Gender Differences in Stock Ownership

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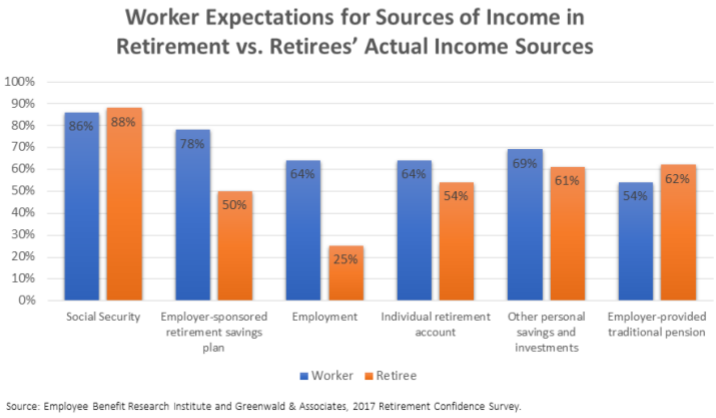
Introduction

- Reasons to invest in stocks
  - Provide a better return
- Factors that affect stock ownership
  - Age, race, education, wealth, income, risk attitude, and financial knowledge, etc.
- Gender effects on different factors
  - Risk tolerance, wealth, income, financial knowledge, etc.

Introduction

- Why this study?
  - The structure of retirement plans
    - Shift from defined benefit (DB) to define contribution (DC) plans
  - Stock ownership
    - 62% (2001-2008) vs. 54% (2009-2017)
  - The longevity risk of women
    - Longer life expectancy
    - Higher living expenses

Introduction



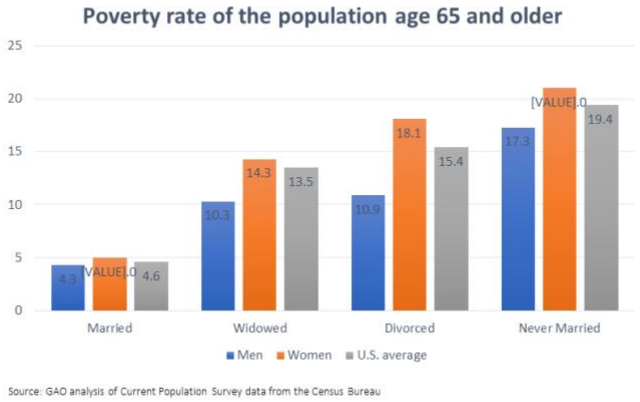
Source: Employee Benefit Research Institute and Greenwald & Associates, 2017 Retirement Confidence Survey.

Introduction

Gender	2001-2008 (%)	2009-2017 (%)	Change
Men	65	56	-9
Women	59	52	-7

Data source: Gallup 2016

Introduction



Source: GAO analysis of Current Population Survey data from the Census Bureau

Introduction

- Research questions
  - Is difference in stock ownership affected by gender in and of itself?
  - Are there gender differences in other aspects that contributed to differences in stock ownership between males and females?
- Purpose of this study
  - Investigate factors that moderate the effect of gender on stock ownership.
- Contribution of this study
  - Provide implications to individual investors and financial planners

Literature Review

Characteristics	Effects	Relevant studies
Gender and stock ownership	Single women are less likely than single men to choose "mostly stocks" for their DC plans.	Sunden & Surette (1998)
	Women participate significantly less than men.	Almenberg & Dreber (2015)
	Women are more likely to choose the guaranteed interest fund for employer stocks.	Bajtelsmit & VanDerhei (1997)
	There is no significant evidence that women hold a lesser percentage of their retirement funds in stocks.	Arano, Parker, & Terry (2010)

Literature Review

Characteristics	Effects	Relevant studies
Wealth/income and stock ownership	Stock market participation increase with net worth.	Shum & Faig (2006)
Financial knowledge and stock ownership	Financial literacy positively affect stock market participation and risky asset share.	Jappelli & Padula (2013)
Risk tolerance and stock ownership	Risk tolerance was positively associated with allocation of stocks.	Gilliam, Chatterjee, & Grable (2010)
	Risk-tolerant individuals are more likely to choose a smaller proportion of risk-free assets.	Hariharan, Chapman, & Domian (2000)

Literature Review

Characteristics	Effects	Relevant studies
Age	Age positively affected the proportion of net worth in risky assets	Gilliam, Chatterjee, & Grable (2010)
Education	Individuals who had Bachelor's and graduate degrees exhibited more aggressive investment behavior.	Grable et al. (2009)
Investment horizon	Individuals whose planning horizon was more than 10 years used more stocks.	Hariharan, Chapman, & Domian (2000)
Three months emergency funds	Having 3 months emergency funds increased the likelihood of risky asset ownership.	Gutter & Fontes (2006)

Hypothesis

- Based on literature reviews, we developed the following hypothesis
  - H1. Women are less likely than men to invest in stocks.
  - H2. The gender difference in stock ownership is moderated by other variables that affect stock ownership.

Methods

- Data
  - The 2016 Survey of Consumer Finances (SCF)
  - Total sample size=6,248
- Sample selection criteria
  - Individual household who was not married
  - Positive net worth
  - Final sample size for this study=1,938

Methods

- Dependent variable
  - Stock ownership (1=yes, 0=no)
  - Financial assets invested in stock
    - Directly-held stocks
    - Stock mutual funds
    - IRA/Keoghs invested in stocks
    - Other managed assets with equity interest
    - Thrift-type retirement accounts invested in stocks
    - Savings accounts or other accounts invested in stocks

Methods

- Dependent variables
  - Demographic characteristics
    - Gender, race, age, education.
  - Socioeconomic characteristics
    - Employment, financial knowledge, home ownership, defined-benefit plan ownership, use of a financial planner, emergency funds, income, income uncertainty, net worth.
  - Expectations
    - Investment horizon, health status, risk tolerance

Methods

- Data analysis
  - Binary logistic analysis
- Model
  - Reduced model: exclude the set of interaction terms and the indicator for gender.
  - Intermediate mode: add gender indicator.
  - Interaction model: add gender indicator and interaction terms.

Main Results

- **H1 confirmed: interaction model vs. reduced model**
  - There is a gender difference in stock ownership
- **H2 confirmed: interaction model vs. intermediate model**
  - Gender difference in stock ownership is moderated by variables that affect stock ownership in men and women:
    - Education
    - Financial knowledge
    - Ownership of define benefit plan
    - Income uncertainty

Main Results

- Men
  - Compare with men who have high school or lower degree, men who had college degree or higher were 1.05 times more likely to own stocks.
  - Compare with men who did not answered all three financial knowledge questions correctly, men have adequate financial knowledge were 38.8% more likely to invest in stocks.
  - Compare with men who did not have income uncertainties, men with income uncertainties were 13% more likely to invest in stocks.
  - Compare with men who did not defined-benefit plans, men with defined-benefit plans were 6.4 times more likely to invest in stocks.

Main Results

- Women
  - Compare with women who have high school or lower degree, women who had college degree or higher were 1.07 times more likely to invest in stocks.
  - Compare with women who did not answered all three financial knowledge questions correctly, women have adequate financial knowledge were 22% more likely to invest in stocks.
  - Compare with women who did not have income uncertainties, women with income uncertainties were 86% less likely to invest in stocks.
  - Compare with women who did not defined-benefit plans, women with defined-benefit plans were 4.0 times more likely to invest in stocks.

Implication

- Policy makers should be aware of financial education needs of women.
- Uncertainty reduced women's willingness to invest in stocks.
- When working with female clients, financial planners should pay special attention to their education, expectation of income uncertainty and defined benefit plan ownership.

Question ?

Thank you!

Female Gender Role Attitude, Housework, and Self-employment Decision

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Abstract

In this paper, we empirically investigate the impact of gender role attitude on female's self-employment motives in China and find that women with traditional gender identity tends to be self-employed more frequently than those with egalitarian gender identity. We further explore possible mechanisms which could provide an explanation for why gender role attitude can impact a woman's self-employment motives and find empirical evidence to show that traditional women are relatively more willing and have more time to do housework through self-employment.

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Does "Potential" Experience Bias Gender Wage Discrimination Estimates?

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Introduction

With the emergence of women's rights in the mid-20th century, various issues related to gender differentials have increasingly become an important research area. In terms of economics, the main focus has been on the wage differential in labor market employment. This gained wide attention in the 1970s, generating a substantial literature that influences the profession even today. On the whole, both the findings then and now, strongly suggests that a significant level of discrimination did exist and continues to persist. This pattern is not unique to the U.S. Though the magnitude may vary, the apparent wage discrimination against females is almost universal.

Amidst the sizable literature, there has always been a lingering question regarding whether the "overstated" potential" market experience will bias the estimated gender wage gap. It is argued that since the measure of market experience is overstated (especially for married females), thus the returns to "experience" is underestimated. Since the difference in shadow prices are attributed to the "discrimination" or "unexplained" portion of the gender wage gap, this will tend to overstate the extend of gender wage discrimination. In light of this, some studies have made extensive use of Heckman-style selection bias correction methods to cope with labor force participation decisions, some have tried to use "predicted" market experience, while some limited there data to new market entrants or young labor force. They each solve part of the problem, but at the same time generate other, perhaps even more damaging, problems.

This study claims nothing novel in terms of modeling or estimation technique, but attempts to address this question in a most direct fashion. It uses data from a lesser studied nation -- Taiwan, and an improved market experience measure (for married females). In addition, we will attempt to investigate the effect of this improved experience measure on the earning profile of different levels of education attainment. The remainder of the paper is structured as follows. Section II will summarize the literature, followed by the description of the data source (Section III). The model will be outlined in Section IV, with the empirical result presented in Section V. A summary will conclude the analysis.

Literature Review

Wage differential studies have mostly relied on a Mincerian hedonic wage model with a gender dummy variable to capture shift differences across gender, or apply the Oaxaca approach to decompose the observed pay gap into an explainable portion (due to "endowment" differences) and a "discrimination" component (Oaxaca 1973). The literature is vast and fairly accessible.[1] To economize, we have chosen to survey the studies that focus on, as this paper, the Taiwan situation.

Of which, Gannicott (1986) is perhaps the best known. The methodology is the aforementioned Oaxaca decomposition, while the data source is the 1982 Manpower Utilization Survey (conducted by the Directorate-General of Budget, Accounting and Statistics, or DGBS) or the MUS data, Gannicott found that "discrimination" accounted for 60 to 65% of the total pay gap.

Liu and Liu (1987) used the 1984 MUS data and run separate hedonic wage regressions for males and females. The regressors included a set of occupation dummies. They found evidence of compensation wage differentials for job related risk (from the aforementioned dummy variables).

[1] For those that are not familiar with this literature, Blau and Kahn (2000) serves as a good background material.

Their examination of the gender pay gap is somewhat unique. From the OLS wage regression results, they constructed an occupation specific equations by allowing the intercept to vary while the slope remained constant. In other words, when examining the "control" occupation, the decomposition of the observed gender pay gap was simply via the OLS regression, dropping all occupation dummies. When decomposing the wage gap for occupation *i*, the slope coefficients remain the same, while the intercept is the original intercept plus the coefficient of the *ith* occupation dummy. They found that "discrimination" cost female wages between 7.86% to 18.63%, depending on the occupation. Liu (1988) used the 1987 MUS data to examine the degree of discrimination across industry and occupation. She found significant difference in the gender discrimination across industry and occupations. However, when reverse regression was used, the discrimination coefficient was in general much lower.

Both Chung (1987) and Lin (1988) concentrated on the within occupation pay gap. Chung used the 1986 MUS data and found that 0.49% to 10.89% of the gender pay gap is due to occupational segregation (i.e. inter-occupational difference), while the bulk of the wage differential (58.17% to 78.17%) is due to intra-occupational differences (or, as Chung puts it, identical jobs but different pay). Lin was concerned with the accuracy of using "age-education-6" as the measure of market experience. He felt, as most economist would agree, that such measures might be acceptable for males, but due to the potential segmented career of females, such measure may overstate the market experience females. To avoid such biases, Lin limited his sample (1984 MUS data) to new entrants. The empirical results concluded that the gender discrimination was not through occupational segregation, but rather by intra-occupational differences (i.e., by violating the "comparable worth" principle). The intra-occupational differential was 131.99% of the actual gender wage gap, while the inter-occupational differential was -11.49% (i.e. actually helped in reducing the gender gap).

Concerned with the same labor force participation (and hence measurement error in market experience) issues, Wu (1988) and Jian (1988) also restricted themselves to partial samples. Wu limited her sample to college graduates of the academic 1983/84 year. She ran two regressions, one for those that have graduate for 8 months, one for those that have graduated for 1 year and 8 months. She found that the rate of returns to education was around 12% for both groups, and the coefficient of the binary gender dummy indicates that the gender discrimination increased with length since graduation.

Jian (1988) believed that the gender wage gap is primarily due to the difference in labor force participation patterns, and this should not be viewed as "discrimination". To remedy this, Jian used 1986 Mus data (limiting to those with a junior high degree) to estimate a human capital stock via a life-cycle labor force participation adjustment. He then substituted this for the experience variable in the wage regression. This reduced the gender pay gap of married workers by 1.92%, while for the single population, the coefficient decreased 15.77%.

Hou (1991) was concerned about the differential pay structural between the public and private sectors. He used a 10% stratified random sample of the MUS data series from 1978 to 1985, via a Heckman selection bias correction for "dual" selection (to capture the unique civil servant qualification system in Taiwan) to improve the estimation of the residual term in the Oaxaca decomposition. The study found significant gender wage discrimination in both the private and the public sectors. If the shadow prices are used (to estimate the female ale wage), the wage discrimination against females is 13.3% for the private sector, and 15.6% for the public sector. If switched to female shadow prices, the magnitude of the discrimination amplifies to 21.5% and 27.14%, respectively. Regardless, the evidence suggests that there is more severe gender discrimination in the public sector.

Kao, Polachek, and Wunnava (1994) used the 1989 MUS data, also under a life-cycle human capital approach. They incorporated expected lifetime labor force participation rates to compute expected human capital investments. The evidence suggests that labor force attachment/commitment positively affects the investment and accumulation of human capital. Once this is captured, 84% of the wage differential was explained, suggesting that the gender discrimination found in the literature may simply be due to the lack of measures to account for human capital investments over the lifetime of workers.

A strand of literature focuses on the “cause” rather than the measurement of the gender pay gap. Though this is somewhat outside of the objective of this paper, it is perhaps still worthwhile to summarize the findings. Seguino (2000) suggested that the high *physical* capital mobility of Taiwan (relative to South Korea) was the main cause of a wider gender earnings gap. Her conclusion that dissimilar characteristics of outward FDI between Taiwan and Korea was one of the main reasons for the disparity. Indeed, in real terms Taiwan was the largest source of FDI in China in the 1990s (Hou and Zhang, 2000 and 2001), and such vulnerabilities manifested itself during the subprime crisis (Hou

2013). Similarly, Berik (2000) found that export orientation low was the wage for both men and women, but improves gender equality,[2] while the conversion towards salary jobs tend to increase gender inequality. The focus on the effect of the external sector is hardly surprising as Taiwan is extremely dependent on trade, as evident that in terms of trade volume it is ranked as the 14th largest economy in the world.

Data Description

Based on the above survey, it can be seen that the measurement of market experience are all in terms of "potential" experience. However, due to marriage and child bearing/rearing, the market participation of women are often fragmented, thus overstating the market experience via the "potential" experience practice. This will undoubtedly lead to a measurement-error bias in the estimation results. To counter this, some researchers have limited themselves to the study of new market entrants, where such fragmentation is presumably absent. However, as this is a very special subset of the population, the results are of limited use, and any generalization towards the whole population (labor force) is to be taken with extreme caution. What we propose is to merge another supplemental survey with the commonly used MUS data. This will allow us to use the full sample, but also correct the bias inherent in the potential experience measure.

As can be seen, all the studies on Taiwan use the MUS (Manpower Utilization Survey). This is actually somewhamisleading. The MUS is a supplemental survey of the Manpower Resource Survey (MRS) conducted by the DGBS (of the Executive Yuan). The MRS is done every month (much like the Current Population Survey, or CPS, of the U.S.), while the MUS is a supplement for the May survey (again similar to the CPS of the U.S., where the May CPS is a full length survey with detailed labor market and individual characteristics). The MRS has individual information such as gender, age, marital status, education (even academic major, where applicable), labor supply information, and current occupation (and industry). However, it does not contain data on income. The MUS supplement, on the other hand, contains information on individual income, short term fluctuations, and for those without jobs, labor force participation preferences. Thus, though studies typically cite the MUS as their data source, it is actually the combination of the MRS and the MUS.

The MRS/MUS is based on a two stage sampling procedure. The first stage is a random sampling of villages or similar small divided areas; the second stage is households within these areas. The (household) sample size rose from 12,000 in 1978 (the first year the DGBS began the survey) to around 22,000 in 1997. The current sample contains about 60,000 individuals (only those aged 15 or above -- Taiwan's definition of potential labor force -- are surveyed). It should be noted that the survey is done through actual interviews at the homes of the sampled households, thus the accuracy and completeness of the data is far superior than most large scale surveys done in the West (such as, again the Current Population Survey, which is a mailing survey).

However, as noted earlier, the traditional method of measuring (potential) labor market experience as Age-Education-6 may overstate the actual experience of married females, which may in turn bias the discrimination estimates, we chose to merge the MUS with another special/specific supplemental survey of the MRS, the Female Marital, Child Birth, and Employment Survey (we will simply denote this as FMES). This survey includes the beginning and ending dates of non-labor force periods of females, be it due to marriage, child bearing/rearing, or other factors. This will allow us to calculate the "actual" market experience of married females. In addition, the FMES also includes the number/age of children, and husband income (where available). These will be important in determining the labor force participation decision of married females.

Though both the MUS and the FMES are supplemental surveys attached to the MRS survey, they are not conducted in the same month. The MUS is done May every year, while the FMES is implemented once every few years, and done in August. Though the actual sample is obviously different, however, the months are fairly close (May versus August), the sample design and implementation procedure are identical. Thus, theoretically, both sample should represent the same population. To be judicious, we carried out a series of Chi-square tests to test the distributional homogeneity on the married females in the two samples.

The null hypothesis is that the two independent sample came from the same population. The variables tested included age, education, marital status, labor force participation, job (industry and occupation), employment status, academic major (for vocational school and college graduates),

[2] Interestingly, Bao, et al. (2011) also found that export orientation for China did not increase wagers as predicted by the Stopler – Samuelson theorem.

income distribution, etc. The p-values are generally quite high (some as high as 0.999876). The lowest was labor force participation (p-value 0.14) and income distribution (0.276821). These two are most sensitive to seasonal changes, but still high enough that we cannot reject the null hypothesis that the two samples originated from the same population.

The sample used is the 1993 MUS and FMES.[3] The male and single female (defined as never married) came from the MUS, while married (including divorced, widowed) females came from the FMES. The sample selection rule is: ages between 15 and 65;[4] with paid employment (including employers and self-employed); and work for at least 20 hours. This left us with a usable sample size of 29,382 individuals. The key variables are defined as followed:

W: Log of wage rate of primary job

EDU: Years of schooling. As these are entered as categorical data, the conversion is as followed:

Illiterate = 0 Self-Educated = 1
Primary School = 6 Junior High = 9
Normal and Vocational High School = 12
Junior College = 14 College/University = 16
Post Graduate (no distinction between MA or PhD) = 18

EXP: Potential experience, unit of count is number of months.

For females, it is the standard Age-EDU-6
For males, due to the two year mandatory military service it is calculated as Age-EDU-8

EXPSQ: EXP squared to capture non-linearity in the returns to experience

EXR: Real or actual experience, unit of count is number of months.

For males and single (never married) females, it is the same as EXP
For married (including divorced or widowed) females, it is defined as Age-EDU-6-(number of months out of labor force). The last term is the combination of leaving the labor force due to marriage and the first time due to child bearing/rearing.[5]

EXRSQ: EXR squared

Marital Status:

SINGLE: never married, used as control group;
MARRIED: married, including co-habitation;
DIVORCED: divorced, including separated;
WIDOWED: widowed.

Academic Major:[6]

Non-major: Normal high school (or less) have no academic major. It is viewed as a "general" education, and used as the control group.
LITERATURE: when examining the wage regression of vocational high school and post-secondary education, this major is used as the control group.
The other majors include: LAW, BUSINESS, SCIENCE, ENGINEER, AGRICULTURE, MEDICAL, MILIT-POLICE (military academies and law enforcement institutions), EDUCATION, OTHERS

Employment Status: EMPLOYER, SELF-EMPLOYED, GOVERNMENT, PRIVATE.

Geographic Locale:

TAIPEI: Taipei city, used as control group;

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[3] The last time the FMES was gathered was in 1993.

[4] In the FMES data set, those that are over 65 are only asked the number of children they had. No information were gathered on the age of the children, husband income, and the dates they were out of the labor force. Due to the absence of such critical information, combined with the fact that of this age group, the percentage of individuals working for pay is minimal, they were excluded from the sample.

[5] The FMES only asked for the first time that the female left the labor force to bear or rear a child. The logic being that many females have children at fairly close intervals, hence will leave the labor force for several years to have several (perhaps all her) children. In addition, once the female has re-entered the labor force, her probability of leaving again (before retirement) is much lower. Due to this fact EXR may still be an overestimate of the actual labor market experience, but should be superior to the potential experience measure

[6] Lin (2010) found that the inclusion of such academic major dummy variables does enhance the proportion of the characteristic effects of the Oaxaca decomposition (i.e. the "E" portion discussed in Section V below). However, he also found that the gender wage gap within majors are mostly negligible, with the exception of medicine.

KAOHSIUNG: Kaohsiung city
NORTHERN, CENTRAL, SOUTHERN, EASTERN regions

Job Characteristics:

IND*i*: binary industrial dummy variables based on a 2-digit classification. A total of 70 variables, with Electric and Electronic Equipment Manufacturing and Maintenance as the control industry.

OCC_i: binary occupational dummy variables based on a 2-digit classification. A total of 35 variables, with Officer Clerical as the control occupation.

Number of Children:

CHILD3: number of children less than 3 years old;
CHILD6: number of children between 3 and 6 years old.

Other Variables:

HUSB-Y: Husband income (if present)
WORKEXP: binary dummy variable for whether worked before marriage.

The summary statistics are presented in Table 1. As the focus of this study is to examine the effect of a "corrected" experience measure has on the gender earnings gap, and the "correction" come from merging the married females from a different sample, it is obviously prudent to contrast the married (MARRIED, DIVORCED, and WIDOWED) with the never married (SINGLE). Furthermore, as we are also interested in the earnings differential (and the effect of the experience correction) between groups with different educational attainments, we will also distinguish between three groups in terms of education: Normal High School or Below, Vocational High School and Junior College, University and Post Graduate. This latter inquisition is not merely to investigate whether education differences affect the labor force participation decision, but also to reflect the fact that education carries a far higher social/cultural value compared with the WEST.

As can be seen, females earn significantly less than male in every division. For the overall sample, females earn about 70% of the wage for males. This gross wage ratio is worse for married females, who make only 67% of their male counterpart, while single females fair somewhat better (79%). In terms of the division by education attainment, the rule is as expected: higher educated females fair better than their lesser educated sisters. For the high school or below group, the female-to-male wage ratio is just under 68%. For those with post secondary degrees (Bachelors or better), this ratio is close to 76%.

The key variable for this study is the EXP (potential experience) and EXR (real experience). Note, EXP and EXR only differ for married (including divorced or widowed) females. The summary statistics show that on average potential experience overstates the actual labor market experience of married females by 65.6 months, or 29.3%! Though, a priori, we do not know how much of a bias this will cause in terms of the gender discrimination estimates, the sheer magnitude is something worthy of concern. Another interesting (though not unexpected) point is that the higher the education attainment, the lower the gap between EXP and EXR. This may reflect the higher opportunity cost and quicker human capital depreciation of the higher educated workers.

The level of education is remarkably similar across gender. This is hardly surprising considering the extremely egalitarian education system in Taiwan. The distribution of academic majors is also sharply different. Males are disproportionately majoring in Engineering, while females concentrate in Business. This is especially evident in the Education (2) group, or vocational high school and junior colleges. Though unobservable here (as it is a pure cross section), this distribution pattern has been changing over time (Hou 1997), and coincides with the period where Taiwan's occupation distribution between gender has gone through radical changes (Fuess and Hou 2009).

As expected, females are much less likely to be self-employed (more than 2:1 in favor of males), and even less likely to be employers. The probability of being civil servants (GOVERNMENT) is about equal, though somewhat surprisingly that among married workers, females have a lower probability of working for the government (than males), but the pattern is reverse among single workers. It is counter-intuitive in the sense that public sector jobs tend to be more stable (both in terms of employment and hours), less stress and overtime. These are, presumably characteristics attractive to married females. However, as Hou (1991) found, everything else equal, public sector tend to have more gender discrimination than the private sector. This may be one of the reasons leading to this seemingly counter-intuitive statistic.

Empirical Model and Group Classification

Once the compatibility of the two samples are established, we stand ready to proceed with the empirical estimation. As mentioned at the beginning of the paper, we claim not innovation either in terms of theory or estimation models. The primary objective is to establish a more accurate measure of work experience, so as to directly examine the effect of the overstated potential experience on the estimated gender wage discrimination. We will also exploit this further by contrasting the rate of return to experience (across several groupings) between the traditional "potential" experience and our more accurate measure.

Empirical Model

The wage regression will be the standard Mincerian hedonic wage function, estimated separately for the male and female sub-sample. Specifically,

(1) $W_{mi} = a_m X_{mi} + e_{mi}$

(2) $W_{fi} = a_f X_{fi} + e_{fi}$

where m, f = denote male and female respectively.
W_i = log real hourly wage rate of current, primary job.
a_j = vector of coefficients.
X_i = Explanatory variables, including most of the variables listed in the previous section, with the exception of CHILD3, CHILD6, HUSB-Y, AND WORKEXP.
e_j = error term

The "gross" wage differential is defined as

$$G = \overline{W}_f - \overline{W}_m$$

where $\overline{W}_f$ and $\overline{W}_m$ are the average female and male wage rates, respectively. By definition,

$$\overline{W}_j = \hat{a}_j \overline{X}_j \qquad j = f, m \ (\hat{a}_j \text{ is the least squares estimate of } a_j)$$

Further define

$$\widehat{W}_{jk} = \hat{a}_k \overline{X}_j \qquad j, k = f, m \text{ and } j \neq k$$

This is the "expected" wage of a gender (*j*) if they were paid according to the shadow prices of the other gender (*k*). The "gross" gender gap can be decomposed into two parts, as follows

$$G = \overline{W}_f - \overline{W}_m = \left(\overline{W}_f - \widehat{W}_{jk}\right) + \left(\widehat{W}_{jk} - \overline{W}_m\right) = D + E$$

where "E" represents the wage differential which is due to or can be "explained" by differences in characteristics (i.e. "endowments"), while "D" is the residual difference or "discrimination" term. The decomposition can be implemented in two different ways depending on the shadow price which is used as the base. If the male shadow prices are used as the base, then[7]

(3)
$$G = \overline{W}_f - \overline{W}_m = \left(\overline{W}_f - \widehat{W}_{fm}\right) + \left(\widehat{W}_{fm} - \overline{W}_m\right)$$
$$= \left(\hat{a}_f - \hat{a}_m\right)\overline{X}_f + \hat{a}_m\left(\overline{X}_f - \overline{X}_m\right) = D1 + E1$$

If the female shadow prices were held as the base, equation (3) turns into

(4)
$$G = \overline{W}_f - \overline{W}_m = \left(\overline{W}_f - \widehat{W}_{mf}\right) + \left(\widehat{W}_{mf} - \overline{W}_m\right)$$
$$= \hat{a}_f\left(\overline{X}_f - \overline{X}_m\right) + \left(\hat{a}_f - \hat{a}_m\right)\overline{X}_m = E2 + D2$$

[7] $\widehat{W}_{fm}$ is to be interpreted as the expected wage for females if they were paid according to the male shadow prices.

Equations (3) and (4) will in general lead to different measures, which handicaps the wage discrimination estimation (for more details refer to Neumark 1988). This is further complicated by the fact that many of the industry and occupation dummies are unique to one gender.[8] To account for this we adopt the "randomized" effect approach of Hou (1991).

Due to the concern for selection bias arising from the endogeneity of the labor force participation decision of female (especially married female) workers, we will begin with a Heckman (1976) style two-stage least squares to see whether the selection bias is a problem. The first stage is a standard probit function:

(5) $$I_i = \beta Z_i + \varepsilon_i$$

where β_i = binary dummy variable, with value 1 if participate in the labor force and 0 otherwise.
Z_i = variables that affect the labor force participation decision, such as education, age, marital status, children, husband income, and whether the (married) female worked prior to her marriage.
β, ε_i = a vector of coefficients and the error term, respectively.

Based on this, the second stage of the estimation is the modified gender wage regressions

(2)' $$W_{fi} = a_f X_{fi} + s_f g_{fi} + e_{fi}$$

where s_f is the covariance of the errors of the probit function and the wage equations, while g_{fi} is the inverse Mill's ratio or the Heckman-Lee type selection bias correction variable. The decomposition remains in the fashion of equations (3) and (4).

Groups of Interest

The core focus of this study is on the effect of "real" experience (as opposed to "potential" experience) on the gender wage discrimination, and the returns to experience before and after the modified improved measure of market work history. In light of this, and the fact that the measurement error in "experience" primarily affects married females, we will therefor partition separate the sample by marital status. Furthermore, as it is well established that the rate of return to market experience (proxy for "general" OJT)[9] is a function of the initial human capital stock (Ben-Porath 1967), which can be proxied by education attainment, it may be well worthwhile to examine the wage profile by education levels.

Based on the above, we will estimate three groups of regressions, calculate the discrimination components of the gender gap, and compare the returns to experience. We will start off with the full sample (Group I), there will be one male regression and two female wage regressions (one using EXP as the measure for experience, one using the improved EXR). Next, we will separate by marital status into single vs. married. For the single category, there will be one regression for males and one for females (since EXP = EXR for single females, as they are not in the FMES survey). For the married group, there will be once more one male and two female wage regressions.

Finally, as we are interested in the interactive effect of the improved experience measure and the rate of return to experience across different education attainments, we will distinguish between three levels of education: normal high school or lower (HS/Below), vocational high school and junior College (VHS/JC), and college/university and above (Univ.). The emphasis on education has several layers of reasons, especially for Twain or East Asia nations. First of all, from a human capital theory point of view, education is a major source of human capital buildup, and is indeed the foundation of further human capital investment, and will greatly increase the efficiency of such investments. We all can recall conversation with industry practitioners on the effect of education (especially post-secondary education) as mainly the ability to learn (on the job).

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[8] Recall, most studies only have broad (i.e. a 1-digit) industry/occupation controls. Thus the problem of empty cells is almost certainly avoided.

[9] It must be noted that the literature typically also use the "tenure" measure to proxy for "specific" OJT. However, we are unable to do so due to data restrictions. Though the MUS data does contain the tenure measure, the FMES does not.

Furthermore, the Asian cultural tradition (perhaps due Confucian influence) places an enormous respect, and hence "value", on the acquisition of education (Hou, et al, 1995, and Hou 1996). The seeming superior performance of students of Asian descent is a manifestation of this respect for education. Finally, perhaps also due to the above element, unlike most of the studies on Western economies, Taiwan seems to exhibit an increasing returns to education. And, for females at least, a sense of screening/signaling, or "credentialism" (Hou 1991).

Empirical Evidence

In this section we will present and discuss the empirical estimates of the above specification, and across different group partitions. We will start with the probit estimates, then address the question of selection bias, before we proceed with the wage regression estimation. After the various wage regressions are discussed, the observed gross wage differential will be decomposed into an "explainable" portion (i.e. the compensation wage differential) and the residual, which the literature has typically viewed as "discrimination." Finally, we will graphically illustrate the ceteris paribus wage-experience profile, the contribution of experience to a typical worker's wage growth pattern over his/her work career.

Probit Estimates

This part is to address the question of labor force participation decisions of females, as outlined by Equation (5). Column one in Table 2a is the probit estimate for the full sample. Consistent with theory, education attainment has a positive effect on labor force participation, while age has a negative effect. Both are highly significant. As expected, married females have a much lower probability of working, while divorced females have an equally strong opposite effect (i.e. much more likely to be in the labor force).

With the exception of Business and Education, academic majors do not appear to matter much. And the two that do matter, one can easily imagine the demand for such female personnel in certain industry/occupations. What is somewhat different (with respect to Western literature) is the regional differences in labor force participation of females. Recall, the control group is Taipei city (which, depending on the definition, accounts for nearly 13% of the population), with Kaohsiung as the other major metropolitan (in the south), while in contrast, the other regions are relatively rural. As can be seen, categorically, the "rural" areas tend to have a higher female labor force participation. The cause may be many. There is a fairly severe drainage of prime age males into the major metropolitans, forcing females to pick up much more slack. In addition, many of the manufacturing factories are located outside of major cities for a variety of reasons. Finally, many manufacturers of small parts or souvenirs like to contract out to housewives (even single females living with their parents) for much of the hand made products.

The effect of young children is precisely as expected, and the younger the children the more negative the effect on labor force participation. Husband's income (HUSB-Y) will reduce the probability of a (married) female entering the labor force, while having worked prior to being married (WORKEXP) is the single most important predictor of female labor force participation. These last four variables are obviously directly related with being married. We next ran the probit estimate for the married female sub-sample. This is presented in column two of Table 2a.

The effect of education is reduced (though still significant), but the deterrent aspect of age is much more pronounced. What is most interesting for the married female sample is the significantly more importance of the academic majors. We are tempted to ask whether this merely reflects the market demand for such majors, or is this part of the optimal (academic majors) choice in light of a potential fragmented labor market career? The other interesting result is the reduction in both magnitude and significance level of HUSB-Y and WORKEXP. This suggests that these two variables, in the full sample probit, were picking up the difference in the nature of labor force participation between single and married females.

As we plan to examine the gender discrimination for three specific education groups, there corresponding probit functions are also estimated. These are presented in Table 2b. We will only highlight some of the differences across the three groups. First of all, the effect of age on female labor force participation is quite different across groups. For the less educated, it remains a significant negative effect, but for the other two groups, age enhances the probability of being in the labor force (though not statistically significantly for the higher or university educated females).

The pattern of the academic majors (not relevant for the lower educated) and regional differences

also differ. Academic majors are generally insignificant for the medium educated (VHS/JC), but much more significant for the highly educated. As for the regional difference, the aforementioned pattern is only present in the lower educated group. This is consistent with the original explanation, as the factory workers and housewives making hand craft at home are all lower end jobs typically associated with less skilled, less educated workers. Furthermore, lower educated workers tend to seek jobs locally, whereas higher educated workers search for jobs over a much bigger region,[10] thus the regional differences for the low end jobs will not be eliminated via labor mobility. This is also substantiated by the lack of regional differences for the higher educated groups.

The negative effect of having young children decreases as the children gets older, but also decrease in general with the education level. In fact, for college (or above) educated women, the presence of young children have no significant impact on the labor force participation decision. This perhaps reflect two things. First of all, the opportunity cost (and the rate that the accumulated human capital depreciates) for highly educated women are much higher, and second, their own wage earnings combined with their husband's income (which are also typically higher) may allow domestic help or day care for the young ones.

Also as expected, the labor force participation of the highly educated females seem independent of the husband's income, while those with lower levels of education see much stronger negative influence. And, consistent with many of the above observations, those that have worked prior to their marriage have a much higher probability of staying or re-entering the labor force. In fact, with the exception of perhaps the intercept, this is the single most significant predictor (it is certainly by far the most significant statistically).

Selection Bias from Endogenous Labor Force Participation?

Following tradition, we next ran the Heckman-style selection bias corrected wage regressions for the (married) females (i.e. Equation (2)'). We found no significant selection bias in any of the female wage regressions. The lowest and the highest educated group were significant at the 10% level under the EXP model, but insignificant for the EXR model. We experimented with various specifications of the probit function but still no such bias was found. To this end, we concluded that there is no selection bias.

This is different from Liu and Liu (1987). However, one must keep in mind that Liu and Liu used the 1984 MUS data, while our time period is 1993, nearly a decade later. It may well be that the labor force participation pattern of married females in Taiwan has undergone significant changes. Indirect evidence are abound. For example, Fuess and Hou (2009) found dramatic changes in the occupation distribution across gender since 1986/87. They conjecture that the increased occupation "segregation" stems from the fact that the service sector took off, thus creating jobs that are particularly suitable and attractive to females on a massive scale. Another piece of evidence is the decrease in the labor force participation rate between single and married females. In 1984 (Liu and Liu's sample year), the married females' force participation rate was still 19.5% below that of single females. By 1993 (our time period), the gap had decreased to only 8 percentage points.

Wage Regression Estimates

Keeping with tradition, and to avoid unnecessary bias,[11] we dropped the inverse Mill's ratio and ran simple OLS wage regressions (Equations (1) and (2)). The various sets of regressions, by gender, are presented in Tables 3a through 5. The content and sequence are as outlined in Section 3.2 above.

Table 3 is for the full sample. There is no surprise for the male wage regression. The returns to experience is positive (indicative of human capital buildup via OJT), but the returns is diminishing (as seen by the negative coefficient of the quadratic term EXPSQ). The returns to education (i.e. the wage increase that would result from one extra year of schooling) is a mere 1.2%. Far below the real market interest rate (of 3 to 4%). Also, consistent with Western literature, married men earn an 10.9% wage premium over their single counterparts.

[10] For Taiwan, this can easily cover multiple regions, as the nation is only the size of Connecticut plus Rhode Island; or, using a different measure, the Los Angeles metropolitan is about a third of Taiwan (not to mention more than half of Taiwan's terrain is uninhabitable mountain ranges).

[11] There is concern that the inverse Mill's ratio, being non-linear in nature, is simply picking up such (non-linear) relations in the regression. If the selection bias was significant, we would have be inclined to have it in the specification, as it is now, we feel it is not worth to do so.

For the female wage regression, there are two. Hereon, the EXP/EXR regression or version refers to the regression using potential/"real" experience measure, respectively. Contrasting the EXP version with that of the male regression reveal several interesting differences. Off the bat, the returns to experience is markedly lower for females, at least in terms of the "linear" coefficient. The presence of the quadratic term makes it hard to grasp the difference as it differs over the work life and is a "dynamic" in that sense. Precisely because of this, we will have a separate section below that tries to capture such dynamism graphically.

The fact that the (linear) rate of return to experience for females is only half of that of males (though countered somewhat by the lower rate of the diminishing returns) suggests a much lower OJT for females, clearly a sign of discrimination. However, one is cautioned that this is based on the reputed biased EXP or potential experience measure, and hence any conclusion should bear this in mind. At the same time, the return to education is nearly 3 times as high for females (3.5% relative to the 1.2% for males). We believe that this may well also be a sign of gender discrimination. It may suggest that males will not be handicapped by a low level of education, but females need a much higher education to obtain similar jobs to males. Such evidence was found in Hou (1991).[12]

The wage premium for being married is much lower for females than for males. This is also consistent with the literature, as the employer may perceive a married women as more likely to quit, need maternity leave, or sudden short leaves due to illness of their children, or taking care of sick elderly. This argument has often been termed as statistical discrimination. But once again, as the EXP is especially problematic for married females, this low premium may well be at least partially due to measurement error in market experience.

When one compares the EXP and EXR regressions, two differences immediately catch the eye. First, The rate of return to education (both the linear and quadratic terms) are now much more compatible to that of males. Second, the earnings premium for being married has doubled, though still lower than the male sample. These results suggest that the apparent lower OJT and practice of statistical discrimination so often seen in the literature is at least partially due to the bias introduced by the overestimation of market experience for married females when "potential" rather than "real" experience is used.

It is natural then, to partition the data into single and married. Table 3a contains the regression results for the singles sub-sample. As there is no correction data on labor force participation, there is only one regression for females. As can be readily seen, the returns to experience is much closer across gender, and though females still exhibit a premium for education, the magnitude is smaller. Such is not true for the married sample (Table 3b). Though the "linear" returns to experience appear the same, the profile for the married female is much less concave than the male. As for the importance of education, the differential is much higher than the singles group. For the EXR version, the returns to experience does not change much, only increasing the concavity slightly. The returns to education remain unchanged.

When comparing the results of Table 3a and Table 3b, it is obvious that the returns to education and experience are much higher for the single group, regardless of gender. Once realizing that, categorically, the single group implies a younger class of workers, the explanation is apparent.

Building on the rather significant difference in the returns to education, we then divided the full sample into three group based on education attainment (Section 3.2). The empirical estimates are shown in Table 4a, Table 4b, and Table 4c. For the lower educated group (normal high school or below), the aforementioned stylized facts are observed, i.e. less concave profile from the returns to experience, significantly higher returns to education, and a much smaller premium for being married. However, the latter two were much more pronounced. For males, the returns to education is practically zero, which is hardly surprising given that they are most likely employed in menial labor type of jobs where strength and agility is far more important than whether one can recite Shakespeare. And the apparent statistical discrimination against married females is ever so clear. For a married male, the wage premium was 12%, compared to a mere 0.3% for the females.

After correcting for the measurement error in experience, the EXR version yielded similar effects. It increased the concavity of the wage-experience profile, had little effect on the returns to education, but significantly increased the wage premium for being married (by nine folds), but still far short of the male counterpart. It is not until one compares across the three education levels that an interesting pattern emerges.

[12] Following Goodman (1979), Hou included a set of dummy variables for highest degree completed. These variables were insignificant for males, but jointly significant (especially in the public sector) for females. He concluded that such "credentialism" for females clearly indicate a prejudice hiring practice against females.

The effects of EXR on the wage-experience profile is less pronounced for the higher educated (both the VHS/JC, and the Univ. & above). The gender difference in the returns to education decreases with level of education, and disappears for the highly educated. This is in line with our earlier speculation that the lower educated workers are employed in menial jobs that education have little bearing. Another significant difference across the three education groups is the marital premium. There was practically no premium for low educated married females (even with the EXR regression), as discussed above. However, the gap decreases dramatically with the level of education. For the medium educated (VHS/JC), the comparison of male/female marital premium is 8.3% to 6.5% (or 3.2% when EXP is used). For the highly educated (Table 4c), the female marital premium actually exceeds that of men (9% to the 16.8% under EXR). We are at a loss as to the explanation. Further investigation is undoubtedly needed.

Discrimination or Compensating Differentials?

We next turn to the decomposition of the observed wage differential. The "gross" wage differential, in log terms, was -0.36 for the full sample. When subdivided into single and married, it was -0.23 for single workers, and -0.40 for married workers. When grouped by education attainment, the gross differential was -0.39 for the lower educated (HS/Below), -0.36 for the medium educated (VHS/JC), and -0.28 for the highly educated (Univ. /Above). Several patterns can be seen. First, a significant differential exists, and is larger among married workers than for single workers. Second, the observed gross wage differential between gender seems to diminish with education.

These numbers are crude measures, and less intuitive as they are in log terms. To this end, we converted the log differentials into percentage differences. For example, the observed -0.36 gap for the full sample is equivalent to -30.27% wage disadvantage for female workers. We then decomposed the observed gross wage differential for various groups by both Equations (3) and (4). The results are presented in Table 5.

As can be seen, though the size is smaller (than the gross differential), the discrimination component dominates (with the exception of the highly educated). The relative size of the discrimination is the same as the aforementioned pattern for the gross differential. Taking D1 of the EXP model for example, the discrimination caused females to be paid 23.28% lower than males. In other words, 76.92% of the observed wage differential is due to "discrimination." The discrimination is more severe against married women (28.24%) than for single females (14.99). From a different point of view, the dominant portion (85.72) of the gender wage differential among married workers is unexplainable, and hence attributed to discrimination.

The discrimination among the lower educated workers is similar to the married category discussed above, both in terms of size (females earn 27.01% less than males) and the intensity -- 83.47% of the gross differential is due to discrimination. As the education attainment rises, wage discrimination seems to decrease. For the highest educated group, wage discrimination against females decreased to only 6.57% (or 27.15% of the total difference). Though not surprising, the size is still smaller than what we had expected.

Before we compare the EXP vs. the EXR model, it may warrant a caution regarding the severe discrimination that is observed for the low educated group. In a nutshell, we feel the discrimination may be overstated. If one examines Equations (3) and (4), especially the discrimination component (D1 and D2), it is clear that any difference in the coefficients is considered "discriminatory". The logic is straight forward. For the same productive "trait", the returns or shadow price should be the same across gender, otherwise it is gender discrimination. This is intuitive, but also debatable.

Consider the following two examples. First, due to anticipated fragmentation of work career, an optimizing female may choose an academic major that has smaller depreciation (when out of labor force), say Literature, while a similar male may have chosen Engineering (which has a much higher rate of human capital depreciation when out of the labor market). It is common knowledge that the shadow price of an engineering major is higher than that of a literature major. Thus, even if both have the same years of education, the female rate of return to education will be lower than that of the male. This will be classified as discrimination under the Oaxaca decomposition, but is it discrimination? We feel this is one of the major drawbacks of this method. To compensate for this, we included, when possible, a set of binary dummies for academic major. As can be seen throughout the tables, the difference of these variables across gender is quite astounding.

The second example is much more relevant to the case at hand. The lower educated workers (our HS/Below group) are mainly employed in menial jobs that have a much for demand for physical abilities. It is also an unchallenged fact that, on the average, men have more brute strength than

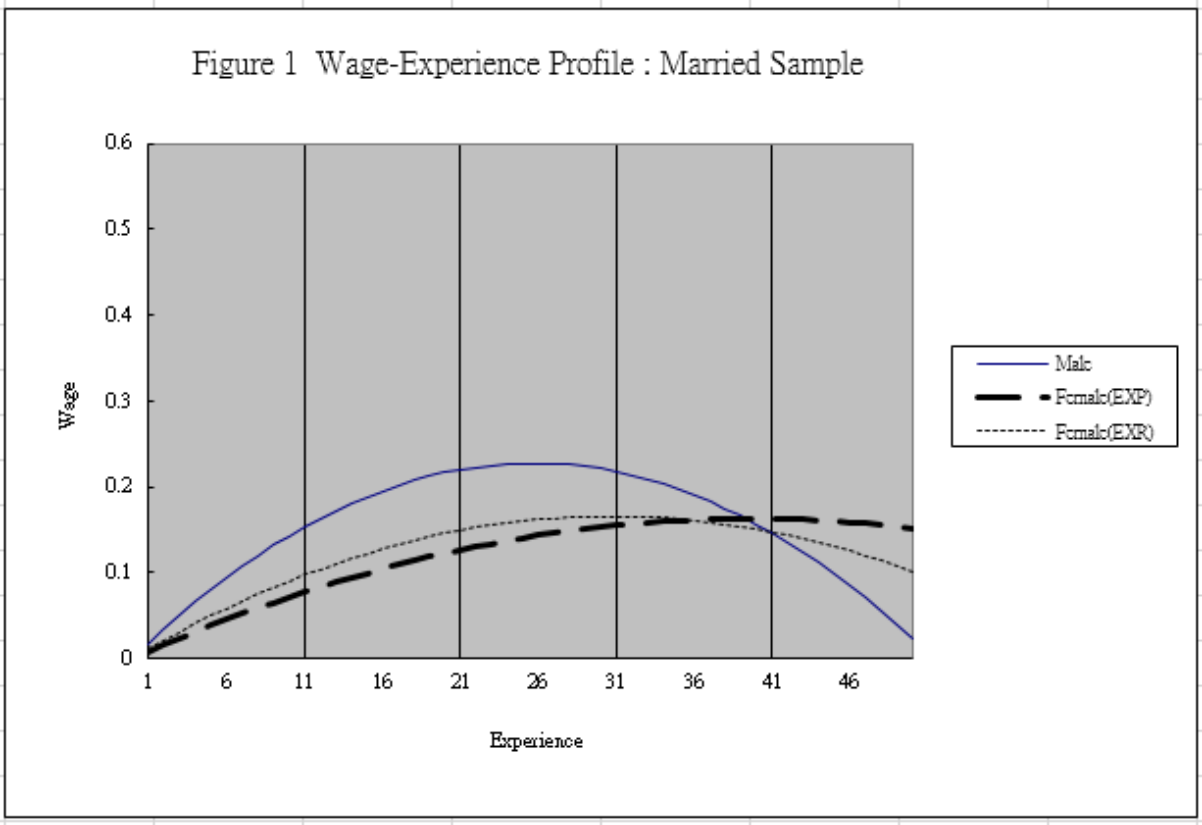
women. Then, the male furniture mover will be more productive than a female mover, hence the shadow price for the occupation of furniture mover will be much higher for the males than for females. The traditional method will again notch this under the category of discrimination, even though it is clearly a compensating difference due to disparity in productivity.

Finally, the introduction of the improved experience measure EXR did lower, as expected, the discrimination component of the gender pay gap (with the exception the D2 version of the lower educated group). However, the size may be small for some readers. But even a negative results still has its value. If this finding is robust, then our continuing usage of potential experience will be under a much clearer conscience.

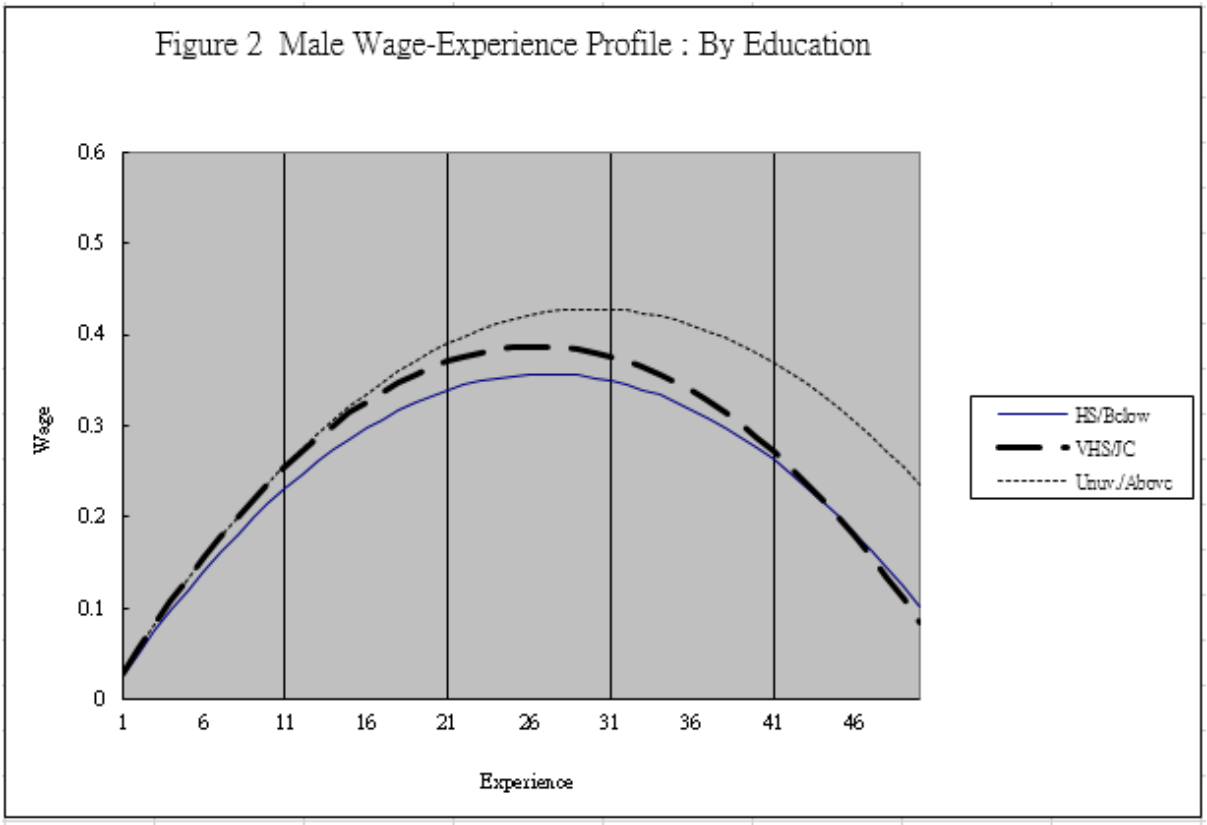
Wage-Experience Profiles

In this section, we focus on the ceteris paribus wage-experience profiles. To conserve space, we will focus only on those that will highlight the effect of the improved experience measure, rather than do an exhaustive comparisons. As EXR is modified based on the labor force exit/re-entry of married females, it is logical to start with the comparison of married males to married females (with both measures of experience, EXP and EXR). This is shown in Figure 1. As can be clearly seen, the EXP model will overstate the "discrimination" portion (as measured by the vertical distance between the male profile with the EXP or EXR profile of the female workers).[13]

Figure 1 Wage-Experience Profile : Married Sample

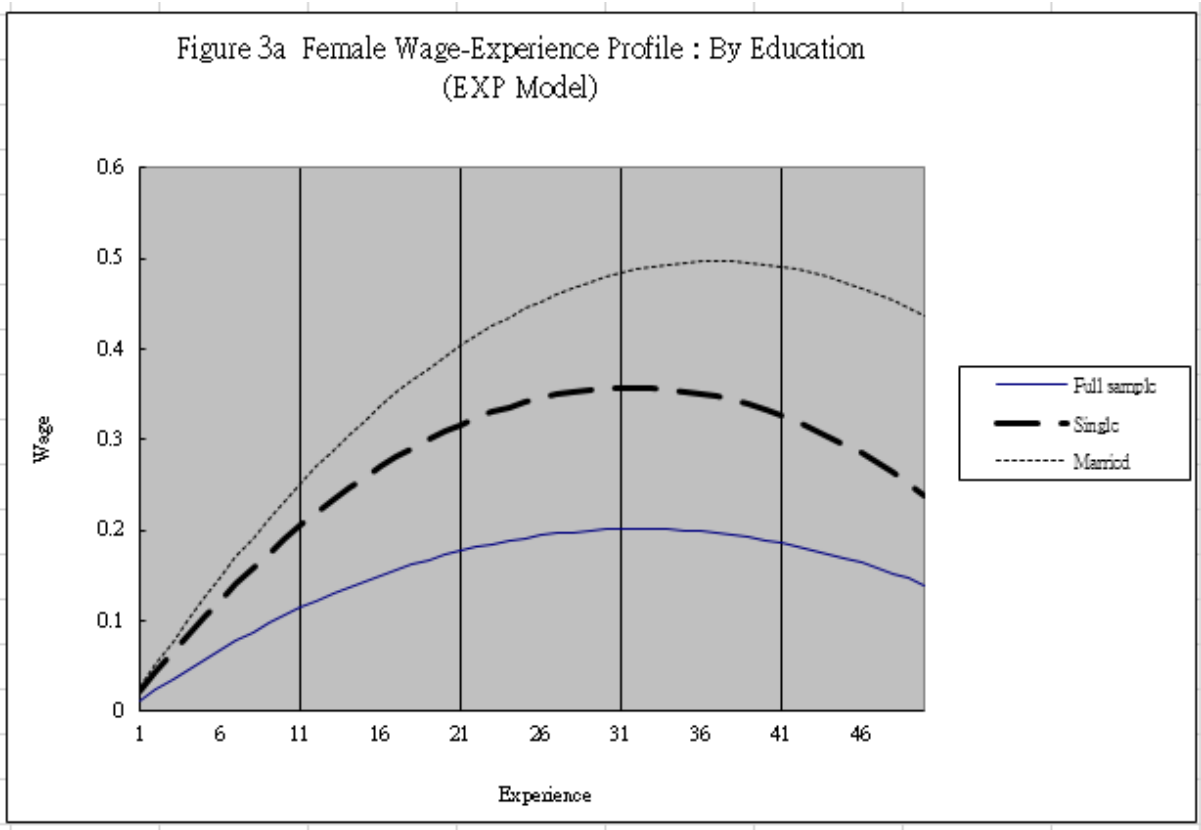


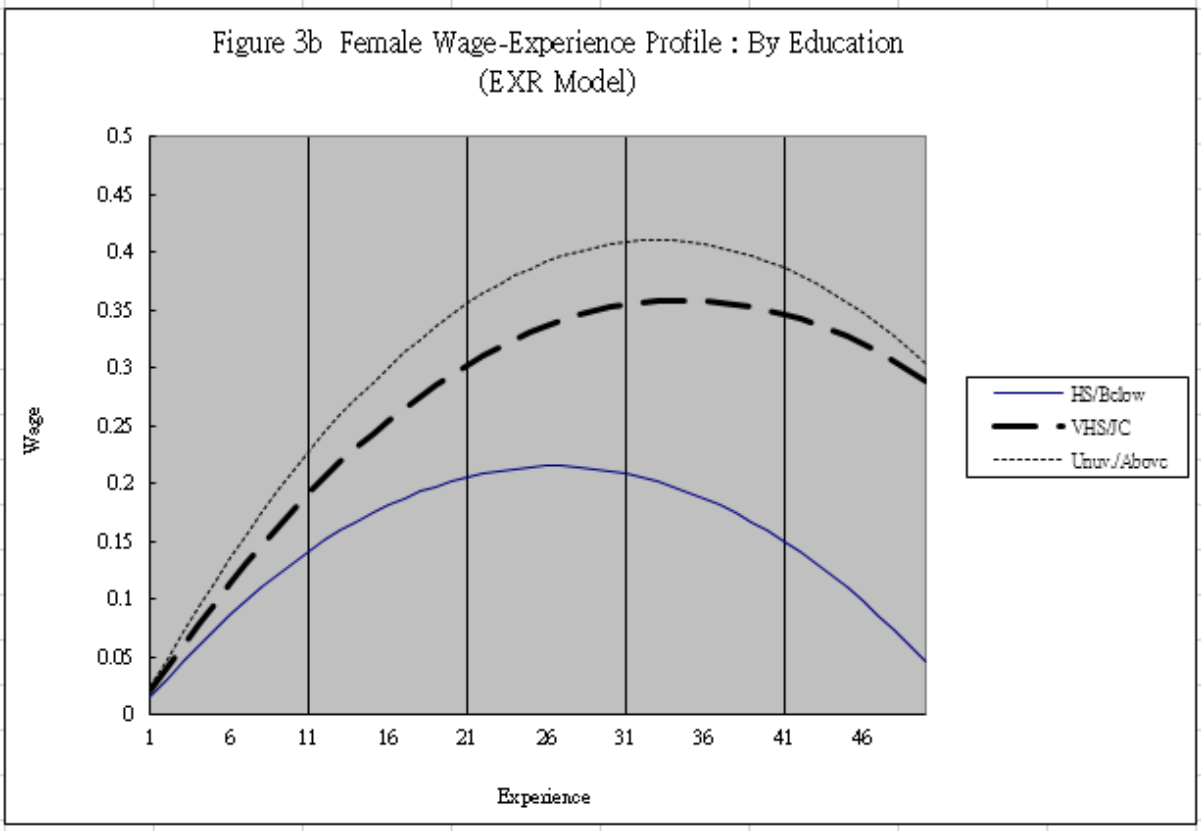
[13] Though it appears that women earn more (from experience accumulation) towards the tail end of their careers, it should be taken with a grain of salt. Our sample is drawn from the age between 15 to 65, hence the whole profile is technically within sample range, the variance is bound to be amplified towards the end of the spectrum.



We next turn to the wage-experience profiles for each gender, by education level. For males (Figure 2), the profile is much closer than one may expect. The VHS/JC group exhibit a higher and more concave profile than the low education group (HS/Below). As for the two higher educated groups, the profiles almost overlap for the first 15 years of the work career. After that, the medium educated show a much more rapid diminishing returns than the higher educated (Univ./Above). This may be viewed as evidence that those with a university (or better) education have acquired the ability to learn and can hence offset the depreciate and the diminishing returns better.

The female picture is much more interesting. Figure 3a shows the wage-experience profiles based on the EXP measure. As can be seen, the gap between all three education levels are pronounced and distinctive, much more so than the male sample. This once again substantiates our claim that the returns to education for females may harbor some form of discrimination not yet being able to account for. Though the three profiles still exhibit the

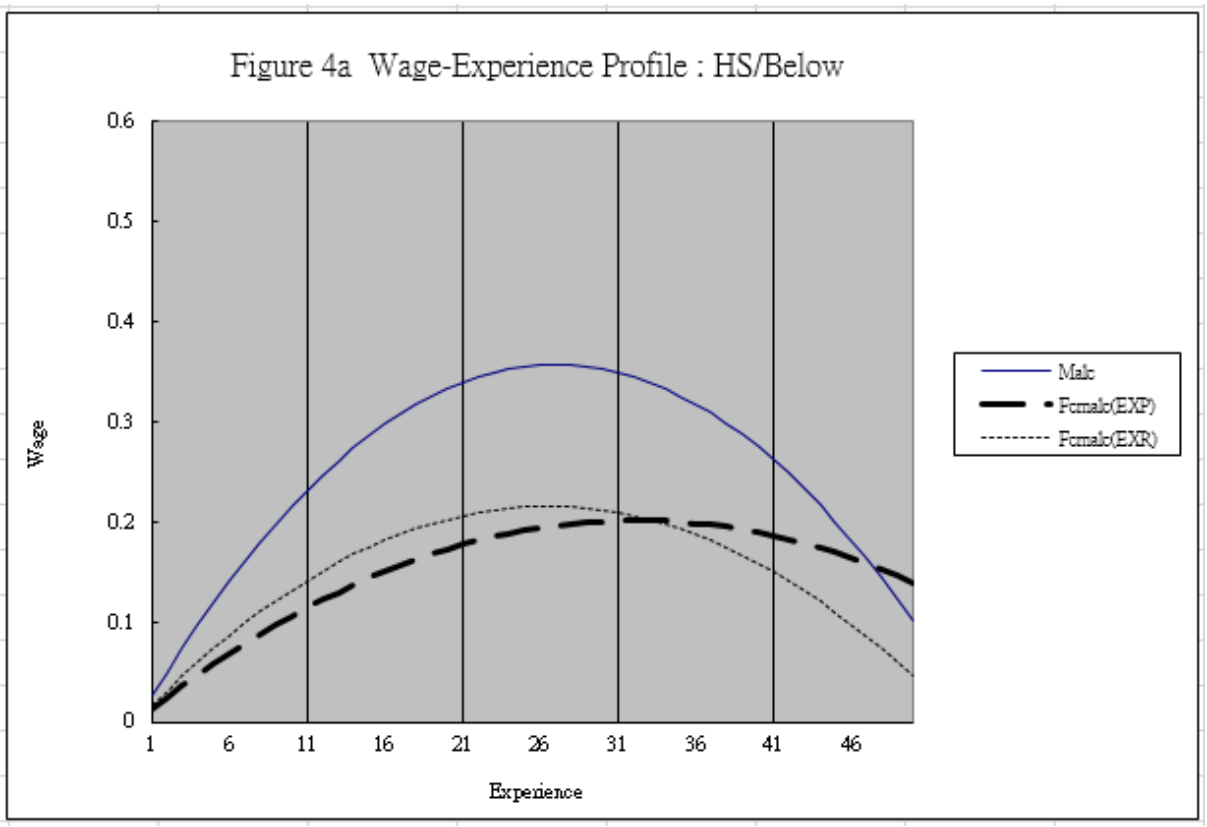


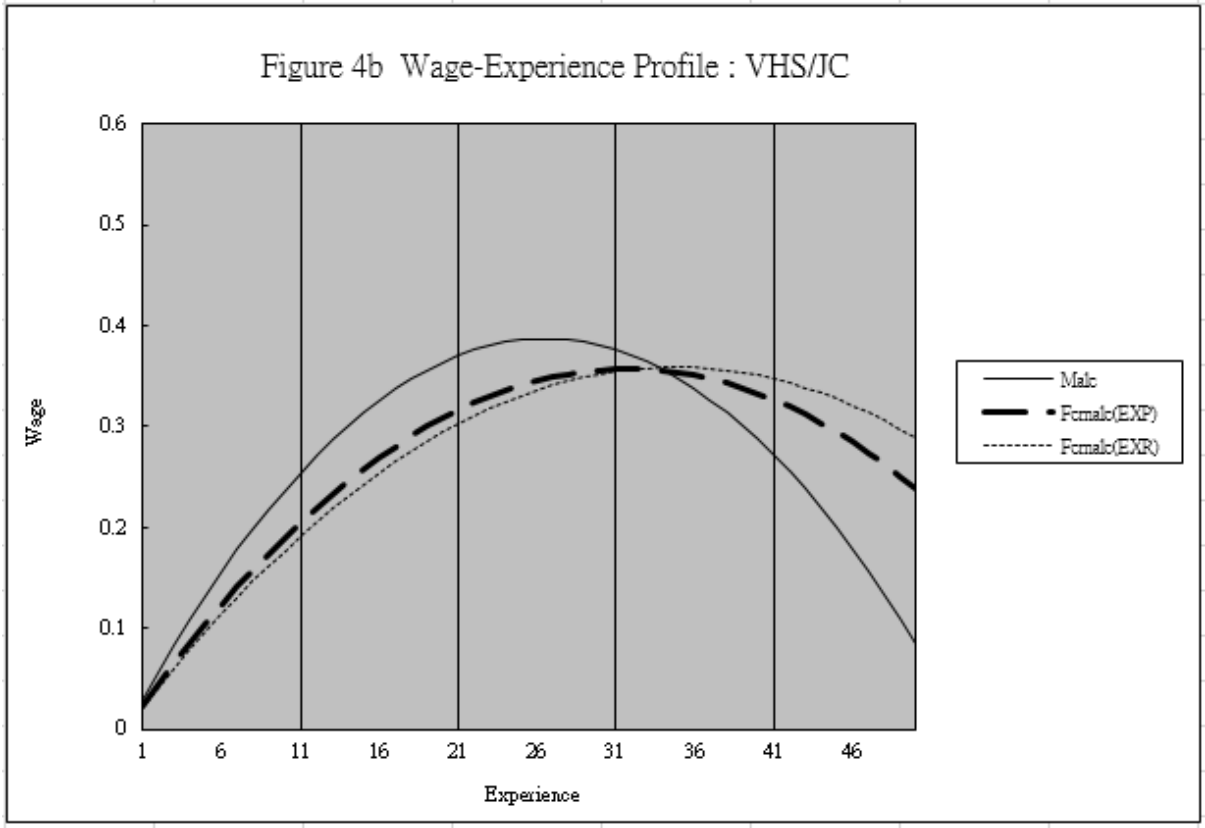


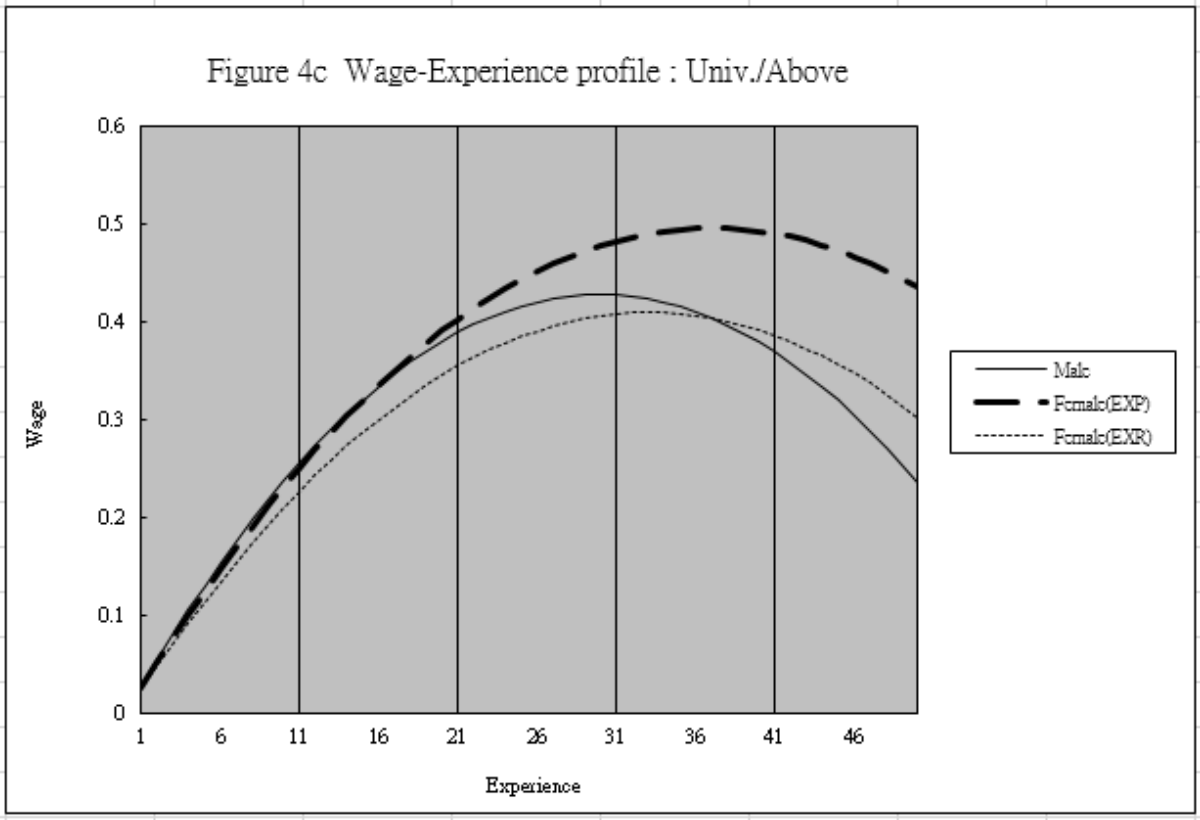
same ranking order, the EXR model shows many significant changes. For the lower educated, the concavity is markedly higher. This is also true for the highly educated. The medium group (VHS/JC) showed a decrease in concavity, but more importantly, the large premium of college/university

educated over the lesser VHS/JC has shrunk dramatically. We do not have enough understanding to comfortably offer an explanation.

Finally, we compared the male and female profiles for each of the three education groups. For the HS/ Below group (Figure 4a), the EXP version will tend to overstate the discrimination portion of wage growth due to experience accumulation for most of the meaningful career range (up to 31 years of employment). The pattern is reversed for the medium educated group (Figure 4b), but the difference is negligible. What is interesting is that towards the end of the career (perhaps outside of relevant range for some readers), females may even overtake the males.







The most dramatic graph is still the most highly educated group: University/Above (Figure 4c). Based on the EXP measure, the wage-experience profile of male and females are very close at the beginning. After 15 years in the labor force, females will accumulate more experience related wage growth than males. This is quite surprising and certainly seems to contradict with reality. However, when using the

EXR measure, this observation dissipates. The gap between the gender does appear to increase over time initially (consistent with Wu 1988), but then narrows and eventually the females will overtake the males. Though once again, some may argue, for all practical purposes, it will never happen (or be observed) since it will require a longer career than is seen in the real world.

Summary and Conclusion

The objective of this study is not to expand the theoretic model or estimation techniques. Rather, it uses data from a lesser studied nation -- Taiwan, and calculates a much more accurate market experience measure for married females. What we try to answer is whether the overestimation (in our sample, by 65.6 months, or 29.3%) of market experience of married females, via using the traditional "potential" experience, biases the measure of gender (wage) discrimination. And if so, by how much.

The empirical evidence shows that by using the re-calculated "real" experience (EXR) over the "potential" experience (EXP), the coefficient estimates do change, but neither the magnitude nor the resulting effect on gender "wage discrimination" is substantial. If this finding proves to be robust, our practice of using potential experience may be less damaging than we thought.

Two results are worth further research. First, contrary to Liu and Liu (1987), we found no evidence of selection bias caused by the endogenous labor force participation decision of females. It is not necessarily a contradiction, as the two samples a almost a decade apart (we used the 1993 sample, while the Liu brothers used the 1984 sample). It may simply state that the nature of labor force participation decision between male and female (and single versus married) have changed.

Second, of the effect of the improved EXR measure, the largest impact was found for the highly educated group of workers (which we classified as those with at least a Bachelor's degree). Indeed, in many ways, this group of female workers have showed they are quite different. This deserves much more detailed scrutiny, but also brings severe caution to those study that focus on college graduates (e.g. Wu 1988). Any generalization of the findings in these studies, explicit or implicit (by the reader) must be strongly advised against.

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Table 1 Summary Statistics

	Full Sample		Single		Married		HS/Below		VHS/JC		Univ./Above	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Main Variables												
LNW	4.8806	4.5202	4.7303	4.4963	4.9339	4.5343	4.7848	4.3940	4.9536	4.5960	5.3838	5.1070
EXP	270.6	211.5	124.2	79.2	322.5	289.7	326.0	289.2	176.9	124.2	197.5	120.4
EXR		170.3		79.2		224.1		222.1		107.8		117.3
EDU	9.84	9.96	10.90	11.97	9.46	8.78	7.70	7.37	12.61	12.49	16.24	16.15
Marital Status												
SINGLE	0.2619	0.3714	1.0000	1.0000			0.2162	0.2131	0.3620	0.5644	0.2245	0.5199
MARRIED	0.7009	0.5535			0.9496	0.8805	0.7372	0.6718	0.6152	0.4068	0.7571	0.4572
DIVORCED	0.0259	0.0324			0.0351	0.0515	0.0298	0.0428	0.0205	0.0206	0.0163	0.0168
WIDOWED	0.0113	0.0427			0.0153	0.0680	0.0168	0.0723	0.0023	0.0082	0.0021	0.0061
Academic Major												
NON-MAJOR	0.6181	0.5411	0.5103	0.3105	0.6564	0.6773	1.0000	1.0000				
LITERATURE	0.0107	0.0280	0.0069	0.0389	0.0121	0.0215			0.0090	0.0125	0.1091	0.3517
LAW	0.0050	0.0040	0.0031	0.0051	0.0057	0.0034			0.0030	0.0020	0.0567	0.0489
BUSINESS	0.0630	0.3079	0.0594	0.4430	0.0642	0.2281			0.1502	0.7219	0.2273	0.3654
SCIENCE	0.0065	0.0025	0.0069	0.0054	0.0064	0.0008			0.0038	0.0020	0.0737	0.0260
ENGINEER	0.2276	0.0426	0.3494	0.0796	0.1844	0.0207			0.6675	0.1032	0.2925	0.0306
AGRICULTURE	0.0272	0.0085	0.0266	0.0151	0.0274	0.0046			0.0803	0.0199	0.0326	0.0107
MEDICAL	0.0099	0.0253	0.0077	0.0362	0.0107	0.0188			0.0145	0.0561	0.0744	0.0489
MILIT-POLICE	0.0168	0.0002	0.0151	0.0003	0.0175	0.0002			0.0432	0.0003	0.0482	0.0015
EDUCATION	0.0110	0.0125	0.0071	0.0170	0.0124	0.0099			0.0192	0.0184	0.0701	0.0810
OTHERS	0.0040	0.0274	0.0075	0.0489	0.0028	0.0147			0.0093	0.0637	0.0156	0.0352
Job Status												
EMPLOYER	0.0713	0.0221	0.0240	0.0070	0.0880	0.0309	0.0667	0.0224	0.0777	0.0214	0.0829	0.0229
SELF-EMPLOYED	0.2446	0.1176	0.0805	0.0216	0.3028	0.1744	0.3242	0.1840	0.1322	0.0431	0.0460	0.0168
GOVERNMENT	0.1227	0.1141	0.0728	0.1112	0.1404	0.1158	0.0597	0.0523	0.1903	0.1468	0.3711	0.4281
PRIVATE	0.5614	0.7462	0.8227	0.8602	0.4687	0.6789	0.5495	0.7413	0.5998	0.7887	0.5000	0.5321
Regions												
TAIPEI	0.0923	0.1151	0.0862	0.1069	0.0945	0.1200	0.0684	0.0782	0.1042	0.1331	0.2450	0.3119
KAOHSIUNG	0.0576	0.0562	0.0578	0.0694	0.0574	0.0483	0.0518	0.0398	0.0653	0.0783	0.0729	0.0581
NORTHERN	0.2738	0.2782	0.2733	0.2624	0.2740	0.2874	0.2746	0.2860	0.2725	0.2717	0.2727	0.2523
CENTRAL	0.2776	0.2575	0.2567	0.2735	0.2850	0.2480	0.2848	0.2717	0.2798	0.2488	0.2068	0.1927
SOUTHERN	0.2550	0.2500	0.2685	0.2427	0.2502	0.2543	0.2718	0.2726	0.2393	0.2338	0.1792	0.1606
EASTERN	0.0437	0.0431	0.0574	0.0451	0.0388	0.0420	0.0485	0.0517	0.0388	0.0344	0.0234	0.0245
Sample Size	19409	9973	5083	3704	14326	6269	11997	5396	6000	3923	1412	654

Table 2a Female Labor Force Participation: Probit Estimates

	Full Sample		Married	
	Coefficient	T-value	Coefficient	T-value
INT.	-1.288	-19.350 ***	0.190	2.063 **
EDU	0.035	8.704 ***	0.018	4.085 ***
AGE	-0.005	-3.784 ***	-0.024	-17.305 ***
WORKEXP	1.511	66.976 ***	0.549	20.786 ***
Marital Status				
MARRIED	-0.211	-5.269 ***		
DIVORCED	0.373	5.632 ***	0.523	8.583 ***
WIDOWED	0.117	1.979 **	0.390	8.309 ***
Academic Major				
LITERATURE	0.106	1.510	0.504	5.026 ***
LAW	-0.053	-0.345	0.332	1.511
BUSINESS	0.101	3.530 ***	0.171	4.770 ***
SCIENCE	-0.063	-0.328	0.451	1.051
ENGINEER	0.026	0.479	0.192	2.282 **
AGRICULTURE	-0.085	-0.812	-0.112	-0.739
MEDICAL	0.132	1.933 *	0.709	6.507 ***
MILIT-POLICE	-0.560	-1.116	-0.282	-0.371
EDUCATION	0.265	2.541 **	0.580	4.133 ***
OTHERS	0.040	0.619	0.183	1.822 *
Region				
KAOHSIUNG	-0.163	-3.579 ***	-0.313	-5.809 ***
NORTHERN	0.129	3.899 ***	0.090	2.325 **
CENTRAL	0.033	0.980	-0.014	-0.368
SOUTHERN	0.127	3.751 ***	0.108	2.722 ***
EASTERN	0.262	4.839 ***	0.284	4.416 ***
Family Variables				
CHILD3	-0.399	-15.770 ***	-0.488	-19.201 ***
CHILD6	-0.176	-7.153 ***	-0.215	-8.787 ***
HUNSB-INCOME	-1.51E-06	-2.503 **	-7.292E-07	-1.218
Log-Likelihood	-12594.15		-9597.539	
Chi-square	6365.926		1780.578	
Sample size	23040		15513	

Note : *, **, *** denote statistically significant at 10%, 5%, and 1%, respectively.

Table 2b Female Labor Force Participation: Probit Estimates

	HS/Below		VHS/JC		Univ./Above	
	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
INT.	-0.614	-7.433 ***	-3.4068	-13.511 ***	-5.6931	-4.557 ***
EDU	0.013	2.808 ***	0.14076	7.269 ***	0.27946	3.624 ***
AGE	-0.018	-12.067 ***	1.30E-02	4.138 ***	1.07E-02	1.233
WORKEXP	1.074	40.682 ***	2.4035	46.233 ***	2.7275	20.146 ***
Marital Status						
MARRIED	0.096	1.855 *	-0.75542	-10.493 ***	-0.35366	-1.766 *
DIVORCED	0.631	8.133 ***	-0.10571	-0.685	0.12254	0.336
WIDOWED	0.429	6.337 ***	-0.50278	-2.264 **	0.18517	0.288
Academic Major						
LITERATURE			7.70E-02	0.413	-0.64039	-2.131 **
LAW			1.9685	2.408 **	-1.0615	-3.058 ***
BUSINESS			7.23E-02	0.974	-0.56957	-1.908 *
SCIENCE			-0.21131	-0.533	-0.32967	-0.757
ENGINEER			2.15E-02	0.239	-0.81771	-2.143 **
AGRICULTURE			-3.96E-02	-0.286	-1.3467	-2.663 ***
MEDICAL			0.12552	1.186	-0.35409	-0.935
MILIT-POLICE			-1.1106	-1.263	-0.62516	-0.787
EDUCATION			-1.24E-03	-0.008	-0.37786	-1.082
OTHERS						
Region	-0.204	-3.259 ***	-8.48E-02	-1.077	-6.95E-02	-0.318
KAOHSIUNG	0.214	4.817 ***	5.61E-02	0.94	-0.11251	-0.814
NORTHERN	0.144	3.211 ***	-2.81E-02	-0.464	-0.21614	-1.499
CENTRAL	0.238	5.254 ***	5.95E-02	0.959	1.40E-02	0.087
SOUTHERN	0.423	6.320 ***	4.79E-02	0.437	-0.49542	-1.658 *
EASTERN						
Family Variables	-0.536	-15.333 ***	-0.2393	-5.939 ***	-0.14945	-1.102
CHILD3	-0.243	-7.535 ***	-9.11E-02	-2.237 **	4.15E-02	0.296
CHILD6						
HUNSB-INCOME	-1.52E-06	-2.004 **	-4.86E-06	-4.198 ***	-4.94E-07	-0.181
Log-Likelihood	-8280.327		-3287.28		-408.2875	
Chi-square	2455.744		3736.535		947.2153	
Sample size	14313		7454		1273	

Note : *, **, *** denote statistically significant at 10%, 5%, and 1%, respectively.

Table 3a Wage Regression Estimates: Full Sample

	Male		Female-EXP		Female-EXR	
	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
INT.	4.403	127.851 ***	4.036	110.755 ***	4.059	120.920 ***
EXP	0.002	25.404 ***	0.001	14.279 ***		
EXPSQ	-3.3E-06	-26.065 ***	-1.6E-06	-10.047 ***		
EXR					0.002	15.322 ***
EXRSQ					-2.45E-06	-11.246 ***
EDU	0.012	6.969 ***	0.035	15.153 ***	0.033	16.588 ***
Marital Status						
MARRIED	0.109	12.161 ***	0.031	2.736 ***	0.062	6.154 ***
DIVORCED	0.057	2.883 ***	0.064	2.727 ***	0.095	4.185 ***
WIDOWED	0.019	0.643	0.086	3.849 ***	0.120	5.550 ***
Academic Major						
LITERATURE	0.103	3.262 ***	0.151	5.435 ***	0.141	5.154 ***
LAW	0.116	2.623 ***	0.155	2.495 **	0.143	2.308 **
BUSINESS	0.051	3.419 ***	-0.001	-0.081	-0.008	-0.654
SCIENCE	0.118	3.034 ***	0.209	2.750 ***	0.211	2.775 ***
ENGINEER	0.030	2.926 ***	0.016	0.739	0.010	0.454
AGRICULTURE	0.031	1.590	-0.051	-1.241	-0.057	-1.372
MEDICAL	0.121	3.034 ***	0.045	1.123	0.039	0.978
MILIT-POLICE	0.058	2.209 **	0.310	1.123	0.313	1.137
EDUCATION	0.041	1.061	0.090	2.246 **	0.084	2.109 **
OTHERS	-0.001	-0.019	-0.076	-3.043 ***	-0.080	-3.227 ***
Job Status						
EMPLOYER	0.311	19.942 ***	0.377	11.245 ***	0.377	11.267 ***
SELF-EMPLOYED	0.089	8.371 ***	0.071	4.503 ***	0.069	4.382 ***
GOVERNMENT	0.111	7.138 ***	0.243	12.691 ***	0.240	12.586 ***
Region						
KAOHSIUNG	-0.046	-2.869 ***	-0.136	-6.990 ***	-0.139	-7.158 ***
NORTHERN	-0.068	-5.898 ***	-0.080	-5.848 ***	-0.084	-6.185 ***
CENTRAL	-0.121	-10.281 ***	-0.164	-11.717 ***	-0.168	-12.084 ***
SOUTHERN	-0.131	-11.050 ***	-0.182	-12.841 ***	-0.184	-13.008 ***
EASTERN	-0.098	-5.599 ***	-0.084	-3.900 ***	-0.084	-3.925 ***
R-SQR	0.428		0.407		0.409	
ADJ-RSQ	0.424		0.399		0.402	
F-value	114.582		54.024		54.611	

Note : *, **, *** denote statistically significant at 10%, 5%, and 1%, respectively.

Table 3b Wage Regression Estimates: Single

	Male		Female-EXP	
	Coefficient	T-value	Coefficient	T-value
INT.	4.007	69.952 ***	3.718	68.127 ***
EXP	0.003	27.133 ***	0.003	15.884 ***
EXPSQ	-5.1E-06	-20.138 ***	-4.7E-06	-8.351 ***
EXR				
EXRSQ				
EDU	0.037	10.440 ***	0.057	14.843 ***
Academic Major				
LITERATURE	0.145	2.367 **	0.070	2.038 **
LAW	0.022	0.234	0.109	1.447
BUSINESS	-0.005	-0.188	-0.045	-2.910 ***
SCIENCE	0.024	0.392	0.150	2.026 **
ENGINEER	0.001	0.045	-0.023	-0.999
AGRICULTURE	0.019	0.589	-0.071	-1.634
MEDICAL	0.121	1.714 *	0.045	0.957
MILIT-POLICE	0.043	0.892	0.636	1.479
EDUCATION	-0.006	-0.070	0.050	1.068
OTHERS	-0.060	-1.007	-0.109	-4.048 ***
Job Status				
EMPLOYER	0.312	7.996 ***	0.516	7.254 ***
SELF-EMPLOYED	0.090	4.305 ***	0.221	6.035 ***
GOVERNMENT	0.058	1.815 *	0.166	6.672 ***
Region				
KAOHSIUNG	-0.088	-3.431 ***	-0.137	-5.479 ***
NORTHERN	-0.024	-1.278	-0.058	-3.099 ***
CENTRAL	-0.068	-3.535 ***	-0.124	-6.542 ***
SOUTHERN	-0.108	-5.605 ***	-0.128	-6.639 ***
EASTERN	-0.093	-3.522 ***	-0.048	-1.682 *
R-SQR	0.383		0.445	
ADJ-RSQ	0.368		0.427	
F-value	25.845		24.768	

Note : *, **, *** denote statistically significant at 10%, 5%, and 1%, respectively.

Table 3c Wage Regression Estimates: Married

	Male		Female-EXP		Female-EXR	
	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
INT.	4.690	103.079 ***	4.280	81.695 ***	4.293	93.771 ***
EXP	0.001	11.929 `	0.001	4.476 ***		
EXPSQ	-2.4E-06	-13.901 ***	-7.2E-07	-3.189 ***		
EXR					0.001	5.686 ***
EXRSQ					-1.22E-06	-4.189 ***
EDU	0.007	3.641 ***	0.024	8.383 ***	0.024	9.776 ***
Academic Major						
LITERATURE	0.087	2.368 **	0.164	3.888 ***	0.151	3.652 ***
LAW	0.123	2.431 **	0.167	1.807 *	0.152	1.647 *
BUSINESS	0.061	3.361 ***	0.014	0.765	0.007	0.406
SCIENCE	0.137	2.851 ***	0.123	0.672	0.124	0.680
ENGINEER	0.021	1.565	0.017	0.425	0.010	0.248
AGRICULTURE	0.034	1.428	-0.080	-1.067	-0.087	-1.163
MEDICAL	0.107	2.260 **	0.001	0.008	-0.006	-0.088
MILIT-POLICE	0.048	1.542	0.137	0.330	0.134	0.322
EDUCATION	0.048	1.084	0.057	0.914	0.048	0.772
OTHERS	0.036	0.514	-0.041	-0.908	-0.046	-1.040
Job Status						
EMPLOYER	0.302	17.220 ***	0.354	8.881 ***	0.351	8.819 ***
SELF-EMPLOYED	0.080	6.360 ***	0.055	2.737 ***	0.050	2.485 **
GOVERNMENT	0.126	6.984 ***	0.292	10.596 ***	0.287	10.435 ***
Region						
KAOHSIUNG	-0.028	-1.446	-0.124	-4.455 ***	-0.126	-4.539 ***
NORTHERN	-0.085	-6.087 ***	-0.084	-4.519 ***	-0.088	-4.733 ***
CENTRAL	-0.142	-9.935 ***	-0.183	-9.476 ***	-0.186	-9.706 ***
SOUTHERN	-0.139	-9.582 ***	-0.212	-10.895 ***	-0.213	-11.000 ***
EASTERN	-0.101	-4.532 ***	-0.106	-3.560 ***	-0.106	-3.556 ***
R-SQR	0.429		0.418		0.420	
ADJ-RSQ	0.424		0.407		0.408	
F-value	86.590		36.506		36.758	

Note : *, **, *** denote statistically significant at 10%, 5%, and 1%, respectively.

Table 4a Wage Regression Estimates: HS/Below

	Male		Female-EXP		Female-EXR	
	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
INT.	4.469	81.945 ***	4.263	75.667 ***	4.228	80.481 ***
EXP	0.002	17.999 ***	0.001	6.585 ***		
EXPSQ	-3.4E-06	-20.300 ***	-1.3E-06	-6.005 ***		
EXR					0.001	8.226 ***
EXRSQ					-2.13E-06	-7.183 ***
EDU	0.003	1.394	0.020	6.794 ***	0.022	8.790 ***
Marital Status						
MARRIED	0.120	9.252 ***	0.003	0.167	0.028	1.661 *
DIVORCED	0.056	2.168 **	0.050	1.554	0.073	2.378 **
WIDOWED	0.032	0.942	0.064	2.164 **	0.087	3.199 ***
Job Status						
EMPLOYER	0.331	15.297 ***	0.419	9.091 ***	0.416	9.035 ***
SELF-EMPLOYED	0.077	5.729 ***	0.063	3.113 ***	0.056	2.807 ***
GOVERNMENT	0.122	4.636 ***	0.263	6.707 ***	0.254	6.496 ***
Region						
KAOHSIUNG	-0.034	-1.445	-0.170	-5.016 ***	-0.171	-5.066 ***
NORTHERN	-0.054	-3.062 ***	-0.088	-3.863 ***	-0.092	-4.056 ***
CENTRAL	-0.105	-5.918 ***	-0.172	-7.436 ***	-0.176	-7.657 ***
SOUTHERN	-0.126	-7.103 ***	-0.197	-8.507 ***	-0.199	-8.601 ***
EASTERN	-0.088	-3.561 ***	-0.079	-2.512 **	-0.080	-2.525 **
R-SQR	0.371		0.242		0.245	
ADJ-RSQ	0.365		0.226		0.230	
F-value	61.897		15.589		15.910	

Note : *, **, *** denote statistically significant at 10%, 5%, and 1%, respectively.

Table 4b Wage Regression Estimates: VHS/JC

	Male		Female-EXP		Female-EXR	
	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
INT.	4.108	41.573 ***	3.682	35.475 ***	3.691	35.616 ***
EXP	0.002	14.852 ***	0.002	9.685 ***		
EXPSQ	-3.8E-06	-12.212 ***	-2.5E-06	-4.746 ***		
EXR					0.002	8.856 ***
EXRSQ					-2.07E-06	-3.683 ***
EDU	0.044	7.990 ***	0.070	10.949 ***	0.070	10.919 ***
Marital Status						
MARRIED	0.083	6.408 ***	0.032	2.245 **	0.065	5.052 ***
DIVORCED	0.077	2.290 **	0.080	2.034 **	0.113	2.902 ***
WIDOWED	-0.020	-0.211	0.003	0.048	0.024	0.398
Academic Major						
LAW	-0.078	-0.820	-0.014	-0.116	-0.042	-0.336
BUSINESS	-0.063	-1.244	-0.126	-2.597 ***	-0.120	-2.478 **
SCIENCE	-0.067	-0.764	0.136	1.080	0.137	1.088
ENGINEER	-0.074	-1.484	-0.100	-1.974 **	-0.097	-1.915 *
AGRICULTURE	-0.066	-1.269	-0.198	-3.247 ***	-0.197	-3.228 ***
MEDICAL	-0.029	-0.465	-0.148	-2.484 **	-0.141	-2.368 **
MILIT-POLICE	-0.113	-2.083 **	0.292	0.737	0.294	0.742
EDUCATION	-0.057	-0.838	-0.036	-0.571	-0.042	-0.665
OTHERS	-0.129	-1.874 *	-0.201	-3.834 ***	-0.197	-3.762 ***
Job Status						
EMPLOYER	0.335	13.906 ***	0.427	8.348 ***	0.427	8.342 ***
SELF-EMPLOYED	0.130	6.891 ***	0.141	4.770 ***	0.144	4.888 ***
GOVERNMENT	0.135	6.325 ***	0.193	8.458 ***	0.190	8.311 ***
Region						
KAOHSIUNG	-0.036	-1.553	-0.106	-4.444 ***	-0.109	-4.569 ***
NORTHERN	-0.066	-3.922 ***	-0.068	-3.752 ***	-0.071	-3.941 ***
CENTRAL	-0.115	-6.715 ***	-0.150	-8.098 ***	-0.151	-8.173 ***
SOUTHERN	-0.108	-6.192 ***	-0.169	-8.954 ***	-0.171	-9.069 ***
EASTERN	-0.094	-3.443 ***	-0.080	-2.504 **	-0.079	-2.463 **
R-SQR	0.430		0.444		0.444	
ADJ-RSQ	0.418		0.426		0.427	
F-value	36.028		25.098		25.120	

Note : *, **, *** denote statistically significant at 10%, 5%, and 1%, respectively.

Table 4c Wage Regression Estimates: Univ./Above

	Male		Female-EXP		Female-EXR	
	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
INT.	3.042	11.796 ***	2.986	7.052 ***	3.068	7.191 ***
EXP	0.002	6.313 ***	0.002	4.265 ***		
EXPSQ	-3.3E-06	-4.716 ***	-2.5E-06	-1.822 *		
EXR					0.002	4.131 ***
EXRSQ					-2.6E-06	-1.977 **
EDU	0.107	6.965 ***	0.111	4.345 ***	0.107	4.149 ***
Marital Status						
MARRIED	0.090	3.077 ***	0.141	3.964 ***	0.168	4.869 ***
DIVORCED	0.050	0.630	-0.056	-0.467	-0.026	-0.209
WIDOWED	-0.036	-0.182	0.190	1.034	0.258	1.406
Academic Major						
LAW	0.014	0.293	0.056	0.801	0.054	0.772
BUSINESS	0.036	1.019	-0.033	-0.943	-0.031	-0.868
SCIENCE	0.019	0.436	0.014	0.139	0.024	0.233
ENGINEER	0.027	0.761	-0.088	-0.893	-0.073	-0.737
AGRICULTURE	0.057	0.976	-0.019	-0.146	-0.027	-0.201
MEDICAL	0.040	0.534	0.087	0.832	0.094	0.888
MILIT-POLICE	0.007	0.136	-0.626	-1.550	-0.577	-1.410
EDUCATION	-0.019	-0.406	-0.005	-0.085	-0.001	-0.018
OTHERS	0.022	0.263	-0.100	-1.202	-0.099	-1.178
Job Status						
EMPLOYER	0.105	2.274 **	-0.348	-2.084 **	-0.314	-1.872 *
SELF-EMPLOYED	0.037	0.603	0.039	0.333	0.051	0.431
GOVERNMENT	0.020	0.664	0.223	4.813 ***	0.223	4.770 ***
Region						
KAOHSIUNG	-0.090	-2.256 **	-0.057	-0.874	-0.071	-1.080
NORTHERN	-0.093	-3.484 ***	-0.018	-0.454	-0.024	-0.603
CENTRAL	-0.134	-4.641 ***	-0.128	-3.017 ***	-0.135	-3.148 ***
SOUTHERN	-0.123	-4.075 ***	-0.067	-1.452	-0.066	-1.414
EASTERN	-0.056	-0.891	-0.038	-0.413	-0.052	-0.551
R-SQR	0.419		0.503		0.494	
ADJ-RSQ	0.367		0.409		0.399	
F-value	8.044		5.395		5.125	

Note : *, **, *** denote statistically significant at 10%, 5%, and 1%, respectively.