Speaking for Herself: Changing Gender Roles in Survey Response

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Speaking for Herself: Changing Gender Roles in Survey Response

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Abstract

Among married and cohabiting couples, the percentage of female respondents has increased substantially in the PSID (Panel Study of Income Dynamics) from 9% in 1968 to 60% in 2015. This shift in gender composition has taken place despite a formal policy that historically designated male heads of household as respondents. We use this shift as a case study to explore which characteristics are associated with women responding to the PSID and how different respondent gender compositions may affect data quality. First, we find that women are increasingly less likely to respond as their husband’s income increases or if their husband is highly educated. Women are more likely to respond if they are more educated than their husband. Second, we find that male respondents tend to report incomes about $5,000 higher than female respondents. Had the gender composition of respondents been closer to 50/50, average household income would have been reduced by as much as $2,500. Our research provides important insights into the quality of survey data and the changing role of women in households.
I. INTRODUCTION

Surveys often rely on a single respondent to provide information about their entire households. In the past, this person was labeled the head of household and was typically the male in heterosexual married or cohabiting couples. While some surveys such as the Census discontinued their use of the head of household designation several decades ago, the University of Michigan’s Panel Study of Income Dynamics (PSID) continues to use it. Despite the continued use of this terminology, there has been a large increase in female respondents over the history of the PSID. As Graph 1 shows, men were 91% of PSID respondents in 1968, but the gender composition of respondents was evenly split in 1992. By 2015, the gender composition reversed to women serving as the majority of respondents. This suggests that the policy of targeting male head of households as respondents may have been relaxed over time, though there was no explicit change in survey procedures.

Graph 1: Respondents by Gender for Married/Cohabiting Couples

Source: PSID, Authors’ calculations
We use this shift in the gender composition of respondents as a case study to explore two issues. First, we examine what factors are associated with women responding to surveys over time, particularly when there has not been an overt policy change by the surveyors, and after accounting for year-specific characteristics. We find that women who are married to men with higher educational attainment are less likely to respond to the survey, but women who are more educated than their husbands are more likely to respond. We also find that as male labor incomes increase, women are less likely to respond.

We provide two analyses of income, a common focus of research with the PSID, to show how results may be affected by differing respondent gender compositions. If there are any differences in the way men and women report information about their household, these differences may affect research using historic PSID data. We find that there are significant differences in reported household and labor income depending on the gender of the respondent. Specifically, for a given year, male respondents report household incomes of about $5,000 higher on average than female respondents. Performing a simple counterfactual exercise, we find that if a balanced gender composition had been implemented in earlier years, average household incomes may have differed by as much as $3,200 in each year. These results suggest that an imbalance in respondent gender composition could affect data quality.

Our paper is one of the first to study the increase of female respondents within the PSID and how that relates to income and education\(^1\). Our results have two key implications. For researchers, our results show that respondent gender should be accounted for in empirical analysis to produce more accurate estimates. For survey designers, our work demonstrates why surveys need to have a balanced respondent gender composition.

\(^1\) Lee and Lee (2012) also document a shift in the respondent composition, but focus on the gender earnings gap.
This paper is organized as follows. Section II will provide background information. Section III describes our econometric model. Section IV explores the results of the model. Section V describes two exercises we use to explore the potential impact of skewed gender composition of respondents on the analysis of income. Section VI concludes.

II. BACKGROUND

A. Head of Household and historical Context

The head of household is a common concept in survey design. United States Census Bureau (Census) surveys, like the Current Population Survey (CPS), and the University of Michigan’s PSID are examples of surveys that used the head of household designation. The PSID, for example, explicitly instructed its interviewers to substitute another respondent for the head of household only if they would otherwise lose the interview, resulting in over 90 percent of interviews being taken with the male head of household (Morgan and Smith 1969). If a household chose to report a married woman as the head of household in Census surveys, the Census Bureau would edit the response in order to record the husband as the head of household (Presser 1998). These examples demonstrate the seriousness with which major surveys sought out male head of household respondents.

Surveys like the CPS and PSID have existed since the mid-1900s, but household dynamics have changed drastically over time as women gained more legal protections, educational attainment, and opportunities in the workplace. Since the 1960s, women’s rights have been solidified by new laws and regulations. Some increased women’s reproductive control, enabling them to decide when to have children. For example, the birth control pill was approved for contraceptive use by the U.S. Food and Drug Administration in 1960, and the Roe v. Wade Supreme Court decision legalized abortion in 1973. Other laws improved conditions for
women in the workplace. The Equal Pay Act of 1963 required men and women to be paid equally for equal work in the same establishment, while the Equal Opportunity Act of 1972 gave the Equal Employment Opportunity Commission the authority to bring lawsuits to federal courts for employment discrimination based on sex. Finally, new laws protected women from domestic abuse and sexual assault. The Violence Against Women Act of 1994 allocated greater funds toward the investigation and prosecution of domestic violence and sexual assault cases. These legal and regulatory changes gave women greater decision-making power in the household and workplace.

Simultaneously, women’s daily lives were changing. Women began participating more in the labor force. The average labor force participation for women was 32.7% in 1948, but peaked at 60% in 1999 before settling at 57% in 2017 (FRED/BLS). While women would continue to make less than men, their earnings were on a steady upward trajectory (Graph 2). Women were becoming more educated and even surpassing men in educational attainment. From 1940 to 2017, the share of college educated women increased by over 30 percentage points and, beginning in 2007, more women had a bachelor’s degree than men (Graph 3). These lifestyle changes have resulted in greater financial independence for women, potentially influencing their decision-making power in the household.
Graph 2: Median Usual Weekly Earnings by Gender

Source: BLS, Haver Analytics
Note: Data not available before 1970

Graph 3: Bachelor Degree Attainment by Gender (As Percent of Total)

Source: Census Bureau, Haver Analytics
In this changing environment, the use of the head of household designation was potentially problematic. It assumed that the male head of household was responsible for household decisions, rather than allowing the household to report their own family structure. The head of household designation may have affected data quality because women were not seen as primary providers. This could, for example, result in an undercount of women’s earnings and labor force participation. At its most extreme, the head of household designation had the potential to ignore, discount, or misrepresent the characteristics of half of the married population. As a result, the Census discontinued its use of the head of household terminology, but the PSID has chosen to continue its use for data continuity. Despite this continuation in policy, there has been an increase in women respondents in the PSID. This may be, in part, due to concurrent social changes.

B. Related Literature

Quality of Survey Data on Women

We are not the first to draw attention to issues about women and household survey data. These issues often exist due to social norms, survey design, or a whole host of other reasons and are most pronounced in developing countries. A United Nations Foundation initiative, Data2X, has been started to explicitly combat this issue. Data2X argues that unbiased data on women is needed in order to diagnose the size and nature of disadvantages, identify underlying causes of disadvantages, measure consequences, and design effective policy. However, such data is often unavailable due to lack of resources or gendered assumptions about the head of households. Women are consequently underrepresented.

The U.S., however, has not been immune from these issues. Previous work has shown that the head of household concept led to incomplete or biased data on women. In particular,
Folbre and Abel (1989) argue that the Census undercounted female-lead households by designating a male in the household as the “family head”, even if the selected man simply owned property in which a woman lived. This discounted a surge of female boarders who supported themselves and lived independently of men – approximately 14% of working women. Presser (1998) documents the dismantling of the head of household concept by a group of female social scientists. The terminology was successfully removed from the Census in 1980, but continues to be used in Census publications and many other household surveys.

Who Responds Matters

Some work has also been done to document how data can be affected by who responds to surveys. Moore (1988) reviews the literature on proxy bias and finds the evidence of such bias is still fairly mixed. The author also highlights papers that show differences in how husbands and wives perceive purchasing decisions, economic characteristics, and other shared experiences. More recent literature has focused on the healthcare industry. For example, Kelfve et al (2013) show that proxy respondents tend to be older, less-educated, and female more often than self-respondents. Beyond proxy bias, Murray-Close and Hegness (2018) explore how gendered social norms influence survey response. By matching CPS data to income-tax records, the authors find that “nontraditional” couples (in which the wife earns more than the husband) tend to inflate the earnings of husbands and deflate the earnings of wives, regardless of which spouse is answering the survey.

C. Data

Structure

The PSID is a national panel dataset collected through the University of Michigan. It provides data on individuals and their descendants from 1968 to present. The survey covers
many topics such as demographics, health, income, wealth, and employment. The data are available annually from 1968-1997 and biennially from 1999-present. PSID data have been widely used by researchers across the social sciences and several thousand papers have been published that have been based on the dataset.

One of the main advantages of the PSID is its self-replacing design. Families surveyed in 1968 are followed for as long as possible. New individuals may be added to the PSID through births, adoptions, and marriages to the original PSID family members. Additionally, an immigrant refresher sample was added to the PSID in 1997 to represent changing demographics in the U.S. This survey design provides rich information on individuals over their life cycle as well as multigenerational family dynamics.

**Terminology**

For the majority of the PSID, the term “head” has been applied to the male and the term “wife” applied to the female in the case of heterosexual married/cohabiting couples. This terminology was adopted from the Census Bureau when the PSID first began in 1968. Starting in 2015, the female within a couple is now referred to as the “spouse/partner” but the term “head” continues to refer to the male. Within the PSID, one person serves as the sole respondent for their entire household. As mentioned above, the head (or in other words, the man) was initially targeted to be this sole respondent.

Despite the initial policy of targeting the male, we observe more females serving as respondents over our sample period. We need to examine the differences between households by respondent gender to understand whether the changing respondent gender composition is due to an external trend or an increase in the types of households that are likely to have female

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2In the case of households with a single adult, the term “head” can be applied to either sex.
respondents. Ironically, the “head” terminology limits us somewhat to do this because the “wife” variables are not as consistently available across the PSID. For example, we have no information about the wife’s race until 1985; information on the wife’s education is not available for the first few years of the PSID. Specific information about female data availability is given in Table 1 (Panel C).

Summary Statistics

For our selected sample, we only include married/cohabiting couples. We do not include the years 1976 or 1985 because the PSID required self-response for both men and women in these years. Additionally, we drop “NA” or “unknown” values and drop any households with negative income. Our total sample yields 15,738 households with 139,288 observations, for about 3,500 households each year.

The summary statistics of our sample are presented in Table 1 in three panels: Panel A presents household characteristics, and Panels B and C present male and female characteristics, respectively. Each panel shows how male and female respondents differ compared to all respondents combined. As mentioned above, Panel C includes an additional column on data availability.

Table 1: Average Characteristics of Sample

Panel A: Household Characteristics

<table>
<thead>
<tr>
<th></th>
<th>All Respondents</th>
<th>Male Respondents</th>
<th>Female Respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Kids</td>
<td>1.3</td>
<td>1.2</td>
<td>1.3</td>
</tr>
<tr>
<td>Owns Home</td>
<td>70.4%</td>
<td>71.7%</td>
<td>68.2%</td>
</tr>
<tr>
<td>Region</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Northeast</td>
<td>15.9%</td>
<td>17.4%</td>
<td>13.5%</td>
</tr>
<tr>
<td>North Central</td>
<td>24.5%</td>
<td>26.6%</td>
<td>21.2%</td>
</tr>
<tr>
<td>South</td>
<td>41.8%</td>
<td>38.3%</td>
<td>47.5%</td>
</tr>
<tr>
<td>West</td>
<td>17.5%</td>
<td>17.5%</td>
<td>17.6%</td>
</tr>
<tr>
<td>Alaska/Hawaii</td>
<td>0.2%</td>
<td>0.3%</td>
<td>0.1%</td>
</tr>
</tbody>
</table>
### Panel B: Male Characteristics

<table>
<thead>
<tr>
<th></th>
<th>All Respondents</th>
<th>Male Respondents</th>
<th>Female Respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>43.3</td>
<td>43.4</td>
<td>43.1</td>
</tr>
<tr>
<td>Labor Income</td>
<td>$22,705</td>
<td>$35,986</td>
<td>$22,004</td>
</tr>
<tr>
<td>Annual Hrs Worked</td>
<td>2,142</td>
<td>2,137</td>
<td>2,151</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>70.1%</td>
<td>74.4%</td>
<td>63.2%</td>
</tr>
<tr>
<td>Black</td>
<td>23.7%</td>
<td>20.7%</td>
<td>28.7%</td>
</tr>
<tr>
<td>Hispanic</td>
<td>4.4%</td>
<td>3.3%</td>
<td>6.0%</td>
</tr>
<tr>
<td>Other</td>
<td>1.8%</td>
<td>1.6%</td>
<td>2.1%</td>
</tr>
<tr>
<td>Employment status</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed</td>
<td>80.7%</td>
<td>81.1%</td>
<td>80.1%</td>
</tr>
<tr>
<td>Unemployed</td>
<td>3.6%</td>
<td>3.1%</td>
<td>4.4%</td>
</tr>
<tr>
<td>Not in Labor Force</td>
<td>15.7%</td>
<td>15.7%</td>
<td>15.5%</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; High School</td>
<td>27.0%</td>
<td>26.0%</td>
<td>28.5%</td>
</tr>
<tr>
<td>High School Only</td>
<td>32.9%</td>
<td>32.0%</td>
<td>34.5%</td>
</tr>
<tr>
<td>Some College</td>
<td>19.2%</td>
<td>19.1%</td>
<td>19.3%</td>
</tr>
<tr>
<td>College Degree +</td>
<td>20.9%</td>
<td>22.9%</td>
<td>17.7%</td>
</tr>
</tbody>
</table>

### Panel C: Female Characteristics

<table>
<thead>
<tr>
<th></th>
<th>All Respondents</th>
<th>Male Respondents</th>
<th>Female Respondents</th>
<th>Data Availability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>40.7</td>
<td>40.8</td>
<td>40.4</td>
<td>Full Sample</td>
</tr>
<tr>
<td>Labor Income</td>
<td>$9,564</td>
<td>$8,627</td>
<td>$11,128</td>
<td>Full Sample</td>
</tr>
<tr>
<td>Annual Hrs Worked</td>
<td>1,539</td>
<td>1,492</td>
<td>1,604</td>
<td>1985-present</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
<td>1979-present</td>
</tr>
<tr>
<td>White</td>
<td>72.4%</td>
<td>77.3%</td>
<td>67.4%</td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>21.8%</td>
<td>17.1%</td>
<td>26.6%</td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>2.3%</td>
<td>2.0%</td>
<td>2.4%</td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>3.6%</td>
<td>3.6%</td>
<td>3.6%</td>
<td></td>
</tr>
<tr>
<td>Employment status</td>
<td></td>
<td></td>
<td></td>
<td>1979-present</td>
</tr>
<tr>
<td>Employed</td>
<td>61.1%</td>
<td>58.9%</td>
<td>64.1%</td>
<td></td>
</tr>
<tr>
<td>Unemployed</td>
<td>2.9%</td>
<td>2.4%</td>
<td>3.4%</td>
<td></td>
</tr>
<tr>
<td>Not in Labor Force</td>
<td>36.0%</td>
<td>38.7%</td>
<td>32.5%</td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td></td>
<td>Full Sample</td>
</tr>
<tr>
<td>&lt; High School</td>
<td>20.8%</td>
<td>19.7%</td>
<td>22.3%</td>
<td></td>
</tr>
<tr>
<td>High School Only</td>
<td>36.6%</td>
<td>37.8%</td>
<td>34.6%</td>
<td></td>
</tr>
<tr>
<td>Some College</td>
<td>19.5%</td>
<td>17.5%</td>
<td>23.0%</td>
<td></td>
</tr>
<tr>
<td>College Degree +</td>
<td>23.1%</td>
<td>25.0%</td>
<td>20.2%</td>
<td></td>
</tr>
</tbody>
</table>

Source: PSID and authors’ calculations

For many basic demographic variables, male respondent and female respondent households look fairly similar. On average, male respondent households have spouses that are about the same age as female respondent households. The average number of kids is also about
the same across male and female respondent households. All respondents are predominantly from the southern region of the U.S. and the vast majority of men and women are also employed.

There are, however, some key differences between male respondent and female respondent households. For example, female respondent households have a higher proportion of black individuals compared to male respondent households. Additionally, there are more women participating in the labor force and more men that are unemployed in female respondent households. There are some interesting differences across labor earnings as well. Through Graph 4 we see that the gap between male and female respondents is much wider for the male’s labor income as opposed to the female’s labor income. Specifically, in a given year, the men typically report their own labor income roughly $3,000 higher than when women serve as respondents (Panel A). Comparatively, women report their own labor income to be about the same amount as when men serve as respondents (Panel B). Looking at aggregate household income, it follows that on average, male respondents report higher household income than female respondents (Graph 5). To gather more information about household dynamics, we plot the percentage of women that earn more than their spouses by male respondent and female respondent households (Graph 6). We see that the share has steadily risen in both types of households but in female respondent households the share is slightly higher.
Graph 4: Average Labor Income by Respondent Gender

Panel A: Male Labor Income

Panel B: Female Labor Income

Source: PSID, Authors’ calculations
Graph 5: Average Household Income by Respondent Gender

Source: PSID, Authors’ calculations

Graph 6: Percentage of Women Earning More Than Their Husband by Respondent Gender

Source: PSID, Authors’ calculations
Lastly, there are some differences in education level across male respondent and female respondent households. In male respondent households, there are more men with a college degree or higher. There is not as clear of a pattern in female respondent households. We also know that over time, an increasing number of women became more educated than their spouses. Graph 7 illustrates the proportion of females that were more educated than their spouses by household respondent gender. Here we can see that the proportion of women more educated than their husband was stagnant in male respondent households. However, in female respondent households, the proportion increased from about 15% at the beginning of our sample to about 25% in 2015.

Graph 7: Percentage of Women More Educated than Husband by Respondent Gender

Source: PSID, Authors’ calculations
Note: We define a woman is being more educated than her spouse if she is in a higher education category than him (less than high school, high school diploma, some college or more). Education data for women is not consistently available before 1972.
III. Model

In order to examine the extent to which income and educational attainment are associated with women responding to the PSID, we estimate a binomial probit model. In our model, household i’s probability of having a female respondent is regressed on household and individual characteristics. From this model, we are able to isolate each characteristic’s independent relationship with the probability of having a female respondent.

We estimate two types of probit regressions. First, we estimate panel regressions over multiple years of our sample period. In these regressions, we include year fixed-effects so we can control for time specific shocks.

The following equation mathematically describes our panel regression model:

\[ P(Y_{i,t} = 1) = \alpha_{i,t} + B_1 FemaleIncome_{i,t} + B_2 FemaleEducation_{i,t} + B_3 MaleIncome_{i,t} + B_4 MaleEducation_{i,t} + \gamma_{i,t}, \]

where \( Y_{i,t} = 1 \) if household i has a female respondent and 0 otherwise in year t. We focus on female income and education but also include male income and education as they often share close relationships. \( \gamma_{i,t} \) is a vector that includes the rest of our controls. Specifically, we control for household region, homeownership status, number of children, male and female race, male and female age, and male and female employment status.

We estimate four different specifications of our panel regression model in order to account for differences in data availability for wives. Our first panel regression covers all years in our sample, from 1968 to 2015. It includes all variables for men in the sample and only variables for women that have data over the entire sample period (age and hours worked).
Second, we include years 1972 to 2015 and add a variable for the female’s education. Third, we cover years from 1979 to 2015 and add a variable for the female’s employment status. Our fourth panel regression includes data from 1986 to 2015 and adds a variable for the female’s race. Therefore, the fourth panel regression is the most comprehensive in regards to the female’s information and will be our preferred specification.

Second, we estimate cross-sectional regressions for each year in order to explore how the significance of characteristics varies over time. From this analysis, we are able to identify in what year characteristics become associated or stop being associated with women responding to the survey. In cross-sectional regressions, we can add more nuance to our results and capture the effect of historical context. For example, it is possible that we see an increasing likelihood of employed women responding to the survey in 1972 after the equal opportunity act is passed.

The following equation mathematically describes our cross-sectional regression model:

\[ P(Y_i = 1) = \alpha_i + B_1 FemaleIncome_i + \beta_2 FemaleEducation_i + B_3 MaleIncome_i + B_4 MaleEducation_i + \gamma_i, \]

where \( Y_i = 1 \) if household \( i \) has a female respondent and 0 otherwise. The variables and data used in our cross-sectional regressions are identical to our panel regressions. We run a regression for each year and use all available data for that year.

We estimate a primary and alternative specification of our cross-sectional and panel regressions. In the first set of regressions, we include logged incomes and categorical variables for educational attainment, i.e. whether or not a male or female has a high school degree. These variables enable us to explore differences in income and educational attainment across households. In our alternative specification, we replace these variables with variables that
measure differences within households. For income, we include a variable indicating whether a woman earns a higher labor income than her spouse. For education, we include a similar variable indicating whether a woman is more educated than her spouse.\(^3\)

The coefficients of our probit regressions only tell us the direction of the association between characteristics and the likelihood that a household has a female respondent. For example, a positive coefficient tells us that a characteristic is associated with a greater probability that a household would have a female respondent. In order to quantify the extent to which each characteristic is associated with the likelihood of a household having a female respondent, we use the coefficients estimated from our cross-sectional and panel regression models to calculate marginal effects. The marginal effect of a characteristic measures how much a characteristic changes the probability of a household having a female respondent when all other characteristics equal their sample mean. In this paper, we report marginal effects in order to better discuss the extent to which the characteristics in our sample change the probability of wives responding to the survey.

**IV. Results**

**A. Panel**

We first estimate panel regressions to explore which characteristics are associated with women responding to the survey when accounting for time fixed effects. Table 2 reports the results for our most comprehensive panel regression. Our initial findings are that women who are married to men with higher educational attainment are less likely to respond to the survey, but

\(^3\) We define a woman as having higher labor income if she makes at least one dollar more than her spouse. We define a woman as being more educated than her spouse if she has a higher level of educational (less than high school, high school only, or at least some college) than him.
their own educational attainment is not associated with their likelihood of responding. We also find that as male or female labor income increases, women are less likely to respond.

For our analysis of income, we use the logged labor income for men and women in our sample. We see the marginal effects for logged male labor income is strong and negative. According to our results, women are 0.9% less likely to respond to the survey with about each additional 1% increase of their spouses’ labor income. The marginal effects for logged female labor income is also strong and negative, though the magnitude is smaller than that for logged male labor income. Our results show that women are 0.6% less likely to respond to the survey with about each additional 1% increase of their own income. Combined, these results suggest that women are more likely to respond in low income households and less likely to respond in higher-income households, regardless of which spouse earns a higher income.
Women’s educational attainment, on the other hand, does not have a clear impact on her likelihood of responding, but higher male education is unequivocally associated with a woman being less likely to respond. For our analysis of education, we omit households in which men have less than a high school degree as our comparison group. We find that women married to men with some college education or higher are less likely to respond to the survey when compared to households in which men have less than a high school degree. If a husband has at least a college degree, his wife is 13.5% less likely to serve as the respondent. On the other side, our results suggest that women who are married to men with less than a high school degree are
more likely to respond to the survey in comparison to households with more highly educated men. Our results are in line with literature such as Smith et al (2010) which document that an individual is more likely to serve as a financial respondent if they are more educated, but the husband’s education has a much larger impact than his spouse’s education.

One possible interpretation of our results is that we are seeing the difference between two types of households – traditional and nontraditional. In historically traditional households, men are expected to be breadwinners who have higher income and/or educational attainment than their spouses. In these households, it is possible that men assume the traditional head of household role while women are primarily responsible for taking care of the children and doing the housekeeping (Becker (1981) amongst many others have done work on this type of specialization within a marriage). This may be why we see a negative coefficient for male labor earnings and for higher levels of male educational attainment.

It is possible that in nontraditional households women have more decision making or bargaining power. Nontraditional households may include those in which men earn less labor income, men have lower educational attainment, or women earn higher labor income. Past work such as Smith et al (2010) document that men are the “default” option for some financial decision making, unless they have poorer cognitive abilities. Additionally, men with lower labor earnings or educational attainment may be less able to financially support their households. Work such as Wilkie (1991) has documented this shift in household dynamics with the decline of the man’s traditional role as the sole breadwinner for his household and this trend is particularly concentrated amongst men with low education. Furthermore, households in which women have higher labor earnings may be reacting to this need for multiple breadwinners. A woman may be earning higher labor income because her spouse was unable to earn enough to support the
household. When women begin earning higher labor income, they may be less available to respond to surveys or have fewer domestic responsibilities.

Next, we estimate an alternative specification of our panel regressions using two variables indicating whether a woman earns more labor income than her spouse and whether a woman is more educated than her spouse to investigate household dynamics. The key results from our additional specification show that household dynamics are relevant for determining who responds to household surveys. Specifically, we find that if a woman is more educated than her spouse, she is about 5% more likely to respond to the survey (Table 3). While the category of female educational attainment lacks explanatory power, the female’s education in comparison to her spouse’s education has an effect on the probability of her responding to the survey. Fonseca et al (2012) find related results in that an individual’s education relative to their spouse matters most for financial decision making. A woman earning higher labor income, however, does not have a statistically significant effect. This is in line with the historical context since women have experienced much more progress in education, relative to men, than in income. As previously mentioned, by 2007 more women were receiving bachelor’s degree than men and yet the gender pay gap remains steady at about 82% (BLS 2018). The gains women experienced in education, particularly over our sample period, are likely to have contributed to the rise in female respondents.
### Table 3

<table>
<thead>
<tr>
<th></th>
<th>Panel 1</th>
<th>Panel 2</th>
</tr>
</thead>
</table>
| **Education and income differences** | Wife is more educated than her husband       | 0.042***  
(0.009) | 0.052***  
(0.012) |
|                        | Wife has higher labor income than her husband | 0.007  
(0.004) | 0.003  
(0.004) |
| **Years included**     | 1980-2015                                    | 1986-2015                                    |
| **Year fixed-effects** | YES                                          | YES                                          |
| **Spousal and household controls** | YES                                          | YES                                          |
| **Observations**       | 72,214                                       | 58,561                                       |
| **Households**         | 11,779                                       | 10,571                                       |

Notes: Standard error in parenthesis

*** Significant at the 1 percent level
**  Significant at the 5 percent level
* Significant at the 10 percent level

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**B. Cross-sectional**

Compared to the panel regressions, the cross-sectional regressions enable us to gain a more nuanced view of the association between income and education, and the likelihood of women responding to the PSID. We are interested in seeing whether the characteristics remain consistently significant over time or are related to certain time periods.

For the most part, our findings on female income and education in the panel regressions are confirmed in the cross-sectional regressions. Once again we find that women are less likely to respond when men earn higher labor income. Male logged labor income is consistently significant throughout most of our sample period (Graph 8). Female logged labor income, however, is relatively insignificant, which is inconsistent with our panel regression results. It is possible that the smaller sample size in our cross-sectional regression, and particularly the smaller share of high-earning women, affects the significance of female labor earnings in our regression. However, the smaller marginal effects for female labor earnings in our panel regression, relative to the marginal effect for male labor earnings, shows that female labor
earnings change the likelihood of a woman responding to the survey less than male labor earnings.

**Graph 8: Cross Sectional Marginal Effects, Income**

![Graph 8](image)

Source: PSID, Authors’ calculations

Note: Significant coefficients (at the 10% level or greater) are denoted with a diamond symbol.

The education channel has held fairly steady (Graph 9). All levels of educational attainment are consistently and strongly significant for men after 1974 (Graph 9, Panel A). Once again, the female’s education coefficients are mostly insignificant (Graph 9, Panel B).
Source: PSID, Authors’ calculations
Note: Significant coefficients (at the 10% level or greater) are denoted with a diamond symbol.
Turning to our alternative specification on inter-household education and income levels, we once again see that education differences matter more than labor income differences (Graph 10). Across most years in our sample, a woman being more educated than her spouse is strongly associated with the likelihood of women responding to the survey. The effect peaks in 2009 in which wives were 15.4 percentage points more likely to respond to the survey if they were more educated. Put together, it seems clear that household dynamics play a part in how likely a woman is to respond across our whole sample period.

Graph 10: Cross Sectional Marginal Effects, Male/Female Comparisons

Source: PSID, Authors’ calculations

Note: Significant coefficients (at the 10% level or greater) are denoted with a diamond symbol.

V. Effects of an increase in female respondents

Identifying characteristics that make a woman more likely to respond is an important aspect of working with household data, but more importantly, an underrepresentation of female respondents may affect data quality. If men have a tendency to report systematically different
values, this could affect the quality of historic data when men were largely the only ones being surveyed. To explore if this is a concern, we will conduct two exercises focusing on income, as this is one of the most common topics studied with PSID data. The first exercise will examine how average household incomes may have differed had the 1968 respondent composition been carried forward or, conversely, if the 2015 composition had been carried backward. The second exercise will take several measures of income inequality and see how they differ by male and female respondents. These exercises all show that the gender composition of respondents matters a great deal when studying income dynamics.

**A. Average Income**

Our first exercise asks whether average household income would look different across time if the gender composition of respondents remained constant. This cannot be measured directly, so as an approximation we perform the following counterfactual exercise. We first use the 1968 respondent composition of about 90% males and 10% females to create a weight for responses in subsequent years. For the males, for example, we take 0.9 times the number of total respondents in a particular year. For 1968, this will be the actual number of male respondents. For other years with fewer male respondents, this means their responses will be weighted heavier. Next, we take that number times the average household income that male respondents reported. We perform a similar procedure with the female respondents. Adding the male and female numbers together and then dividing by total respondents will give us a new average household income, properly weighted by the 1968 gender composition. The same process is applied for the 2015 respondent composition of about 40% males and 60% females.

The counterfactual exercise can be expressed mathematically as the following:

$$\overline{hhinc}_t = \frac{p_{m,1968}n_t\overline{hhinc}_{m,t} + p_{f,1968}n_t\overline{hhinc}_{f,t}}{n_t}$$
\[
\overline{hhinc_t} = \frac{p_{m,2015}n_t\overline{hhinc_{m,t}} + p_{f,2015}n_t\overline{hhinc_{f,t}}}{n_t}
\]

Where \( p \) is the proportion of (male or female) respondents in either 1968 or 2015 and \( n \) is the total number of respondents at time \( t \).

As seen in Graph 11, the mean household income using the 1968 gender composition remains persistently higher than both the actual data and the 2015 composition. Specifically, if the 2015 composition had existed back in earlier survey years, average household incomes may have been lower by as much as $2,500 in a given year. Since the earlier years of the PSID contains more male respondents, this is consistent with the literature and the previous finding in Graph 5 that male respondents report higher household income values than female respondents, on average.

Graph 11: Household Income Counterfactual Exercise

One explanation for the fact that male respondents report higher household incomes than female respondents is that they might inflate values of income. Put differently, perhaps men tend
to over-report and women tend to under-report income. Bollinger (1998), Reynolds and Wenger (2011), and Murray-Close and Heggeness (2018) all find this to be true within CPS data.

We perform the same counterfactual exercise on the male and female’s labor income. For the male’s labor income, a similar trend emerges in that the mean labor income using the 1968 gender composition is higher than the actual data and the 2015 composition is often lower (Graph 12, Panel A). However, for the female’s labor income, the levels are remarkably consistent across the 1968 composition and 2015 composition compared to the actual data (Graph 12, Panel B). These findings imply that male labor income values are higher when men are self-reporting compared to when women are reporting. However, this is not true for female labor income values. We take no stand on which reported value is more accurate, but simply state it is important to note the persistence of these reporting tendencies.

Graph 12: Labor Income Counterfactual Exercise

Panel A: Male’s Labor Income
Another explanation for the gender difference in reported incomes is that perhaps males serve as respondents when they happen to have higher incomes. In other words, there may not necessarily be a reporting tendency but rather self-selection. The average difference between the reported household income values for male respondents and female respondents is about $5,000. An Oaxaca decomposition is one technique that could provide some additional information about the difference in means between the two respondent groups. Typically, an Oaxaca decomposition is used to explain the wage differential across sexes by controlling for other characteristics that might explain differences in wages such as education, experience, health, etc. After controlling for these characteristics, there is a residual difference that remains unexplained and is usually attributed to discrimination. For our purposes, we apply the same technique to the male/female respondent differential for logged household income. We control for education, age, employment, race, homeownership, region, and number of children. Detailed results are reported...
in Table 4. Overall, we find that observables about the head and his household explain roughly two thirds of the difference in reported logged household income. However, a third of the difference remains unexplained. The decomposition does not fully mitigate the selection issue. However, it does suggest that while it’s true male respondents often have higher incomes due to education, employment, race, and other observables, this does not fully explain the difference in reported income.

Table 4: Oaxaca Decomposition

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
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</thead>
<tbody>
<tr>
<td>Group 1 Mean (Male Respondents)</td>
<td>10.488***</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Group 2 Mean (Female Respondents)</td>
<td>10.351***</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Difference in Means</td>
<td>0.137***</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Explained</td>
<td>0.089***</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Unexplained</td>
<td>0.048***</td>
<td>(0.005)</td>
</tr>
</tbody>
</table>

Notes: Standard error in parenthesis

*** Significant at the 1 percent level
**  Significant at the 5 percent level
*   Significant at the 10 percent level

In light of these findings, we conclude that it is likely that reported incomes within the PSID have measurement error due to the striking change in respondent composition. Specifically, household incomes may be biased to the upside at the beginning of the PSID sample. A $5,000 (on average) difference may not seem significant to some researchers, but the consistency of the reporting difference may obscure otherwise accurate results. Controlling for the gender of respondents could easily mitigate this.

**B. Inequality Measures**

If the gender of respondents affects income measures, it also follows that the gender of respondents affects measures of income inequality. To test this, we examine two common
measures of inequality: the Gini coefficient and the 90th to 10th percentile ratio. Both measures are useful to look at because the Gini coefficient is a measure of the overall distribution of wealth while the p90/p10 ratio focuses on the upper and lower 10% of the income distribution. It has been fairly well documented that both of these measures have been increasing over time (OECD 2015), but we will determine how these measures differ within the PSID by respondent gender.

First, we calculate a Gini coefficient of household income for each year in the PSID sample. A Gini coefficient can range from 0 to 100, where 0 represents perfect equality (each person has the same income) and 100 represents perfect inequality (one person earns all of the income). For reference, the United States has a Gini coefficient of about 41, while Norway has a Gini Coefficient of 27.5 (World Bank). In order to calculate a Gini coefficient on our data, we separate the data into 2 groups according to gender of respondent. The results (Graph 13) suggest that inequality is increasing over time, regardless of respondent gender group. However, the magnitude is slightly different across the two respondent groups. For the female respondent group, income inequality is higher at the beginning of the sample but lower towards the end of the sample. One qualification for these results is that the sample size for female respondents is fairly small at the beginning of the sample given that only about 10% of total respondents were female for the first few years of the PSID. However, even when there are more female respondents (i.e. 1993 to present) there exists differences in the Gini coefficient across the groups.
Next, we calculate the ratio of the 90th percentile to the 10th percentile for household incomes in the PSID, split again by respondent gender. The female respondent measure is fairly volatile in the beginning of the sample (Graph 14). We largely attribute this to the low number of female respondents, as mentioned previously. However, after 1993 (when the gender of respondents is roughly balanced), the female line is considerably smoother. In later years, we see that the p90/p10 ratio is somewhat higher for the male respondents compared to the female respondents. It does appear, though, that this gap is beginning to close in the most recent years of our sample.
In this paper, we document an increase in female respondents within the PSID. We use this trend as a case study to examine which characteristics are associated with women responding to a household survey. Through our panel and cross-sectional regression estimates, we find that women are less likely to respond when their husbands have higher educational attainment, but women who are more educated than their husbands are more likely to respond to the survey. We also find that as male labor earnings increase, women are less likely to be respondents.

A substantial change in the composition of respondents has two key implications for PSID data. First, income measures may be higher at the beginning of the PSID sample compared to if the gender of the respondents was balanced. Second, inequality measures may change depending on the gender composition of the respondents.
Our work also has important implications for survey design. First, while it is important the data we gather reflect the population we are studying, it is also important to make sure the survey respondents themselves are representative. Not including the voices of half of the population may result in lower quality data. Second, imposing a household structure that is not present may affect the data. In the case of the PSID, the survey reflected language of the 1960s and did not evolve much over time. Keeping consistency in the wording of questions should certainly be a priority, particularly for panel data, but this should not come at the cost of data quality.

There are many opportunities for future work on the gender composition of survey respondents. First, it is likely that the information available to us within the PSID does not fully capture all characteristics associated with survey response. Other surveys for which we can observe the gender of respondent could be used to see what other characteristics may be associated with response. Second, papers that have used PSID data in the past may be affected by the shift in gender composition if this was not previously taken into account. As we have shown, just one example of this is for reported income values, variables which are very commonly used within the PSID. Lastly, our paper further exposes the importance for gathering better quality data on women. Data on characteristics such as education, employment, and race are available for the man but not always for the woman at the beginning of the PSID sample. If instead of the man, the “head of household” was designated as say, the oldest individual, much more information on women may have been available in the PSID. We cannot change how data was collected in the past, but we can learn from past surveys and improve data collection methods in the future.
REFERENCES


