasing returns to skill type k. Note that wages without gaps are,

$$\omega_t^i = \sum_{k=1}^{n} \left[\alpha_k \Theta_k^i + \gamma_k \left((1 + \delta_{k,e}) \theta_{k,t-1}^i - \Theta_k^i \right] \Theta_k^i \right), \tag{3}$$

where $\delta_{k,e}$ is the return to experience for skill type k. Wages right after a gap period at $t - 1$ are,

$$\omega_t^i = \sum_{k=1}^{n} \left[\alpha_k \Theta_k^i + \gamma_k \left((1 + \delta_k) \theta_{k,t-2}^i - \Theta_k^i \right) \Theta_k^i \right]. \tag{4}$$

3.3 Maximization Problem

The agents maximization problem is to choose the optimal $\{\Theta_k\}_{k=1}^n$ by maximizing expected utility, taking transitions into and out of the labor market into account,

$$\begin{aligned} \max_{\{\Theta_k\}_{k=1}^n} \quad & (1+\beta\pi_{ee}^g(1+\beta))\sum_{k=1}^n \left[\alpha_k\Theta_k^i + \gamma_k\left(\theta_{k,0}^i - \Theta_k^i\right)\Theta_k^i\right] + \\ & \beta^2\pi_{eh}^g\pi_{he}^g\sum_{k=1}^n \left[\alpha_k\Theta_k^i + \gamma_k\left(\theta_{k,2}^i - \Theta_k^i\right)\Theta_k^i\right] + C(b,\Pi^g,\beta). \end{aligned} \tag{5}$$

The first term is the net present value of wages if the individual does not have a home spell, the second term is the last period wage if the individual took a gap year in period one, and the last term summarizes the utility from all periods the individual may spend at home.

With a home spell, $\theta_{k,2} = \theta_{k,0}(1+\delta_k)$, the resulting FOCs are (omitting individual superscripts):

$$(\beta_1+\beta_2)(\alpha_k - 2\gamma_k\Theta_k) + (\beta_1+\beta_2(1+\delta_k))\gamma_k\theta_{k,0} = 0,$$

where $\beta_1 = (1+\beta\pi_{ee}^g(1+\beta))$ and $\beta_2 = \beta^2\pi_{eh}^g\pi_{he}^g$. Therefore, the optimal occupational choice for skill type k is,

$$\Theta_k^\star = \frac{\alpha_k}{2\gamma_k} + \frac{(\beta_1+\beta_2(1+\delta_k))}{2(\beta_1+\beta_2)}\theta_{k,0}. \tag{6}$$

3.4 Comparative Statics

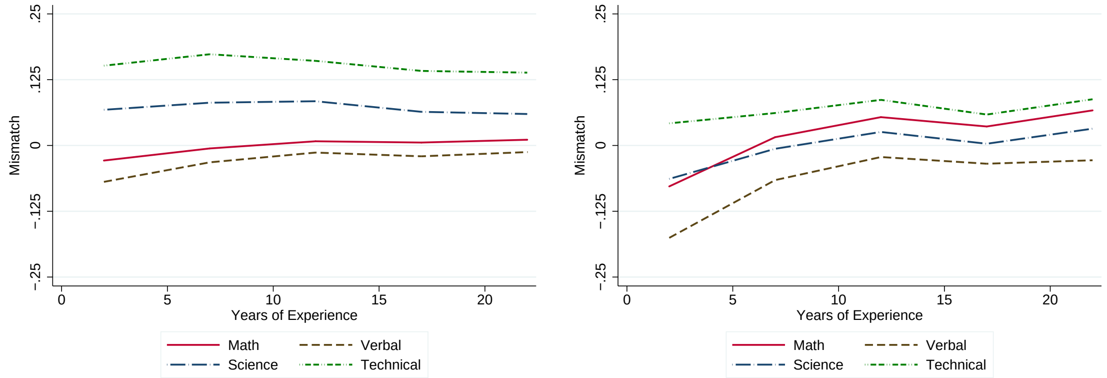
The outcomes of interest in this model are most easily seen from the comparative statics. From Equation (6) higher skilled individuals choose more skill-demanding occupations. Moreover, women will sort into lower skill requirement occupations, since $\hat{\beta}^m > \hat{\beta}^f$, where $\hat{\beta} = \frac{(\beta_1+\beta_2(1+\delta_k))}{2(\beta_1+\beta_2)}$. In the extreme case, i.e., men never drop out, $\nu_e^m = 0$, men have much stronger assortative matching then women. Since $\delta_k < 0$ and $\frac{\partial\hat{\beta}}{\partial\delta_k} > 0$. In contrast, women will be increasingly mismatched across skill types with larger absolute depreciation rates. In summary, gap-prone individuals, when maximizing lifetime income, will pick a lower skill occupation when the absolute depreciation rate, δ_k (atrophy plus repair), is larger.

More realistically, assume a finite combination of skill requirements in the economy exist. The set of occupations requires, for example, high math and low verbal or higher verbal and lower math skills. Women would be more likely to sort into the occupations where the dominant skill has lower depreciation rates. For example, if the computer revolution fostered an environment where math and science skills could quickly become obsolete, but there was no similar effect on verbal skills, women would self-select into occupations that require relatively more verbal skills. That is, taking into account the absolute depreciation rates of skills, if women are more likely to take prolonged career gaps, it is optimal for women to choose occupations high in verbal skills and low in math/science skills. Of course, women may also choose different careers due to simple occupational preferences, i.e., women prefer verbal-intensive occupations over technically-intensive occupations. The model presented here only captures the difference in monetary terms, disregarding preference differences.

4 Empirical Analysis

4.1 Individual Mismatch

Combining the O*net skill content with the ASVAB test scores for the NLSY cohort provides a measure of mismatch in individual skills and occupation requirements. Figure 1 graphs the average mismatch between individual skills and occupation requirements by total accumulated work experience. Since we are interested in gender differences, the figure shows the average mismatch of women relative to men in percentiles, where a positive number indicates women are more mismatched than men, and the reverse holds for negative values. The computation is done in five year intervals, with individuals' relative



(a) Non-college (b) College

Figure 1: Gender Gap Mismatch of Skills by Education

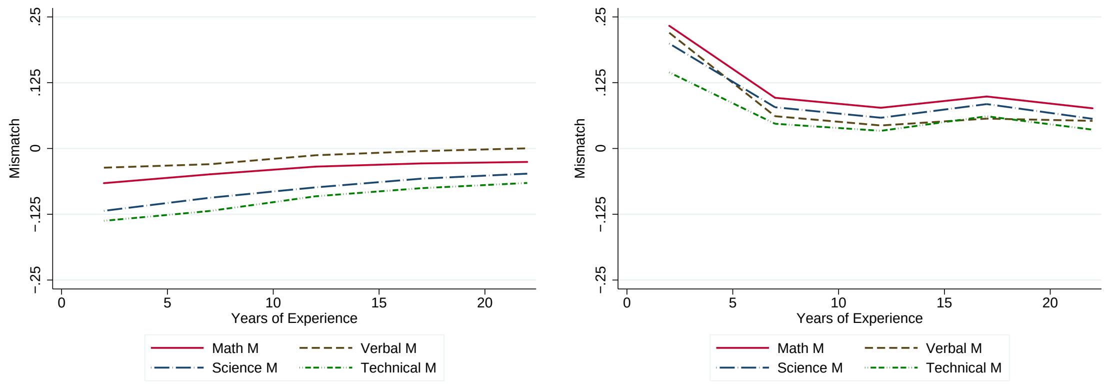
Notes: Average mismatch measures are computed using NLSY 1979 sample weights for all workers (part- and full-time). Results graph average differences between women and men. See text for details.

skill ranking, similarly to the occupational rankings, computed for each year. That is, each year we re-rank the individuals remaining in the NLSY sample.[9] The figure assumes that the distributions for males and females are identical in 1980 (the year of the ASVAB test), e.g., the 90th percentile woman has the same skill level as the 90th percentile man. We later relax this assumption, allowing men and women to follow different career paths prior to the exam date.

Positive gender gaps exist in math, science and technical fields, with gaps increasing as workers accumulate years of experience. While the math gap for non-college graduates is nearly zero, the science gap for college graduates is approximately zero. In contrast, the opposite gender gap is observed for verbal skills, i.e., women are less mismatched than men.

We expect that individuals will exhibit learning-by-doing and move toward better occupation-skill matches as experience increases. The initial mismatch gap (i.e., workers without work experience) for men follows this theory, with men learning about their skill

[9]The results are not sensitive to any of the above ranking assumptions (e.g., sorting individuals according to their ranking in the base year 1979 provides very similar quantitative patterns).



(a) Non-college (b) College

Figure 2: Male Mismatch of Skills by Education

Notes: Average mismatch measures are computed using NLSY 1979 sample weights for all workers (part- and full-time). Results graph average mismatch for men only. See text for details.

set and finding more suitable jobs over time (see figure 2).[10] This is true for both education groups, although the process is much faster and steeper for college graduates. In direct contrast, women seem to exhibit very little "learning with time" (graph omitted here), explaining the evolution of the gender gap mismatch (see figure 1). Part of this higher persistent mismatch for women could be due to an age effect. That is, as women are more likely to take work gaps, groups with low levels of work experience are more heterogeneous across age.

4.2 Monetized Mismatch

If skills are underutilized in the labor market, individuals may face lower wages and tenure. Figure 1 implies that women could be particularly exposed to any negative effects of skill mismatch across the non-verbal skill dimension. However, observed skill mismatch alone does not necessarily lead to suboptimal outcomes in terms of maximizing wage returns. One approach is to compare individuals' current match to the optimal skill-matched

[10] Stinebrickner & Stinebrickner (2014) show that students attempt math-heavy college majors and learn about their abilities through failure, moving to more suitable college majors in the process. We postulate that this same mechanism might apply to the labor market.

occupation, and assess the wage difference. To understand which skills are most sensitive to mismatching with respect to wages, Figures 4 and 5 graph the average "monetized" mismatch. This monetized mismatch concept is partial equilibrium in nature and computes the cost of skill mismatch for women and men assuming no depreciation of skill over time and identical work experience for all individuals. That is, this type of mismatch computation abstracts from individual-specific optimal choices related to skill depreciation rates, work experience accumulation, and any general equilibrium effects affecting skill returns.

Given the economic theory above, combined with data on the occupation skill requirements, individuals' skill rank, hourly wages, and other individual characteristics, we can compute skill prices by running the following regression by year, based on Equation (3),

$$\begin{aligned}\log(w_{i,t}) \quad = \quad & \sum_k \alpha_{k,t}\Theta^i_{k,t} + \sum_k \gamma_{k,t}(\theta^i_k - \Theta^i_{k,t})\Theta^i_{k,t} + \sum_k \gamma_{ke,t}\left(\theta^i_k \times \exp^i_t\right)\Theta^i_{k,t} + \\ & \sum_k \gamma_{ke2,t}\left(\theta^i_k \times \left(\exp^i_t\right)^2\right)\Theta^i_{k,t} + X'_{it}\beta_t + \epsilon_{i,t}, \qquad (7)\end{aligned}$$

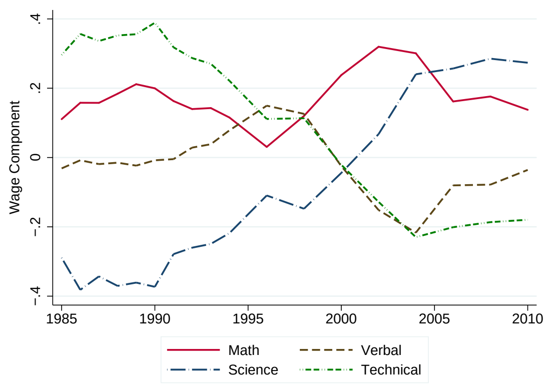
where X_{it} includes age, age squared, race, work experience, work experience squared, marital status, region and degree dummies. $\Theta^i_{k,t}$ is the skill requirement of each occupation from O*net data, θ^i_k is the skill of each individual from ASVAB test scores (we use the percentile rank measure as before) and exp is work experience measured in weeks. Initial skill from the ASVAB test scores interacted with years of experience give current skill levels, $\theta^i_{t,k} = \theta^i_k \times \exp^i_t$. This specification means that α provides the monetized occupational return to math, verbal and science in the economy, and γ provides any wage premium for overqualified individuals or wage penalty for underqualified individuals if $\gamma > 0$. Regressions are run for all years from 1985 to 2010 separately for individuals with and without a college degree. We do this only using full-time working males. Women might be negatively or positively selected into certain occupations, especially if our hypothesis of larger women's mismatch and absolute depreciation differences by skill type is true, potentially biasing any skill prices. In addition, we only include men who have not had substantial working gaps throughout their entire working-lives. We define individuals without substantial working gaps as individuals that have been employed at least 75 percent of their potential working-life (this includes every week since the time of graduation from their highest schooling choice). This sample restriction drops about 18 to 25 percent of the male sample, with 18 percent being dropped in 2006 and 25 percent dropped in 1985. Not surprisingly, when conditioning on educational attainment, this restriction only reduces the college sample by six percent through the whole time period. For further details see Section 2 above. We also experiment with more strict definitions, e.g. 80 percent, with results robust to further restrictions. This sample selection ensures the results do not capture the impact of a gap (or the absolute depreciation rate).

Given Equation (7), the monetized mismatch is then,

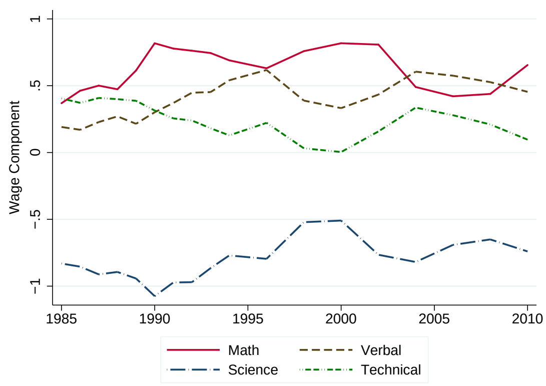
$$
\begin{aligned}
m^i_{kt} \;=\; & \sum_k \hat{\alpha}_{k,t} \left(\Theta^\star_{k,t} - \Theta^i_{k,t}\right) - \sum_k \hat{\gamma}_{k,t} \left\{ \left(\Theta^\star_{k,t}\right)^2 - \left(\Theta^i_{k,t}\right)^2 \right\} + \\
& \sum_k \left(\hat{\gamma}_{k,t} + \hat{\gamma}_{ke,t}\widehat{\exp}_t + \hat{\gamma}_{ke2,t}\widehat{\exp}^2_t\right) \theta^i_k \left(\Theta^\star_{k,t} - \Theta^i_{k,t}\right), \qquad (8)
\end{aligned}
$$

where $\Theta^\star_{i,t}$ is the occupation that would maximize an individual's wage in each year irrespective of any equilibrium effects. This specification accounts for a finite number of occupations, with given math/technical/science/verbal combinations, rather than a continuum of possibilities as presented in the theoretical model. Potential experience in weeks is denoted with $\widehat{\exp}$, which is approximated by the average weeks of experience from the wage regression sample of full-time males without major employment gap history. The monetized mismatch presented here simply assumes a world without depreciation, where men and women have the same work histories in terms of hours.

Figure 3 shows the average wage component attributable to each skill type for the above wage sample. For college men the skills contribute steady shares to wages, with math and verbal having the largest contribution. Science plays no role in wages, and point to lower average wages for men working in high science occupations. For non-college men, the wage



(a) Non-College



(b) College

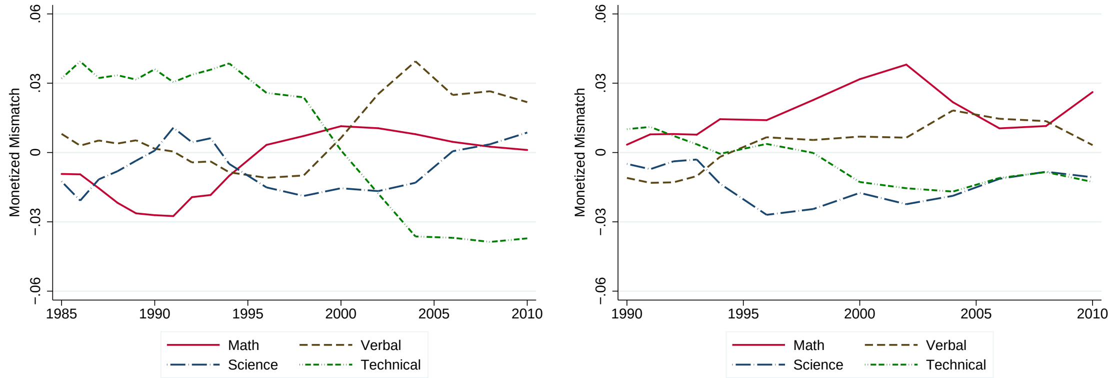
Figure 3: Wage Skill Component

Notes: Skill returns are computed from yearly regressions of hourly log wages of full-time/attached male workers on percentile O*net skill measures, percentile O*net skill measures versus ASVAB test score mismatch, interactions of O*net skill measures with ASVAB test scores and experience/experience squared, experience, experience squared, age, age squared, dummies for race (Black, Asian, and White), region, marital status (married, never married, and other), and last school degree (high school drop out, high school graduate, some college, college graduate, and post-college graduate).

contribution of science has seen the largest upward trend, although technical returns were historically most relevant. Math has always yielded positive returns.

Figure 4 shows the monetized mismatch from Equation (8) for women versus men (i.e., the gender gap) by education level. As before, the figure shows the average mismatch of women relative to men (now) in "monetized" percentiles. A positive number indicates a mismatch of women relative to men that contributes to a positive gender wage gap, with the reverse holding true for negative values.

Non-college women saw the largest monetized mismatch in technical skills during the past century. That is, would women have better matched their technical abilities to occupational requirements, *ceteris paribus*, the wage gap of the average uneducated woman would have been roughly three percentage points smaller, although this monetized mismatch disappeared by 2000. Therefore, a decrease in occupations emphasizing technical skills could have potentially contributed to the narrowing gender gap for uneducated women (see also the literature on employment polarization and the disappearing routine



(a) Non-College

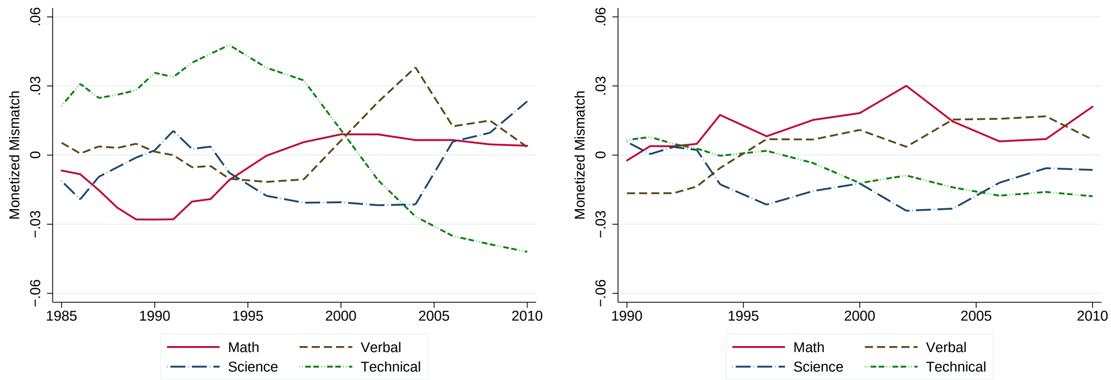
(b) College

Figure 4: The Gender Gap of Monetized Mismatch (Pre-AVSAB)

Notes: Average mismatch measures are computed using NLSY 1979 sample weights for all workers (part- and full-time). Results graph average differences between women and men. See Equation (8) and text for details.

occupations, e.g., Autor & Dorn, 2013). For college-educated women, the largest contributor to the gender gap, in terms of skill mismatch, has always been math. Had women been better matched to occupations in terms of their math abilities, the gender wage gap between the average college-educated male and female should have been roughly one to three percentage points smaller. While the monetized math mismatch has been steadily increasing over the sample, the financial crisis corresponds with a temporary dip in the monetized mismatch of math skills.

To explore the idea that women and men may have pursued different skill-specific education, potentially constraining their occupational choices later in life, we specify a regression using standardized test scores adjusted by age only. The age adjustment is necessary as all individuals took the ASVAB test in 1980 and were, therefore, different ages. Not adjusting for gender then allows for the fact that, even by age 16, men and women may already have chosen to emphasize different school subjects leading to different skill outcomes. The reproduced monetized mismatch results (based on Equation (8)), using this skill measure, are depicted in Figure 5. The skill wage components are virtually the same as the original specification, since this experiment mostly affects the relative position



(a) Men

(b) Gender Gap

Figure 5: The Gender Gap of Monetized Mismatch (AVSAB)

Notes: Average mismatch measures are computed using NLSY 1979 sample weights for all workers (part- and full-time). Results graph average differences between women and men. See Equation (8) and text for details.

of women to men, and skill prices are only computed using full-time male workers. The qualitative patterns do not change with this post-education skill measure, but the relative gender gap is slightly smaller for college women. This may suggest that women make schooling choices with future career paths (occupations) in mind. However, the differences are not large enough to make any statistical inference.[11]

4.3 Atrophy and Repair

The above results beg the question: Why are women mismatched, especially in math skills for college graduates and technical skills for non-college graduates? We investigate if the underlying mechanism points to differences in atrophy and repair rates. To estimate absolute depreciation rates we estimate a wage regression based on Equations (3) and (4), which is akin to extending the above regression Equation (7) to allow for individuals with

[11]It is important to note that these results do not capture any differences in college education choices. Only those schooling choices made before taking the ASVAB test are captured.

gaps and the cost of taking a gap. The regression to be estimated is then,

$$\begin{aligned}
\log(w_{i,t}) \;=\; & \sum_k \alpha_{k,t}\Theta^i_{k,t} + \sum_k \gamma_{k,t}\left(\theta^i_k - \Theta^i_{k,t}\right)\Theta^i_{k,t} + \\
& \sum_k \gamma_{ke,t}\left(\theta^i_k \times \mathrm{exp}^i_t\right)\Theta^i_{k,t} + \sum_k \gamma_{ke2,t}\left(\theta^i_k \times \left(\mathrm{exp}^i_t\right)^2\right)\Theta^i_{k,t} + \\
& \sum_k \gamma_{kg,t}\left(\theta^i_k \times \mathrm{gap}^i_t\right)\Theta^i_{k,t} + \sum_k \gamma_{kg2,t}\left(\theta^i_k \times \left(\mathrm{gap}^i_t\right)^2\right)\Theta^i_{k,t} + \\
& X'_{it}\beta_t + \epsilon_{i,t}, \qquad (9)
\end{aligned}$$

where, in addition to the previous wage Equation (7), gap measures the number of weeks out of the labor force. As in Robst & VanGilder (2000), we use both a cumulative and short-run measure for a gap. The cumulative measure is computed by summing all gaps from the year of graduation, while the current measure only accounts for gaps within the 52 weeks prior to the interview date. Since quadratics on gaps are not statistically significant, the below results do not include the quadratic results. The regressions use the same controls as the computation of skill prices above, e.g., experience, experience squared, age, age squared, dummies for race (Black, Asian, and White), region, marital status (married, never married, and other), and last school degree (high school drop out, high school graduate, some college, college graduate, and post-college graduate), plus year and a part-time dummies if part-time workers are included. An interaction between marital status and gender, since women and men tend to have different "marriage premia," is also included. In line with the literature, ordinary least squares (OLS) estimates from a pooled regression are provided. This follows given the number of observations and the limited number of gaps observed in the data.[12]

Since the results are estimated using panel data and individuals are follwed over time, there is a potential for serially correlated error terms biasing estimates. Consequently, we also discuss result from generalized least squares (GLS) regressions assuming the error is composed of an unobserved individual effect and a random component, $\epsilon_{i,t} = \mu_i + \nu_{i,t}$.

[12] Time trends do show similar results, but exhibit somewhat larger standard errors.

Table 3 includes only full-time workers (results including part-time workers and GLS estimations can be found in Appendix C). The general patterns described below are robust to the inclusion of part-time workers or accounting for serially correlated error terms with GLS. The reported variables use the post-ASVAB test scores (i.e., allow for men and women to pre-sort into different study paths). Results with pre-test measures are similar, but usually marginally smaller in magnitude. In addition to gap rates, which are gaps in weeks multiplied by individual skill ranking and occupational skill ranking, the tables also report the return to occupational-specific skills, $\hat{\alpha}$.

Columns (1) and (2) in Table 3 show results when only including the cumulative gap measure, columns (3) and (4) shows results for only recent gaps, and column (5) and (6) show the joint estimates for non-college and college graduates respectively. As in prior research (e.g., England, 1982; Robst & VanGilder, 2000), the cumulative gap measure shows no-negative impact on wages; if anything the return to gaps is positive. However, the cumulative gap measure interacted with math skills reveals some small effects. For example, a college graduate ranked in the 100th math skill percentile and working in the 100th percentile math occupation faces a wage loss of 0.38 percentage points after taking a one month (4 week) gap. In contrast, an individual in the 50 percentile rank in terms of skills and occupation faces a wage penalty of 0.10 percentage points only. The loss for an identical non-college worker would be 0.08 percentage points.

The regression R-squared, at about one-third, is somewhat larger than standard estimates in this literature (see for example Robst & VanGilder, 2000). Given the additional detailed information on skill requirements by occupations and individual skill measures, this is to be expected. Returns to math, verbal and technical skills are, in line with Figure 3, positive and statistically significant for college graduates. Only the returns to science have negative coefficients. For non-college graduates only returns to technical skills are large and positive, further corroborating the findings in Section 4.2.

As in Robst & VanGilder (2000), a recent gap has a larger wage impact. For example,

Table 3: Full-Time Worker's Depreciation Rates

VARIABLES	LTC (1)	C+ (2)	LTC (3)	C+ (4)	LTC (5)	C+ (6)
Math	-0.054	0.451***	-0.070	0.394***	-0.035	0.475***
	(0.053)	(0.126)	(0.053)	(0.123)	(0.054)	(0.126)
Verbal	-0.004	0.751***	0.002	0.760***	-0.027	0.707***
	(0.047)	(0.108)	(0.047)	(0.105)	(0.048)	(0.108)
Science	-0.365***	-0.992***	-0.359***	-0.937***	-0.367***	-1.006***
	(0.058)	(0.175)	(0.059)	(0.170)	(0.059)	(0.177)
Technical	0.607***	0.351***	0.614***	0.383***	0.595***	0.373***
	(0.041)	(0.127)	(0.041)	(0.126)	(0.042)	(0.130)
Cumm Gap	0.304***	0.481***			0.317***	0.489***
	(0.034)	(0.070)			(0.034)	(0.070)
Last Gap			-0.723***	-1.080***	-0.721***	-1.069***
			(0.079)	(0.264)	(0.079)	(0.264)
Cumm Gap M	-0.075***	-0.095***			-0.072***	-0.087***
	(0.015)	(0.023)			(0.015)	(0.023)
Last Gap M			-0.951*	-2.706**	-0.796	-2.442**
			(0.490)	(1.186)	(0.493)	(1.165)
Cumm Gap V	0.059***	0.047**			0.056***	0.041*
	(0.013)	(0.023)			(0.013)	(0.022)
Last Gap V			0.359	1.958**	0.270	1.873*
			(0.428)	(0.975)	(0.426)	(0.974)
Cumm Gap S	0.043***	0.086***			0.041***	0.082***
	(0.014)	(0.029)			(0.014)	(0.029)
Last Gap S			0.602	0.917	0.478	0.734
			(0.485)	(1.284)	(0.485)	(1.262)
Cumm Gap T	-0.003	-0.009			-0.000	-0.009
	(0.011)	(0.023)			(0.011)	(0.022)
Last Gap T			0.459	-0.370	0.463	-0.408
			(0.342)	(1.176)	(0.344)	(1.183)
Observations	40,411	14,345	40,411	14,345	40,411	14,345
R-squared	0.302	0.319	0.302	0.320	0.305	0.324

Statistical significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Robust standard errors in parentheses.

Math (M), verbal (V), science (S) and technical (T) variables are denoted by their respective first letter.

All regressions include experience, experience squared, age, age squared, dummies for years, race (Black, Asian, and White), region, gender, marital status (married, never married, and other), interaction terms between gender and marital status, and last school degree (high school drop out, high school graduate, some college, college graduate, and post-college graduate).

the college graduate ranked in the 50th math percentile and working in the 50th percentile math occupation faces a wage penalty of 2.71 percentage points when taking a one month gap from the labor force, with the top ranked individual facing a gap four times as large. In general, a college graduate already faces a 4.32 percentage point general penalty for the one month employment gap. While the quantitative results decrease from column (4) to (6), the difference is small. Unlike college-graduates, we do not see a similar math skill-specific penalty gap for non-college graduates. We conjecture that the tasks preformed by a non-college worker with regards to numerical skills have been robust towards technological innovation, while the numerical skills of a college graduates have had to adapt to the recent (ICT) technology innovation.

The positive coefficients on verbal skills interacted with gap measures provide a possible explanation for women choosing occupations with considerable verbal skills, if these occupations are immune to skill destruction. However, since selection might be an issue, we also run regressions conditional on gender and education. Table 4 shows the gender-specific results (GLS results can be found in Appendix C). Columns (1) and (3) report the effects for non-college men and women, and columns (2) and (4) list the effects for male and female college graduates, respectively. Large differences can be easily seen when comparing skill returns across gender within education groups. Given women are more positively matched on verbal skills, the returns to high-verbal occupations are large and positive, while the returns to math are insignificant.

For college-graduates the depreciation rates are very similar to Table 3. The verbal gap measure (significant at five percent) completely offsets the math gap measure. One possible interpretation is that women can self-insure against the adverse effects of taking a working gap by picking occupations relatively low in math requirements, but high in verbal requirements. Therefore, this results could explain the observed mismatch patterns from Sections 4.1 and 4.2 of college graduates.

For non-college women the results show no skill-specific depreciation rates, but instead

Table 4: Gender-Specific Depreciation Rates

	Male		Female	
VARIABLES	LTC (1)	C+ (2)	LTC (3)	C+ (4)
Math	0.029	0.884***	-0.004	0.140
	(0.079)	(0.171)	(0.072)	(0.173)
Verbal	-0.310***	0.596***	0.270***	0.862***
	(0.073)	(0.149)	(0.064)	(0.165)
Science	-0.202**	-1.779***	-0.501***	-0.519**
	(0.085)	(0.257)	(0.081)	(0.231)
Technical	0.534***	0.787***	0.479***	0.210
	(0.056)	(0.187)	(0.076)	(0.197)
Cumm Gap	0.272***	0.396***	0.416***	0.577***
	(0.047)	(0.097)	(0.049)	(0.097)
Last Gap	-0.765***	-1.036***	-0.759***	-1.293***
	(0.109)	(0.371)	(0.123)	(0.404)
Cumm Gap M	-0.061**	-0.093***	-0.081***	-0.056*
	(0.024)	(0.031)	(0.019)	(0.033)
Last Gap M	-1.185*	-1.648	0.080	-2.841*
	(0.656)	(1.744)	(0.700)	(1.595)
Cumm Gap V	0.096***	0.076***	-0.003	0.005
	(0.021)	(0.029)	(0.017)	(0.033)
Last Gap V	0.315	0.589	-0.243	3.050**
	(0.607)	(1.516)	(0.613)	(1.353)
Cumm Gap S	-0.020	0.115***	0.096***	0.081**
	(0.021)	(0.044)	(0.019)	(0.037)
Last Gap S	0.788	0.537	0.034	0.892
	(0.611)	(2.158)	(0.795)	(1.480)
Cumm Gap T	0.017	-0.074**	0.006	-0.022
	(0.016)	(0.030)	(0.022)	(0.040)
Last Gap T	0.456	0.093	0.998	-1.460
	(0.435)	(1.785)	(0.885)	(1.692)
Observations	22,663	7,876	17,748	6,469
R-squared	0.255	0.319	0.309	0.281

Statistical significance levels: *** p<0.01, ** p<0.05, * p<0.1

Notes: Robust standard errors in parentheses.

Math (M), verbal (V), science (S) and technical (T) variables are denoted by their respective first letter.

NLSY (females or males aged 14-22 in 1979). See Table 3 for further details.

reveal only general wage loss with gap periods. The skill-specific depreciation rates do not seem to be the main contributor of skill mismatch. An explanation based on stereotypes or preferences could potentially be more relevant (Bordalo et al., 2014).

5 Conclusion

We propose and evaluate the idea that women make occupational choices based on skill-specific atrophy and repair with respect to employment expectations. This is a coherent and consistent theory supporting differences between male and female occupational choices. That is, women may choose an occupation with a perceived wage penalty if the penalty for time-off is small. The model presented generates significant economic incentives for women to: (1) strongly prefer occupations that exhibit lower skill-specific depreciation; and (2) pursue the accumulation of skills that are robust to work gaps. The examples provided indicate that the combination of skills within an occupation is more important than the occupation itself. That is, if the largest skill component within an occupation is robust to career gaps, then the other skill requirements' atrophy can be offset.

Using the NLSY panel dataset and O*net occupational skills information, we assess the importance of skill-specific atrophy-repair rates on wages when faced with employment breaks. The model presented leads directly to the empirical exercise and the regression equations employed. The results strongly support the idea that college educated females avoid math-heavy occupations, and pursue verbal-heavy occupations instead. This is due to the high skill atrophy associated with math skills, and the ability of verbal skills to act as "skill insurance" against gaps. Additionally, for college educated individuals, math is the skill most vulnerable to loss during employment gaps, which also implies a slow rebuilding post-break. In contrast, non-college educated individuals experience a much smaller math skill loss. In general, the math content of an occupation appears to be a significant negative for individuals who experience or expect employment gaps, but this is especially true for college educated individuals.

While we find large atrophy-repair rates, the current exercise is unable to estimate how important these rates are for female occupational choices. Moreover, the analysis presented above ignores the general equilibrium effects. That is, if women switch to other occupations, it would change specific skill wage rates. Thus, a general equilibrium model is required to further pursue specific questions, such as: How does skill mismatch contribute to the persistent wage gap? Lastly, we have ignored any educational differences post-ASVAB testing, meaning that education decisions taken in college are not included. In ongoing research we study the educational differences between men and women in college. We take these microeconomic estimates of atrophy and repair by skill type and develop a model to account for equilibrium wages and college education choices. We then ask: How much of the observed gender education differences and the overall gender (wage) gap can be explained by women, accounting for both wage expectations and skill-specific atrophy-repair functions when making educational/occupational choices.

References

Adda, J., Dustmann, C., & Stevens, K. (2012). The Career Costs of Children. Economics Working Papers ECO2012, European University Institute.

Autor, D. H. & Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review*, *103*(5), 1553–97.

Bordalo, P., Gennaioli, N., & Shleifer, A. (2014). Stereotypes. NBER Working Papers 20106, National Bureau of Economic Research.

Cawley, J., Heckman, J., & Vytlacil, E. (1998). Understanding the Role of Cognitive Ability in Accounting for the Recent Rise in the Economic Return to Education. NBER Working Papers 6388, National Bureau of Economic Research, Inc.

England, P. (1982). The Failure of Human Capital Theory to Explain Occupational Sex Segregation. *The Journal of Human Resources*, *17*(3), pp. 358–370.

Goldin, C. (2014). A Grand Gender Convergence: Its Last Chapter. *American Economic Review Forthcoming*, *104*.

Goldin, C., Katz, L. F., & Kuziemko, I. (2006). The Homecoming of American College Women: The Reversal of the College Gender Gap. *Journal of Economic Perspectives*, *20*(4), 133–156.

Hsieh, C.-T., Hurst, E., Jones, C. I., & Klenow, P. J. (2013). The Allocation of Talent and U.S. Economic Growth. Working Paper 18693, National Bureau of Economic Research.

Lazear, E. P. & Rosen, S. (1990). Male-Female Wage Differentials in Job Ladders. *Journal of Labor Economics*, *8*(1), pp. S106–S123.

McDowell, J. M. (1982). Obsolescence of Knowledge and Career Publication Profiles: Some Evidence of Differences among Fields in Costs of Interrupted Careers. *The American Economic Review*, *72*(4), pp. 752–768.

Mincer, J. & Ofek, H. (1982). Interrupted Work Careers: Depreciation and Restoration of Human Capital. *The Journal of Human Resources*, *17*(1), pp. 3–24.

Mincer, J. & Polachek, S. (1974). Family Investment in Human Capital: Earnings of Women. *Journal of Political Economy*, *82*(2), S76–S108.

Polachek, S. W. (1981). Occupational Self-Selection: A Human Capital Approach to Sex Differences in Occupational Structure. *The Review of Economics and Statistics*, *63*(1), 60–69.

Robst, J. & VanGilder, J. (2000). Atrophy Rates in Male and Female Occupations. *Economics Letters*, *69*(3), 407–413.

Roy, A. D. (1951). Some Thoughts on the Distribution of Earnings. *Oxford Economic Papers*, *3*(2), pp. 135–146.

Stinebrickner, R. & Stinebrickner, T. R. (2014). A Major in Science? Initial Beliefs and Final Outcomes for College Major and Dropout. *Review of Economic Studies*, *81*(1), 426–472.

A National Longitudinal Survey of Youth 1979 (NLSY)

The NLSY is a nationally representative sample of individuals aged 14 to 22 in 1979. Surveys were conducted on an annual basis until 1994 and biannually thereafter. The original sample included 12,686 men and women.

Wage information is reported at the survey dates, and is adjusted to constant 2000 US Dollars. Survey observations without wage data are dropped from the sample, as are those without occupation information. We also drop individuals with military occupations as-of the interview date because their wage observation may not be determined by the general labor market forces.

The NLSY sample provides weekly observations for employment status from which career breaks are constructed. Thus, each observation in the data set has two measures of employment gaps in weeks: (1) cumulative length of all gaps; and (2) length of prior gap. These gap measures account for employment status values in an conservative manner. I.e., the six labor force status values (e.g., unemployed, active military service) used when an occupational code is not provided are considered unemployment spells. This means the number and length of gaps is likely overestimated, reducing the effect of each gap on wages. The reason military service is considered an work gap concerns how employers view this experience. If the tasks performed while undertaking military service are relevant to the formal labor market, then military service could be considered employment. However, it is not clear how relevant military service tasks are to employers, and coding these values as unemployment is a conservative assumption. Note that individuals employed full-time within military service were dropped prior to the employment gap variable construction, leaving only individuals with short-term military service.

After accounting for missing and inconsistent information, the data set contains individual-level observations across time for wages, occupation, employment gap measures and multiple individual characteristics, such as gender and education. Thus, the final sample contains 5,652 individuals, of which 2,782 (49 percent) are males.

B Occupational Information Network (O*net) and Armed Services Vocational Aptitude Battery (ASVAB)

The Occupational Information Network (O*net) database contains detailed descriptive information for more than 900 occupations, and succeeds the Dictionary of Occupational Titles (DOT). Whereas the DOT is based on direct expert observations of occupations, the O*net sends questionnaires to a random sample of workers based on their occupations. Each worker completes one-quarter of the questions, which are organized into eight broad categories. Three categories are of particular interest:

- Knowledge: Biology, Building and Construction, Chemistry, Computers and Electronics, Engineering and Technology, English Language, Mathematics, Mechanical, Physics
- Skill: Equipment Maintenance, Equipment Selection, Installation, Mathematics, Operation and Control, Reading Comprehension, Repairing, Science, Technology Design
- Ability: Trouble Shooting, Deductive Reasoning, Inductive Reasoning, Information Ordering, Mathematical Reasoning, Number Facility, Oral Comprehension, Written Comprehension

Besides recording standard survey questions regarding family status and work, the NLSY respondents took the Armed Services Vocational Aptitude Battery (ASVAB) in the summer and fall of 1980, which was administered by the US Departments of Defense and Military Services. The ASVAB was designed to provide high school graduates with career guidance compared to a simple general or academic ability test. The test components can be grouped into four major skill types/components:

1. Math is composed of “Arithmetic Reasoning” and “Mathematics Knowledge.”

2. Verbal is composed of “Word Knowledge” and “Paragraph Comprehension.”

3. Technical is composed of “Auto and Shop, Mechanical Comprehension” and “Electronics Information.”

4. Science is composed of “General Science Knowledge.”

In an effort to make career matching easier for new high school graduates, the ASVAB Career Exploration Program decided to match occupational information from O*net data to the ASVAB test components. For this purpose, 26 occupational descriptors of the O*net were matched to the ASVAB tests sections listed above. The descriptors included information of knowledge, skill and ability required in preforming each O*net occupation. As the list of O*net descriptors above reveals, each has a natural mapping into math, verbal, technical and science skill components. The mapping to four ASVAB components was determined by experts using a six-point scale ranging from “Highly related” to “Not at all related.” Experts came from the field of industrial/organizational psychology, general psychology, and psychometrics.

C Results Appendix: Depreciation Rates

Table C.1 includes part-time workers. The results are similar in sign and magnitude to the results for full-time workers only (see Table 3).

Table C.2 provides GLS results for the base regression outlined in Table 3. The results are similar in sign and magnitude to the OLS estimates for full-time workers.

Table C.3 shows depreciation rates for male and female workers using GLS to account for serially correlated errors. The coefficients are slightly smaller for college educated women compared to OLS. However, the general hypothesis still holds, with high math occupations experiencing larger wage penalties for gaps and high verbal (and science) occupations off-setting some of the penalty. In addition, the results now also suggest a penalty in highly technical occupations. For non-college women the skill-specific depreciations are now statistically significant, albeit still smaller than for college graduates.

Table C.1: Depreciation Rates

VARIABLES	LTC (1)	C+ (2)	LTC (3)	C+ (4)	LTC (5)	C+ (6)
Part-time	-0.097***	-0.146***	-0.070***	-0.103***	-0.069***	-0.103***
	(0.007)	(0.014)	(0.007)	(0.015)	(0.007)	(0.015)
Math	-0.084*	0.400***	-0.097**	0.367***	-0.061	0.442***
	(0.047)	(0.111)	(0.048)	(0.113)	(0.049)	(0.116)
Verbal	-0.012	0.631***	-0.004	0.686***	-0.027	0.628***
	(0.040)	(0.095)	(0.042)	(0.095)	(0.043)	(0.098)
Science	-0.388***	-0.904***	-0.392***	-0.866***	-0.406***	-0.949***
	(0.051)	(0.155)	(0.054)	(0.154)	(0.054)	(0.160)
Technical	0.599***	0.376***	0.613***	0.375***	0.597***	0.377***
	(0.037)	(0.112)	(0.038)	(0.114)	(0.039)	(0.118)
Cumm Gap	0.347***	0.484***			0.353***	0.487***
	(0.033)	(0.067)			(0.033)	(0.067)
Last Gap			-0.402***	-0.664***	-0.398***	-0.629***
			(0.049)	(0.167)	(0.049)	(0.167)
Cumm Gap M	-0.068***	-0.091***			-0.066***	-0.085***
	(0.014)	(0.021)			(0.014)	(0.021)
Last Gap M			-0.670**	-1.291**	-0.473	-1.092*
			(0.290)	(0.641)	(0.293)	(0.633)
Cumm Gap V	0.044***	0.050**			0.041***	0.049**
	(0.011)	(0.022)			(0.011)	(0.021)
Last Gap V			0.316	0.121	0.208	0.014
			(0.249)	(0.593)	(0.250)	(0.591)
Cumm Gap S	0.048***	0.094***			0.047***	0.091***
	(0.013)	(0.027)			(0.013)	(0.027)
Last Gap S			0.521*	1.245	0.369	1.006
			(0.288)	(0.771)	(0.287)	(0.764)
Cumm Gap T	-0.002	-0.010			0.000	-0.013
	(0.010)	(0.022)			(0.010)	(0.022)
Last Gap T			0.095	0.133	0.107	0.210
			(0.206)	(0.687)	(0.209)	(0.687)
Observations	47,862	16,353	47,862	16,353	47,862	16,353
R-squared	0.328	0.348	0.327	0.346	0.330	0.351

Statistical significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Robust standard errors in parentheses.

Math (M), verbal (V), science (S) and technical (T) variables are denoted by their respective first letter.

See Table 3 for further details.

Table C.2: Depreciation Rates (GLS)

VARIABLES	LTC (1)	C+ (2)	LTC (3)	C+ (4)	LTC (5)	C+ (6)
Math	-0.074***	-0.052***	-0.074***	-0.115***	-0.049***	-0.055***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Verbal	-0.151***	0.302***	-0.145***	0.281***	-0.169***	0.254***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Science	-0.137***	-0.270***	-0.139***	-0.220***	-0.156***	-0.258***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Technical	0.352***	0.208***	0.355***	0.262***	0.351***	0.224***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Cumm Gap	0.042***	0.101***			0.051***	0.107***
	(0.000)	(0.001)			(0.000)	(0.001)
Last Gap			-0.545***	-0.980***	-0.531***	-0.966***
			(0.001)	(0.003)	(0.001)	(0.003)
Cumm Gap M	-0.038***	-0.057***			-0.035***	-0.055***
	(0.000)	(0.000)			(0.000)	(0.000)
Last Gap M			-1.070***	-0.418***	-1.034***	-0.339***
			(0.006)	(0.010)	(0.006)	(0.010)
Cumm Gap V	0.038***	0.020***			0.036***	0.016***
	(0.000)	(0.000)			(0.000)	(0.000)
Last Gap V			0.338***	1.723***	0.300***	1.708***
			(0.005)	(0.009)	(0.005)	(0.009)
Cumm Gap S	0.035***	0.041***			0.031***	0.040***
	(0.000)	(0.000)			(0.000)	(0.000)
Last Gap S			1.129***	-0.365***	1.068***	-0.424***
			(0.005)	(0.013)	(0.006)	(0.013)
Cumm Gap T	0.000	0.035***			0.003***	0.038***
	(0.000)	(0.000)			(0.000)	(0.000)
Last Gap T			-0.008**	-0.376***	-0.007*	-0.438***
			(0.004)	(0.011)	(0.004)	(0.011)
Observations	40,411	14,345	40,411	14,345	40,411	14,345
Individuals	3,796	1,385	3,796	1,385	3,796	1,385

Statistical significance levels: *** p<0.01, ** p<0.05, * p<0.1

Notes: Standard errors in parentheses.

Math (M), verbal (V), science (S) and technical (T) variables are denoted by their respective first letter.

See Table 3 for further details.

Table C.3: Gender-specific Depreciation Rates (GLS)

	Male		Female	
VARIABLES	LTC (1)	C+ (2)	LTC (3)	C+ (4)
Math	-0.061***	-0.098***	0.010***	-0.006***
	(0.001)	(0.002)	(0.001)	(0.002)
Verbal	-0.293***	-0.019***	0.014***	0.563***
	(0.001)	(0.002)	(0.001)	(0.002)
Science	-0.121***	-0.269***	-0.185***	-0.504***
	(0.001)	(0.003)	(0.001)	(0.003)
Technical	0.348***	0.370***	0.252***	0.404***
	(0.001)	(0.002)	(0.001)	(0.002)
Cumm Gap	0.014***	0.046***	0.132***	0.203***
	(0.001)	(0.001)	(0.001)	(0.001)
Last Gap	-0.631***	-1.026***	-0.490***	-0.768***
	(0.001)	(0.004)	(0.001)	(0.004)
Cumm Gap M	-0.009***	-0.022***	-0.056***	-0.043***
	(0.000)	(0.001)	(0.000)	(0.001)
Last Gap M	-1.400***	1.001***	-0.417***	-1.777***
	(0.007)	(0.015)	(0.009)	(0.014)
Cumm Gap V	0.035***	0.017***	-0.001***	0.025***
	(0.000)	(0.001)	(0.000)	(0.001)
Last Gap V	0.041***	2.402***	0.041***	1.224***
	(0.007)	(0.015)	(0.008)	(0.013)
Cumm Gap S	-0.014***	-0.020***	0.088***	0.087***
	(0.000)	(0.001)	(0.000)	(0.001)
Last Gap S	1.430***	-2.151***	0.608***	1.323***
	(0.007)	(0.020)	(0.009)	(0.015)
Cumm Gap T	0.036***	0.074***	-0.004***	-0.058***
	(0.000)	(0.001)	(0.000)	(0.001)
Last Gap T	0.219***	-0.513***	0.389***	-0.654***
	(0.005)	(0.017)	(0.010)	(0.017)
Observations	22,663	7,876	17,748	6,469
Individuals	1,872	671	1,924	714

Statistical significance levels: *** p<0.01, ** p<0.05, * p<0.1

Notes: Robust standard errors in parentheses.

Math (M), verbal (V), science (S) and technical (T) variables are denoted by their respective first letter.

See Table 3 for further details.