Income Inequality and Household Labor: Online Appendicies

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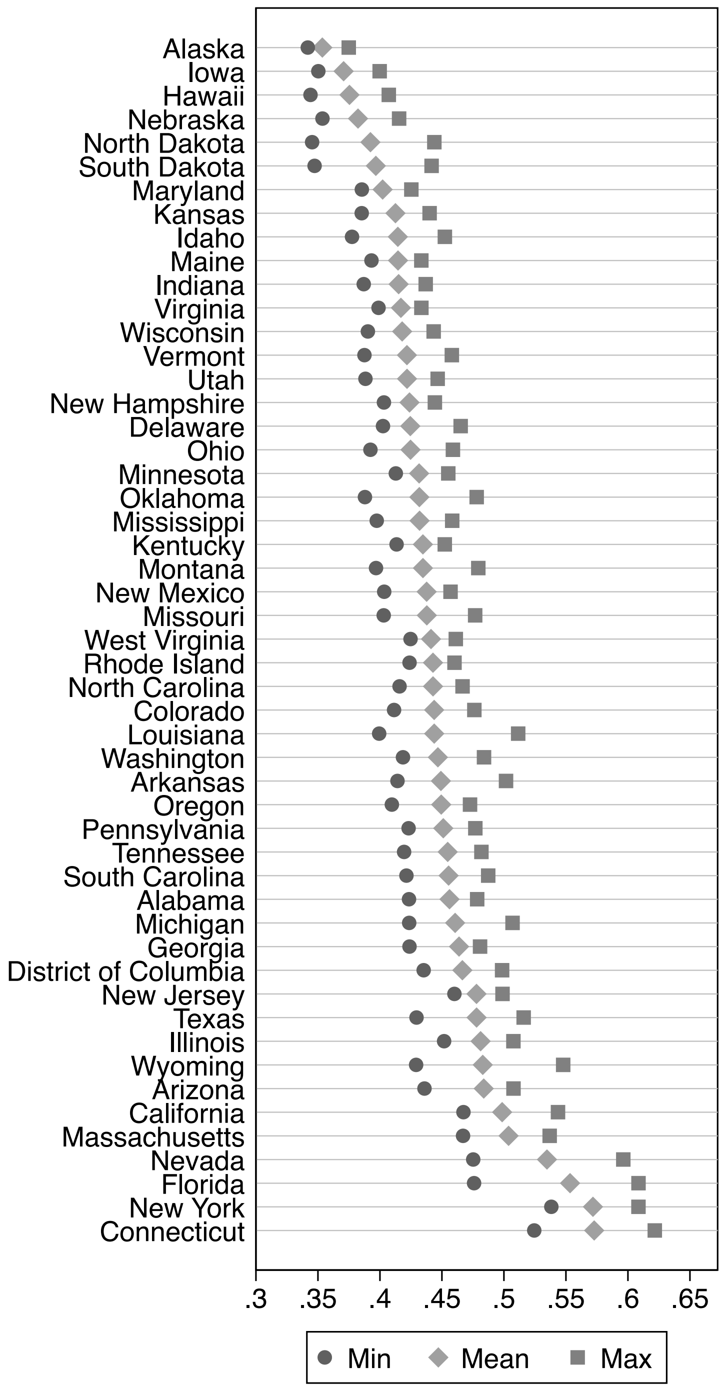
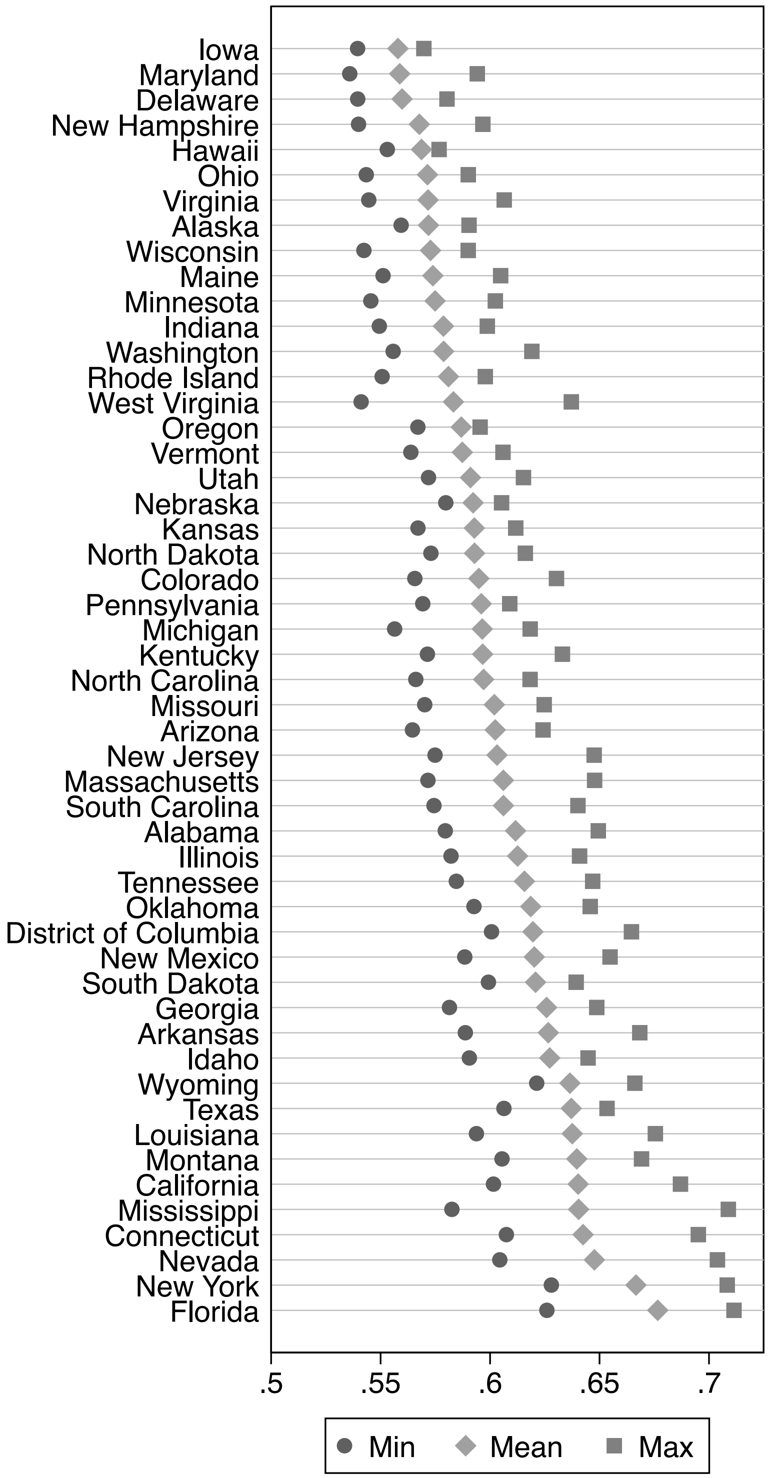
Appendix 1: Income Inequality By State

Mean and Range of Top 10% Income Share by State



Note: Years 2003–2013. Estimates calculated by Frank et al. (2015) based on IRS income tax return data.

Mean and Range of Gini Index by State



Note: Years 2003–2013. Estimates calculated by Frank (2014) based on IRS income tax return data.

Appendix 2

Descriptives of All Variables in Main Models presented in Table 1 (N = 18966).

	mean	sd	min	max
Individual-level variables				
Completed College	0.40		0	1
High Family income	0.24		0	1
Family income (categories)	12.0	3.36	1	16
Household size	4.22	1.12	3	16
Age	38.5	8.39	18	64
Non-Hispanic white	0.69		0	1
Non-Hispanic black	0.065		0	1
Non-Hispanic Asian	0.050		0	1
Non-Hispanic Native American/other	0.0063		0	1
Non-Hispanic multirace	0.0073		0	1
Hispanic	0.18		0	1
Student	0.063		0	1
Interview conducted on Saturday	0.14		0	1
Interview conducted on Sunday	0.15		0	1
Interview conducted on a holiday	0.018		0	1
Owns home	0.80		0	1
Unemployed	0.043		0	1
Not in labor force	0.30		0	1
Absent from work in current week	0.038		0	1
Regular work hours	23.7	19.8	0	120
Spouse: non-Hispanic white	0.69		0	1
Spouse: non-Hispanic black	0.070		0	1
Spouse: non-Hispanic Asian	0.046		0	1
Spouse: non-Hispanic Native American/other	0.0078		0	1
Spouse: non-Hispanic multirace	0.0100		0	1
Spouse: Hispanic	0.18		0	1
Spouse: age	41.0	9.07	16	85
Spouse: high school diploma or GED	0.26		0	1
Spouse: some college	0.24		0	1
Spouse: completed college	0.38		0	1
Spouse: unemployed	0.11		0	1
Spouse: absent from work in current week	0.024		0	1
Spouse: regular work hours	40.1	17.6	0	99
Metro central city	0.22		0	1
Metro outlying area	0.47		0	1
Metro central city/outlying area combined	0.14		0	1
Nonmetro	0.16		0	1
Metro status not identified	0.0066		0	1
State-level variables				
Gini coefficient	0.61	0.037	0.54	0.71
Top 10% income share	0.47	0.050	0.34	0.62
Unemployment rate	6.79	2.18	2.60	13.7
Mean income	58221.4	9135.7	35102.6	93323.1
Fraction of working-age non-college-completed female immigrants	0.076	0.053	0.0029	0.18
Fraction non-hispanic white	0.66	0.15	0.22	0.96

Fraction non-hispanic black	0.12	0.078	0.0018	0.58
Fraction non-hispanic other	0.071	0.052	0.012	0.68
Fraction married	0.40	0.023	0.22	0.47

Note: Descriptives are calculated using survey weights.

Appendix 3

Effects of Income Inequality on Class-Gaps in Women's Housework Time (All Coefficients from Table 1)

	Model 1	Model 2	Model 3	Model 4
Completed college × Top 10% Income Share	-67.2*			
High family income × Top 10% income share		-78.2**		
Completed college × Gini coefficient			-123.3**	
High family income × Gini coefficient				-119.7*
Top 10% income share	49.0	42.3		
Gini coefficient			83.5	74.2
Completed college	-9.35***	-10.2***	-9.42***	-10.2***
High family income (dichotomous)		-6.07**		-6.14**
Family income (continuous)	-1.89***		-1.88***	
Household size	7.23***	7.25***	7.21***	7.24***
Age	4.39**	4.12**	4.39**	4.11**
Age squared	-0.047**	-0.044**	-0.047**	-0.044**
Non-Hispanic black	7.04	6.10	7.17	6.09
Non-Hispanic Asian	22.2***	22.2***	22.2***	22.2***
Non-Hispanic Native American/other	3.70	5.53	3.66	5.46
Non-Hispanic multirace	7.15	7.57	7.04	7.66
Hispanic	20.0***	20.9***	19.9***	20.8***
Enrolled in school	-19.9***	-20.1***	-20.0***	-20.1***
Interview conducted on Saturday	20.7***	20.7***	20.7***	20.7***
Interview conducted on Sunday	13.3**	13.2**	13.3**	13.3**
Interview conducted on a holiday	4.97	5.25	5.04	5.32
Owns home	-6.22+	-9.01*	-6.17+	-8.95*
Unemployed	28.3***	28.9***	28.4***	28.8***
Not in the labor force	20.3***	20.5***	20.4***	20.5***
Absent from work in preceding week	35.7***	35.5***	35.8***	35.5***
Usual work hours	-1.28***	-1.32***	-1.28***	-1.32***
Spouse Characteristics				
Spouse: non-Hispanic black	-15.4+	-13.3	-15.6+	-13.4
Spouse: non-Hispanic Asian	15.9**	16.1**	15.9**	16.2**
Spouse: non-Hispanic Native American/other	6.44	6.79	6.07	6.65
Spouse: non-Hispanic multirace	1.56	2.08	1.42	1.87
Spouse: Hispanic	20.5***	21.5***	20.3***	21.4***
Spouse: age	2.02+	1.94	2.04+	1.95
Spouse: age squared	-0.017	-0.016	-0.017	-0.016
Spouse: unemployed	-10.3+	-8.82	-10.4+	-8.88
Spouse absent from work in preceding week	-11.0	-10.8	-11.0	-10.7
Spouse usual work hours	0.18*	0.16+	0.18*	0.16+
Spouse: high school diploma or GED	-13.8**	-15.8***	-13.8**	-15.8***
Spouse: some college	-18.1***	-21.4***	-18.1***	-21.3***
Spouse: completed college	-15.1**	-18.9***	-15.1**	-18.8***
Metro Characteristics (Baseline: Metro central city)				
Metro outlying area	0.90	0.62	0.74	0.49
Metro central city/outlying area combined	-3.52	-3.49	-3.56	-3.50
Nonmetro	6.33+	7.02*	6.21+	6.91*
Metro status not identified	-2.81	-3.22	-2.96	-3.33

Time Varying State Characteristics				
Fraction married	-168.0	-152.9	-210.3	-205.9
Fraction non-hispanic white	394.6	416.6	424.0	454.2
Fraction non-hispanic black	950.9*	963.6*	967.9*	980.6*
Fraction non-hispanic other	632.0	667.6	608.1	646.9
Unemployment rate	-0.40	-0.19	-0.56	-0.36
Mean household income	0.00074	0.00077	0.00084	0.00089
Fraction of non-college completed female immigrants	178.5	139.6	220.0	195.1
Constant	-496.3*	-530.8*	-506.8*	-542.9*
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	18966	18966	18966	18966

$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$

Note: The models are weighted and the standard errors are adjusted for clustering within states.

Appendix 4: Supplemental Models

We consider several additional models using the American Time Use Survey (ATUS).[1]

Alternative Measures of Income Inequality
First, we consider alternative measures of inequality. We rerun our main models using each of the two high-SES indicators, but in place of the Gini or top 10% income share, we substitute the top 1% income share, Theil entropy index, and Atkinson index calculated from the IRS data. These are available for all analysis years 2003-2013 and for all respondents. We then consider the state-level Gini coefficient, top 5% income share, and top 20% income share calculated from the American Community Survey (ACS). The state-level Gini calculated from ACS data is also available for all respondents and all analysis years, but the top 5% and 20% shares are only available from 2006-2013. These checks are designed to assess whether other measures of inequality, at the same level of aggregation and for generally the same set of respondents and analysis years, produce comparable results.

Both the IRS and ACS data have benefits and drawbacks. Data from the ACS may better capture low incomes, but the IRS data likely better captures high income data, as the IRS, does, in fact, punish respondents for underreporting income. Because of these differences, there is substantial variation between the inequality measures calculated from these two data sources (for example, the state-year Gini coefficients in the IRS and ACS are correlated at .71 in our dataset). We present additional results with the ACS inequality data in our robustness checks, but again caution that we are missing some of the series for top 5% and 20% shares.

Table A1 presents the results using alternative measures of inequality. Each row contains the results from a different state-level inequality measure. In Column 1 we use obtained a Bachelors degree as our key indicator of high SES, while in Column 2 we use high family income. Each cell presents the interaction term coefficient from a separate regression model. The interaction term coefficients are negative and significant in every model.

CSA-level Income Inequality
We also consider how our results are affected when we substitute measures of CSA-level income inequality for state-level measures. A CSA is a group of adjacent metropolitan and micropolitan statistical areas that are combined by the US Office of Management and Budget (OMB) based on commuting patterns. As such, they may better capture the labor market than the state level. This is both a theoretical question and a methodological question. While it may be that smaller aggregations better capture the labor market dynamics that allow for a class divide in housework and outsourcing, it may also be the case that states, on average, better capture these markets than CSAs. More narrowly, any discrepancies between the state-level and CSA-level results could also be driven by the substantial data limitations on the CSA-level measures. Many women in the ATUS did not reside in or were not identified with a CSA. Further, the CSA-level measures of inequality are only available beginning in 2006. Only 19% of the women in our state-level analyses could also be included in our CSA-level analyses. While acknowledging these limitations, we present results using

[1]References for citations in this appendix appear in main article.

these measures to complement the state-level inequality analysis.

Table A2 presents the results of models that substitute CSA-level measures of inequality for the preferred state-level measures. Here, the models include CSA fixed-effects rather than state fixed-effects and replace the state-level control variables with CSA-level control variables.

We interact each of the inequality measures from the ACS with college completion (Column 1) and high family income (Column 2). The coefficients are consistently negative and of very similar size and sign to the same ACS state-level measures. However, in part perhaps due to the much smaller sample size and year range truncation, the coefficients are not statistically significant, except for marginally significant ($p < .1$) interaction terms between the Gini and high family income and the Top 5% Income Share and high family income.

Sensitivity to Controls

A recurrent issue in research on the effects of inequality on social and economic life is the trade-off between "under-controlling" for possible sources of unobserved heterogeneity versus "over-controlling" for the pathways through which inequality might affect a given outcome. For instance, in the debate over inequality and health, Wilkinson and Pickett (2009) suggest that there is a real risk of mistaking pathways for sources of bias and that researchers must have a strong theoretical basis for distinguishing the two. While there is some risk then of "over-controlling," in Table A3 we consider the influence of our control variables by estimating nested models with the sample from our final model. We begin with a model with only our measures of inequality, high-SES indicators, and their interaction term (Column 1). In each successive column we add additional controls. First, in column 2, we add in state and year fixed effects, then respondent demographic controls, spouse demographic controls, respondent economic controls, spouse economic controls, and lastly state-level controls. Our results are extremely robust to our choice of controls. The key coefficient is negative and significant in every model. We observe that the size of the coefficient generally becomes smaller as we add in more controls (i.e., move to the right in the columns). These nested results then show that accounting for other individual and state characteristics does reduce the inequality-housework gradient relationships, but we believe that this is generally due to confounding rather than over-controlling.

Outlier States

Fourth, we assess the sensitivity of our models to outlier states. We do so by re-running each of the main models while excluding, one state at a time, all of the observations from each state (and the District of Columbia). Changes in the size, sign, or significance of the results with the exclusion of the individuals residing in a given state would suggest that the inequality regime of that state or some time-variant characteristic of that state might unduly influence the results. We find no substantial change in the magnitude or direction of our main interaction term when we exclude any given state from the analysis. All of the key interaction terms are statistically significant at $p < 0.05$ level.

Women's Own Earnings

Fifth, while our main models measure socio-economic status using either women's educational attainment or family income, we also examine how the results might vary when we substitute women's own personal earnings or men's own personal earnings in place of family income. We categorize female respondents as being high income if their own earnings are in the top quartile of earnings or not (we find similar results using the top quintile). We similarly categorize female respondents' spouses' incomes as being in the top quartile of earnings or not. We then re-estimate our main models but focus on the interaction between state-level income inequality and each of these measures of gender-specific earnings rather than family income. We compare these models with our main models to test whether income-inequality related outsourcing is a privilege of household class or of women's own economic status.

To conduct this test, we use a smaller subsample of households where both the husbands and wife's earnings are known, so we include additional columns that present the results of the main models after re-estimating them on this same sub-sample of cases. These results are contained in Table A4. The interaction of women's high income with both measures of inequality is small and not statistically significant (Models 2 and 5). The interaction of men's high income with both measures is larger and negative, but not significant either (Models 3 and 6). For this subsample, we see that the interaction of high family income and both measures of inequality is still negative and at least marginally significant (Models 1 and 4). Thus, we find little support then for the idea that it is women's own earnings, in particular, that drive reductions in housework time. Instead, it appears that it is family income in contexts of inequality that serves to steepen the class gradient in women's housework time.

Men's Housework Time

Finally, sixth, we expect that household outsourcing dynamics will play an important role in explaining any variation in the class gradient in women's housework time by level of income inequality. An alternative is that the interaction between class and inequality in predicting women's housework time is the result not of outsourcing, but of a re-allocation of domestic labor within the household. Specifically, it is possible that men married to highly educated women or in high income households do more housework in more unequal contexts and this permits their female partners to do less. This could be the result of an unobserved relationship between gender egalitarianism, class, inequality, and housework time. We cannot directly measure gender egalitarianism in the ATUS data. We also cannot look at the within-couple division of housework time since we only have time diary reports from one member of the couple. However, we can test whether men married to highly educated women or living in high-income households do more housework in more unequal contexts. Such a result would support a gender-egalitarian re-allocation of housework. Alternatively, the outsourcing perspective would suggest that these men would either be unaffected or, like their wives, do less housework in more unequal contexts as outsourcing reduces their housework burden as well.

To conduct these tests, we again re-estimate our main models, but now take men's housework time as the outcome variable. It is important to note that these men are not the spouses of the women being sampled, but men in different households. However, the same restrictions on being married with children are applied and all the same variables are used in the models. These results are presented in Table A5. If re-allocation does explain our main findings, we would expect a significant positive interaction term between household SES and state-level income inequality when predicting men's housework time. In contrast, we find that the interaction term is negative in all four models, and statistically significant in one of them. In sum, there does not seem to be a substitution effect in which high SES households share the housework more equally as inequality increases.

Appendix 4, Table A1: Effects of Income Inequality on Class-Gaps in Women's Housework Time, Robustness to Use of Alternative State-Level Inequality Measures

	Criteria of High SES		
	College Degree	High Family Income	Observations
Inequality Measure			
Top 1% Income Share (IRS)	-74.1*	-84.7**	18966
Theil entropy index (IRS)	-19.3**	-20.7**	18966
Atkinson index (IRS)	-89.6*	-91.9*	18966
Gini Coefficient (ACS)	-231.0*	-298.6***	18966
Top 5% Income Share (ACS)	-261.5*	-337.2**	12915
Top 20% Income Share (ACS)	-310.0*	-377.0**	12915

* $p < .05$, ** $p < .01$, *** $p < .001$

Note: The data sources of each inequality measure are noted in parentheses in the table. Each coefficient is the interaction term between the inequality measure listed in the left hand column and either college completion or high family income, with each estimated with a separate model. Each model also includes individual-level controls, state-level controls, and state and year fixed effects. The models are weighted and the standard errors are adjusted for clustering within states.

Appendix 4, Table A2: Effects of Income Inequality on Class-Gaps in Women's Housework Time, Robustness to Using CSA-Level Inequality Measures

	Criteria of High SES		
	College Degree	High Family Income	Observations
Inequality Measure			
Gini Coefficient	-174.3	-202.0^{+}	4593
Top 20% Income Share	-183.1	-151.0	4593
Top 5% Income Share	-205.9	-223.5^{+}	4593

$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$

Note: The data sources of each inequality measure are noted in parentheses in the table. Each coefficient is the interaction term between the inequality measure listed in the left hand column and either college completion or high family income, with each estimated with a separate model. Each model also includes individual-level controls, and CSA and year fixed effects. The models are weighted and the standard errors are adjusted for clustering within CSA.

Appendix 4, Table A3: Effects of Income Inequality on Class-Gaps in Women's Housework Time, Robustness to Exclusion of Control Variables

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Completed college × Top 10% share	-159.3*	-155.2*	-91.7*	-84.9*	-69.1*	-70.1*	-67.2*
High family income × Top 10% share	-169.2**	-183.8***	-105.3***	-99.0**	-77.4**	-86.1**	-78.2**
Completed college × Gini coefficient	-289.7***	-296.6***	-178.3**	-168.3**	-121.8**	-123.6**	-123.3**
High family income × Gini coefficient	-239.6***	-273.3***	-141.1**	-132.0**	-113.5**	-123.5**	-119.7*
Observations	18966	18966	18966	18966	18966	18966	18966
Sets of controls							
State fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Respondent demographics	No	No	Yes	Yes	Yes	Yes	Yes
Spouse demographics	No	No	No	Yes	Yes	Yes	Yes
Respondent economic	No	No	No	No	Yes	Yes	Yes
Spouse economic	No	No	No	No	No	Yes	Yes
Time-varying state-level	No	No	No	No	No	No	Yes

* $p < .05$, ** $p < .01$, *** $p < .001$

Note: Each coefficient is the interaction term between the inequality measure listed in the left hand column and either college completion or high family income, with each estimated with a separate model. Each model also includes individual-level controls, state-level controls, and state and year fixed effects. The models are weighted and the standard errors are adjusted for clustering within states.

Appendix 4, Table A4: Effects of Income Inequality on Gaps in Women's Housework Time by Men's and Women's Own Earnings and by Family Income

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Interaction of Inequality and SES						
High family income × Top 10% income share	-76.3^{*}					
High woman's earnings × Top 10% income share		33.3				
High man's earning × Top 10% income share			-26.4			
High family income × Gini coefficient				-96.3^{+}		
High woman's earnings × Gini coefficient					19.8	
High man's earning × Gini coefficient						-65.8
Inequality						
Top 10% income share	14.8	-10.9	2.11			
Gini coefficient				-43.3	-76.7	-57.6
Criteria for High-SES						
High family income	-4.83^{*}			-4.99^{*}		
High woman's earnings		-2.99			-2.92	
High man's earning			-4.12			-4.17
Observations	15257	15257	15257	15257	15257	15257

$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$

Note: The sample is restricted to observations where both the husband's and wife's earnings are known. Each model also includes individual-level controls, state-level controls, and state and year fixed effects. The models are weighted and the standard errors are adjusted for clustering within states.

Appendix 4, Table A5: Effects of Income Inequality on Class-Gaps in Men's Housework Time

	Model 1	Model 2	Model 3	Model 4
Interaction of Inequality and SES				
Completed college × Top 10% income share	-18.4			
High Family Income × Top 10% income share		-1.42		
Completed college ×Gini coefficient			-67.0**	
High Family Income × Gini coefficient				-51.1
Inequality (mean centered)				
Top 10% income share	57.7	49.9		
Gini coefficient			12.8	2.82
Criteria for High-SES				
Completed college	0.66	1.16	0.74	1.17
High Family Income (dichotomous)		-1.63		-1.37
Family income (continuous categories)	0.18		0.19	
Observations	17224	17224	17224	17224

* $p < .05$, ** $p < .01$, *** $p < .001$

Note: Each model also includes individual-level controls, state-level controls, and state and year fixed effects. The models are weighted and the standard errors are adjusted for clustering within states.