Dear Chairman Himes, Ranking Member Steil, and Members of the House Select Committee on Economic Disparity and Fairness in Growth. My name is Rhonda Vonshay Sharpe, and I am the President and Founder of the Women's Institute for Science, Equity and Race, WISER. Our mission is to expand women-focused research to include the needs of Asian, Black, Hispanic, Multiracial and Native American women. Thank you for your invitation to participate in this roundtable about measuring economic disparities.

Disparities are a condition of inequality that pivots differences historically used to exclude. Difference defined by gender (sexism) has been used to exclude women, difference defined by race and ethnicity (racism) has been used to exclude non-Whites, and difference defined by class has been used to exclude the poor from full participation in economic activities. Given this, disaggregating data by broad aggregate groups like race/ethnicity or gender masks disparities in outcomes.

The Women's Institute for Science, Equity and Race advocates for disaggregating data by the characteristics that lived experiences and research have shown to influence an outcome. Disaggregating data provides the mechanics of subdividing the data by these characteristics. For the three reasons discussed below, we believe disaggregating data in this manner will provide insights for crafting more effective policies.

1. Intersectional Analysis
Disaggregated data acknowledge our complex identities. Once data are disaggregated, intersectional analysis can be used to understand how the complex interplay between various identities may influence economic and social status. At the micro-level of individual experience, these identities reflect interlocking systems of privilege and oppression, but they reflect the social structure at the macro-level.

2. Inequality Hidden in the Aggregate

We use data to make inferences about socioeconomic outcomes. Data follow distributions that provide information about measures of central tendency, mean, median, and mode. Under certain circumstances, the inferences may not be informative and may even be misleading. Aggregate data for multiple subgroups are likely to have more dispersion – less symmetric. As data become less symmetric, more diverse (an increase in dispersion), and more extreme-influenced (higher kurtosis), measures of central tendency become less informative. For some groups, disaggregating data by the characteristics believed to influence the outcome may produce more symmetric data, resembling the standard normal distribution, thereby allowing for a single measure of central tendency across sub-groups. Therefore, disaggregated data expose nuanced differences in distributions that are hidden in the aggregate groupings.

For example, the discourse about women and labor force participation during the pandemic has focused on childcare. The framing of this conversation is flawed. Elementary and secondary schools are not childcare; this was a conversation about "mothers," not women. Therefore, conflating the educational system and the childcare services industry as is done in the Household Pulse Survey data makes it challenging to disentangle why a mother may not have worked when K–12 schools closed or had limited in-person learning. Acknowledging this data limitation, we analyzed the Household Pulse Survey data to examine the lack of childcare for parents. Figure 1 shows women were more likely, on average, to report childcare as the reason for not working. Black men were more likely, on average, to report childcare as the reason for not working relative to other men.

![Figure 1. Childcare reason for not working by gender, ethnicity, and race (percent)](chart)

For each group of women, race produces a different distribution across educational attainment. Black women with no high school diploma were more likely to report a lack of childcare as the reason for not working, and Asian women were the least likely (see Figure 2). However, for women with a bachelor's degree, Asian women were more likely to report childcare as the reason for not working, and Black women were the least likely to give childcare as the reason (see Figure 4). Although the distribution is different, disaggregating the data by race/ethnicity, educational attainment, and marital status shows that married women were more likely to give childcare as the reason for not working. This finding holds across ethnicity, race, and educational attainment. Having an employed spouse may have afforded these women the option to be at home.

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2 Email exchange with Patrick Mason, October 25, 2021.
Each reader may glean additional insights from these figures depending on their lived experience. Additionally, if the data were disaggregated by household income, we would gain more insight into the influence of income on mothers working when there is no childcare.

Disaggregating data by key characteristics may also help identify vulnerable populations, defined as populations at greater risk for poor economic, educational, health, and political status or outcomes. Often the factors that cause a population to be vulnerable are rooted in institutional racism, systemic sexism, and the often overlooked structural classism, the wedge between those who own the means of production and wealth and the working-class folks who do the labor. Structural classism colors the language used to describe the poor. When structural classism intersects with institutional racism and systemic sexism, the result is the criminalization of the poor, a devaluing of low-wage workers, and widening economic inequality.

Figure 2. Childcare reason for women not working: No high school diploma (percent)

Figure 3. Childcare reason for women not working: High school diploma (percent)
3. Cultural Bias

Finally, disaggregating data in this way moves us away from cultural bias in how we report and interpret outcomes. Class, ethnicity, gender identity, race, and sexual orientation are hierarchical social constructs that segment societies by elevating cultural norms and characteristics. These social constructs function similarly to prices, becoming metrics for deciding who gets scarce resources, who owns the capital, and who is the labor. Therefore, data disaggregated by broad race/ethnicity categories assume "White" as the norm, and data disaggregated by male-female categories assume "cisgender male" as the norm.

Marlene Kim offered gendered racism, the intersection of racial and gender stereotypes, to explain the persistent labor market disparities and subsequent inequalities observed for racialized minorities and White women.³ She suggested that stereotypes about ethics, intellect, masculinities, leadership, and nurturing, ascribed to race, ethnic, and gender groups, are reinforced by education, legal, and penal systems, sustaining institutionalized inequality. These stereotypes may influence how data are collected and reported,⁴ limiting data availability to identify discrimination or other biases.

An often-overlooked factor in economic disparities is framing. When ethnicity, namely Hispanic, is used in racial comparisons, the analysis is misleading. In the U.S., people of Hispanic/Latino ethnicity are of varied racial backgrounds and are defined (U.S. Office of Management and Budget, 1997) as:

Hispanic or Latino. A person of Cuban, Mexican, Puerto Rican, Cuban [sic], South or Central American, or other Spanish culture or origin, regardless of race. The term "Spanish origin" can be used in addition to "Hispanic or Latino."

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Therefore, any analysis that includes Hispanics in racial group comparison erases the racial identity and is misleading. Racial demographic data from the 2020 Census provided two estimates, one with Hispanics as a category in the racial comparison and the other without. The estimates with Hispanics as a category led to media headlines about the decline of Whites in the U.S. population.⁵

Sociologist Nancy Lopez noted that the box checked for race might not reflect the respondent's "street race," the race a stranger would assign based on phenotype.⁶ The disconnect between one's street race and the self-identified race will be problematic for lawyers to sue based on racial or ethnic discrimination and for social scientists researching racial or ethnic inequality. As Lopez pointed out, the Census and other datasets do not capture ascribed racial characteristics that may influence the street race for Hispanics; such arguably applies to multiracial individuals as well. Therefore, studies that use these data will likely underestimate the occurrence and costs of discrimination and inequality or miss the nuanced differences in outcomes that result from differential treatment based on street race.

Ethnicity is not the only way framing may hide disparities. When reports use women to be synonymous with white women, it denies white women knowledge about their position relative to men and other women. It denies White women information about how gender operates to oppress them and how their whiteness provides benefits. Failure to disaggregate White women as a category denies them the opportunity to see themselves in the data.

Additionally, "women of color," "people of color," BIPOC, or minorities erases identity and ignores a wealth of information about the unique experience of each group. This is particularly problematic in a rapidly diversifying country, where increasing shares of the population identify as Asian, Black, Native American, "multiracial," or "other." Researchers must understand that shared experiences among various groups may not lead to similar outcomes.

**Data Limitations**

The example above shows how disaggregating data by a few characteristics provides additional insights that may help craft policies targeted at vulnerable groups. But some datasets do not allow for disaggregation by key characteristics across groups.

The *Economic Situation* monthly report by the U.S. Bureau of Labor Statistics (BLS) does not disaggregate data for Asians by gender or by age groups. As hate crimes increased against Asian Americans during the pandemic, disaggregated labor market data for Asian Americans would have provided crucial insights into how the rhetoric about the origins of COVID-19 affected Asian Americans. The *Economic Situation* also does not report any information on the employment status of Native Americans. BLS provides an online tool for researchers to create tailored tables for several racial, ethnic, and gender groups; however, these estimates are not seasonally adjusted for many of these groups.⁷

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⁷ Seasonal adjustment is a statistical technique that attempts to measure and remove the influences of predictable seasonal patterns to reveal how employment and unemployment change from month to month.
Another example is population projections provided by the U.S. Census Bureau, which are provided by race and ethnicity, but not by race, ethnicity, and gender; therefore, data on the future demographic position of women are not available. Not only do population projections need to be made based on gender, but they need to be broken down by race/ethnicity and gender – intersectional projections. This lack of data treats gender as inconsequential for policy planning and assumes only race/ethnicity is important. Furthermore, the lack of population data delineated by race/ethnicity-gender may result in parental rights, reproductive rights, and childcare policies that are not inclusive of the needs of these women, who are more likely to be the most vulnerable. Trivializing race-gender and ethnicity-gender data has implications for economic growth.

There is also a need for data appropriate for analyzing the fluidity of sexual orientation and gender identity (SOGI). The results of a BLS and U.S. Census Bureau study "did not identify any significant issues that would make collecting SOGI information in the CPS infeasible, though there are many outstanding issues identified in the full study reports that must be studied and addressed prior to any implementation efforts." The concerns expressed were grounded in agency, who can report an individual's SOGI, and privacy, willingness to report SOGI. Although the U.S. Census via the American Community Survey and Decennial Census collects information on same-sex households and marriages, these data are poor proxies for SOGI analysis. Researchers have used these data to evaluate U.S. lesbian and gay couples.

U.S. Department of Education data allow respondents to choose other in addition to male or female. However, like race, a respondent's choice may not align with their "street gender." So, while EEOC law prohibits discrimination on the basis of gender identity or sexual orientation, the data do not allow researchers to describe the frequency or costs of discrimination against these groups. In 2016, the state of Minnesota adopted Counting All Student (CAS) legislation. CAS requires the state to update the Racial and Ethnic Demographic Form every five years to reflect the most populous categories in Minnesota per the American Community Survey.

There is a need for more detailed data and analysis about wealth. Analysis of the wealth gap is an example of how reporting by the aggregates masks outcomes. The Black-White wealth gap is presented as if the distribution of the gap is uniform. Income distributions differ by race, ethnicity, family structure, occupation, education, and region; therefore, the distribution of the wealth gap must also differ by these characteristics. Thus, the wealth gap must be analyzed for various income distributions and demographic factors like family structure and educational attainment. There is evidence that debt in general, and student loan debt in particular, influence the accumulation of wealth-building assets.

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10 https://education.mn.gov/MDE/dse/count/
Research on the influence of student loan debt and homeownership lack data on three critical questions:
1. Do you want to purchase a home?
2. Have you applied for a loan to buy a home?
3. Were you denied a loan to purchase a home due to student loans, i.e., student loans increased your debt-to-income ratio beyond the acceptable limit?

It is recommended that these questions be added to the Survey of Consumer Finance, a dataset commonly used to evaluate wealth.

**Business Sector and Economic Growth**
The disaggregation of data is not limited to individuals but also has value for analyzing business outcomes and economic growth.\(^\text{13}\) Reports that analyze entrepreneurship must disaggregate by demographics, location, and business sector. Understanding the distribution of women-owned businesses by sector provides additional insight into how women transfer skills and the barriers to entry, such as previous business experience, difficulty obtaining financial support, and gender-biased networking.\(^\text{14}\) Given that women entrepreneurs increase the demand for women workers, which increases the earnings and social mobility of female owners and employees, understanding why women entrepreneurs are concentrated in sectors with easy entry and low skill requirements is vital for economic growth.\(^\text{15}\)

Additionally, the motivation for the surge in women-owned businesses is thought to result from structural obstacles in traditional corporate employment. The departure of women from the labor force during the pandemic may fuel a spike in women-owned businesses.

**Conclusion**
Any metric for evaluating inequality is only as good as the data and analysis. Therefore, to have a more equitable society, we must collect data that address the inequalities we seek to eliminate. Additionally, we encourage an analysis that disaggregates the data by the characteristics believed to influence the outcome. We also promote the use of intersectionality to contextualize patterns of inequality.

Fairness in economic growth is achieved when policies are enacted to mitigate patterns of inequality.

\(^\text{13}\) See “Disaggregating Growth” for a discussion of disaggregation applied to GDP. https://equitablegrowth.org/research-paper/disaggregating-growth/
