

The Gender Wage Gap and the Fair Calculations Act*

September 2017

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Abstract

If enacted as a law, the Fair Calculations Act would require forensic economists to ignore an injured party's gender when forecasting the loss in future earnings. We discuss how this would affect the size of awards for men and women, and some of the issues that would arise if the law is enacted. Of particular interest is the extent to which gender-differences in earnings, earnings growth, and work-life expectancy are the result of sex-discrimination in labor markets as opposed to sex-differences in preferences. We present evidence that gender differences in human capital characteristics explain a large share of gender differences in in labor market outcomes, there is considerable disagreement about how to interpret the results. We also show that gender differences are diminishing over time, but it is not likely that the gap will disappear in the near future. Finally, we discuss how forensic economists may have to rely on additional information when forecasting earnings if they are no longer allowed to use gender.

* We thank seminar participants at the Western Economics Association meetings for helpful suggestions. Additional results and copies of the computer programs used to generate the results presented in the paper are available from David Macpherson at dmacpher@trinity.edu.

I. Introduction

If the Fair Calculations Act is enacted, forensic economists will be forced to provide gender neutral forecasts of earnings loss. This article discusses how this would alter estimates of earnings losses and evidence on the extent to which gender differences in earnings are the result of discrimination, or sex-differences in tastes that lead to differences in human capital accumulation. While most studies find that an important share of gender differences in earnings can be attributed to sex-differences in human capital, the wide range of estimates and their interpretation will make it difficult for policy makers to incorporate this information into law.¹ We also believe that if forensic economists are required to ignore gender in their forecasts, it will make sense to improve information available for making forecasts on factors that lead to gender differences in earnings – for example, occupation or more detailed educational background.

II. Background

In most instances, the method for estimating the present value of the loss in life-time earnings is based on an equation like the following:

$$(1)PV(Earnings) = \sum_{t=0}^T y_0(1 + g_t)^t / (1 + r_t)^t$$

¹ Stanley and Jarrell (1998) provide a meta-analysis of 41 studies of sex discrimination in earnings illustrating the wide range of estimates across studies. Recent studies [e.g. Blau and Kahn (2017)] point out some of the issues in using regressions to sort out what is “discrimination.” Blau et al. (2014) provide a good review of the literature on gender differences in earnings and labor market outcomes.

Where y_0 is the is annual earnings at the beginning of the period that damages begin, g_t is the growth rate in earnings between period $(t-1)$ and (t) , and r_t is the annual interest rate used to discount earnings t periods in the future to present value, and T is the number of periods of remaining work-life expectancy at the date damages begin.

In the above expression, the forensic economist may make gender-specific assumptions about base period earnings (y_0) from which future earnings are projected, the growth rate in earnings over the career (g_t), or the remaining work-life expectancy (T). It is hard to imagine a case for making sex-specific interest rate assumptions.

In the case of assumptions about base period earnings, the use of sex specific values will generally depend on whether the injured party has established a work history. If, for example, a person has been in the labor force for several years and has an established earnings history, the forensic economist typically uses that earnings history to establish the earnings base. On the other hand, if the injured party does not have an established earnings history, the forensic economist may attempt to predict what earnings would be at some future starting point using sex-specific tables. This would be true, for example, in the case of forecasting earnings for an injured child who has not yet entered the work force, a student enrolled in college who may have an earnings history but one that is not representative of post-graduation earnings, or an adult who was not engaged in employment in recent years but had the capacity to do so.

In terms of assumptions about earnings growth (g_t), there are several approaches that forensic economists currently use. Several of these approaches are gender neutral. For example, according to surveys of prevailing practices among forensic economists [Slesnick et al. 2012; Luthy et al. 2015], there are several methods for projecting earnings growth including projected growth in the employment cost index provided by the Congressional Budget Office;

earnings growth projections from the Social Security Administration, or historical averages for earnings growth based on gender and education. Of the three methods described, the first two approaches would be gender neutral.

Finally, the forensic economist is very likely to rely on estimates of work-life expectancy that are specific to a given education and gender.² The most commonly used sources for work-life expectancy provide estimates by gender and educational attainment. Sex-neutral estimates are not provided, except for Allen (2017).

If the forensic economist is required to use gender-neutral methods for estimating losses, it will cause estimated losses to increase for women and decrease for men. This is because existing evidence suggests that, women earn less than men, have a shorter worker life-expectancy, and lower earnings growth rates. We will discuss the evidence on these points later in this article.

There are arguments for and against the use of gender-specific statistics for estimating damages. One argument against gender-specific estimates is that this is a form of “statistical discrimination” since it makes use of a person’s group status to form projections about their individual characteristics.³ Economic theory has been used to show that statistical discrimination can be profitable and sustainable in a competitive market. For example, car insurance companies charge higher rates for male than female drivers because statistical evidence suggests that women are safer drivers. While statistical discrimination might be profitable for business, some might argue that this is unfair since some men might be safer drivers than some women. Nevertheless, most (but not all) states allow insurance companies to

² Skoog et al. (2011) and Krueger and Slesnick (2014) provide work-life expectancy by gender and education.

³ See Phelps (1972) for a discussion of statistical discrimination based on race and sex.

consider gender in setting car insurance premiums.⁴ Gender-specific rates are also allowed for life-insurance.⁵ Because women have longer life expectancies than men, insurance companies charge women a lower rate than men for life-insurance, but a higher price for a given life-annuity. On the other hand, federal law does not allow defined benefit pension plans to use gender-specific life-tables when determining benefit payouts. If this were allowed, holding career earnings and service constant, women would receive a lower annual pension benefit than men since they have longer life expectancy. In contrast, companies selling life-annuities sell them at a discount to men since they men have shorter life expectancies.⁶

The Federal Equal Pay Act of 1963 and Title VII of the Civil Rights Act of 1964 prohibit sex-specific discrimination in labor markets. For example, an employer might have evidence that there are sex-differences in quit rates or productivity. If the employer is found guilty of discriminating on the basis of sex, they may be required to provide some form of relief (e.g. backpay, hiring, promotion) to offset any loss to the injured party.

The above examples show that existing law is not entirely consistent in terms of when it allows firms to make decisions based on gender. There are strong economic incentives for companies to use gender when it lacks relevant information about an individual, but in some cases law prohibits such behavior.

In the case of estimating economic damages, knowledge of the injured party's gender can improve the accuracy of forecasting earnings, earnings growth, and work-life expectancy. On the other hand, there are a few arguments against the use of gender-based statistics. First, one

⁴ Hawaii, Massachusetts, North Carolina don't allow gender to be used in setting insurance rates. Michigan, Montana, and Pennsylvania apply similar rating factors to men and women and allow small differences in premiums. <https://www.insurancequotes.com/auto/surprising-impact-of-age-gender-marriage-on-car-insurance>.

⁵ For an illustration of these price differences, <http://www.quickquote.com/blog/female-vs-male-term-life-insurance-premiums/>

⁶http://www.schwab.com/public/schwab/investing/accounts_products/investment/annuities/income_annuity/come_annuity_calculator

might be philosophically opposed to using one's gender to forecast any type of outcome. While membership in a group might provide useful information for forecasting, some view this as immoral or unjust. A second argument is that, in the case of labor market outcomes, gender differences are the result of discrimination and should therefore be ignored when estimating economic losses. That is, if women earn 20% less than equally skilled men because of discrimination, it would be unjust for the courts to perpetuate this injustice when determining economic damages. On the other hand, if women earn 20% less than men because their preferences cause them to systematically choose different occupations, work hours, and labor force participation rates, one might be inclined to consider the use of gender as fair.

Given the above philosophical issues regarding whether gender should be used in forecasting future earnings loss, the remainder of this paper focuses on evidence regarding the reasons that men and women have different earnings, earnings growth, and work-life expectancies.

III. Evidence on Gender-Differences in Life-time Earnings

In this section, we provide background on gender differences in earnings. We focus entirely on wage and salary earnings and leave the issue of differences in fringe benefits for other researchers. The information on gender differences in earnings is drawn from the March Current Population Surveys administered between 1962 and 2016. While the CPS is administered monthly, the March survey includes the Annual Social and Economic Supplement (ASEC) which collects information on annual earnings in the year prior to the survey. Thus, for example, the March 2016 ASEC will contain information about worker's annual earnings in

2015. The ASEC also includes all the demographic and geographic information contained in the monthly CPS.

To provide an estimate of earnings by sex, we restrict the sample to those who indicate they were wage and salary workers in the prior year. Self-employed workers are dropped from the sample. Also, since earnings are top-coded across time and the real value of the top-codes change over time, we focus on median rather than mean earnings since the medians are not affected by the top-codes whereas the means are.⁷

Figure 1 presents the female-male ratio of median earnings between 1962 and 2016. The ratio is presented separately for all workers and for workers identified as full-time full-year.⁸ A couple of points are worth noting. First, median earnings are lower for women than men, but the gap has narrowed substantially over the past 50 years. In the 1960s, median annual earnings for women were about 45 percent of that for men. By 2010, this rose to about 70 percent. Second, part of the reason that earnings are lower among women than men is that, among the employed, women are less likely to be full-time full-year workers. When the sample is restricted to full-time full-year workers, women's earnings rise relative to men's, but the effect of this has diminished over time. This illustrates that women's hourly earnings have risen relative to men's over time, but also that gender differences in time spent working has diminished.

Figure 2 provides a sense of how the female-male earnings ratio changes over the life-cycle and how it has evolved over time. In this diagram, we track different birth cohorts grouped by decade of birth and plot the female-male ratio of median annual earnings for full-time full-year workers.⁹ Consistent with figure 1, the evidence in figure 2 is that the gender gap

⁷ Spizman (2013) discusses some of the advantages of using the median instead of the mean for estimating earnings losses, though there is no explicit discussion of the impact of top-coding on the quality of the estimates.

⁸ A full-time full-year workers are defined as those working 35 or more hours per week for 50 to 52 weeks per year.

⁹ Provide details of smoothing process used to generate graphs.

in earnings is lower among more recent birth cohorts. Figure 2 also makes it clear that the gender gap in earnings grows as workers age. There are several plausible explanations for this difference in earnings growth that we discuss later.

Since some of the gender difference in earnings could be due to differences in educational attainment, figure 3 repeats the analysis in figure 2 for workers with exactly a high school education, or exactly a Bachelor's degree. For each education group, the gender gap in earnings grows with age for cohorts born in the 1970s and later, though evidence from cohorts born in the 1930s through 1960s suggests that the earnings gap may eventually narrow at older ages. This might be the result of differential selection of workers out of the labor force in later years. For example, if low wage women are more likely to drop out of the labor force (or move to part-time work) as they age, the median earnings of the women who remain as full-time full-year workers will rise.

To provide a sense of sex differences in earnings growth, we used data from the 1990, 2000 Census and the American Community Survey for the years 2005 to 2015. We restricted the sample to full-time year round wage and salary workers between the ages of 19 and 65 and estimated a regression of real annual earnings on a quartic in age by sex and educational attainment. The model also includes controls for the year of birth for each worker. Table 2 summarizes the implied earnings growth rate by age, sex and educational attainment. The sex difference in earnings growth is also provided.

For both men and women, earnings growth is greatest when they first enter the labor market and gradually declines until it becomes negative. At early ages, men's growth rates exceed that for women's for all education groups. There are a few instances in late ages where

women have higher growth rates (or lower declines) than men. Generally speaking, however, men's earning growth rates exceed those of women.

Given the above evidence on gender differences in earnings levels and earnings growth, it should be fairly clear that a switch to gender-neutral estimates of earnings losses would increase estimated losses for women and decrease them for men. As noted earlier, whether it is appropriate to ignore gender in making forecasts of earnings losses could depend on whether the gender gap in earnings is the result of discrimination or gender differences in career choices driven by gender differences in preferences. We now turn to evidence on this point.

IV. Explanations for Gender Differences in Earnings

Becker (1957) was the first to develop economic theories of discrimination. In his model, gender (or race) differences be discrimination based on tastes of employers, employees, or customers. If any group has a "distaste" for a particular race or sex, it could result in reduced earnings for that group. Subsequent research has provided evidence on the existence of these different types of discrimination. In some cases, competition will drive out employers who discriminate because they will have higher costs than those who do not discriminate. On the other hand, other types of discrimination can be profitable and would persist in a competitive market.

Statistical discrimination occurs when an employer uses a group characteristic to predict the behavior of an individual.¹⁰ For example, an employer may not be able to accurately predict a person's probability of quitting, but knows that, on average, women are more likely to quit than

¹⁰ Phelps (1972) was one of the first to develop a formal theory of statistical discrimination.

men. As a result, if employee turnover is costly, employers may discriminate against women when hiring. Several studies document evidence of sex-discrimination in hiring, but they are unable to determine whether employers are discriminating because of their tastes or because of statistical discrimination.¹¹ Another theory of sex discrimination in hiring, proposed by Goldin (1986), turns on employers expecting that women are more likely to quit than men. In this theory, if firms use deferred pay to reduce monitoring costs, it is less effective at reducing shirking for workers with a high quit rate. As a result, when monitoring costs are high, firms discriminate against women when hiring. Evidence in support of the theory is that women are over-represented in jobs where output is easy to monitor and paid piece-rates, whereas men are over-represented in jobs where it is more difficult to monitor output.

While discrimination is one possible explanation for the gender gap in earnings, an alternative explanation is that there are sex-differences in preferences that lead to different levels of educational attainment, investments in human capital, and experience. Mincer and Polachek (1974, 1978) provide a theory of sex-differences in earnings based on human capital theory. The model assumes that workers are paid according to their productivity, and productivity is based on a person's skills (human capital).

The theory implies that sex-differences in earnings result if women are more likely to work fewer hours when they have children (or withdraw from employment entirely).¹² These "career interruptions" lead to a reduced incentive to invest in human capital since the returns to

¹¹ Riach and Rich (2006) find evidence of hiring discrimination against women in male occupations, and against men in female occupations. Neumark et al. (1996) find hiring discrimination against women in high price restaurants, and against men in low price restaurants. Goldin and Rouse (2000) report evidence of discrimination against women by symphony orchestras.

¹² See Becker (1985) for a discussion of the economic incentives for married households to have one spouse specialize in household production and the other specialize in the labor market. Evidence on gender differences in career interruptions and the consequences for earnings is provided by Spivey (2005), Light and Ureta (1995), Blau and Kahn (2000).

the investment are reduced when careers are shorter. The lower incentive to invest in human capital leads to lower earnings levels as well as lower earnings growth after entering the labor force. It also creates incentives for women to enter occupations where human capital depreciates at a slower rate when they are out of the labor force (Polachek 1981) and may explain why there is “occupational segregation” by sex – i.e. men and women are not equally represented across occupations.¹³ There is mixed evidence on whether the occupational sorting can be explained by such motivation (see, for example, England 1982). Another explanation for occupational segregation is that women may value greater flexibility in work hours and this may cause them to sort into certain kinds of jobs within occupation (Goldin 2014).

An alternative explanation for occupational segregation by sex is that employers practice statistical discrimination against women.¹⁴ If employers are making an investment in firm specific human capital, they would prefer to invest in workers with a low probability of quitting. If women, on average, are more likely to quit a job than men, employers with high training costs may be less willing to invest in women.

An implication of the above theories is that declining fertility rates in the U.S. and the increased labor force attachment of women should cause the gender gap in earnings to fall. In fact, there is a good deal of evidence showing that this has happened. Over the past 50 years, women have become more attached to the labor market and are less likely to interrupt their careers when they have children.¹⁵ This in turn, has contributed to a decline in gender differences in education, labor force participation, and experience. There has also been a

¹³ England (1982) provides empirical evidence counter to Polachek’s explanation for occupation segregation. Altonji and Blank (1999) provide a good review of the literature on gender differences in labor market outcomes including a lengthy discussion of occupational segregation.

¹⁴ Phelps (1972) was one of the first to develop the theory of statistical discrimination. Altonji and Blank (1999) provide a good review of the literature on statistical discrimination.

¹⁵ See, for example, Even and Macpherson (2001).

decline in sex segregation across occupations (Blau et al. 2013; Blau and Kahn 2017). All of these trends have helped reduce the gender earnings gap. Though it has been noted that has been less progress since the 1990s (Goldin 2014).

In summary, gender differences in earnings could be the result of either sex differences in decisions about human capital accumulation or occupational choice, or some type of discrimination where equally productive workers are paid differently.

To investigate how much of the earnings gap is due to discrimination as opposed to differences in labor market characteristics, economists frequently use regression analysis. The human capital model of wages is the starting point. Wages (or log-wages) are hypothesized to be a function of a worker's human capital. Standard controls for human capital include level of education, years of labor market experience, and age. A more complete model might include controls for occupation, industry, firm size and/or unionization. After estimating the model using standard regression methods, the male-female gap in earnings can be split into two parts.

The explained part of the gap is the portion of the gap that can be attributed to differences in the human capital characteristics of men and women. For example, if each year of additional experience is associated with an extra \$.50 per hour and men, on average, have two more years of experience than women, the gender gap in experience "explains" \$1.00 of the gender gap in wages. To the extent that gender differences in the values of the human capital characteristics are the result of different choices made by men and women, the explained part of the wage gap is not considered to be discrimination.

The unexplained gap in wages is frequently referred to as "discrimination" because this is the portion of the gender gap in wages that cannot be "explained" by gender differences in human capital characteristics. Put in different words, the unexplained gap is the predicted

gender wage gap that would exist if men and women had, on average, the same human capital characteristics.

Formally, consider the following regression model:

$$(2) w_{ij} = X_{ij}\beta_j + e_{ij}$$

where i indexes the individual, j indexes sex (m =male, f =female) w_{ij} is the wage (log-wage) of person i of sex j X_{ij} is a vector of human capital characteristics, and β_j is the coefficients representing the price of the characteristics, and e_{ij} is a random error. Oaxaca (1973) shows that the wage gap can be written as

$$(3) \bar{w}_m - \bar{w}_f = (\bar{X}_m - \bar{X}_f)\beta_m + X_f(\beta_m - \beta_f) \\ = \textit{Explained} + \textit{Unexplained}$$

That is, the average difference between the wages (or log-wages) of men and women ($\bar{w}_m - \bar{w}_f$) can be divided between the portion explained by gender differences in human capital characteristics ($\bar{X}_m - \bar{X}_f$) and the portion that is due to gender differences in the prices for those characteristics ($\beta_m - \beta_f$).¹⁶

One of the issues surrounding such analysis is whether gender differences in some of the human capital characteristics are the result of discrimination. There is strong evidence that men and women are not equally represented across occupations and that women tend to be in lower paying occupations. For example, one measure of the degree of segregation is the Duncan index

¹⁶ There are alternative formulations of the decomposition that place different weights on the differences in human capital characteristics and the differences in the prices for the characteristics. See, for example, the original articles by Oaxaca (1973) and Blinder (1973) or the follow-up work by Neumark (1988) and Oaxaca and Ransom (1994).

which estimates the percentage of workers would have to switch occupations in order that the distribution of workers across occupations be gender neutral. If the Duncan index is 100, men and women are completely segregated across occupations and any given occupation is either 100% men or 100% women. If the Duncan index is 0, every occupation has the same male-female mix of workers and occupations are completely integrated. Evidence presented in Blau and Kahn (2017) is out that the index was virtually unchanged from 1900 until 1970. It then fell from 64.5 in 1970 to 51.0 in 2009, but the rate of decline slowed in recent decades. Moreover, they review evidence that the decline in occupational segregation of the sexes was greater among more educated workers.

If occupational segregation is the result of men and women voluntarily choosing to pursue different career paths, most economists would argue that earnings differences caused by gender differences in occupation and industry are “explained” and not the result of discrimination. On the other hand, if women avoid certain occupations because they anticipate that they will have difficulty being hired, for example, in a male-dominated field, the resulting gap in wages would be considered discriminatory. Because of uncertainty about the cause of gender differences in occupation, there is no universal agreement about whether occupation controls should be included in the wage regression used for the decomposition. In fact, some studies present estimates of the unexplained (discriminatory) component with and without including controls for occupation and industry.¹⁷ Moreover, as noted by Blau and Kahn (2000), any approach which relies on such statistical methods will be open to questions about whether there are omitted variables that are correlated with sex-differences in productivity and how this would bias the estimates.

¹⁷ See, for example, Blau and Kahn (2017) or Goldin (2014).

With the above as background, we now turn to some of the recent evidence on gender differences in earnings. Blau and Kahn (2017) examine the gap in hourly wage. A focus on hourly wages removes any gender differences in annual earnings due to differences in weekly hours or weeks worked per year. Most human capital models focus on explaining variations in the hourly wage rate, though some investigate the role of part-time work on hourly wages (Hirsch (2005)).

In table 1, we provide the results of the Blau and Kahn decomposition of the gender wage gap in hourly wages. The analysis is performed separately for 1980 and 2010 data and done for a human capital specification, and a full specification. The human capital specification includes control for education, experience, region and race. The full specification includes all of the human capital controls and adds controls for unionization, industry and occupation.

The results reveal that the gender gap in wages is falling over time. The male-female gap in log-wages fell from .477 to .231 points between 1980 and 2010. This implies that the ratio of women's to men's average hourly wage rose from .62 to .79 over this 30 year period.¹⁸ Also, it's clear that controls for human capital characteristics alone leave the majority of the gender wage gap unexplained – in both the 1980 and 2010 data. Only .137 of the .477 gender gap in log-wages is explained by gender differences in human capital characteristics in 1980. By 2010, the gender gap had shrunk to .231, but only .034 of the gap was explained.

Adding controls for unionization, occupation, and industry, increases the explained portion of the gap sharply. In the simple model, 71 (85) percent of the wage gap was unexplained in 1980 (2010). In the full specification, the unexplained share of the gap drops to 48 (38) percent 1980 (2010). In the full model, the most important factors contributing to the

¹⁸ The ratio of women's to men's wages is calculated as e^{-a} where a is the gap in average log-wage between men and women.

explained gap in wages are gender differences in occupation, industry, and experience. Over time, women's education attainment has caught up with and passed that of men. As a result, gender differences in education favor women and reduce the gender gap in wages. Also, gender differences in experience have diminished over time and helped shrink the gender wage gap. In 1981, average years of experience was 6.8 years lower among women than men. By 2011, this had shrunk to a 1.4 year differential.

With the above empirical evidence, there may still be disagreement about the extent to which the unexplained gender wage gap is discrimination. Several issues arise. First, should the model control for occupation, industry and unionization? If gender differences in these characteristics are driven by employer discrimination, one could argue that they should not be included in the model. On the other hand, if men and women voluntarily choose different occupations, industries, or unionization rates because of differences in preferences, one could reasonably argue that gender differences in earnings that arise from such choices should not be considered discrimination.

Another potential concern with the above estimates is that the unexplained gap in wages might be over- or under-stated due to a failure to control for relevant job characteristics. For example, there may be gender differences in job attributes within occupation or industry in terms of risk of job injury, physical demands, and flexibility in hours. For example, Goldin (2014) shows that much of the gender earnings gap is due to "within occupation" differences in earnings that arise due to differential penalties for flexible work hours. Her theory is that women are less willing or able to work long hours and/or need greater flexibility in the timing of their work hours. She provides evidence that the earnings penalty for being female tends to be highest in jobs where the rewards to long hours are greatest. As a result, even within occupation, there

may be sorting of workers across jobs by sex that can lead to significant earnings differentials. To the extent that such behavior explains the gender gap in earnings within occupations, a regression that controls for occupation alone will not correctly control for the importance of work hours and will overstate the extent of discrimination against women.

As discussed earlier, there is some controversy about interpreting the decomposition methods used to examine wage discrimination – particularly with respect to the appropriate set of controls to include and whether there is an omitted variable bias. Nevertheless, there is fairly wide consensus on a few points. First, an important share of the gender gap in earnings is due to differences in labor market experience, hours worked, occupation and industry (e.g Blau and Kahn 2000, 2017). Second, a narrowing of sex differences in labor market experience, education, and occupation has reduced the gender gap in earnings over time, but the rate of decline has slowed since the 1990s (Goldin 2014, Blau and Kahn 2017). Overall, our expectation is that gender differences in labor market outcomes will gradually diminish, but there is a good chance that the differences will not disappear entirely.

V. Gender Differences in Earnings Growth.

Once the forensic economist has chosen a method for determining an earnings base, assumptions about earnings growth are required. As noted earlier, some methods for forecasting earnings growth are gender neutral, whereas others rely upon a worker's gender and perhaps education.

The evidence we provided earlier suggests that women have lower earnings growth than men thus causing the gender earnings gap to rise with labor market experience or age. Several

empirical studies provide similar evidence, and some show that the widening gender gap occurs within narrow job groups (e.g. MBAs, lawyers).¹⁹ There are several possible explanations for why women might experience lower wage growth than men.

Returning to human capital theory, one reason wages grow with labor market experience is that workers accumulate human capital on the job. The return to any investment in human capital depends on the effect on subsequent wages as well how many hours and years the investment will generate returns. As a result, workers who expect to work more years or more hours per year will have a greater incentive to invest in human capital and will have greater earnings growth. As a result, if women, on average, expect to spend fewer hours or years in the labor force, they will invest less in human capital and will have lower earnings growth.

Yet another explanation of differential earnings growth is that employers use statistical discrimination when deciding which worker to invest in. To the extent that the employer and employee share in the cost of any investment in human capital, the employer has an incentive to discriminate against workers who are likely to work fewer hours or years. As a result, statistical discrimination against women could cause employers to invest less in female employees and lower their earnings growth. As an alternative, employers could use screening devices (such as deferred pay or a backloaded pension) to sort out quitters. Even and Macpherson (1990) show that the gender gap in earnings is lower in jobs where such screening devices are used. It is also possible that gender differences in earnings growth are driven entirely by tastes of employers, co-workers, or customers. The models of discrimination based on tastes of various parties developed by Becker can also be used to explain differential promotion rates for men and

¹⁹ See, for example, Loprest (1992), Manning and Swaffield (2008), Bertrand et al (2010), or Goldin (2014).

women. It is worth noting, however, that there is mixed evidence on whether gender differences in promotion rates are the result of discrimination.²⁰

The final element required for forecasting future earnings loss is work-life expectancy or the probability of being employed at different ages through the life-cycle. Estimates of work-life expectancy are typically provided by age, sex, and education. As shown in table 3 which is based on Skoog, Ciecka, and Krueger (2011), for virtually every age and education, work-life expectancy is greater for men than women. This could be the result of women be more likely to interrupt and restart employment prior to retirement, or an earlier retirement.

Are these differences in work-life expectancy a result of discrimination in the labor market? This is very difficult to ascertain given the wide range of factors that can influence when a person retires or whether a person temporarily leaves the labor force. For example, men and women may have different pension coverage rates and different types of pension plans that create different incentives for when to retire. To the extent that sex differences in pensions are partly responsible for differences in retirement ages, one would have to determine whether pension differences are the result of discrimination or sorting on the basis of tastes.

Another possible explanation for sex-differences in retirement ages is that married couples frequently coordinate their retirement dates.²¹ Since women marry a man that is typically older by a few years, spousal coordination of retirement dates could lead to women retiring sooner than men.²²

²⁰ See Blau and DeVaro (2007) for a discussion of studies examining gender differences in promotions and earnings growth.

²¹ See, for example, Pienta and Hayward (2002).

²² Copen et al. (2012) show that, between 2006 and 2010, the median age of first marriage is 2.5 years lower for women than men (25.8 versus 28.3) in the United States. Pienta and Hayward (2002) report that husbands are 2.8 years older than wives in the Health and Retirement Study.

As noted earlier, career interruptions prior to retirement are more common among women than men and will also contribute to shorter work life expectancies. It is difficult to ascertain whether gender discrimination is the reason that women have more frequent career interruptions. There are numerous possible explanations for gender differences. These include sex-differences in the tendency to stay at home with a young infant, who is a care-giver for parents, and so on. To the extent that economic models of household decision making are accurate, other things being the same, if one person has to stay in the home to provide a service, the person with the lower wage would be chosen. If women have lower wages than their husbands because of wage discrimination, the wage discrimination could be blamed for women's shorter work life expectancy.

The issues described above make it difficult to determine whether gender differences in earnings, earnings growth, or work-life expectancy are the result of discrimination. There is unlikely to be a consensus among economists about the amount of sex discrimination in the labor market. Nevertheless, it is worth considering how one might proceed if there was agreement. Suppose that all economists agree, for the sake of argument, that one-third of the gender gap in each of the relevant variables (wages, wage growth and work-life-expectancy) is due to discrimination. One might argue that, to make the most accurate forecast possible, the economist should start with gender specific values of the relevant variables and then adjust them upward to offset any effect of discrimination on the overall estimate. Alternatively, one might argue that sex should never be used in making a forecast since it is unfair to treat an individual as if they share the attributes of the group they happen to belong to. In this case, one might use male values to estimate what females would earn, or alternatively, use estimates that are based on the population of males and females.

While choosing between these options above may be relatively simple depending on one's beliefs about using gender to forecast the future, life is a bit more complicated when the injured party already has an established earnings history. For example, if a man and a woman have identical earnings history, should the woman's earnings be adjusted upward by the average amount of discrimination based on empirical studies? Should the earnings history be ignored entirely and the economist forced to rely upon averages for the worker based on educational background and experience? Or should the earnings histories be adjusted only if it can be proved that this particular person suffered from wage discrimination? In general, one must ask the question of how to handle cases with established earnings histories that may have been affected by sex discrimination.

VI. Summary and Conclusions.

If the Fair Calculations Act is made into law, forensic economists will be required to provide "gender neutral" forecasts of earnings losses. This article discusses some of the issues that arise with respect to such a ruling. Earnings forecasts generally require assumptions about a base wage at the beginning of the forecast period for earnings, wage growth, and work-life expectancy. For all three variables, gender differences are such that a forecast of earnings loss will be greater for men than women. It is worth noting, however, that these differences are falling over time as the gender gap in labor market attachment, educational attainment, and occupational choices has closed – but it has not yet been eliminated.

One philosophical question that emerges in the discussion ties to whether gender differences in labor market outcomes are the result of differences in tastes, or discrimination.

We review the evidence on this point. Virtually all the evidence suggests that a sizeable portion of the gender earnings gap is due to differences in human capital characteristics (e.g. occupation, industry, experience). However, there is disagreement over the size of these effects and whether, for example, gender differences in occupation and industry are the result of discrimination in hiring (or the anticipation of such). We find it difficult to imagine that economists or the legislature would reach a consensus on how much of the gender earnings gap is the result of discrimination. Moreover, it's unlikely that all workers experience the same level of discrimination.

While there is a wide literature on the extent to which gender differences in earnings are the result of discrimination, there is not a well-developed literature attempting to explain gender differences in wage growth or work-life. There are, however, theoretical models that might explain such differences even in the absence of discrimination.

If the Fair Calculations Act is approved as law, forensic economists will be forced to use gender-neutral estimates of earnings, wage growth and work-life expectancy. What's unclear is how the act might influence the use of recent earnings history for estimating the earnings base in their forecast. That is, it is possible that the earnings base for a woman was reduced by sex discrimination. Should the forensic economist take this into account? If so, would this be on a case-by-case basis?

If the Fair Calculations Act is approved, the forensic economist may seek out better ways to forecast earnings using the characteristics of the worker. For example, to the extent that men and women pursue different types of education and this is partly responsible for earnings differentials, earnings forecasts and work-life expectancy based on type of education or occupation could be a good replacement for the person's sex.

References

- S.3489 - Fair Calculations in Civil Damages Act of 2016 114th Congress (2015 - 2016). <https://www.congress.gov/bill/114th-congress/senate-bill/3489/text>
- Allen, Craig A. "Gender as a predictor of work life expectancy and the Fair Calculations Act," Paper Presented at Western Economics Association meetings, July 2017.
- Altonji, Joseph G., and Rebecca M. Blank. 1999. "Race and gender in the labor market." *Handbook of Labor Economics* 3: 3143-3259.
- Becker, Gary S. 1957. *The Economics of Discrimination*. Chicago: Chicago University Press.
- _____. 1985. "Human Capital, Effort, and the Sexual Division of Labor." *Journal of Labor Economics*, 3(1): S33-S58.
- Bertrand, Marianne, Claudia Goldin, and Lawrence F. Katz. 2010. "Dynamics of the gender gap for young professionals in the financial and corporate sectors." *American Economic Journal: Applied Economics*, 2(3): 228-255.
- Blinder, Alan S. 1973. "Wage discrimination: Reduced form and structural estimates." *Journal of Human Resources*, 8 (4): 436-455.
- Blau, Francine D., Marianne A. Ferber, and Anne E. Winkler. 2014. *The Economics of Women, Men and Work*. 7th edition. Upper Saddle River, New Jersey: Pearson.
- Blau, Francine D., Peter Brummund, and Albert Yung-Hsu Liu. 2013. "Trends in occupational segregation by gender 1970-2009: Adjusting for the impact of changes in the occupational coding system." *Demography*, 50(2): 471-492.
- Blau, Francine D., and Jed Devaro. 2007. "New evidence on gender differences in promotion rates: An empirical analysis of a sample of new hires." *Industrial Relations*, 46(3): 515-550.
- Blau, Francine D., and Lawrence M. Kahn. 2000. "Gender differences in pay." *Journal of Economic Perspectives*, 14(4): 75-99.
- _____. 2017. "The gender wage gap: Extent, trends, and explanations." *Journal of Economic Literature*, 55(3): 789-865.
- Copen, Casey E., Kimberly Daniels, Jonathan Vespa, and William D. Mosher. 2012. "First marriages in the United States: data from the 2006–2010 National Survey of Family Growth." *National Health Statistics Reports*, 49(1): 1-22.
- England, Paula. 1982. "The failure of human capital theory to explain occupational sex segregation." *Journal of Human Resources*, 17(3): 358-370.

- Even, William E., and David A. Macpherson. 1990. "The gender gap in pensions and wages." *Review of Economics and Statistics* 72(2): 259-265.
- _____. "Children's Effects on Women's Labor Market Attachment and Earnings." *Working Time in Comparative Perspective* (2001): 99-127.
- Goldin, Claudia. 1986. Monitoring costs and occupational segregation by sex: a historical analysis. *Journal of Labor Economics*, 4(1), pp.1-27.
- _____. 2014. "A grand gender convergence: Its last chapter." *American Economic Review*, 104(4): 1091-1119.
- _____. and Cecilia Rouse. 2000. Orchestrating impartiality: The impact of "blind" auditions on female musicians. *The American Economic Review*, 90(4), p.715.
- Hirsch, Barry T. 2005. "Why Do Part-Time Workers Earn Less? The Role of Worker and Job Skills." *Industrial and Labor Relations Review*, 58(4): 525-551.
- Krueger, Kurt V., and Frank Slesnick. 2014. "Total worklife expectancy." *Journal of Forensic Economics*, 25(1): 51-70.
- Light, A. and Ureta, M., 1995. Early-career work experience and gender wage differentials. *Journal of Labor Economics*, 13(1), pp.121-154.
- Loprest, Pamela J. 1992. "Gender differences in wage growth and job mobility." *American Economic Review*, 82(2): 526-532.
- Luthy, Michael R., Michael L. Brookshire, David Rosenbaum, David Schap, and Frank L. Slesnick. 2015. "A 2015 survey of forensic economists: Their methods, estimates, and perspectives." *Journal of Forensic Economics*, 26(1): 53-83.
- Manning, Alan, and Joanna Swaffield. 2008. "The gender gap in early-career wage growth." *Economic Journal*, 118 (530): 983-1024.
- Mincer, Jacob, and Solomon Polachek. 1974. "Family investments in human capital: Earnings of women." *Journal of Political Economy*, 82(2), pp. S76-S108.
- _____. 1978. "An Exchange: The theory of human capital and the earnings of women: Women's earnings reexamined." *Journal of Human Resources*, 13(1): 118-134.
- Neumark, David. 1988. "Employers' discriminatory behavior and the estimation of wage discrimination." *Journal of Human Resources* 23(3): 279-295.
- Neumark, David, Roy J. Bank, and Kyle D. Van Nort. 1996. "Sex discrimination in restaurant hiring: An audit study." *The Quarterly Journal of Economics*, 111(3): 915-94
- Oaxaca, Ronald L. 1973. "Male-female age differentials in urban labor markets." *International Economic Review*, 14(3): 693-709.
- Oaxaca, Ronald L., and Michael R. Ransom. 1994. "On discrimination and the decomposition of wage differentials." *Journal of Econometrics*, 61(1): 5-21.

- Phelps, Edmund S. 1972. "The statistical theory of racism and sexism." *American Economic Review*, 62(4): 659-661.
- Pienta, Amy M., and Mark D. Hayward. 2002. "Who expects to continue working after age 62? The retirement plans of couples." *Journal of Gerontology: Social Sciences*, 57B(4):S199-S208.
- Polachek, Solomon W. 1981. "Occupational self-selection: A human capital approach to sex differences in occupational structure." *Review of Economics and Statistics*, 63(1) 60-69
- Riach, Peter A., and Judith Rich. 2006. "An experimental investigation of sexual discrimination in hiring in the English labor market." *Advances in Economic Analysis & Policy*, 5(2):1-20.
- Skoog, Gary R., James E. Cieccka, and Kurt V. Krueger. 2011. "The markov process model of labor force activity: Extended tables of central tendency, shape, percentile points, and bootstrap standard errors." *Journal of Forensic Economics*, 22(2): 165-229.
- Slesnick, Frank L., Michael R. Luthy and Michael L. Brookshire. 2013. "2012 survey of forensic economists: Their methods, estimates, and perspectives." *Journal of Forensic Economics*, 24(1): 67-99.
- Spivey, C., 2005. Time off at what price? The effects of career interruptions on earnings. *Industrial and Labor Relations Review*, 59(1), pp.119-140.
- Spizman, Lawrence M. 2013. "Developing statistical based earnings estimates: median versus mean earnings." *Journal of Legal Economics* 19(2): 77-82.
- Stanley, T.D. and Jarrell, S.B., 1998. Gender wage discrimination bias? A meta-regression analysis. *Journal of Human Resources*, 33(4): 947-973.

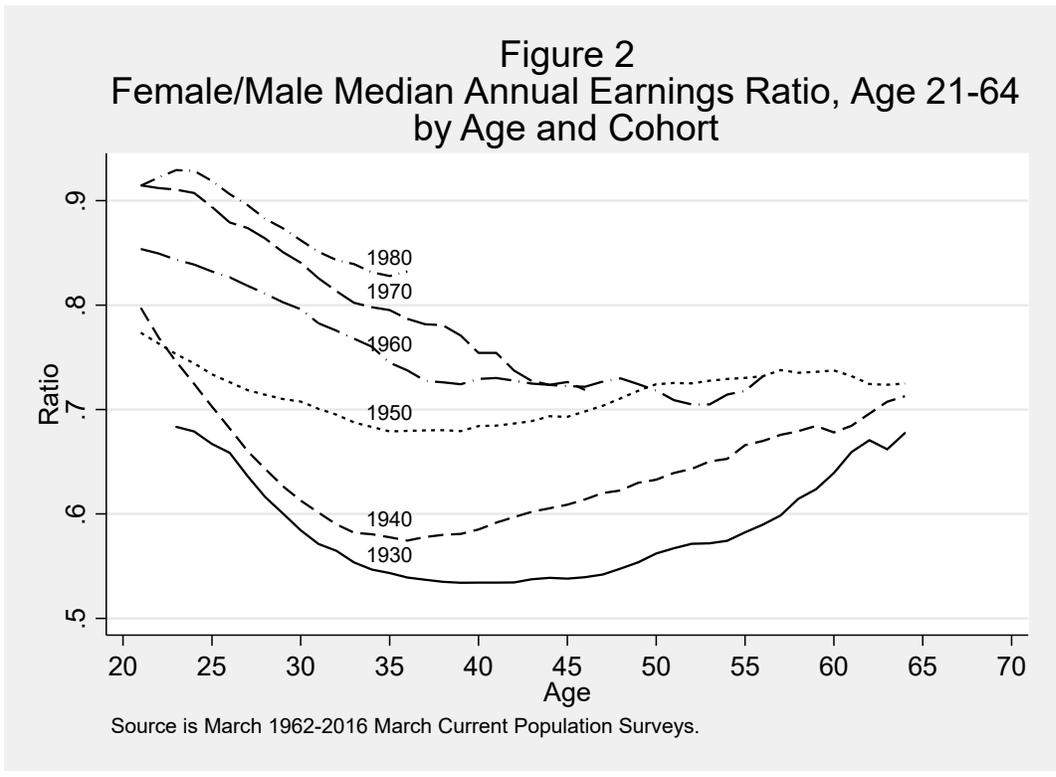
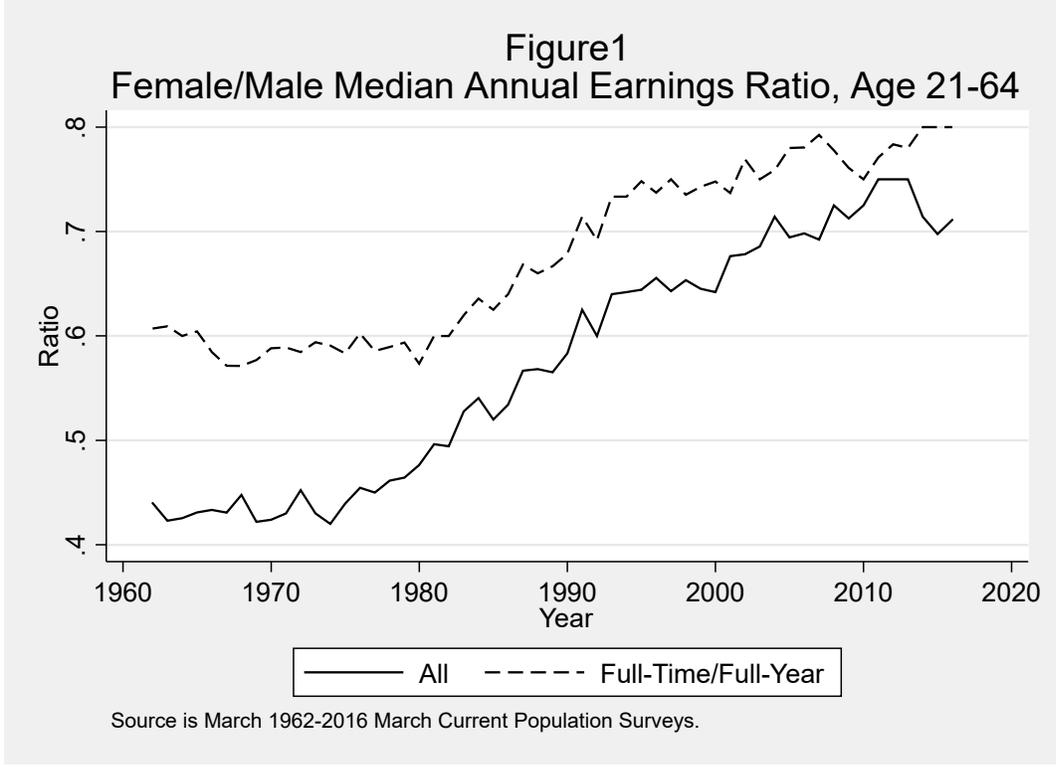
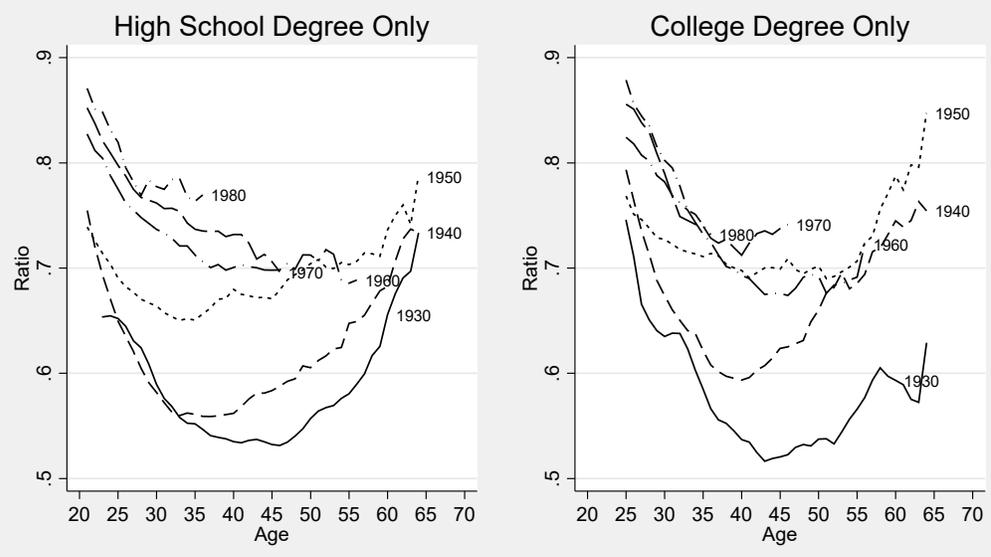


Figure 3
Female/Male Median Annual Earnings Ratio, Age 23-64
by Age and Cohort and Education



Source is March 1962-2016 March Current Population Surveys.

	1980		2010	
	Log Points	Percent of Pay Gap	Log Points	Percent of Pay Gap
Human Capital Specification				
Education Variables	0.013	2.7%	-0.019	-7.9%
Experience Variables	0.114	23.9%	0.037	15.9%
Region Variables	0.002	0.4%	0.000	0.1%
Race Variables	0.008	1.6%	0.015	6.6%
Total Explained	0.137	28.6%	0.034	14.8%
Total Unexplained	0.341	71.4%	0.197	85.2%
Total Pay Gap	0.477	100.0%	0.231	100.0%
Full Specification				
Education Variables	0.012	2.6%	-0.014	-5.9%
Experience Variables	0.101	21.1%	0.033	14.1%
Region Variables	0.000	0.0%	0.001	0.3%
Race Variables	0.007	1.4%	0.010	4.3%
Unionization	0.030	6.2%	-0.003	-1.3%
Industry Variables	0.046	9.6%	0.041	17.6%
Occupation Variables	0.051	10.7%	0.076	32.9%
Total Explained	0.246	51.5%	0.143	62.0%
Total Unexplained	0.231	48.5%	0.088	38.0%
Total Pay Gap	0.477	100.0%	0.231	100.0%
Note: This table is based on Table 4 in Blau and Kahn (2017). The data source is 1980 and 2010 Panel Study of Income Dynamics. The sample includes full time nonfarm wage and salary workers age 25-64 with at least 26 weeks of employment				

Table 2

Real Annual Earnings Growth by Age and Gender and Education

Age	Less Than High School			High School Degree			Some College			Bachelors		
	Male	Female	Male-Female	Male	Female	Male-Female	Male	Female	Male-Female	Male	Female	Male-Female
18	3.84	2.81	1.03	6.43	4.45	1.98						
19	3.51	2.52	0.99	5.90	4.06	1.83	8.20	5.98	2.23			
20	3.20	2.24	0.96	5.40	3.70	1.69	7.49	5.39	2.11			
21	2.91	1.99	0.92	4.92	3.36	1.56	6.83	4.84	1.99			
22	2.64	1.76	0.88	4.48	3.05	1.43	6.20	4.33	1.88	8.71	7.55	1.17
23	2.39	1.54	0.84	4.07	2.76	1.31	5.62	3.85	1.76	7.99	6.74	1.25
24	2.15	1.35	0.80	3.68	2.49	1.20	5.07	3.42	1.65	7.31	5.99	1.31
25	1.93	1.17	0.76	3.32	2.24	1.08	4.56	3.02	1.54	6.67	5.31	1.36
26-35	1.01	0.50	0.51	1.83	1.25	0.58	2.48	1.51	0.98	3.99	2.65	1.35
35-45	-0.01	0.01	-0.02	0.22	0.35	-0.13	0.34	0.29	0.05	1.11	0.44	0.66
46-55	-0.65	-0.01	-0.63	-0.68	0.04	-0.72	-0.67	0.05	-0.72	-0.25	0.16	-0.41
56-65	-1.62	-0.31	-1.31	-2.03	-0.57	-1.47	-2.16	-0.79	-1.37	-1.75	-0.58	-1.17

Note: The sample consists of full-time year-round workers from the 1990 and 2000 5% Census PUMS and 2005-2015 American Community Surveys. Models are estimated with a quartic in potential experience and birth cohort fixed effects.

Table 3.
Work-life expectancy by Sex, Age, and Education for Active Workers.

Education	Age	Men	Women	Difference
High school degree	20	37.3	31.7	5.6
	30	29.6	25.5	4.1
	40	21.1	18.8	2.3
	50	13.3	12.1	1.2
	60	6.6	6.2	0.4
Some College, no degree	20	37.6	34.5	3.1
	30	30	27.5	2.5
	40	21.3	20.3	1
	50	13.3	13	0.3
	60	7	6.8	0.2
Associates Degree	20	39.3	37.5	1.8
	30	31	29.6	1.4
	40	22.2	21.6	0.6
	50	14	13.7	0.3
	60	7.5	6.8	0.7
Bachelors degree	20	40	36.7	3.3
	30	31.2	29.3	1.9
	40	22.9	21.8	1.1
	50	14.1	14	0.1
	60	6.9	7.2	-0.3
Masters degree	25	38.6	34.9	3.7
	30	34.1	31	3.1
	40	24.1	23	1.1
	50	16	14.6	1.4
	60	8.4	7.5	0.9
PhD or Professional Degree	25	40.8	37.7	3.1
	30	36.8	33.6	3.2
	40	27.7	25.2	2.5
	50	18.8	16.9	1.9
	60	10.8	9.4	1.4

Source: Skoog, Ceicka and Krueger 2011.