Women and Careers: 
Skill-Specific Atrophy and Repair*

Andrew Rendall† and Michelle Rendall‡
The University of Zurich

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Abstract

We argue 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 face costly skill atrophy of math skills during a career break. In contrast, verbal skills are very robust to career interruptions. These results support the observed female preference for occupations primarily requiring verbal skills - even though these occupations exhibit lower average wages. Thus, this research suggests that a substantial portion of female occupational sorting could be determined by skill-specific atrophy 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. The traditional Roy (1951) model 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? Favored explanations generally focus on female-male differences in bargaining, fertility, and preferences across occupations (see Goldin, 2014, and references therein). However, the precise mechanism underpinning the differences between female and male occupational choices is still open for debate.

Given new data sources, this study focuses on gender differences in the demand and supply of specific skills such as mathematics and language. The goal of this paper is to quantitatively assess to what extent varying skill-specific depreciation rates exist and whether there is a gender bias in occupational choices based on skill requirements. We believe that women and men have different economic valuations over human capital types, which are underpinned by their employment expectations. 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. That is, although \textit{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.\footnote{In this study, absolute depreciation rates are defined as the depreciation of skill taking into account potential repair rates when reentering the labor market.}

As a first step, we explore if certain types of skills are more likely to become obsolete in the labor market after career breaks. We also document occupational mismatch throughout individuals' life-cycles. That is, we quantify the relative distance in own skills and skill

\footnote{In this study, absolute depreciation rates are defined as the depreciation of skill taking into account potential repair rates when reentering the labor market.}
requirements of an individual’s occupational choice. To do so, we develop a simple model of individual occupational choice. We use the model to derive estimation equations for absolute depreciation rates and a monetized mismatch of skill measure, based on occupation requirements by gender-education groups. The empirical analysis uses the National Longitudinal Survey of Youth 1979 (NLSY) sample and occupational information from the the Occupational Information Network (O*net). The NLSY is ideally suited to compute mismatch and depreciation 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. We find substantial depreciation rates for math skills, but an “insurance” premium for verbal skills for college educated women. There is no clear pattern for non-college women and skill depreciation rates. In addition, the NLSY specific occupation choices based on skills show a mismatch for women relative to men that is surprisingly robust and consistent with the sign of the depreciation rates of specific skills.

Our thesis is based on 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 hypoth-
esize 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. 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.

Hsieh et al. (2013) provide 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 women and from 0.40 to 0.46 for lower educated women. Thus, while men and women have similar \textit{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
and consistent with the skill-biased technical change literature. Our contribution to the literature is two fold. First, we are able to compute relatively nuanced depreciation rates of human capital (i.e., math, verbal, science, technical skills), both for college graduates and non-college workers. 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. Second, we are able to quantitatively estimate the skill-specific gender gap in occupational choice using individuals’ skills and occupational skill requirements.

Section 2 starts with a short summary of the data and the basic facts concerning occupational gender differences in the NLSY sample. Section 3 presents the model. The data analysis, Section 4, documents (1) skill-specific atrophy-repair rates and (2) the mismatch of men and women by skill type from the NLSY. Section 5 concludes.

2 Skills and Occupations

In order to study skill-specific depreciation rates and occupational mismatch, we merge the NLSY from 1979 with the O*net versions 4.0-9.0. These datasets provide two unique descriptive dimensions for individuals and occupations: (1) the NLSY records individual skill measures, occupational choices, and wage returns; and (2) the O*net provides occupation descriptors, where occupations are differentiated by the skills they require.

More specifically, the NLSY records skill-specific test scores for math, verbal, science and technical skills from the ASVAB administered in 1980. 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.

\footnote{An occupation is classified as having female human capital if the share of female workers within that occupation surpasses a certain threshold.}
The NLSY cohort was tested using the 1980 version of these exams, with results for each individual providing relative skill measures. In addition, the *ASVAB Career Exploration Program* has mapped 26 occupational descriptors from O*net into seven ASVAB test types (see Appendices A and B for details on the data).³

Table 1 summarizes the data used in the analysis using broad education groups.⁴ 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.

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³The *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](http://www.asvabprogram.com/downloads/Technical_Chapter_2010.pdf).

⁴“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

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

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.\(^5\) Two measures of ASVAB ranks are

\(^5\)Alternatively, individuals can also be ranked according to their test score in 1980 (one-time ranking). This alternative ranking 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.
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). Since the ASVAB is only taken once in 1980, individual skills assess the (pre-work experience) abilities of individuals. 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

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

Statistical significance levels: *** p<0.01, ** p<0.05, * p<0.1
Notes: Reporting 5-year averages. For detailed see text.
requiring less of a given skill than men. Despite convergence along a number of important
dimensions (e.g., wages), it appears that for the NLSY cohort gender differences actually
grew across all skill categories except verbal. This may point to occupation preferences
and opportunities across gender changing over the life-cycle, as the table summarizes
occupational skill requirements rather than ex ante ability. Thus, women with a college
degree work in occupations with similar verbal requirements as men, but lower math,
science and technical skills. With the gap in math, science and technical skills growing
with age and the gap in verbal shrinking. This pattern is repeated for uneducated women,
but is more skewed toward technical skills.

3 Model of Occupational Choice

We develop a simple occupational choice model based on Roy (1951), where agents choose
a career path when young and taking career breaks (or not) over their working life-cycle.

Individuals have \( n \) skill types \( \theta^k \), \( k = 1, \ldots, n \), which are drawn from a given distri-
bution 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.\(^6\)
We account for some of the potential educational investment in the empirical section. Indi-
viduals live to age \( A \) and can choose from a continuum of occupations at age 0 that differ
by their skill requirements, \( \Theta_k \) for all \( k = 1, \ldots, n \), where \( \Theta_k > 0 \). That is, all occupations
require some skill level of skill type \( k \).

For simplicity, we assume that individuals take, at most, one career break in their
working life. Individuals choose the age at which to take a career break, \( \pi \), and the length
of the break, \( \tau \). When out of the labor force, skills depreciate by \( \delta_{k, hg} < 0 \). However, when
returning to the labor force some skills are recovered \( \delta_{k, he} > 0 \), but \( |\delta_{k, he}| \leq |\delta_{k, hg}| \). The
atrophy and repair rates are skill-type specific. Assume that \( (1 + \delta_{j, g}) = (1 + \delta_{j, he})(1 +
\delta_{j, hg}) < (1 + \delta_{i, he})(1 + \delta_{i, hg}) = (1 + \delta_{i, g}) \) for \( j > i \). That is, skills are sorted according

\(^6\)There are many other possible inputs forming these skill distributions.
to their absolute depreciation rates, $\delta_{k,g} \leq 0$, where a higher skill has relatively higher
destruction of skill. Lastly, learning-by-doing means $\delta_{k,e} \geq 0$.

### 3.1 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,

$$\log(W_{a}^{ij}) = \omega_{a}^{ij} = \sum_{k=1}^{n} \left[ \alpha_{k} \Theta_{k}^{j} + \gamma_{k} \left( \theta_{k,0}^{j} (1 + \delta_{k,e})^{a-\tau} (1 + \delta_{k,g})^{\tau} - \Theta_{k}^{j} \right) \Theta_{k}^{j} \right], \quad (1)$$

where $\theta_{k,a}^{j}$ are individual skill-$k$ measures at age $a$ and $\{\alpha_{k}, \gamma_{k}\}$ are returns to skill. More
specifically, returns to occupations for skill type $k$ are $\left( \alpha_{k} \Theta_{k}^{j} \right)$, the penalty for mismatch
is $\left( \gamma_{k} \left( \theta_{k,a}^{j} - \Theta_{k}^{j} \right) \right)$ and $\left( \left( \theta_{k,a}^{j} - \Theta_{k}^{j} \right) \Theta_{k}^{j} \right)$ is the complementarity of individual skill and
occupation requirements. Wages are a function of the returns to each skill type $\alpha_{k}$, 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 possess, $\gamma_{k} \geq 0$. The interaction between occupation requirement $\Theta_{k}^{j}$ and
skill mismatch $\left( \theta_{k,t}^{j} - \Theta_{k}^{j} \right)$ 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, $\gamma_{k} \theta_{k,t}^{j} \Theta_{k}^{j} - \gamma_{k} \left( \Theta_{k}^{j} \right)^{2}$, 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,

$$\omega_{k}^{j} = \sum_{k=1}^{n} \left[ \alpha_{k} \Theta_{k}^{j} + \gamma_{k} \left( (1 + \delta_{k,e}) \theta_{k,t-1}^{j} - \Theta_{k}^{j} \right) \Theta_{k}^{j} \right], \quad (2)$$
where $\delta_{k,e}$ is the return to experience for skill type $k$. Wages right after a gap period at $t - 1$ are,

$$\omega_t^i = \sum_{k=1}^{n} \left[ \alpha_k \Theta^i_k + \gamma_k \left( (1 + \delta_{k,0}) \theta^i_{k,t-2} - \Theta^i_k - \Theta^i_k \right) \right]. \quad (3)$$

### 3.2 Agents’ Problem

Individuals receive utility from consumption,

$$U(c) = \sum_{t=0}^{\infty} \beta^t \log(c_t). \quad (4)$$

There is no savings mechanism and individuals simply consume their income each period, $\log(c_t) = \log(W^i_t) = \omega_t^i$. Individuals that do not work derive utility $C(b) = \log(c_t)$, the value of their home production.\(^7\)

For simplicity we assume there is no learning-by-doing and allow for only one break.\(^8\)

The agent’s income maximization problem is,

$$\max_{\{\theta_k\}_{k=1}^{n}, \pi, \tau} \quad (1 + \beta_1(\pi, \tau)) \sum_{k=1}^{n} \left[ \alpha_k \Theta^i_k + \gamma_k \left( \theta^i_{k,0} - \Theta^i_k - \Theta^i_k \right) \right] +$$

$$\beta_2(\pi, \tau)C(b) + \beta_3(\pi, \tau) \sum_{k=1}^{n} \left[ \alpha_k \Theta^i_k + \gamma_k \left( \theta^i_{k,3} - \Theta^i_k - \Theta^i_k \right) \right].$$

The first term is the net present value of wages if the individual does not have a home spell, the second term summarizes the utility from the time the individual may spend at home, and the last term is the wage if the individual took a gap year and returned to work.

That is, agents live to age $A$, work $A - \tau$, take break at age $\bar{a}$ with a home spell utility of $(C(b))$. Discount factors are functions of time $\beta_j(\pi, \tau)$, where $\frac{\partial \beta_1}{\partial \tau} < 0$ and $\frac{\partial \beta_3}{\partial \tau} > 0$.

\(^7\)Alternatively, assume the economy has complete markets so income maximization yields the same results as utility maximization.

\(^8\)The empirical analysis accounts both for returns to experience and multiple break.
3.3 Optimal Choice

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. While we do not analyze the optimal timing of breaks, the model also suggests that career breaks should be later in life (e.g., women should delay fertility).

A simple example, Figure 1, illustrates an agent’s productivity schedule and optimal occupation choice over gap length, \( \tau \). The agent has three occupations to choose from that differ in their depreciation rate, \( \delta_{k,g} \), and returns, \( \alpha_k \). Skill-\( m \) occupation has the highest return, but also highest depreciation rate, while skill-\( v \) occupation has the lowest return and depreciation. Skill-\( l \) occupations cuts the distance between the two. The optimal occupational choice is marked with the dashed line. With a short break, the agent would optimally choose occupation \( m \), but as the break length increases it is optimal to switch to occupation \( l \) and later \( v \). More realistically, assume a finite combination of skill requirements in the economy exist. The set of occupations require, for example, high math and low verbal or higher verbal and lower math skills. Individuals that expect to take longer breaks 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, individuals 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.
Formally, the optimal occupational choice for skill type $k$ given $\tau$ and $\overline{\sigma}$ is,

$$
\Theta^*_k = \frac{\alpha_k}{2\gamma_k} + \frac{\tau (1 + \delta_k)}{2 (\beta_1 + \beta_3)} \theta_{k,0}.
$$

(5)

From Equation (5), higher skilled individuals choose more skill-demanding occupations. Assuming women take longer gaps (or potentially earlier gaps), women will sort into lower skill requirement occupations. A longer break, $\tau$, implies a larger $\beta_3$ at a given break time $\overline{\sigma}$. In the extreme case, i.e., men never drop out of the labor force, men have much stronger assortative matching incentives than women. 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, $\delta_{k,g}$ (atrophy plus repair), is larger.
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 2 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 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 set and finding more suitable jobs over time (see figure 3).\(^10\) This is true for both education

\(^{9}\)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).

\(^{10}\)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
4.2 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 depreciation rates. To estimate absolute depreciation rates we estimate a wage regression based on Equations (2) and (3). The

that this same mechanism might apply to the labor market.
regression to be estimated is,

$$\log(w_{i,t}) = \sum_k \alpha_{k,t} \Theta_{k,t} + \sum_k \gamma_{k,t} (\theta_{k,t}^i - \Theta_{k,t}) \Theta_{k,t} +$$

$$\sum_k \gamma_{k,t} (\theta_{k,t}^i \times \text{exp}_{i,t}) \Theta_{k,t} + \sum_k \gamma_{k,t} (\theta_{k,t}^i \times (\text{exp}_{i,t})^2) \Theta_{k,t} +$$

$$\sum_k \gamma_{k,t} (\theta_{k,t}^i \times \text{gap}_{i,t}) \Theta_{k,t} + \sum_k \gamma_{k,t} (\theta_{k,t}^i \times (\text{gap}_{i,t})^2) \Theta_{k,t} +$$

$$X_{it}’ \beta_t + \epsilon_{i,t},$$

where $X_{it}$ includes 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. $\Theta_{k,t}^i$ is the skill requirement of each occupation from O*net data, $\theta_{k,t}^i$ is the skill of each individual from ASVAB test scores (we use the percentile rank measure), exp is work experience measured.
in weeks, and \( gap \) 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. Initial skill from the ASVAB test scores interacted with years of experience give current skill levels, \( \theta_{i,k} = \theta_{i}^{j} \times \exp_{i}^{j} \). This specification means that \( \alpha \) provides the monetized occupational return to math, verbal and science in the economy, and \( \gamma \) 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.

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 normal survey data.\(^\text{11}\) Since quadratics on gaps are not statistically significant, the below results do not include the quadratic results.

Since the results are estimated using panel data and individuals are followed over time, there is a potential for serially correlated error terms biasing estimates. Consequently, we also discuss result from fixed effect model specification omitting gender and race controls.

Table 3 includes only full-time workers. The general patterns described below are robust to the inclusion of part-time workers. 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 occupation-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 columns (5)

\(^\text{11}\)Time trends do show similar results, but exhibit somewhat larger standard errors.
Table 3: Full-Time Worker’s Depreciation Rates

<table>
<thead>
<tr>
<th></th>
<th>LTC (1)</th>
<th>C+ (2)</th>
<th>LTC (3)</th>
<th>C+ (4)</th>
<th>LTC (5)</th>
<th>C+ (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Math</td>
<td>-0.054</td>
<td>0.451***</td>
<td>-0.070</td>
<td>0.394***</td>
<td>-0.035</td>
<td>0.473***</td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td>(0.126)</td>
<td>(0.053)</td>
<td>(0.123)</td>
<td>(0.054)</td>
<td>(0.126)</td>
</tr>
<tr>
<td>Verbal</td>
<td>-0.004</td>
<td>0.751***</td>
<td>0.002</td>
<td>0.760***</td>
<td>-0.027</td>
<td>0.707***</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.108)</td>
<td>(0.047)</td>
<td>(0.105)</td>
<td>(0.048)</td>
<td>(0.108)</td>
</tr>
<tr>
<td>Science</td>
<td>-0.365***</td>
<td>-0.992***</td>
<td>-0.359***</td>
<td>-0.937***</td>
<td>-0.367***</td>
<td>-1.006***</td>
</tr>
<tr>
<td></td>
<td>(0.058)</td>
<td>(0.175)</td>
<td>(0.059)</td>
<td>(0.170)</td>
<td>(0.059)</td>
<td>(0.177)</td>
</tr>
<tr>
<td>Technical</td>
<td>0.607***</td>
<td>0.351***</td>
<td>0.614***</td>
<td>0.383***</td>
<td>0.595***</td>
<td>0.373***</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.127)</td>
<td>(0.041)</td>
<td>(0.126)</td>
<td>(0.042)</td>
<td>(0.130)</td>
</tr>
<tr>
<td>Cumm Gap</td>
<td>0.304***</td>
<td>0.481***</td>
<td>0.317***</td>
<td>0.489***</td>
<td>(0.034)</td>
<td>(0.070)</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.070)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Last Gap</td>
<td>-0.723***</td>
<td>-1.080***</td>
<td>-0.721***</td>
<td>-1.069***</td>
<td>(0.079)</td>
<td>(0.264)</td>
</tr>
<tr>
<td></td>
<td>(0.079)</td>
<td>(0.264)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cumm Gap M</td>
<td>-0.075***</td>
<td>-0.095***</td>
<td>-0.072***</td>
<td>-0.087***</td>
<td>(0.015)</td>
<td>(0.023)</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.023)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Last Gap M</td>
<td>-0.951*</td>
<td>-2.706**</td>
<td>-0.796</td>
<td>-2.442**</td>
<td>(0.490)</td>
<td>(1.186)</td>
</tr>
<tr>
<td></td>
<td>(0.490)</td>
<td>(1.186)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cumm Gap V</td>
<td>0.059***</td>
<td>0.047**</td>
<td>0.056***</td>
<td>0.041*</td>
<td>(0.013)</td>
<td>(0.022)</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.022)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Last Gap V</td>
<td>0.359</td>
<td>1.958**</td>
<td>0.270</td>
<td>1.873*</td>
<td>(0.428)</td>
<td>(0.975)</td>
</tr>
<tr>
<td></td>
<td>(0.428)</td>
<td>(0.975)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cumm Gap S</td>
<td>0.043***</td>
<td>0.086***</td>
<td>0.041***</td>
<td>0.082***</td>
<td>(0.014)</td>
<td>(0.029)</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.029)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Last Gap S</td>
<td>0.602</td>
<td>0.917</td>
<td>0.478</td>
<td>0.734</td>
<td>(0.485)</td>
<td>(1.284)</td>
</tr>
<tr>
<td></td>
<td>(0.485)</td>
<td>(1.284)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cumm Gap T</td>
<td>-0.003</td>
<td>-0.009</td>
<td>-0.000</td>
<td>-0.009</td>
<td>(0.011)</td>
<td>(0.022)</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.022)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Last Gap T</td>
<td>0.459</td>
<td>-0.370</td>
<td>0.463</td>
<td>-0.408</td>
<td>(0.342)</td>
<td>(1.176)</td>
</tr>
<tr>
<td></td>
<td>(0.342)</td>
<td>(1.176)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>40,411</td>
<td>14,345</td>
<td>40,411</td>
<td>14,345</td>
<td>40,411</td>
<td>14,345</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.302</td>
<td>0.319</td>
<td>0.302</td>
<td>0.320</td>
<td>0.305</td>
<td>0.324</td>
</tr>
</tbody>
</table>

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).
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 cumulative 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 5, 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 4.3.

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

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.
Table 4: Full-Time Worker’s Depreciation Rates (3-month Gaps and Growth Rates)

<table>
<thead>
<tr>
<th>Dep. Variable</th>
<th>(log(w_{i,t}))</th>
<th>(log(w_{i,t})) − (log(w_{i,t−1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3-month LTC C+</td>
<td>Any LTC C+ 3-month LTC C+</td>
</tr>
<tr>
<td>Last Gap</td>
<td>-0.567***</td>
<td>-0.805***</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td>(0.265)</td>
</tr>
<tr>
<td>Last Gap Math</td>
<td>-0.815</td>
<td>-1.792</td>
</tr>
<tr>
<td></td>
<td>(0.542)</td>
<td>(1.430)</td>
</tr>
<tr>
<td>Last Gap Verbal</td>
<td>0.468</td>
<td>2.266**</td>
</tr>
<tr>
<td></td>
<td>(0.458)</td>
<td>(1.074)</td>
</tr>
<tr>
<td>Last Gap Science</td>
<td>0.912*</td>
<td>-1.534</td>
</tr>
<tr>
<td></td>
<td>(0.525)</td>
<td>(1.492)</td>
</tr>
<tr>
<td>Last Gap Technical</td>
<td>0.007</td>
<td>1.145</td>
</tr>
<tr>
<td></td>
<td>(0.367)</td>
<td>(1.271)</td>
</tr>
<tr>
<td>Observations</td>
<td>40,411</td>
<td>14,345</td>
</tr>
</tbody>
</table>

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).
Table 4 provides results for three additional specifications (for brevity only results for recent gap measures are provided). Columns (1) and (2) show depreciation coefficients assuming only gaps with length of at least three-month are subject to depreciation of skills (all gaps with shorter duration are coded to zero). Columns (3) through (6) use as dependent variable wage growth between gaps, $\log(w_{i,t}) - \log(w_{i,t-1})$, rather than wage rates after a gap. The results in columns (3) and (4) computed depreciation rates considering any gap length and columns (5) and (6) only gaps of at least three-months. Although, coefficients on specific gap measures are imprecisely estimated and, therefore, not significant at 10 percent, all signs and magnitudes follow a similar pattern as in table 3.

Since selection could be an issue, we also run regressions conditional on gender and education with fixed effects for each individual. Table 5 shows the female-specific results. Columns (1) - (4) report results for the dependent variable of wages, $\log(w_{i,t})$, and columns (5) - (8) for the growth measure, $\log(w_{i,t}) - \log(w_{i,t-1})$. Each specification is run first considering any gap length and later only gaps of at least three month. 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 non-college graduates results are insignificant and flip back and forth in sign without establishing a clear pattern. For college-graduates the depreciation rates (sign and magnitude) are very similar to Table 3. However, only the three-month gap measures are insignificant for math at 10 percent. The verbal gap measure offsets partially 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. The coefficients for Therefore, these results could explain the observed mismatch patterns from Sections 4.1 of college graduates.

\footnote{We have also estimate depreciation rates for gaps of at least one months, two months, etc. The general patterns remain unchanged.}
Table 5: Gender-Specific Depreciation Rates

<table>
<thead>
<tr>
<th>Dep. Variable</th>
<th>(log($w_{i,t}$))</th>
<th>(log($w_{i,t}$) - log($w_{i,t-1}$))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LTC Any</td>
<td>C+</td>
</tr>
<tr>
<td>---------------</td>
<td>--------</td>
<td>----</td>
</tr>
<tr>
<td>Math</td>
<td>-0.052</td>
<td>-0.046</td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td>(0.191)</td>
</tr>
<tr>
<td>Verbal</td>
<td>-0.050</td>
<td>0.548***</td>
</tr>
<tr>
<td></td>
<td>(0.082)</td>
<td>(0.188)</td>
</tr>
<tr>
<td>Science</td>
<td>-0.034</td>
<td>-0.375</td>
</tr>
<tr>
<td></td>
<td>(0.116)</td>
<td>(0.272)</td>
</tr>
<tr>
<td>Technical</td>
<td>0.203*</td>
<td>0.319</td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td>(0.242)</td>
</tr>
<tr>
<td>Last Gap</td>
<td>-0.428***</td>
<td>-0.653*</td>
</tr>
<tr>
<td></td>
<td>(0.121)</td>
<td>(0.377)</td>
</tr>
<tr>
<td>Last Gap Math</td>
<td>-0.605</td>
<td>-1.492</td>
</tr>
<tr>
<td></td>
<td>(0.614)</td>
<td>(1.346)</td>
</tr>
<tr>
<td>Last Gap Verbal</td>
<td>0.039</td>
<td>0.985</td>
</tr>
<tr>
<td></td>
<td>(0.534)</td>
<td>(1.087)</td>
</tr>
<tr>
<td>Last Gap Science</td>
<td>0.703</td>
<td>1.083</td>
</tr>
<tr>
<td></td>
<td>(0.711)</td>
<td>(1.297)</td>
</tr>
<tr>
<td>Last Gap Technical</td>
<td>0.459</td>
<td>-0.504</td>
</tr>
<tr>
<td></td>
<td>(0.817)</td>
<td>(1.512)</td>
</tr>
<tr>
<td>Observations</td>
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<td>6,469</td>
</tr>
<tr>
<td>Individuals</td>
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<td>714</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.288</td>
<td>0.351</td>
</tr>
</tbody>
</table>

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, age squared, years, 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).
Furthermore, by using estimates on depreciation rates by skill it is possible to compute depreciation rates by occupations. Occupation-specific depreciation rates allow us to assess the possibility of a systematic pattern in relative female shares by occupation for a larger sample (e.g., the US Census and American Community Survey). Figure 4 depicts the correlation between female shares by occupation and depreciation rates for college graduates. Figure 4a uses estimates accounting for all gaps (minimum one week). Figure 4b only considers depreciation rates to be different than zero if the gap length was of at least three months. Relative female shares are averaged over the 1970-2010 time period. Although there is a slight weakening in the correlation over time, results are not driven by any particular time period. With the “any gap” measure the correlation of depreciation rates by occupation and female shares by occupation fall from 0.51 in 1970 to 0.49 by 2010. For the three-month gap measure the correlation is in general weaker, falling from 0.25 in 1970 to 0.19 by 2010. That is, the Census sample suggests that women comprise a smaller percentage share of occupations that have large depreciation rates.

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

4.3 Monetized Mismatch

If skills are underutilized in the labor market, individuals may face lower wages and tenure. Figure 2 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 occupation, and assess the wage difference. To understand which skills are most sensitive to mismatching with respect to wages, Figures 6 and 7 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 (2),

\[ \log(w_{i,t}) = \sum_k \alpha_{k,t} \Theta_{k,t}^i + \sum_k \gamma_{k,t} (\theta_k^i - \Theta_{k,t}^i) \Theta_{k,t}^i + \sum_k \gamma_{k,2,t} (\theta_k^i \times \exp_t^i) \Theta_{k,t}^i + \sum_k \gamma_{k,2,t}  \left( \phi_k^i \times (\exp_t^i)^2 \right) \Theta_{k,t}^i + X_{t}^i \beta_t + \epsilon_{i,t}, \]  

where all variables are as defined in Equation (6). 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 are more negatively or positively selected
into certain occupations given evidence on gaps and depreciation rates, 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,

\[ m_{kt}^i = \sum_k \hat{\alpha}_{k,t} (\Theta^*_{k,t} - \Theta_{k,t}^i) - \sum_k \hat{\gamma}_{k,t} \left\{ (\Theta^*_{k,t})^2 - (\Theta_{k,t}^i)^2 \right\} + \sum_k \left( \hat{\gamma}_{k,t} + \hat{\gamma}_{ke,t} \exp_t + \hat{\gamma}_{ke2,t} \exp_t^2 \right) \theta_k^i \left( \Theta^*_{k,t} - \Theta_{k,t}^i \right), \]  

(8)

where \( \Theta^*_{k,t} \) 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 \( \exp \), 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 5 shows the average wage component attributable to each skill type for the above
Figure 5: 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).

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 points to lower average wages for men working in high science occupations. For non-college men, the wage contribution of science has seen the largest upward trend, although technical returns were historically most relevant. Math has always yielded positive returns.

Figure 6 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 mis-
Figure 6: 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.

match 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 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
Figure 7: 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.

outcomes. The reproduced monetized mismatch results (based on Equation (8)), using this skill measure, are depicted in Figure 7. The skill wage components are virtually the same as the original specification, since this experiment mostly affects the relative position 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.\textsuperscript{13}

4.4 Further Evidence and Alternative Explanations

One possible concern may be that individual skills are only measured at the beginning of an individual’s working life. To partly address this, we look to the O*net, which, aside from providing skill measures, documents other general work experience measures for occupations, i.e., the need for “related work experience,” “on-site or in-plant training,”

\textsuperscript{13}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.
Table 6: Work Experience and Female Shares

<table>
<thead>
<tr>
<th></th>
<th>RWork</th>
<th>PT</th>
<th>OTJ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female Share (C+)</td>
<td>-0.47</td>
<td>-0.44</td>
<td>-0.48</td>
</tr>
<tr>
<td>Female Share (LTC)</td>
<td>-0.34</td>
<td>-0.50</td>
<td>-0.55</td>
</tr>
<tr>
<td>Depreciation Rates (C+)</td>
<td>-0.16</td>
<td>-0.18</td>
<td>-0.25</td>
</tr>
</tbody>
</table>

and “on-the-job training.” While these measure are more generic in terms of skill-types, they are indications of specific-skill training. As in Figure 4 we can compute correlations between these experience measures on the female share by occupation. Table 6 summarizes the results for college graduates. Correlations between related work experience (RWork), plant training (PT) or on the job training (OTJ) and female shares by occupations are all negative and similar in magnitude to the correlation of depreciation rates and female shares from Figure 4a. Moreover, the depreciation rates and alternative work experience measures are all negatively correlated (last row). That is, occupations with higher demands of work experience (positive value) have higher depreciation rates (negative value).

However, there could be other reasons why women choose to mismatch in terms of math or science. For example Goldin (2014) suggests that inflexible working hours are the largest contributing factor accounting for the remaining gender wage gap (or the self-selection of women into low wage occupations). Using the information on “Duration of Typical Work Week” from the O*net, Figure 8 graphs the female share by occupation against the share of individuals who work in occupations with more than 40 hours in a typical work week. Both for non-college and college graduates the relationship is negative. However, the correlation is considerably stronger for non-college graduates. This suggests that long work hours could certainly be an explanatory factor for women’s occupational choices complimentary to the skill depreciation theory. However, in contrast to the evidence on skill depreciation rates and mismatch of skill types, it appears to be stronger for non-college than college graduates.
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


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 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 a 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 that the number and length of gaps is likely overestimated, reducing the effect of each gap on wages. The reason military service is considered a 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 better 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 test sections listed above. The descriptors include information of knowledge, skill and ability required in performing 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.