A Time-Series Analysis on Behaviors and Attitudes Towards Women as Economic Agents

BY: LUCIA YU & MEREDITH MANTE

Background / Motivation

In October 2014, National Public Radio (NPR) published a podcast entitled, "When Women Stopped Coding," examining the peculiar sharp decline in the mid-1980's of women in computer science fields compared to the seemingly increasing number of women in physical sciences.[1] This anomalous trend (though yet to be thoroughly explained) has continued to influence the current state of the field and its unequal representation of gender. According to the National Center for Women and Information Technology, the consequence of a missing female labor force in this increasingly important and lucrative field is yet another means by which inequality among the sexes will be further sustained.[2]

And so our project set out to examine the larger social attitudes about women in the work force and its effect on female participation in the field of computer science. However, initial cleaning of the raw dataset revealed the limited amount of data necessary for meaningful statistical analysis. While there were about 60,000 observations for the four decades worth of information from the GSS, there were on average about 6.6 females working in the field of computer science per year. Due to this limitation, the project pivoted to include all women in the workforce not just those in technological fields.

While much research has been dedicated to both the corporate and academic pipeline, our project sought to focus on the less emphasized, overarching social sentiments towards women as economic agents as a potent influence on participation in the field. A study conducted by LeanIn.org and McKinsey and Company focuses heavily on women in the workplace in terms of corporate pipeline and promoting diversity, which noted that women are less likely to be promoted to managerial levels let alone C-suite.[3] Another study sponsored by the AAUW shows that even though the wage gap exists partly because of choices in education or occupation, there are still pay gaps across the board despite education levels or line of work.[4] But how much does public opinion about women and their role as economic agents weigh on the number of women who participate in the labor force, if at all? And if so, are there certain trends we can observe in terms of occupational prestige or job satisfaction which may also affect women in the workplace? What can these general observations tell us about the increasing number of women going into the workforce since the 1970s?

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1 NPR, Planet Money. "When Women Stopped Coding."
http://www.npr.org/sections/money/2016/07/22/487069271/episode-576-when-women-stopped-coding

2 NCWIT. "Girls in IT: The Facts Infographic." https://www.ncwit.org/infographic/3435

3 "Women in the Workplace." 2016. https://womenintheworkplace.com/

4 AAUW. "The Simple Truth." 2016.
http://www.aauw.org/aauw_check/pdf_download/show_pdf.php?file=The-Simple-Truth

Using data from respondents from the General Social Survey (GSS) by the US Census Bureau from 1974 to 2014, we analyzed metrics on:

1) the overall percent change inflation-adjusted income of women in the workforce for each year,
2) average job prestige of women-held occupations per year,
3) the percent change in support of women in the labor force and affirmative action measures from all respondents, and
4) the percent change of job satisfaction for female respondents in the workforce

on the percent of women in the workforce. These are the five major variables upon which we focus.

In adjusting the scope and expectations about the project, we kept the same variables: inflation-adjusted income, support for women in the workforce, occupational prestige, and job satisfaction. Because the overall intent of the project would be unchanged, the same components of the original project would remain relevant. However, interpretations of the variables were adjusted to fit in the context of the overall female participation in the workforce. Whereas before we sought to track the changes in job prestige of computer occupations, now we wanted to see how the average job prestige of women has changed over the years. Income and job satisfaction changed only in the scope of the sample, and support for women remained the same.

DATASET

The historical data was collected from the General Social Survey (GSS), conducted by the US Census Bureau beginning in 1972. The GSS is a 90-minute in-person interview that uses a full-probability, representative sampling of the English-speaking US adult population and geographical distribution. Using the GSS Data Explorer, the data was exported.[5]

Briefly, some quick facts about the dataset:

- The total number of respondents for all years of data: 58,599
    - On average, there are about 1,923 respondents per year
    - About 55.9% of respondents were female (33,313 people)
    - About 44.1% of respondents were male (26,286 people)
- About 72% of the men surveyed participated in the workforce, while only 53% of the women surveyed were workforce participants

Because the variables were of all types and scales, for the purposes of analysis we converted the four major variables into percent change from the previous year. For answers to questions about job satisfaction and support for women, the responses were bucketed into two categories for analysis: positive and negative responses. Neutral responses were not considered.

[5] https://gssdataexplorer.norc.org/

Table 1: All the variables that were used in our project is included above, along with their descriptions presented in an easily digestible table, in comparison to traditional paragraph formatting. Notes about missing years, how non-numerical data was categorized, and other relevant information was included.

	DATA TYPE	DATA SCALE	DESCRIPTION
year	discrete	1972-2014	missing for 1974, 1979, 1981, 1992, 2001, 2003, 2005, 2007, 2009, 2011, 2013
gender	binary	female, male	
job category	nominal	n/a	job categories expand in 1980 and 2010
real income	continuous	\$0 - \$500,000	adjusted for inflation; examined for those that had income > \$0; USD
	DATA TYPE	**DATA SCALE**	**DESCRIPTION**
prestige score	discrete	0-97	developed by Robert W. Hodge, Paul S. Siegel, and Peter H. Rossi; a standardized, subjective aggregate score of occupations based on relative social standing; *average job prestige for a given year=* $\frac{\sum(\text{prestige score of gender for year}, Y)}{\text{number of that gender in the workforce in year}, Y}$
"On the whole, how satisfied are you with the work you do?"	ordinal	very satisfied, mod. satisfied, a little dissatisfied, very dissatisfied; don't know, no answer, n/a	respondent's perception of current job satisfaction; very satisfied and moderately satisfied will be in bucket 'satisfied,' little dissatisfied and very dissatisfied will be in bucket 'dissatisfied,' and no answer, n/a and don't know will be not included *% satisfied, for a given year=* $\frac{\sum(\text{Very Satisfied} \mid \text{Moderately Satisfied})}{\sum(\text{Very Satisfied} \mid \text{Moderately Satisfied}) + (\text{Very Dissatisfied} \mid \text{Moderately Dissatisfied})}$
"Do you approve or disapprove of a married woman earning money in business or industry if she has a husband capable of supporting her?"	binary	approve, disapprove	in GSS 1970-1980; this question was discontinued after 1980; will be analyzed as a percentage of all respondents and women $\% \text{ support} = \frac{\sum \text{Approve}}{\sum \text{Approve+Disapprove}} * 100$
"Because of past discrimination, employers should make special efforts to hire and promote qualified women."	ordinal	strongly agree, agree, neither, disagree, strongly disagree	in GSS 1980-2014; this question first appeared in 1980; strongly agree and agree will be in bucket approve,' disagree and strongly disagree will be in 'disapprove' and neither will be neutral; buckets will be analyzed as percent of both men and women in all fields in conjunction with the approval and disapproval rates in previous question *% support for a given year =* : $\frac{\sum(\text{StronglyAgree} \mid \text{Agree})}{\sum(\text{StronglyAgree} \mid \text{Agree}) + (\text{StronglyDisagree} \mid \text{Disagree})} * 100$

Figure 1: The years for which the chosen GSS variables span, demonstrating the comprehensive coverage of years and showing when variables of support for women and prestige were updated and which year.

One assumption initially made about the data, was that the two questions regarding support of women as economic agents were grouped as one variable; the previous question was discontinued after 1998 seemingly due to the outdated phrasing, and a new question about affirmative action for women in the workplace was implemented. Although the two questions were separate, we initially felt they could be subsumed under the topic of public sentiment of women in the workforce. However, upon examining the graph of the two questions plotted over the four decades (shown below) it was decidedly unwise to have the two questions represent one variable. Therefore in analyzing support for women as economic agents, we limited the scope to the years for which the first question was extant.

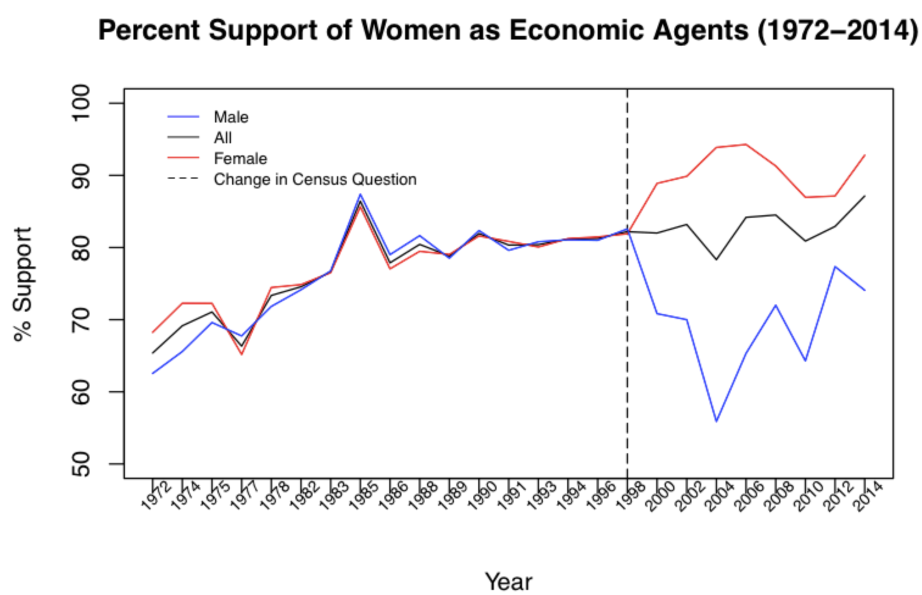
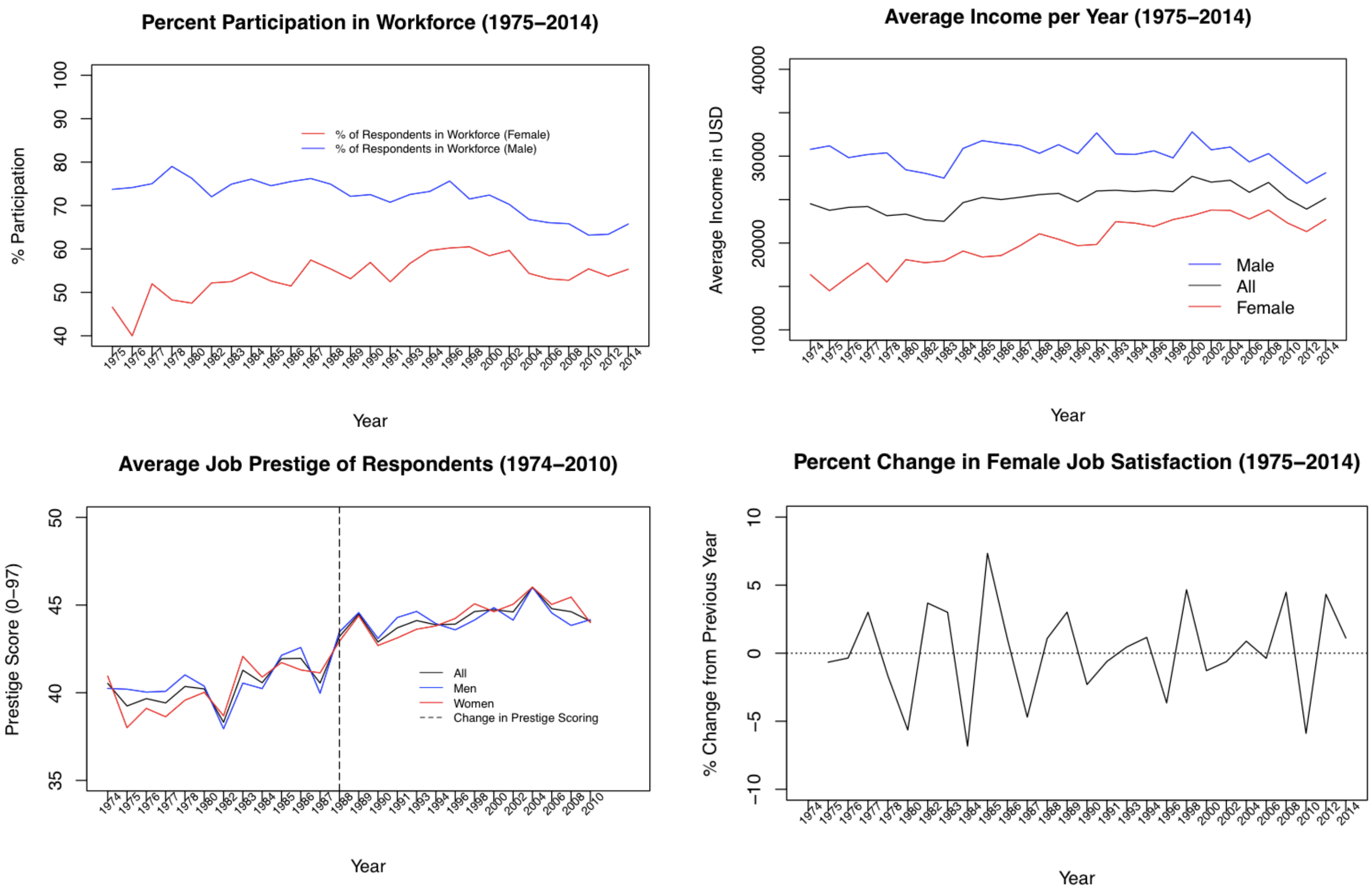


Figure 2: Time-series plot of the variable, Support for Women as Economic Agents, demonstrating that the two questions cannot be subsumed under one topic because they are decidedly too dissimilar

Figure 3.1-3.4: The following four visualizations are the other major variables we examined, and are included here for the reader for preliminary visual analysis. Below are the variables for participation in labor force for men and women, and the average inflation-adjusted income per year by gender and all, average job prestige per year with the change marked for the updated prestige scales, and the percent change in female job satisfaction.



MODEL

Originally, the model of analysis included linear regression, correlational analysis and ARIMA forecasting. However, taking advantage of the fact that the dataset is a time series we expanded our analytical model to include causational analysis – specifically Granger Causation – and shifted focus away from simple linear regression because seeing how the variables interact with each other over time is more relevant than analyzing general time trends of the variables. The motivation for this addition is two-fold: 1) correlation could not explain potential causes of change in female participation – a crucial component of the specified research goal, and 2) the correlation analyses resulted in few significant relationships and none of the correlational values exceeded |0.50|. This being the case, Granger Causation was able to provide a better avenue for meaningful analysis. Given that Granger Causation assumes that one variable contains exclusive information that would explain another variable, we chose to use Granger Causation as an exploratory tool to compare the outcome of variables that seemed likely to have a significant outcome. Originally we analyzed the variables with number of women in the workforce for Granger Causation, however the results were not significant so we moved on to analyze Granger Causation for those variables among themselves in exploration but only pairs that would make sense. For example, we assumed that one's job satisfaction was unrelated to the public support of women as economic agents so Granger Causation was not used on that combination of variables. And for the pairs of variables that we did run Granger Causation on, they seemed more possibly causally related. One of the pitfalls in selecting Granger Causation for our model given this assumption about unique knowledge is that there is no empirical evidence yet to suggest that any one of the variables we chose contains unique information about the other, and so we limit our Granger analysis to an exploratory manner.

The final model of analysis thus comprised of three components: Pearson Product-Moment Correlation, Granger Causation, and ARIMA Forecasts.

In general, the main focus was to have the percent change of participation of women in the work force correlated and analyzed for causation against income, job satisfaction, support for women as economic agents, and occupational prestige. In addition to this, we carried out the same methods for selected relationships of the four variables against each other to further examine the data set in the hopes of finding more significant results. ARIMA forecasting was conducted on the percent participation of men and women in the workforce and percent change in income, using the last five data points and looking five data points into the future. Forecasting future job satisfaction and support for women seemed less relevant to the focus of the research. Some assumptions of our model include that the ARIMA forecasting was that most recent data was going provide for more accurate results; eliminating neutral answers from the total number of respondents would not negatively impact the integrity of the data for that variable; and that in choosing the variables used in this research that they would fully encompass the general public opinion about women as economic agents.

RESULTS

PEARSON PRODUCT-MOMENT CORRELATION

The following table shows the variables for which their correlations were significant:

Variables (X,Y)	Correlation Coefficient	p-value (in order of decreasing significance)
Workforce Part., Support for Women	R = -0.4951612	p = 0.01629
Workforce Part., Job Prestige (W)	R = -0.4458283	p = 0.02551
Support for Women, Income (W)	R = 0.429088	p = 0.04629
Support for Women, Job Prestige (W)	R = 0.3988611	p = 0.07328

(W) indicates subset of data consisting of women in the workforce

Support for Women = Overall Public Support for Women as Economic Agents

Workforce Part. = Participation in Workforce (W)

Table 3: Given that the data was a time series analysis where time is inevitably one of the variables in question, the line graph for correlations is not as efficient as a table representation, where you can easily gather which variables were significant and to what degree (p-value). Had time not been a variable, a plot of the two variables against each other would have sufficed.

These significant correlations demonstrate the weak relationship of variables and are meaningful only in the context of looking at two data points in a given instantaneous moment. To aid the preliminary understanding of the data, correlations provided an idea of what direction the correlated variables provided. But given their weak significance, we examined the interaction of data points over a given range of time in Granger Causation. The figure below visualizes our strongest correlation. The inverse relationship between these two variables can be observed here by visual inspection.

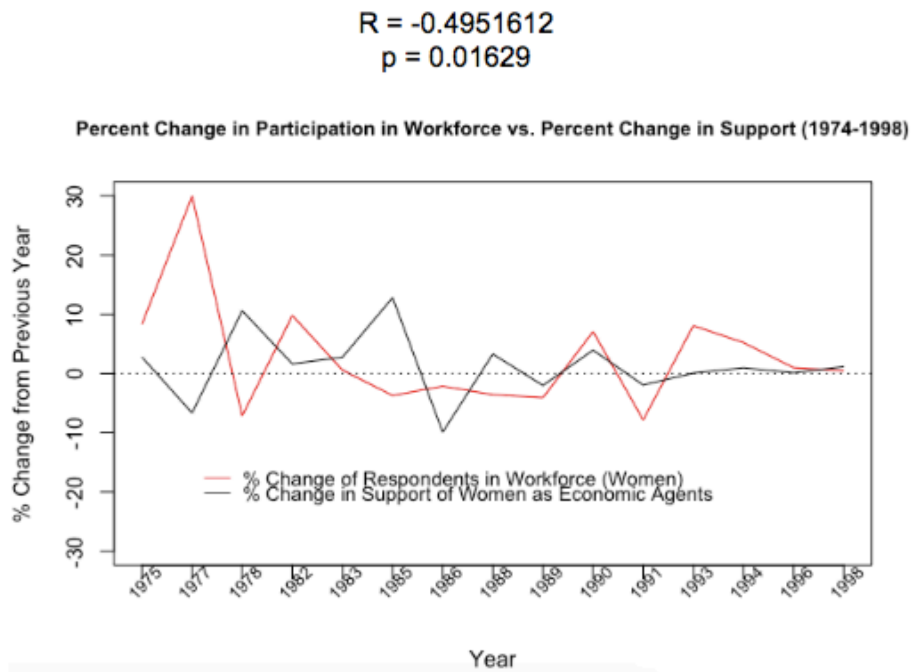


Figure 4: This graph visualizes the most negative correlation result -- between percent change of women in the workforce and percent change in support of women as economic agents. The correlation coefficient (R) and p-value are shown at the top. Since the two variables were time-series, line graphs were chosen to represent them.

GRANGER CAUSATION

The following table shows the variables for which their causations were significant:

Granger Causality	F-value	p-value (in order of decreasing significance)
Workforce Part. (W) ➡ Income (W)	F = 11.718	p = 0.002555
Income (W) ➡ Support for Women	F = 9.2287	p = 0.006497
Support for Women ➡ Job Prestige (W)	F = 6.9516	p = 0.01582
Job Satisfaction (W) ➡ Support for Women	F = 4.4501	p = 0.0477
Support for Women ➡ Workforce Part. (W)	F = 3.2309	p = 0.08738

➡ indicates Granger causality
ex. Time Series X ➡ (Granger causes) Time Series Y

(W) indicates subset of data consisting of women in the workforce

Support for Women = Overall Public Support for Women as Economic Agents

Workforce Part. = Participation in Workforce (W)

Table 4: Given that the data was a time series analysis, plotting a stacked line graph for causations was less efficient than a table, as it does not exploit Tufte's ink to data ratio.

Given that we used Granger causation in an exploratory manner, we were mindful when interpreting our results that third party confounding variables could be causing it to seem as though a Granger causation relationship exists between two variables when it does not. Using intuition based on conventional expectations in economics helped us to further evaluate the significant findings of our Granger causation model.

1. Change in female labor participation causes change in female income.

Conventionally economists conceive of income as a predictor of change in labor participation, given that income and substitution effects are known and well-documented principles. However, our causational results show participation affecting change in income for women. Because this goes against the grain of economic principle, we assume that parallel changes in labor participation and income are generated by some unaccounted for third variable, such as industry shifts, increased educational attainment or otherwise.[6] The figure below illustrates this relationship between the two time series.

Female Workforce Participation is Predictive of Female Average Income

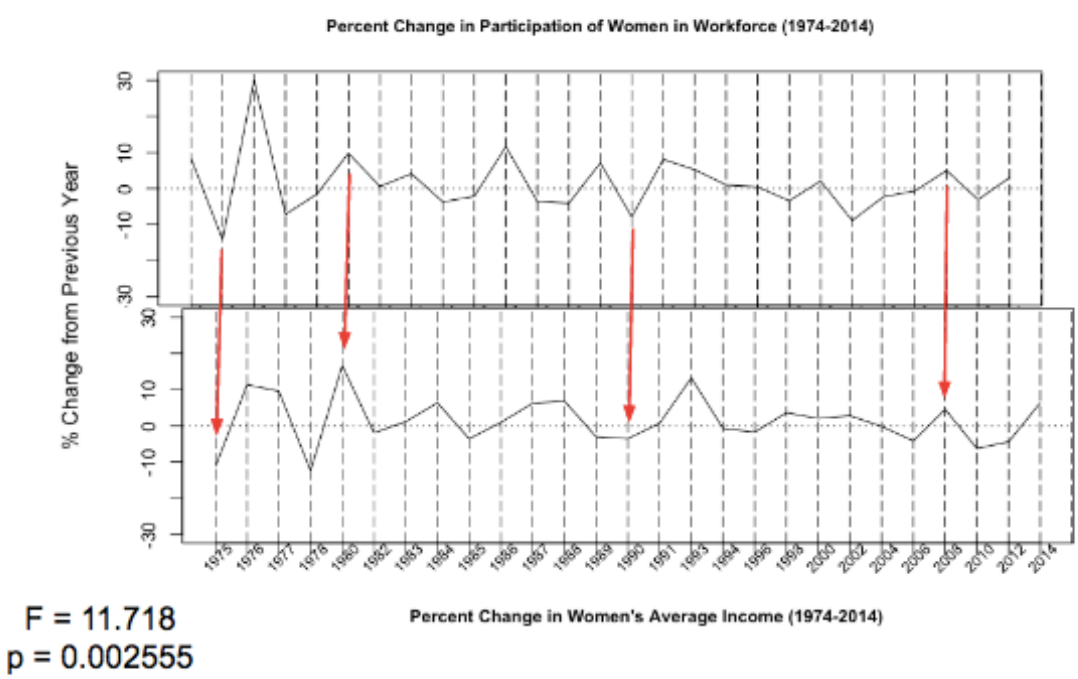


Figure 5: This figure shows our most significant Granger causation result that visually illustrates our model for causation analysis with the results f- and p-value. The time series of Percent Change in Participation of Women in the Workforce is shown to be predictive of the time series of Percent Change in Women's Average Income with a lag of 1 year. The stacked graphs are lined up to match corresponding years since percent participation ranged from 1974-2012 and percent change in income ranged from 1975-2014.

[6] Jacobs, Elisabeth. 2015. "The Declining Labor Force Participation Rate: Causes, Consequences and the Path Forward." http://equitablegrowth.org/research-analysis/declining-labor-force-participation-rate-causes-consequences-path-forward/.

2. Change in both overall and female support for female economic agents causes changes in female labor participation.

Conversely, when there is less support for women as economic agents there are less female participants in the labor force. The common sense explanation for this trend is that when there is a welcoming expectation for women to generate income, more women are going to fulfill that expectation. Translating this as an idea with concrete policy implications, Jacobs writes that, "the absence of family-friendly policies in the United States is a key reason for the decline in the overall labor force participation rate and the stalling out of women's labor force participation."[7] Our causational results show that with more support for women and potentially family-friendly policies, more women will participate in the workforce.

3. Change in female income causes change in support for female economic agents.

This result indicates that income is predictive of support for women, necessarily rejecting that increased support causes increases in female income. Although vague, this important point in conjunction with the idea that increased support causes increased female labor participation may help to explain the persisting wage gap. If increased support causes increased participation from women, yet does not cause increased income of women this shows that in a given year even if more women are working, they are not necessarily making more money.

4. Change in female job satisfaction causes change in support for female economic agents.

Job satisfaction is a broad term that can reflect having a meaningful occupation or even just the agency to shape their work experience.[8] And because satisfaction is a predictor of support for women, it necessarily rejects the idea that support is a predictor for satisfaction. Similar to support of women in the work force and income, support has no significant bearing on women's job satisfaction. This may indicate the inelastic behavior of female job satisfaction with regard to public opinion of women as economic agents.

5. Change in support for female economic agents causes change in female job prestige.

When we see more support for women in the workforce, we see women having jobs with greater prestige. Similar to increased support giving way to increased labor participation, a welcoming attitude towards women overall encourages women to not only take jobs, but take jobs that are seen to have greater socioeconomic reward.

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7 Ibid.

8 http://www.apa.org/monitor/2013/12/job-satisfaction.aspx

ARIMA FORECAST

The following table shows the forecast of labor participation and percent change in average income for both men and women from 2016 – 2024 based on data from 2006 – 2014:

	2016	2018	2020	2022	2024
Participation in Workforce (W)	56.9%	58.6%	60.2%	61.8%	63.4%
Participation in Workforce (M)	68.1%	70.4%	72.8%	75.1%	77.4%
Percent Change in Average Income (W)	17.2%	28.0%	38.8%	49.6%	60.4%
Percent Change in Average Income (M)	14.8%	25.2%	35.5%	45.9%	56.2%

percent values have been rounded to 1 decimal place

Table 5: This table efficiently presents the results of the forecast, broken down by male and female respondents for the next ten years of forecasted data (in two year intervals). While the table more efficiently conveys the actual prediction, the graphical plots provide a visualization of the confidence intervals.

ARIMA forecasting was conducted on the five most recent data points, looking ahead to the next five data points. There are two years between each data point, thus the forecast was conducted on the last ten years for the next ten years. Because the confidence intervals for both forecasts were large and the forecast was performed only on recent trends, the results may reflect the limited information provided by these circumstances.

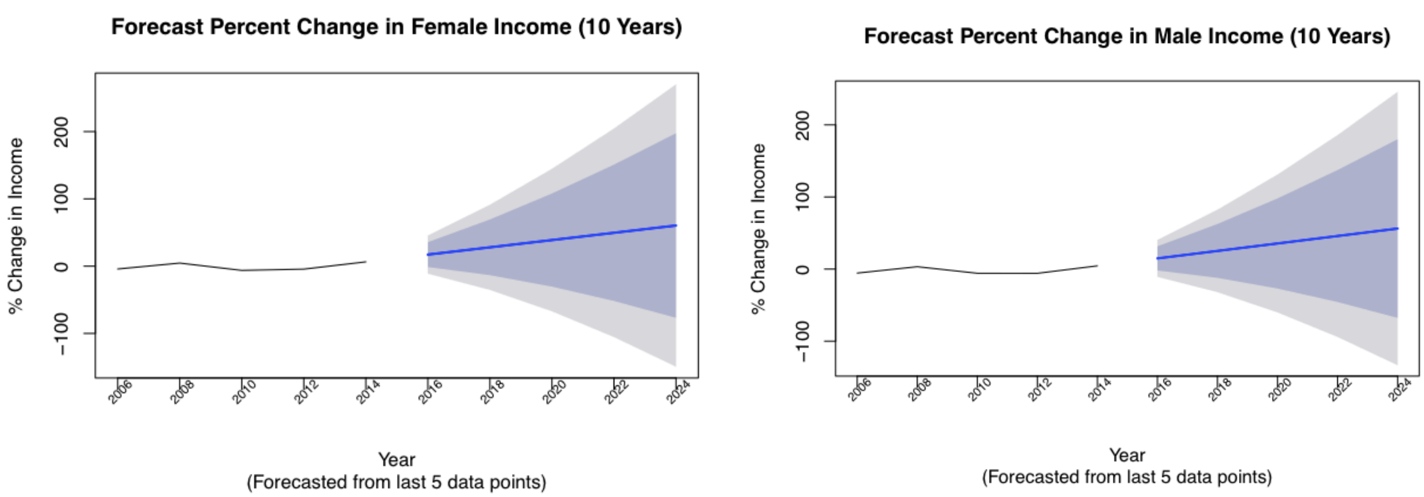
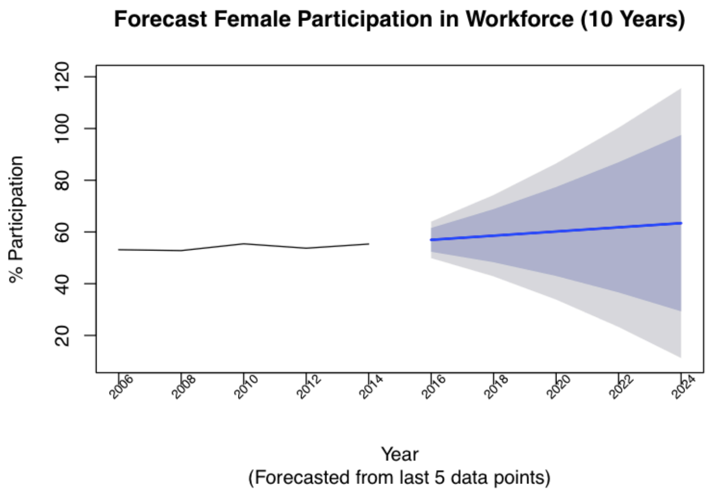


Figure 4.1-4.2: These two graphs indicate the last five data points and the forecasted next five data points, along with the 85% confidence interval (darker grey) and the 90% confidence interval (lighter grey) for percent change in income for females and males. Both genders are expected to have an increase in percent change in average income, with females having a slightly steeper increase.



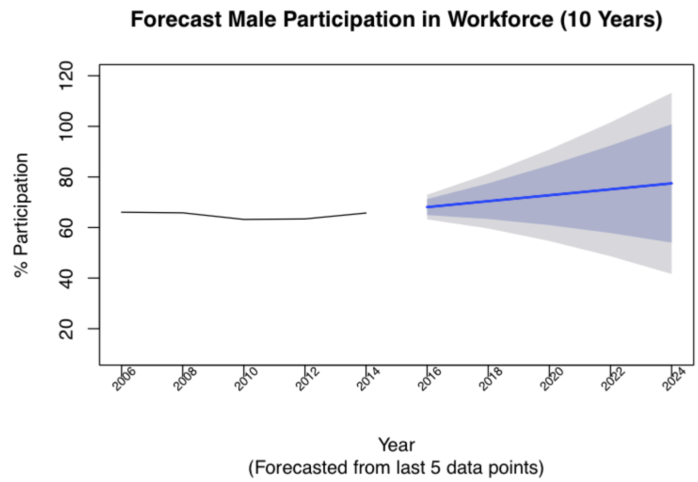


Figure 4.3-4.4: These two graphs indicate the last five data points and the forecasted next five data points, along with the 85% confidence interval (darker grey) and the 90% confidence interval (lighter grey) for percent participation for females and males. The confidence interval for males is narrower than females, indicating a smaller range of possible forecasted values. Although subtle, both females and males are projected to have an increased in labor participation.

EVALUATION

Adding Granger Causation into our analysis model had implications for the evaluation method. Previously, the model only included correlational analysis and ARIMA forecasting and the evaluations were based on AIC for the optimal model, and r- and p-values for correlational strength and statistical significance respectively. But with Granger Causation the Augmented Dickey-Fuller (ADF) test for stationarity, F-values and causational p-values were also included. The table below shows our significant causation and correlation results by error threshold. Evaluation of our correlational model early in the analysis prompted the addition of Granger causation testing on our variables because the significance of our correlations were not very strong as none of the resulting correlation coefficients were greater or less than .5. Our Granger causation testing resulted in significant results at a lower error threshold ($p < 0.01$).

And with our correlational tests, all the r-values were relatively weak, so using causation as an exploratory tool became crucial to the validity of our model. Additionally, prior to performing Granger causality, we used the ADF test for stationarity. Because we had already mapped all of our variables to percent change, linear trend had been eliminated. The ADF test also showed no seasonality for our time series. In performing the Granger causality tests, we selected a lag order of 1 to look for possible Granger causations with a lag of one year. Results of the *varSelect* function from the *vars* package, suggesting an optimal lag order by minimizing four indicators of model fit (the AIC, the Hannan-Quinn information criterion, the Schwarz criterion and the Final Prediction Error) supported this choice. Because of the limitations of our exploratory use of Granger causation, we also relied on intuition about economic expectations to further evaluate whether our significant Granger causation relationships were plausible. In our ARIMA forecasting, we used the *auto.arima* function from the forecast package that also optimized the best-fit model based on minimizing the AIC value.

And beyond the evaluation model, some confounders still exist. For example, the lack of empirical evidence to suggest strict Granger causality presents room for further research on each of the variables individually and how they may relate to one other. In addition, when given two significant p-values for both scenarios in which X may cause Y or Y may cause X we chose the relationship that had a smaller p-value. In theory, this method of evaluation may bring to light some intrinsic challenges brought by using Granger Causation if this dubious outcome is possible. Further, while the variables chosen from the list of all variables included in the GSS there is yet to be an empirical method through which the variables are related with certainty. Gathering information from background research in conjunction with common sense elimination, these variables were chosen. However, if different variables or even segmentation of the variables were utilized more specific results may be captured. Specifically, the state of the economy might be acting as a counfounding variable in our analysis, causing the relationships between our variables.

p-value thresholds	**Correlation (X,Y)**	**Causation X ➡ Y**
p < .01		• Workforce Part. (W) ➡ Income (W) • Income (W) ➡ Support for Women
p < .05	• Workforce Part., Support for Women • Workforce Part., Job Prestige (W) • Support for Women, Income (W)	• Support for Women ➡ Job Prestige (W) • Job Satisfaction (W) ➡ Support for Women
p < .10	• Support for Women, Job Prestige (W)	• Support for Women ➡ Workforce Part. (W)

➡ indicates Granger causality
ex. Time Series X ➡ (Granger causes) Time Series Y

(W) indicates subset of data consisting of women in the workforce

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Table 6: This table summarizes the significant evaluation results of our model, ordered by increasing p-value thresholds for both correlation and causation tests, with a key explaining abbreviations as well.

CONCLUSIONS AND FURTHER RESEARCH

FEMALE OCCUPATIONAL PRESTIGE

Bose and Rossi write that gender components only contribute about 2% points to changes in job prestige, and that job prestige is instead more responsive to education and job demand than gender factors.[9] Contrary to this research however, our causational results provide that support for women in the workplace is a predictor of job prestige. Further study on public sentiment and equality in the workplace should be conducted to provide for more nuanced discussion on the topic.

[9] Bose, Christine E. and Peter H. Rossi. 1983. https://www.jstor.org/stable/2095225?seq=14#page_scan_tab_contents.

FEMALE LABOR PARTICIPATION

Examining the U-shape curve of labor participation by females in a given population, Goldin postulates that changes in the macroeconomic structure of a developing country provide for different shifts in labor participation. For example when educational attainment is limited and the occupations are restricted to male-dominated, labor-intensive professions, when income increases labor participation decreases due to the income effect.[10] In relation to our research, we did not control for macroeconomic factors such as industrialization or major shifts in US macroeconomic structure (ie. Dot-com bubble, the Great Recession) and in future research this could be incorporated to provide for a more illustrative trajectory of women's participation in labor as dependent on major political economy events.

THE INCOME GAP

In an attempt to address the income gap, our research showed that increased female labor participation was a good predictor of increased income for women, indicating that other factors such as educational attainment or increased participation in new industries could be the root cause. For example, increased participation by women in lucrative fields such as technology could be a means of increasing overall female income. Abbate writes, "No women were included among the 'experts' and 'prominent leaders in the field' who were invited to the [1968] Garmisch conference. Especially striking is Grace Murray Hopper's absence…engineering was (and remains) a highly masculine field in the United States and the United Kingdom."[11] Analyzing the prohibitive measures by which women are excluded from various higher paying jobs could be a possible avenue for further exploring the results we obtained for increased female labor participation and income.

TIME SEGMENTATION

While our analysis of the variables' interactions over the length of the time series provided some insights about the relationships between the variables, a different approach focused on segmenting the time series into centuries or decades might provide interesting historical insights about the interactions of these variables over shorter time periods. Our assumption was that while social attitudes would vary over time, the nature of the relationships between these social attitudes and labor force participation by women would be consistent. For example, while we expected waxing and waning support for women in the workforce over time with a general upward trend over the decades, we assumed that if a relationship existed between support for women in the workforce and labor force participation, it would best be measured over the entire length of the time series. One advantage of this approach is that more data points make our analysis of these relationships more robust. Further, as we undertook our analysis, particularly using the Granger causation model, we became focused on identifying predictors that might be used to indicate improvements in the future position of women in the workforce. Further studies could explore the alternate approach that differing social attitudes could have a stronger bearing on labor force participation by women in different decades or centuries.

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[10] Goldin, Claudia. 1994. "The U-Shaped Female Labor Force Function in Economic Development and Economic History." https://core.ac.uk/download/pdf/6402926.pdf.

[11] Abbate, Janet. 2012. "History of Computing : Recoding Gender : Women's Changing Participation in Computing."

STEP-WISE REGRESSION

One potential model alternative, the time-step regression is an attractive option for modeling future data. Using step-wise regression would have allowed us to include more than the four variables that we choose for our model. The step-wise regression model would be ideal for finding all variables from the entire GSS that are directly correlated (instead of assuming that the ones chosen would be the most directly related) to the number of women in the workplace. Variables such as education level, marriages rates across the United States and number of children in the household would be considered for such future research. Step-wise regression in which we isolate only those variables that are correlated is also a good fit for the exploratory manner in which we looked for indicators that are correlated with women's position in the workplace.