Gender-Hours Disparity and Race

By Michael Tom

This paper analyzes data from the 2013 Annual Social and Economic (ASEC) Supplement of the Current Population Survey to examine whether women work fewer hours per week than men across races. I juxtapose reported hours worked in a typical week for White males with those of male and female workers of Black, Hispanic, Asian, and other descent. Several regressions are considered in an attempt to correct for possible violations of ordinary least squares (OLS) assumptions that may weaken both the internal and external validity of the model. Results from the linear regression suggest that women belonging to the ethnic groups studied work approximately 1–2 fewer hours per week on average than their male counterparts. While these gender-based differences vary depending on race, modifications to the regression distinguishing part-time and full-time workers indicate that the estimates are generally robust for full-time employees. Coefficient calculations for part-time work, however, tend to lose their statistical significance for the difference in the number of typical hours worked per week, which suggests that no gender-hours gap exists for some races at the part-time level. Areas for future research are suggested.

I. INTRODUCTION

A. Overview

Although vehemently contested, the presence of gender-based social roles and discrimination is a matter our increasingly liberalized society must address. Past research has emphasized this contention through a variety of approaches, including audit studies of hiring practices, customer discrimination, and wage gaps.[1] Similarly, Goldin and Rouse (2000) have constructed an estimated model reinforcing the issue of gender disparity, demonstrating how gender anonymity can drastically improve the prospects of women seeking to be hired by orchestras.[2] However,

1 1 Joseph Altonji and Rebecca Blank, “Race and Gender in the Labor Market,” *Handbook of Labor Economics* 3C (1999): 3143-259, accessed April 21, 2015.

2 Claudia Goldin, “A Grand Gender Convergence: Its Last Chapter,” American Economic Review 104, no. 4 (2014): 1091-119, doi:10.1257/aer.104.4.1091.

some gender-based differences in the labor market have been reduced as women improve their earnings relative to white and same-race men.[3] Nevertheless, gender inequality within the workplace remains a persistent concern, as is the case with upward mobility. Discrepancies between pervasive gender roles may limit the equality between men and women.

While research suggests that labor market gender inequality has declined over the past several decades, elements affecting the ability to commit to an occupation can slow this progression. Responsibilities arising from a variety of gender-based dynamics, both social and economic, have the potential to disrupt work flow. Setting wage and unemployment differences aside, this paper seeks to determine how much of an extent the gender-hours disparity gap holds true across races. Finding a significant gender-hours gap across races may help to clarify labor market inequality, such as by differentiating between gender time commitments of ethnicities.

B. Compensation and Overwork

While the discrepancy between the compensations of men and women can in part be attributed to a variety of factors ranging from education to discrimination, working fewer hours affects growth potential in overall benefits. Indeed, a study conducted by the nonprofit organization Catalyst, based on a 2008 compensation regression, determined that the blurring the work-life boundary was a significant predictor of salary growth for men.[4] Given that overwork, defined as working 50 or more hours per week, rests on the social foundation that working longer hours requires the support of other household members, gender roles substantially explain the wealth disparities between sexes. Cha and Weeden (2014) suggest that "many employers expect workers to be available whenever clients or supervisors need them, and . . . employees are also complicit in ratcheting up expectations surrounding work hours, often treating long work hours as a way to signal loyalty and commitment to an organization."[5] The fact that work hours are frequently treated as signals of employee commitment only reinforces a labor force payment disadvantage, especially since women are less likely to take on jobs with long work hours due to caregiving obligations. Additionally, it is worth noting that the Center for American Progress Action Fund proposes that American men have less leisure time as compared to women to compensate not only for their wives' household responsibilities, but for their lower wages as well.[6]

Companies offering more stigma-free flexibility and linear compensation regardless of when hours are worked show the lowest gaps in compensation between genders. In fact, Goldin (2014) asserts that the gender-wage gap would "be considerably reduced and might vanish altogether if firms did not have an incentive to disproportionately reward individuals who labored long hours and worked particular hours." Taking time off from work helps to explain the greater difference in compensation as workers age and have children. This is especially true for those employees who are female. Reviewing the earned incomes of men and women 16 years after receiving their MBA, Goldin finds that women make about 55 percent of what men earn;

3 David A. Cotter, Joan M. Hermsen, and Reeve Vanneman, "Systems of Gender, Race, and Class Inequality: Multilevel Analyses," *Social Forces* 78, no. 2 (1999): 433-60, accessed April 21, 2015.

4 Nancy Carter and Christine Silva, *The Myth of the Ideal Worker: Does Doing All the Right Things Really Get Women Ahead?* New York: Catalyst, 2011.

5 Youngchoo Cha and Kim Weeden, "Overwork and the Slow Convergence in the Gender Gap in Wages," American Sociological Review 79, no. 3 (2014): 457-84, accessed May 23, 2015, doi:10.1177/0003122414528936.

6 Jessica Arons, Lifetime Losses: The Career Wage Gap, Washington, DC: Center for American Progress Action Fund, 2008.

two-thirds of the income disparity is credited to the difference in time taken off.[7, 8] The cost of working fewer hours is most apparent in professional services firm Ernst & Young Global Limited's (EY) flexible benefits packages. Having conducted a study that found flexibility to be the most important non-case priority for younger workers, EY began offering paid parental leave to employees of both genders, with full benefits extending to part-time workers. As a result of this change, the proportion of female partners increased from 3 percent to 20 percent and the variance between men and women leaving EY was virtually eliminated.[9]

Past research has examined the gender-pay gap for full-time employees only, so as to prevent a skew in the hours worked. However, restricting the estimate according to this criterion excludes a significant share of men and women working part-time jobs, a population that, if examined, may reveal unique statistics as to the gender inequality.[10] Furthermore, the models from which these estimates are derived do not consider racial or ethnic diversity; the gender-hours gap may exist to varying degrees depending on ethnicity. This study attempts to construct a model that measures the approximate gender-hours gap among the White, Black, Hispanic, Asian, and other races. Several models are proposed to test the sensitivity of the regression results to model specifications, including an interaction between the terms of interest, part-time, and full-time workers. Racial differences in work time disparity may serve to better elucidate the impact of ethnicity, rather than gender alone, on job commitment.

II. Data

A. *Sample Summary and Definitions*

I analyzed data from the 2013 Annual Social and Economic Supplement of the Current Population Survey (March CPS), an extension of the monthly CPS conducted by the United States Census Bureau on an annual basis.[11] The 2013 March CPS sampled the civilian non-institutional population of the United States, divided between "792 sample areas comprising 2,007 counties and independent cities with coverage in every state and in the District of Columbia."[12] All information in the survey is based on reports about the year prior to the March CPS. From this dataset, I restricted the sample of the study to employed White, Black, Hispanic, Asian, and "Other" race men and women, aged 18 and older, who had positive earned incomes in the year prior to the survey. The sample was filtered by dropping individuals not of interest from the dataset, such as children and those who are not in the labor force or unemployed, so as to ensure that the study measured the work hours for both genders, of those employed.

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7 Kay Hymowitz, "Kay Hymowitz: Why Women Make Less Than Men," The Wall Street Journal, April 26, 2012, accessed May 23, 2015.

8 Claudia Goldin and Cecilia Rouse, "Orchestrating Impartiality: The Impact of "Blind" Auditions on Female Musicians," *American Economic Review* 90, no. 4 (2000): 715-41, accessed April 21, 2015.

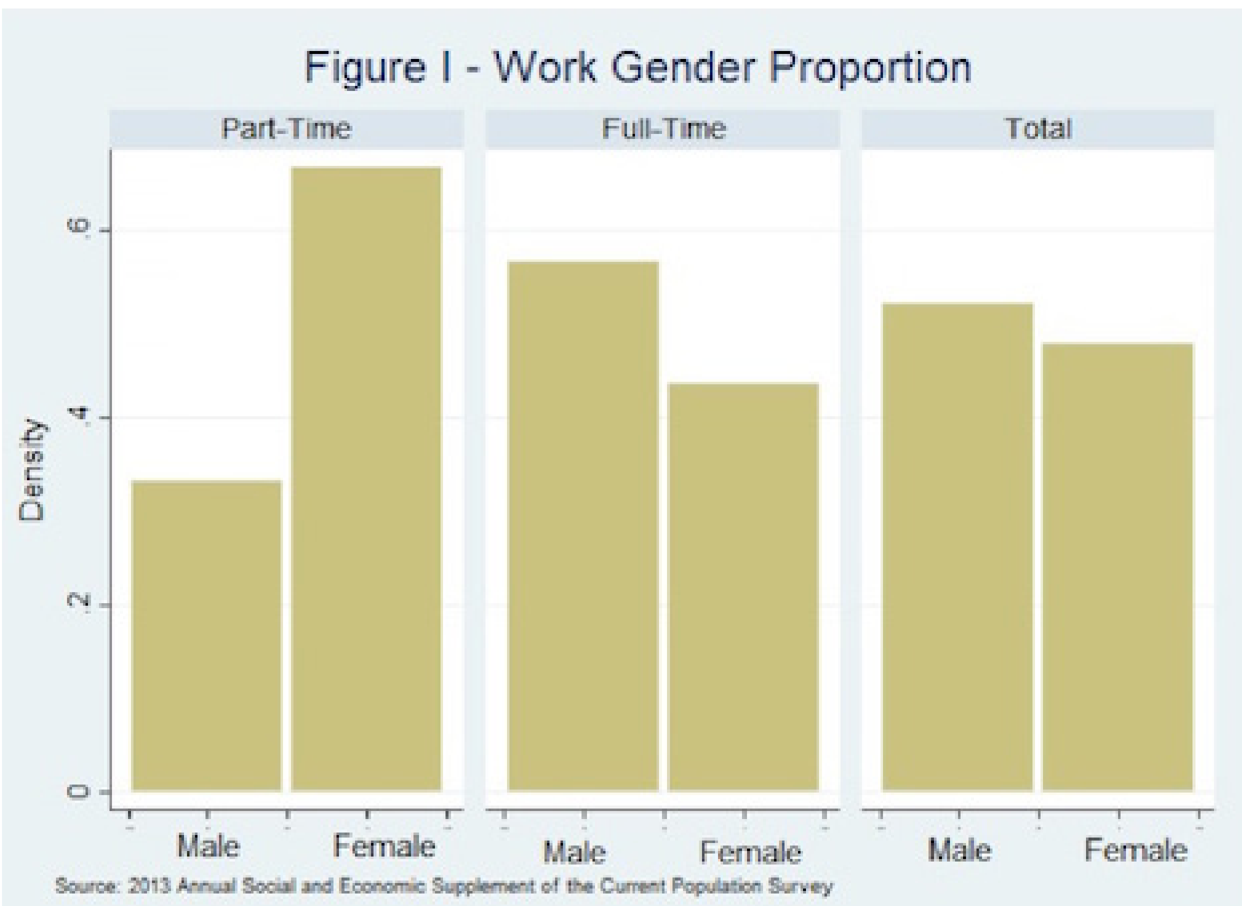
9 Sheelah Kolhatkar, "Why the Gender Pay Gap Persists—and How to Really End It," Bloomberg Businessweek, March 4, 2014, accessed May 23, 2015.

10 Rakesh Kochhar, "How Pew Research Measured the Gender Pay Gap," Pew Research Center, 10 Dec. 2013, Web, 24 May 2015.

11 The Current Population Survey is the monthly survey on which the U.S. unemployment statistics are based.

12 *Current Population Survey, 2013 Annual Social and Economic (ASEC) Supplement*, United States Census Bureau, 2013.

The dependent variable of interest, Hours of Work per Week, is defined as the self-reported number of hours the individual worked at their place(s) of occupation in a typical week. Race is recorded as control binary dummy variables—coded 1 if the individual observation meets the criteria—for Black, Hispanic, and Asian men and women, as well as those individuals who did not identify as White, Black, Hispanic, or Asian, grouped into one dummy variable labeled "Other Race." Age is the individual's age in years, number of household children is the number of individuals under the age of 18 living in the same household, and full-time schedule is a binary variable that is recorded as 1 if the specific observation is employed full-time. Other control variables considered include dummy variables for metropolitan areas, following the Office of Management and Budget's June 30, 2003 definitions; state of residence; national household income percentile rankings (total household income ranked as compared to others in the U.S.); level of education completed from first grade to doctorate; U.S. citizenship; and foreign born citizen status.[13] These are integrated into the model as a means of accounting for economic status and legal work restrictions imposed by the government.



Cotter et al. (1999) took a slightly different approach by restricting their sample to specified ethnicities not designated as "Other," although this study accounts for the "Other" race so as to retain model robustness. Prior to the year 1972, Hispanics were not identified separately from White and Black, unless they were designated as "Other" on the question of race in the

13 Ibid.

survey.[14] As this study solely takes into consideration the most recent 2013 March CPS, the "Other" category of races will be considered, since belonging to this classification (as opposed to the White, Black, Hispanic, or Asian classifications) may be statistically impactful in terms of work hours. Beginning in January 2003, respondents to the March CPS were allowed to report more than one race. Such observations were dropped from the restricted sample since people of multiple races were reported as "mixed" and without the specific ethnicities.[15] Doing so is not expected to seriously impact the results, as "mixed" observations constituted only 2.2 percent of the original dataset and less than 1 percent of the restricted sample.

Table I —Summary Statistics

	Observations	Mean	Standard Deviation	Min./Max.
Typical Weekly Hours Worked	86900	39.40	11.50	1/99
Age	86900	42.55	13.30	18/85
Number of Household Children	86900	0.930	1.157	0/11
Full-Time Workers	70788	—	—	—
Part-Time Workers	16112	—	—	—

Note: Values listed are for observations of interest with sufficient data.

B. Sample Validity

As with all surveys, there is a risk of response bias because this dataset may have excluded some individuals who did not wish to report the number of hours they work per week, their gender as male or female, the number of children in their household, or their citizenship status. This could possibly introduce errors into the actual measurements for these variables, which can ultimately bias the results. While this may pose a serious threat to the external validity of the regression, the United States Census Bureau provides population weights so that results can be better generalized to the entire population of interest within the country; these values place greater weight on individual observations more representative of the U.S. population as a whole.[16] This also ensures that a disproportionate number of certain demographics does not bias the sample of interest in any significantly meaningful way. All results in this study are calculated with population weights to ensure proper applicability to the whole U.S. population.

III. Regression Specification

The linear regression equation takes the form under (1) below, where Y_i is the number of typical work hours per week, β_0 is a constant term, F_i is the female dummy, X_i is the vector of race variables, Q_i is the vector of interacting race and female terms, Z_i is the vector of control variables,

14 David A. Cotter, Joan M. Hermsen, and Reeve Vanneman, "Systems of Gender, Race, and Class Inequality: Multilevel Analyses," *Social Forces* 78, no. 2 (1999): 433-60, accessed April 21, 2015.

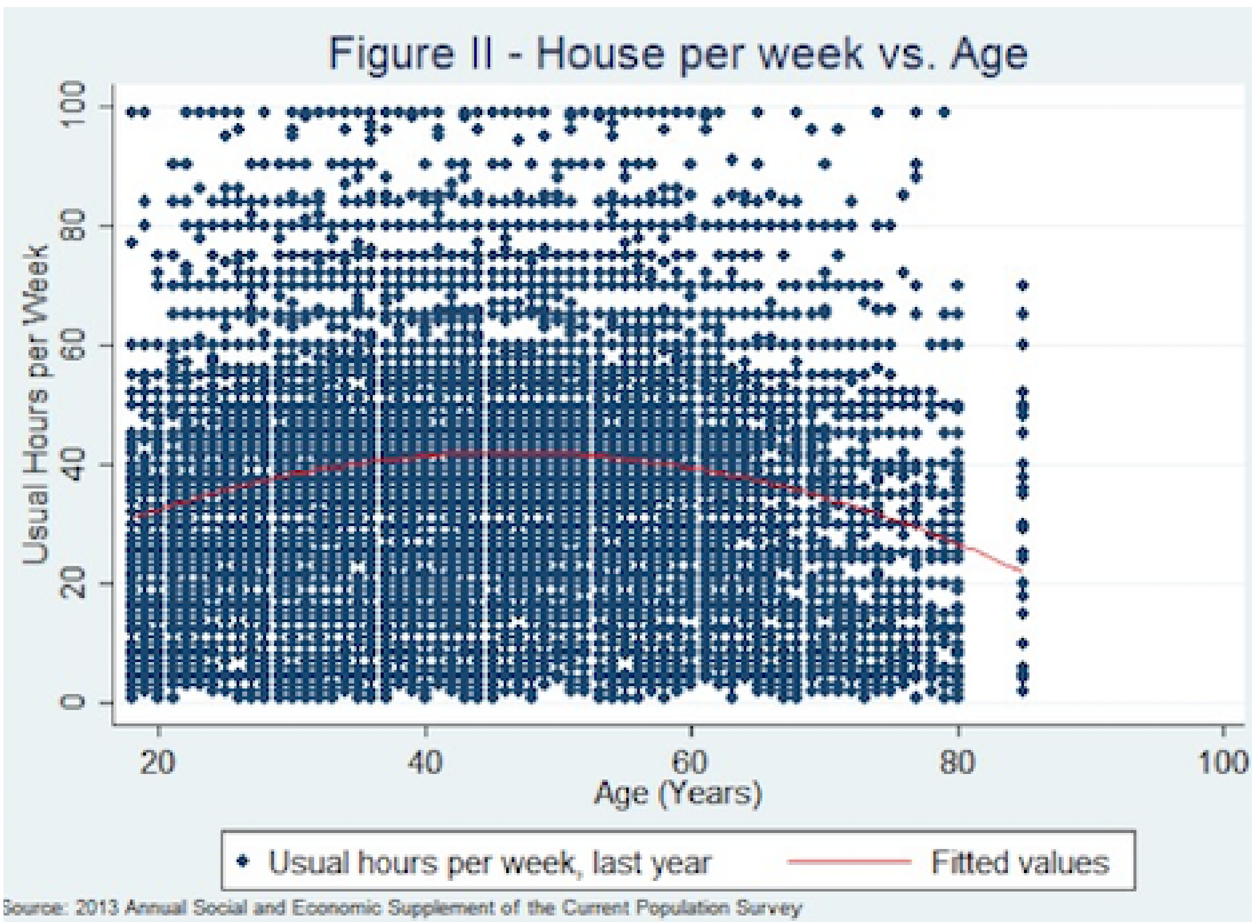
15 *Current Population Survey, 2013 Annual Social and Economic (ASEC) Supplement*, United States Census Bureau, 2013.

16 Ibid.

and u_i the residual, for j=2, 3, and 4 and i corresponding to the observation.

$$Y_i = \beta_0+\beta_1 F_i+\beta_j' X_i+\mu' Q_i+\gamma' Z_i+u_i \qquad (1)$$

As White males are excluded from the right-hand side of Equation 1, the resulting estimated coefficients compare the hours worked in a typical week by females of all races and by members of other races (both male and female) with the hours of White males. The most relevant parameters are the binary variables for female, race, and their respective interacting terms (e.g., Female/Black, Female/Hispanic, and Female/Asian). The interacting terms account for differences in the magnitude of the gender-hours gap that may exist across races. A number of control variables are included as a means of strengthening the statistical significance of this model and reducing bias from omitted variables. Most notable is the term age-squared, as a scatter plot comparing age and number of hours worked in a typical week reveals a roughly non-linear fit (Figure II).



The question of whether women work fewer hours per week than men has several components that can be studied individually. It can be tested that the null hypotheses of coefficients of respective female and female/race terms are equal to 0 to determine the value of a single parameter through t-tests. Furthermore, an F-test, which helps to measure the relevance of a particular variable as compared to the dependent variable, can determine whether the numbers of hours worked for females of all ethnicities considered are unchanged as compared to those for males (H_0: $\beta_1 = \beta_j = 0$). Despite the power of these tests, constructing an ordinary least squares

(OLS) model from the given data may be problematic. Since some of these observations may be of family members, coefficient estimates may at least be partially biased due to a potential lack of independent and identically distributed (i.i.d.) random variables. The sample could additionally be skewed by people refusing to specify their typical number of hours worked per week or any of the dependent variables and omitted variables, in which case the expected value of the residuals given by the observation would not be equal to 0. Nevertheless, the robustness of the model can be tested and amended to address these issues, as discussed in Sections 4B and 4C.

IV. Regression Results

A. *Simple Linear Form*

I deliberate several models, where each equation differs by the independent variables considered. The regressions contrast from each other based on which variables could potentially explain the number of hours people typically work in a given week. Control variables are implemented and removed in subsequent tests in order to determine the level of sensitivity of the results to changes to omitted variables, as well as a failure to reject F-test significance. Relatively similar coefficient estimates would be indicative of rather robust results. Table II provides the approximated coefficients, where the coefficient multiplied by the respective dependent variable provides the effective difference between White male hours per week and the subject. As an illustration, consider the case of Asian women with the controls of (1) in Table II. These individuals meet the criteria for the Female, Asian, and Female & Asian variables, foregoing other controls, which results in the sum of about 2.2 fewer hours per week than White males, who were omitted to prevent perfect collinearity. Similar methods can be applied to compare the hour(s) gap between all genders and races included.

The regressions reveal a negative association between being female and number of hours worked in a typical week. Across races of Black, Hispanic, and Asian, it is estimated that male members usually work a little over 1 additional hour per week, whereas the gap between White men and women is nearly double that. In particular, the gaps between males and females of the

Table II — Regression Results

	(1)	(2)	(3)	(4)
Female (1 = Yes)		-2.285***	-2.403***	-2.316***
	(0.0784)	(0.0788)	(0.0791)	(0.0794)
Black (1 = Yes)		-1.034***	-1.492***	-1.511***
	(0.154)	(0.154)	(0.154)	(0.155)
Hispanic (1 = Yes)		-1.023***	-1.502***	-1.671***
	(0.135)	(0.135)	(0.133)	(0.133)
Asian (1 = Yes)		-1.133***	-0.750***	-0.894***

	(0.196)	(0.196)	(0.197)	(0.197)
Other Race (1 = Yes)	-0.674	-0.663	-0.984**	-1.007**
	(0.410)	(0.411)	(0.413)	(0.417)
Female & Black (1 = Yes)	1.148***	1.125***	1.088***	1.065***
	(0.189)	(0.190)	(0.191)	(0.191)
Female & Hispanic (1 = Yes)	0.969***	0.980***	1.057***	1.070***
	(0.151)	(0.151)	(0.152)	(0.152)
Female & Asian (1 = Yes)	1.172***	1.138***	1.105***	1.065***
	(0.243)	(0.244)	(0.246)	(0.247)
Female & Other Race (1 = Yes)	0.123	0.125	0.172	0.151
	(0.515)	(0.518)	(0.520)	(0.525)
Full-Time Schedule LY (1 = Yes)	20.05***	20.57***	20.31***	20.90***
	(0.0842)	(0.0839)	(0.0821)	(0.0810)
Age	0.324***	—	0.344***	—
	(0.0144)	—	(0.0143)	—
Age-squared		—		—
		—		—
Number of Household Children	0.0110	—	0.0456	—
	(0.0280)	—	(0.0282)	—
Observations	86900	86900	86900	86900
R-squared	0.554	0.550	0.547	0.542

Standard Errors in Parentheses
Significance: * p<0.10 ** p<0.05 *** p<0.01

Black, Hispanic, and Asian categories are approximately 1.2, 1.4, and 1.2 fewer hours, respectively. White women, however, are estimated to possess the largest gender gap deviation from their male counterparts: about 2.4 fewer hours per typical workweek when taking into account each control variable. This can, in part, be considered an effect of lower income minorities reporting more work hours out of necessity to compensate for an average lower pay, which may outweigh differences in work hours due to societal gender roles and education.[17] Removing Age, Age-squared, and Number of Household Children controls (denoted by empty cell spaces) demonstrates little change among the gender/race variables of greatest interest, nor the statistical fit R-squared; column (1) provides the regression that takes into account the variables of prime importance.

While almost all the races considered can be predicted to change the typical hours per week at the 95% confidence level, the Other Race variable presents a large robust standard error for both genders (approximately 0.41 for Other Race and 0.52 for Female & Other Race). As a result, I cannot reject the hypothesis that being either a male or female member of the "Other" race does not present a significant change as compared to the number of predicted hours a white male works in a typical week. Given that the relevant t-tests for the Other Race regressors adapt to both the number of observations available and population weights, the relatively small number of people belonging to this category (the "Other" race constituted only 1.4% of individuals) in the restricted sample decreases the significance. This does not mean that Other Race is necessarily irrelevant to the regression, as it is still a category of race which can be interacted with the Female term to compare the gender-hours gap. Nevertheless, I cannot conclusively claim that being a member of the "Other" race has a significant work hours gap as compared between genders, other than that outside of the standalone Female dummy variable.

Table II includes the relevant significance levels that apply to the particular t-tests, along with the standard errors of the statistics. All gender and race variables—besides "Other"—are supported by 99% confidence intervals that do not engulf 0. Examination of the individual F-statistics rejects the null hypothesis that being male/female does not have an effect on hours worked per week across races. Joint significance between the race and gender variables is also maintained under the same test. The fact that the "Other" race has a relatively large probability under the F-distribution can be interpreted as signifying that the gender-hours gap not being particularly differentiable for people not identifying as Black, Hispanic, or Asian as compared to the gap between White males and females. As previously noted, accounting for minority individuals remains relevant overall to the question of the gender-hours gap; any study on this subject would be incomplete without including the "Other" race.

17 Deborah Ashton, "Does Race or Gender Matter More to Your Paycheck?" Harvard Business Review, Harvard Business School Publishing, 10 June 2014, Web, 26 May 2015.

Table III — F-Test Statistic[2]

	H_0	F	Prob. > F
Female	Female=0	850.37	0.0000
Black	Black=0	95.53	0.0000
Hispanic	Hispanic=0	158.81	0.0000
Asian	Asian=0	20.47	0.0000
Other Race	Other=0	5.83	0.0158
Female & Black	F/B=0	30.96	0.0000
Female & Hispanic	F/H=0	49.58	0.0000
Female & Asian	F/A=0	18.62	0.0000
Female & Other Race	F/O=0	0.08	0.7738
Joint Significance	All=0	138.18	0.0000

2 This test is for (1) in Table II.

Being female has a marginal effect on the number of hours worked per week. This effect, compared to that of White males, is described by the coefficients of the equation

$$Y_i = \beta_1 F_i + \beta_j' X_i + \mu' Q_i + u_i \qquad (2)$$

where F_i is the female dummy, X_i is the vector of race variables, Q_i is the vector of interacting race and female terms, and u_i the residual, for j=2, 3, and 4 and i corresponding to the observation, as solved for in Equation 1 and listed in Table II. This is close to the same as Equation 1, save for removing variables that were not affected by race or gender. Since race and gender are accounted for in binary dummy variables that are not continuous, it is sufficient to examine marginal effects between when the dummy is 1 and when it is 0. For example, if column (1) in Table II were taken, it is estimated what White males typically work 2.359, 2.282, 2.326, 2.214, and 2.910 more hours per week than White, Black, Hispanic, Asian, and Other Race women, respectively. Marginal effects that measure the gender-hours gap across races can be determined from a similar method as was previous shown.

B. Robustness Analysis

Regressions from the previous results rest on the premise that basic OLS assumptions hold true; that is, properties of the model exist such that strict exogeneity, independent and identically distributed random variables, finite fourth moments, and full column rank of the matrix of regressors are assumed.[18] However, a number of potential violations to the OLS assumptions exist from this dataset. Most relevant potential threats to the internal validity of these regression results include omitted variable bias, measurement error in the dependent variable, and the misspecification of the function form.

18 Note: OLS assumptions were $E[ui|\boldsymbol{xi}]=0$; $(Yi,\boldsymbol{xi})$ i.i.d.; $0<E[Yi4]<\infty$ and $0<E[Xi,j4]<\infty$ for j=1,…,k; $\boldsymbol{X}$ has full column rank; and $E[\boldsymbol{xix}'i]$ is invertible. These assure estimates are consistent, unbiased, and asymptotically normal.

Variables that may actually factor into determining the typical hours an observation works weekly may hold the true form

$$Y_i = \beta_0+\beta_1 \mathrm{F}_i+\beta_j{}' \mathrm{X}_i+\mu' \mathrm{Q}_i+\gamma' Z_i+\tau' \mathrm{M}_i+u_i \tag{3}$$

where M_i is a matrix of omitted variables and ′ the corresponding coefficients. Equation 3 holds that, if independent variables such as F_i, X_i, Q_i, and Z_i are uncorrelated with the variable(s) omitted M_i, estimates from Equation 1 will remain consistent and unbiased. However, if the covariance between omitted variables M_i and already-included regressors exists, it is expected that the exclusion of omitted variables would shift the coefficients of gender/race toward 0, as factors such as work ethic, previous work experience, lifestyle choices, and others that could not be included in this study are considered and no longer absorbed through race/gender. In addition, omitted variables related to work qualification, such as work certification and experience, may be negatively correlated with minority-race status due to a variety of factors.

The variable from Equation 1 most likely to have been distorted by measurement errors would be the typical weekly work hours, the dependent variable. In this case, the true form of the function would be

$$\tilde{\mathrm{Y}}_i = \beta_0+\beta_1 \mathrm{F}_i+\beta_j{}' \mathrm{X}_i+\mu' \mathrm{Q}_i+\gamma' Z_i+\tilde{\mathrm{u}}_i \tag{4}$$

where $_i$ is equivalent to Y_i plus a normally distributed error term , with all independent and identically distributed. Thus, the true residual term u_i would also be the sum of $_i$ and measurement error. So long as the error term is effectively random, the condition of exogeneity holds true where and the independent variables are uncorrelated, leaving unbiased estimates for variable coefficients. With regard to measurement errors in the number of hours worked per week, random error in the reported hours does not bias estimates for the coefficients since the error term would be independent and identically distributed.

C. *Model Re-specification*

I will not correct for a possible misspecification of the functional form of Equation 1. The new equation will take the form

$$Y_i = \beta_0+\beta_1 \mathrm{P}_i+\varphi' \tilde{X}_i+\mu' \tilde{Q}_i+\gamma' \tilde{Z}_i+\sigma' \tilde{W}_i+\delta' \tilde{R}_i+u_i \tag{5}$$

where P_i is a binary dummy for a part-time observation; $_i$ a matrix of interaction terms between race and part-time schedules; $_i$ a matrix of interactions between female, part-time, and race; $_i$ a matrix interacting race and full-time schedules; $_i$ a matrix interacting female, full-time, and race; and $_i$ a vector of controls. The definitions of the other terms are the same as those for Equation 1. White males employed full-time are omitted from the new regression to prevent perfect collinearity. An intuitive interpretation of this new functional form is that the gender-hours gap may be different for part-time and full-time workers.

When additional part-time and full-time variables are interacted with gender/race regressors, results do not change drastically for full-time employees (Table IV). It is now estimated that the difference between full-time male and female workers across races has increased by a slight margin—about 6 minutes for White, a half hour for Black and Hispanic, and 12 minutes for Other, with the gender-hours gap between Asians essentially unchanged. Compared to the initial regressions in Table II, these results for full-time workers are reasonably robust, as a change in the regression specification did not alter results by a large margin. However, part-time estimates differ noticeably between male and female members across races. While most women employed part-time work approximately 0.8–1 fewer hours than males of the same race, it is estimated that Black women actually work nearly a half hour longer than Black men. Essentially, the gender-hours gap narrows considerably for part-time workers. Nevertheless, several of these regressors lose their statistical significance at the part-time level; the F-statistic cannot significantly reject the possibility that there is no effect on the number of weekly hours for Asians and Hispanic women. As a result, it seems that reliable conclusions for Asians and Hispanic women can only be drawn from full-time employees. Once again, the Other Race variable is the least significant; I cannot reject the possibility that being a member of a race other than White, Black, Hispanic, or Asian has a significant work hours gap other than the standalone Female dummy variable. Results are indeed sensitive to the regression specification, as compared with the initial form of Equation 1. The independent variables in Equation 5 better explain the variance in the dependent variable, resulting in an increase in the value for R-squared.

Table IV — Part/Full-Time Interactions[3]		
	Part-Time	Full-Time
Part-Time (1 = Yes)	-21.92***	—
	(0.176)	—
Female (1 = Yes)	-0.867***	-2.539***
	(0.196)	(0.0856)
Black (1 = Yes)	1.176***	-1.397***
	(0.399)	(0.165)
Hispanic (1 = Yes)	2.167***	-1.392***
	(0.297)	(0.143)
Asian (1 = Yes)	0.352	-1.229***
	(0.510)	(0.207)
Other Race (1 = Yes)	0.799	-0.873**
	(1.125)	(0.439)
Female & Black (1 = Yes)	1.328***	0.828***
	(0.484)	(0.203)
Female & Hispanic (1 = Yes)	-0.161	0.729***
	(0.368)	(0.163)
Female & Asian (1 = Yes)	-0.004	1.300***
	(0.625)	(0.266)
Female & Other Race (1 = Yes)	-0.168	-0.097
	(1.364)	(0.543)
Observations	86900	
R-squared	0.556	
Standard Errors in Parentheses		
Significance: * p<0.10 ** p<0.05 *** p<0.01		

; Note: Same control variables as those in columns (1) and (2) of Table II included. Number of hour
ed as compared to full-time White men.

V. Conclusion

This paper sought to determine the effect of gender on the typical number of hours a person works per week across races. Data from the 2013 ASEC Supplement of the Current Population Survey was analyzed to contrast the number of hours worked by White males with the numbers worked by Black, Hispanic, Asian, and "Other" race men and women. Initial regressions indicated that women work approximately 1–2 fewer hours per week than their male counterparts, with non-White women working longer than White women. Adjusted to account for a possible misspecification of the functional form, the model demonstrates that women working full-time tend to spend even less time (a few minutes to a half hour) working than men, while part-time comparisons are indeterminate. At least for full-time employees, the gender-hours gap is indeed maintained across races, although it varies in magnitude.

The scope of this study is limited because the available variables only provide data from one year. Further research could examine the gender-hours gap stratified by socioeconomic status and seasonality of occupation. For a time series analysis, CPS data over a period of time could be collected for a more cohesive view of how the gender-hours gap has changed over the last few decades. A behavioral study may also be conducted comparing the number of hours worked by workers who receive hourly compensation with the number of hours worked by those who are salaried. Such a study could determine whether these different payment methods effect how a person perceives the value of their time. Perhaps if a larger sample of part-time minority workers could be surveyed, it would be possible to generate a more significant approximation of the gender-hours gap. Future research should focus its attention on these areas so that a more thorough understanding of the underlying causes of this labor disparity can be evaluated.

VI. References

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