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Who Gets Counted as STEM? A New Approach for Measuring the STEM Workforce and its Implications for Identifying Gender Disparities in the US Labor Market

Drew M. Anderson[1], Matthew D. Baird[1], Robert Bozick[1,2]

[1]RAND Corporation, [2]Rice University, USA

ABSTRACT
Defining who works in STEM has traditionally relied on top-down categorizations of occupations, typically based on predetermined occupational coding schemes. This study takes a bottom-up approach and directly surveys a national sample of workers in the United States to classify their jobs based on their roles and tasks they perform when on the job. With this bottom-up approach, we identify a sizeable group of workers who are in the 'periphery STEM workforce' who report working in STEM jobs but whose occupations fall outside of top-down STEM classifications. When including the periphery STEM workforce as part of the broader STEM workforce, the gender gap in STEM workforce participation decreases substantially because women are more likely to work in the periphery. However, women working in the periphery are compensated less than men, a fact that remains invisible when using current top-down classification schemes.

KEYWORDS
STEM, gender, occupations, labor force, labour force

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INTRODUCTION

Science, technology, engineering, and mathematics majors and occupations have been grouped together and branded collectively as "STEM." The general concept has grown in importance over time, reflecting the reality that gaining skills in quantitative and scientific reasoning is critically valuable in today's economy. As technology advances, more and more jobs require STEM skills in the United States and abroad (Carnevale et al., 2011; Grinis, 2019; Noonan, 2017). American students lag behind their international peers in STEM achievement, and thus the United States may be facing long-term disadvantages in filling those jobs with American workers (Augustine et al., 2005). Workers with degrees in STEM are more likely to be employed and to earn more than their peers with degrees in other subjects (Altonji et al., 2012; Baird et al., 2017; Webber, 2014, 2016). As such, the classification of STEM is quickly becoming shorthand for workers in the top tiers of the economy. Not all socio-demographic groups are equally represented in STEM, however. For example, men work in STEM occupations at higher rates than women (U.S. Equal Employment Opportunity Commission, 2016). In the United States, this gender imbalance has been of particular concern to policy makers.

The validity of these conclusions depends on how exactly STEM is defined and measured. As scientific and quantitative tasks spread with the use of computer technology, any attempt to define the boundaries of STEM learning and STEM employment is somewhat arbitrary. However, the consequences of these definitions are not. For example, in the United States, the STEM designation determines which universities get federal funding and prestige, and which of their foreign graduates get to stay and work in America (Morse & Brooks, 2015). Several states offer tax credits and student debt relief for college graduates who stay and work in the state, but only if they are employed in STEM occupations (Connecticut by the Numbers, 2019; Finance Authority of Maine, n.d.). Moreover, the United States' National Science Foundation devotes considerable financial resources toward programs aimed at improving the school-to-work STEM pipeline, particularly for underrepresented groups such as women. As a result, the measurement of STEM not only has consequences for how we characterize the workforce at the population level, but also with direct policy implications for individuals.

This paper revisits the measurement of STEM employment, with the motivating goal of showing how different measurement approaches can lead to different conclusions about gender disparities in the labor force. We describe traditional measures of STEM employment based on expert classifications of occupations and contrast them with an alternative measure of STEM employment that we create by directly asking workers about their jobs. Our approach has distinct advantages for researchers who rely on survey data to study the labor force. Asking sample members about their jobs gives them an opportunity to classify their occupations based on their daily personal experiences at work. Relying on occupational coding schemes to classify workers, as is often done by social scientists, can slough over and obscure important details that distinguish the actual tasks of workers both within and across different employers and industries. Moreover, many workers form a personal identity around their jobs (Gini, 1998), and so directly asking them about their occupation reveals insights into how they evaluate their knowledge and their skills in relation to their broader role in the economy.

In directly asking workers about their jobs, we are able to document how STEM skills are permeating more jobs outside of occupations traditionally considered to be STEM. While this measure has a number of limitations which we describe in detail, it does reveal some important nuances regarding gender differences *within STEM* that would otherwise be difficult to observe. This paper is not attempting to redefine STEM or to endorse any particular measurement approach. Instead, we introduce a different measure of STEM employment for the purposes of trying to better understand this often used, but somewhat nebulous construct in labor research.

In comparing and contrasting our bottom-up STEM classification approach (which relies on the direct reports of workers) with other existing top-down classification schemes (which rely on predetermined coding schemes derived from expert opinions), our analysis makes three distinct contributions. First, it identifies discrepancies between how workers view their jobs and how policy makers and other administrative decision makers quantify and organize the labor force. Such discrepancies can be informative for future efforts aimed at improving the status of women in STEM, particularly should they reveal STEM pathways that may be commonly pursued by women but are less valued in the labor market. Second, the economy is rapidly changing, with technology increasingly infiltrating nearly every occupation. Consequently, foundational STEM skills and concepts are quickly becoming a prerequisite to labor force participation writ large. Education and labor force researchers need to be adept at monitoring and evaluating these changes. Static measures of STEM are likely to become outmoded quickly, complicating attempts at documenting trends in STEM over time. While we do not endorse any one particular approach, our analysis reveals the complexities of operationally defining STEM and how these complexities matter when assessing labor force outcomes. Finally, much of our understanding about the STEM education-employment ecosystem comes from surveys of students and workers. Survey researchers are still grappling with the most efficient and effective methods of asking questions that accurately measure key occupational constructs. Our study shows that existing methods to estimate the size of the STEM workforce are quite sensitive to differences in operationalization. Collectors and analysts of survey data need to be mindful of these differences when attempting to examine the STEM labor force. Our analysis highlights the consequences of these differences.

Defining the Periphery STEM Workforce

Our study takes place in the United States, which leads the world in spending on research and development. To date, measurement of the STEM workforce in the United States has largely relied on top-down classifications of occupations by federal agencies and research institutes. These definitions are based on what *typical* workers do in each occupation, and thus ignore potential variation in the use of STEM skills *within* an occupation. Concerns about top-down approaches in accurately evaluating "leaks" in the STEM school-to-work pipeline have been expressed by the United States' Bureau of Labor Statistics (Xue & Larson, 2015) and are manifest in a handful of studies which document how heterogeneous skills and roles within the STEM economy contribute to variation in employment outcomes (Deming & Noray, 2018; Light & Rama, 2019). To address the limitations resulting from strict top-down approaches, we measured STEM jobs from the bottom up, by asking workers directly whether the job they do on a daily basis consists of STEM-related tasks and functions, using an original survey that we fielded to a nationally representative sample of working adults. We then used information on the workers' occupations to construct traditional occupation-based STEM classifications, and we contrasted these with workers' subjective job-based STEM classifications.

Table 1 shows how an individual worker may sort into existing top-down classifications and into our bottom-up classification. Cells (c) and (d) on the second row form the official estimate of the STEM workforce produced by the federal government and many research institutes, based on occupational classifications. This ignores the shaded cell (b), containing STEM workers whose *jobs* use STEM skills and knowledge, but fall outside top-down STEM-classified *occupations*. We call workers in cell (b) the "periphery STEM workforce." In this study, we pay special attention to this segment of the STEM workforce by showing that estimates of the size of the STEM workforce and outcomes of STEM workforce participation vary depending on whether this segment is included or excluded from the broader STEM classification.

Table 1: Two-Dimensional Measurement of the STEM Workforce

		Bottom-up approach (based on self-reports)	
		Non-STEM	STEM
Top-down approach (based on pre-determined lists of occupations)	Non-STEM	(a) Core non-STEM workforce	(b) Periphery STEM workforce
	STEM	(c) Periphery non-STEM workforce	(d) Core STEM workforce

The value of using a bottom-up definition of STEM jobs is its flexibility in identifying atypical workers in an occupation. Consider an occupation where 90 percent of the workers within that occupation are not involved in STEM-specific tasks. In this case, using existing classification schemes, all workers in this occupation would be classified as non-STEM. However, this leaves 10 percent of the workers who perform STEM tasks and functions but are nonetheless excluded from official classifications of STEM workforce membership. Likewise, the STEM workforce estimates using occupation-based classifications would include people in the non-

STEM periphery—individuals whose occupations are typically considered STEM, but who do not perform STEM tasks in their specific jobs.

A risk of using this bottom-up measurement is that some workers may incorrectly classify their jobs as STEM. Our approach takes answers at face value, including for example from workers employed as social workers, counselors, and librarians (traditionally classified as non-STEM occupations). As we discuss in detail below, each STEM measure is subject to different sources of error. The bottom-up approach suffers from variability in survey respondents' understanding of the meaning of STEM. We attempted to mitigate this with a clear definition in our survey prompt. However, these drawbacks are a necessary consequence of using individual responses to get a more nuanced view of a construct like STEM employment. To address these concerns, we look for indicators that the periphery STEM workforce is substantively different from the rest of the traditionally classified non-STEM workforce in terms of worker characteristics and in terms of wages. We find consistent gender differences: Women are over-represented in the periphery STEM workforce, but they are not necessarily better compensated for periphery STEM work.

Gender Gaps in STEM

A large literature documents the existence, causes, and consequences of gender wage gaps (Denning et al., 2019). As context for the present study, here we focus solely on how STEM contributes to gender differences in careers and compensation. The gap in STEM participation by gender begins early, when girls and boys are first introduced to STEM subjects in elementary school, and compounds over time (Card & Payne, 2021; Fryer Jr & Levitt, 2010; Hill et al., 2010; Jaeger et al., 2017; Key & Sass, 2019). By the time they enroll in college, women are less likely than men to choose majors in STEM fields, and women who begin as STEM majors are less likely than men to persist in those majors through graduation (Arcidiacono et al., 2016; Chapa & De La Rosa, 2006; Chesler et al., 2010; Sovero et al., 2021). Conditional on graduating with a bachelor's degree in STEM, women are less likely than men to work in a STEM occupation (Baird et al., 2017). As a result of this cumulative process across the life cycle, the STEM workforce has been measured to be disproportionately male (Gonzalez et al., 2016, 2017).

These gender differences in the STEM workforce have persisted even as longstanding gender disparities in general education have attenuated, and in some cases have reversed. For example, women are now less likely than men to drop out of high school and are more likely to enroll in and complete college (McFarland et al., 2018). Women earn higher grades and have higher post-secondary aspirations (Fortin et al., 2015). Although women attain fewer bachelor's degrees in STEM overall, they now comprise a majority of degree recipients in biology, biomedical sciences, and psychology (National Center for Education Statistics, 2019). Men, however, have maintained an advantage in physics, computer science, engineering, and math, across all levels and selectivity of colleges (Schneider et al., 2015). Even after earning a STEM degree, processes of "horizontal occupational sex segregation" oftentimes operate via labor market sorting, whereby women select into jobs with traditional gender-conforming tasks for females and men select into jobs with traditional gender-conforming tasks for males (Charles & Grusky, 2005). Thereby, occupational sex segregation is reinforced within sought-after STEM occupations that on face-value should improve women's standing relative to men.

Women's advancement in STEM education and in STEM employment has therefore been uneven, and we lack definitive explanations for this phenomenon and its consequences. Concerns about female representation in STEM have intensified amid warnings about a shortage of STEM workers in the United States (Olson & Riordan, 2012). While gender pay gaps can be partially explained by differences in such things as occupational choice, career changes, and temporary exits from the workforce (such as for maternity leave and childrearing), women still earn less than men after accounting for these factors (Graf et al., 2018; Kronberg, 2020; Moore, 2018; Petrescu-Prahova & Spiller, 2016). The gender composition of the workforce has implications for wages and benefits as well (Erlandsson, 2019; Levanon et al., 2009). In this paper, we put forth the hypothesis that a significant proportion of women's participation in the STEM workforce, and differences in compensation, is obscured by how the STEM workforce is operationally measured. The next section details existing definitions and measurements, as well as our new measure.

Current Approaches to Measuring the STEM Workforce in the United States

Our study is based in the United States, which, as a nation, invests heavily in research and development. Our analyses are "United States-centric" by design, but they highlight broader challenges that all developed economies face as they grow and manage their STEM workforces. The main federal vehicles for research and development in the United States include the Department of Defense, the National Institutes of Health, and the National Science Foundation. Of particular relevance to our study is the National Science Foundation, which is responsible for developing a pipeline of well-trained STEM workers to support the nation's interests. The National Science Foundation provides direct support to schools, colleges, and universities to build and to enhance their STEM curricular offerings, as well as to employers and community stakeholders to develop local and regional STEM workforce development initiatives. Additionally, the National Science Foundation funds research and development across all fields of study within the family of STEM disciplines. As a result, all federal agencies, most state and local governments, and many research institutes follow the Foundation's directives and guidelines regarding STEM.

The STEM acronym originated within the National Science Foundation in the 1990s as "SMET," before being rearranged into the existing pronunciation (Lund & Schenk Jr, 2010). This change foreshadowed additional efforts to refine and strengthen the concept as the economy evolved and the demand for STEM skills intensified. This paper compares and contrasts the two most widely used methods of classifying STEM employment in the United States—one from the U.S. Census Bureau and one from the Brookings Institution. Additionally, it introduces a third method that we have developed to potentially compensate for some of the shortcomings in the first two methods. All three methods have subtle differences that have implications for who is and who is not considered part of the STEM workforce.

The U.S. Census Bureau classification comes from the Standard Occupational Classification Policy Committee, a consortium of nine federal agencies charged with standardizing occupational definitions. In the United States, all possible occupations are given a standard numerical code. To support the National Science Foundation's efforts at expanding the STEM workforce, in 2012 the committee recommended that workers in 62 of the 539 standard occupations should be defined as STEM. The Census classification is widely used throughout federal agencies and by many researchers to officially measure the size of the STEM workforce. However, it relies on predetermined subjective judgments about occupational categories, which can be quite broad in a number of cases. As a top-down approach, it does not consider how workers directly evaluate their roles and tasks performed on the job.

An alternative measure was developed by the Brookings Institution, one of the leading public policy research institutes in the United States. A 2013 Brookings Institution report categorized tasks based on the input of workers and researchers, and then calculated a rating for each occupation according to its component tasks (Rothwell, 2013). The Brookings Institution approach uses the Department of Labor's Occupational Information Network (O*NET), which classifies the types of knowledge required for work tasks. For each occupation and for each of the four STEM fields (i.e., science, technology, engineering, and mathematics), Rothwell created a 7-point score indicating the level of knowledge required from that STEM field for that occupation's component tasks. Occupations with a knowledge score of at least 1.5 standard deviations above the mean in at least one STEM field were classified as "high STEM occupations." A high STEM occupation could be "high" in mathematics, but potentially "low" in science, technology, and engineering. Combining the scores across all four fields of STEM, occupations with a knowledge score of at least 1.5 standard deviations above the mean were classified as "super STEM" occupations.

The Brookings approach results in a broader definition of STEM, uncovering what they called the "hidden STEM economy" of STEM jobs requiring less than a bachelor's degree. The government has directed far less money to build the educational pipeline to these "hidden" STEM jobs, which are concentrated in manufacturing, healthcare, and construction industries.

Our approach to classifying the STEM workforce was to directly survey workers and ask if their job is STEM. The approaches used by the Census Bureau and by Brookings assess STEM qualities at the occupation level. The Bureau of Labor Statistics defines an *occupation* as "a set of activities or tasks that employees are paid to perform. Employees that perform essentially the same tasks are [grouped] in the same occupation, whether or not they work in the same industry." (Bureau of Labor Statistics, undated) We instead classify individuals based on their job, where we define a *job* as a match between a worker and a firm, or the specific work arrangement of a given individual including the exact tasks they perform. Two different workers in the same occupation would have different jobs and may perform different tasks. With our approach, we are most interested in how workers personally assess the STEM-nature of their jobs.

RESEARCH QUESTIONS AND EMPIRICAL APPROACH

Using the three approaches to measuring the STEM workforce described in the previous section as an empirical foundation, we empirically address the following three research questions:

1. How does self-reported STEM job classification (i.e., a bottom-up approach) differ from the existing occupation-based classifications (i.e. top-down approaches)?
2. Are women and men differentially sorted into the periphery STEM workforce?
3. Conditional on worker and job characteristics, are there any observed differences in compensation for working in the periphery STEM workforce?

Data

To answer our three research questions, we analyze data from the RAND American Life Panel (ALP), a nationally sampled online panel that permits generalization to the non-institutionalized population of adults in the United States. The panel receives periodic surveys on different topics, as well as a standard module on household characteristics fielded every quarter. Technical documentation provides additional information on the ALP sample, weighting, and data collection methods (Pollard & Baird, 2017).

In the summer of 2017, the authors developed and administered the following question to ALP members as part of survey #MS480:

> The next few questions are about your schooling and its relationship to your work experiences. Specifically, we are going to talk about school and work experiences in STEM—an acronym for "Science, Technology, Engineering, and Mathematics." This includes all sciences, from earth sciences (example, geology and astronomy) to life sciences (example, biology and chemistry) to social sciences (example, psychology, and political science). Technology includes all forms of computer science and network applications.
>
> Are you currently working in a STEM job? Note that this relates to the tasks you do, and not the industry you work in. For example, an engineer for a bioengineering research firm would be in a STEM job, but an administrative assistant at the same bioengineering research firm would NOT be in a STEM job.

In the survey, respondents also provided their occupation, allowing us to classify them by both the Census and Brookings approaches. The occupation question uses a dropdown menu populated by the Standard Occupation Codes (SOC) which prompts the respondent to choose the occupation that best resembles their own.

ALP survey #MS480 received 3,569 responses, a response rate of 82 percent among those in the randomly sampled population of the ALP. Given our focus on the employed workforce, we limited the sample to adults under the age of 65 who were employed at the time of the STEM question, and who provided an occupation code, leaving 1,694 responses.

ALP survey #MS480 contained only a broad set of occupational codes, consisting of 23 major Standard Occupation Codes and no data on wages, limiting our ability to compare STEM jobs with STEM occupations and to measure compensation. To address this problem, we merged ALP survey #MS480 with ALP survey #MS436, one of the periodic standard modules administered in the summer of 2015 which included a question asking sample members to report their occupation. In all, 1,494 of our sample members reported an occupation in the earlier survey, and 1,055 of them maintained the same broad occupation between surveys. We excluded those whose broad occupation changed, because their 2015 occupation was unlikely to reflect their 2017 occupation. We predict that the 2015 occupation is accurate in 2017 for about 98 percent of the remaining individuals. **Appendix A** provides supporting details. The final 1,055 respondents are weighted to match the Current Population Survey (CPS), which is a monthly nationally representative survey used by the U.S. Department of Labor to calculate unemployment rates. **Appendix B** describes the weighting procedure. Shrinking the sample size from 1,819 down to 1,055 slightly increased the rate of self-reported STEM work, but otherwise there were no major differences between the matched analysis sample and the broader sample of respondents on observed socio-demographic characteristics.

Wages come from responses in the 2015 survey to annual compensation from the sample member's primary job, the typical hours worked per week, and the number of weeks worked (including paid time off) per year. Details on corrections and adjustments to the wage data appear in **Appendix C**. Respondents also indicated whether their job provided paid time off, health insurance, and retirement benefits. Non-wage compensation is an important aspect of total compensation, which if ignored can misstate the true value of a STEM degree as it is applied in different work settings (Baird, 2017). We use the benefits questions to estimate non-wage compensation in dollar terms, using fringe rates from the Bureau of Labor Statistics (Bureau of Labor Statistics, 2016). The procedure is described in **Appendix D**.

Table 2 presents the summary statistics for our sample, where overall demographics match the weighted Current Population Survey and thus approximate national averages: 45.7 percent of workers are women, 30.1 percent are racial minorities, and 37.6 percent have at least a bachelor's degree. About 15 percent of total compensation comes from benefits. The sample is representative of the current workforce, with multiple generations and varying gender demographics that are obscured by aggregates in this table but are explicitly included in our regression analyses.

Table 2 gives us our first look at the size of the STEM workforce, which ranged from 5.7 percent of workers using the Census approach up to 26.5 percent of workers using Brookings approach (with "high STEM" and "super STEM" combined). Meanwhile, our approach using self-reports yielded an estimate in between the two, at 19.8 percent of workers.

Table 2: Summary Statistics for the RAND American Life Panel (ALP)

Variable	Mean	Standard deviation	Minimum value	Maximum value
Women (%)	45.7			
Racial minority (%)	30.1			
Highest education: Bachelor's degree	20.3			
Highest education: Graduate/professional degree	17.3			
Age	42.6	11.7	21.0	64.0
Years working for current employer	8.3	8.4	0.0	50.0
Family income ($1,000s)	90.3	60.4	2.5	250.0
Hourly wage ($)	35.6	99.2	7.3	1,302.1
Non-wage compensation/hour ($)	5.9	7.6	0.0	113.0
STEM, Census approach (%)	5.7			
High STEM, Brookings approach (%)	14.7			
Super STEM, Brookings approach (%)	11.8			
STEM, Brookings approach (%)	26.5			
Self-reported STEM, our approach (%)	19.8			

N = 1,055
Source: RAND Corporation’s American Life Panel, United States
Note. Estimates weighted to approximate the 2015 Current Population Survey.

Empirical Approach

The first research question assesses the *size* of the periphery STEM workforce. To answer this question, we present cross-tabulations and descriptive figures from our survey data based on the alternative STEM classifications.

The second question assesses the *composition* of the periphery STEM workforce. To answer this question, we first take each occupation and conduct a t-test for the probability of being in that occupation for the two samples of those in the STEM periphery and all other workers. We do this separately by gender and present a sorted list of the top 10 occupations with presence in the STEM periphery. Next, we use linear regression to predict the probability of being in the STEM periphery (conditioning the sample on those in the STEM periphery or core STEM) on socio-demographic characteristics to determine which characteristics predict STEM periphery, and how the gap between men and women changes when including other covariates.

Finally, the third question serves to validate the market importance of the periphery versus core STEM workforce concepts. To do so, we estimate regressions predicting the log of hourly wages, log hourly value of non-wage compensation, and the log total of the two, controlling for individual characteristics and including indicators for STEM classifications of different types by gender. The base reference group for each gender is men in the core non-STEM workforce.

To address the classic selection bias in observing wages imposed by selection into working, we use a Heckman correction in a two-stage model. The first stage predicts selection into paid employment, and the second stage predicts wages conditional on working. We use the number of dependents and the number of dependents interacted with gender as predictors of employment in a first-stage equation, along with the covariates of the second stage. These are common choices for the first-stage excluded instruments in a Heckman selection regression, with the assumption that women with dependents are more likely to not be in the labor force (as some choose to primarily raise their children while outside of the labor force), while men are more likely to be in the labor force when having dependents (feeling additional pressure to provide for their dependents). The key assumption is that having dependents has no direct effects on earnings outside of the effect through entry into the labor force. The conclusions are similar regardless of whether or not we use a two-stage Heckman selection model or a simple OLS model.

RESULTS

Size of the Periphery STEM Workforce

Table 3 provides two empirical implementations of the comparisons highlighted in Table 1. The four cells within each of the two panels sum to 100 percent. The periphery STEM workforce is shaded in gray. The total size of the periphery STEM workforce missed by traditional approaches was 15.8 percent of all workers by the Census approach, and 9.4 percent of all workers by the Brookings approach. These are substantial proportions of workers, and particularly of STEM workers. There were more workers in the Census-based STEM periphery (15.8 percent) than in the core STEM (4.0 percent) or even the total official STEM workforce (4.0 percent plus an additional 1.7 percent in the other off-diagonal). The Brookings-based STEM periphery (9.4 percent) was approximately the same size as the core STEM workforce (10.3 percent). All proportions are statistically different from zero at $p<0.001$.

Table 3: The Periphery STEM Workforce

		Our approach	
		Non-STEM	STEM
Census approach	Non-STEM	78.5% (1.3%)	15.8% (1.1%)
	STEM	1.7% (0.4%)	4.0% (0.6%)
Brookings approach	Non-STEM	64.0% (1.5%)	9.4% (0.9%)
	STEM	16.2% (0.9%)	10.3% (0.8%)

Source: RAND Corporation’s American Life Panel, United States

Note. Estimates weighted to approximate the 2015 Current Population Survey. The gray cells indicate the periphery STEM workforce. Standard error of mean in parentheses.

Composition of the Periphery STEM Workforce

We evaluated gender parity in three different groups of workers: all workers, workers with any post-secondary credential in a STEM field (including associate degrees, certificates, and bachelor’s degrees), and workers with a bachelor's degree or higher in a STEM field. To do so, we plotted the estimated percentage of women in the STEM workforce using the different measurement approaches (Figure 1). As shown in Figure 1, women were better represented in the STEM workforce as education increased, reflecting the overall trend of women advancing in some fields and acquiring more high-level degrees than men.

Across all levels of education, there were clear differences between our self-reported job measure and the top-down approaches used by the Census and Brookings. When using the Census definition or either of the Brookings’ definitions, there were significantly fewer women in STEM at all education levels. Using our bottom-up approach, we find near parity between the genders, especially among those with any STEM postsecondary credentials (50 percent women in the middle gray bar).

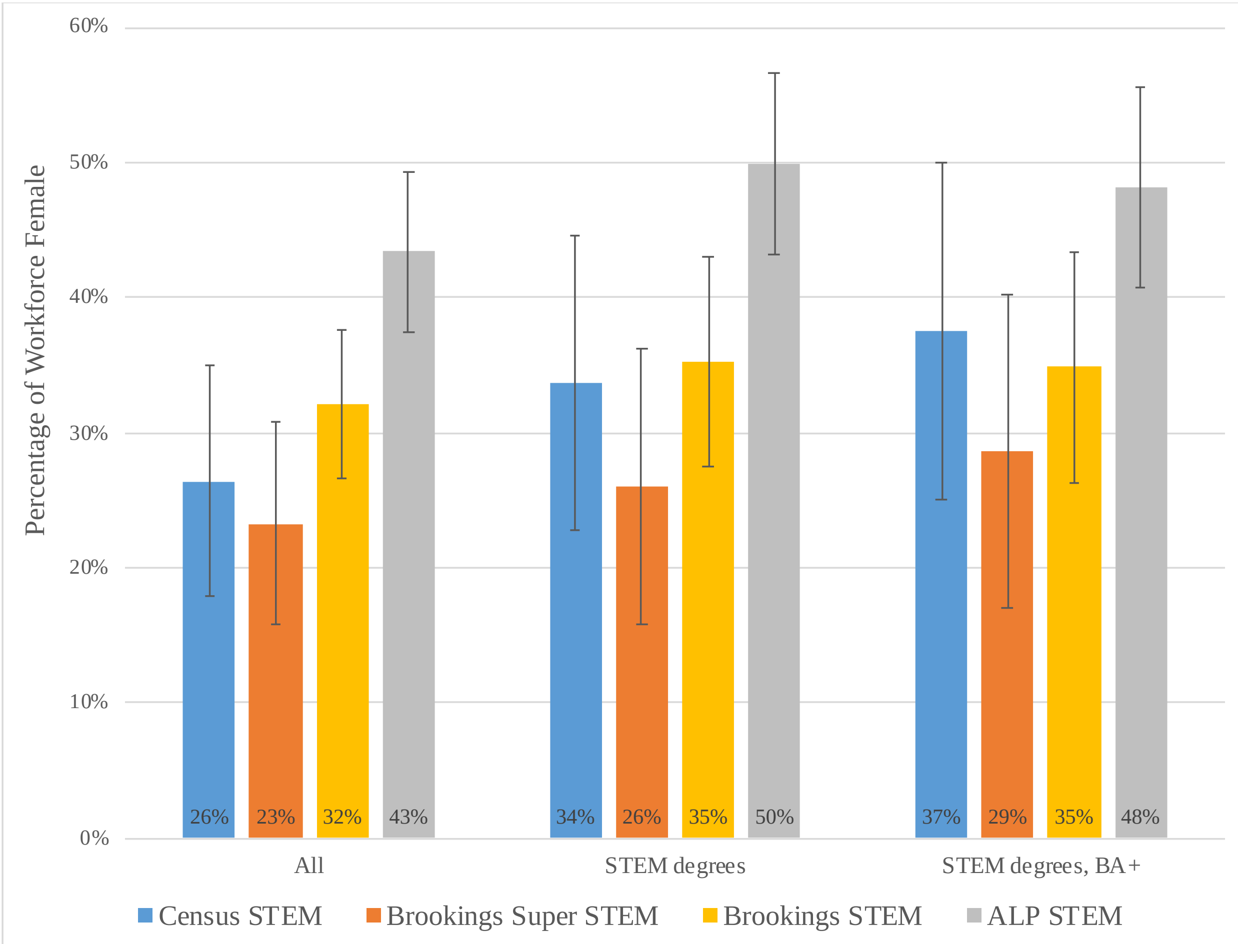

Figure 1. Gender composition of STEM workforce by level of education and classification approach.
Source: RAND Corporation's American Life Panel, United States
Note. Estimates weighted to approximate the 2015 Current Population Survey. Whiskers denote 95% confidence intervals around the estimates.

To understand the nature of these discrepancies, Table 4 reports the top 10 most common occupations for men and women in the periphery STEM workforce, contrasted with all other workers. The most common occupations in the STEM periphery are not necessarily the most common occupations overall. For example, 11.1 percent of all women in the periphery STEM economy were working in "Miscellaneous Healthcare Support Occupations," while only 3.8 percent of women not in the STEM periphery in the sample worked in this occupation group.

For women, the industries that contributed most to discordance across classification schemes were in healthcare and education. Healthcare support workers, social workers, counselors, educators, dental hygienists, and librarians all appeared in the periphery because they reported using STEM skills outside traditional STEM occupations. For men, the occupations most represented in the periphery seem to be comprised of a different set of occupations, such as managers, post-secondary instructors, law clerks, and salespersons.

Some occupations here at first glance seem less objectively STEM-related: for men, truck drivers and for women, customer service. Our approach is to take answers at face value. We cannot distinguish between classifications that might be considered a misunderstanding of the survey question, and classifications that truly represent periphery workers using STEM skills in their jobs. Without additional insight into respondents' interpretation of STEM, we assume that women and men are subject to the same sources of potential measurement error. We discuss the implications of such measurement error when contrasting the advantages and disadvantages of each classification approach in our conclusion.

Beyond gender differences, we sought to identify other characteristics associated with working in the STEM periphery. To do so, we estimated regressions using the sample of STEM workers broadly defined, with a binary outcome indicating whether the STEM worker is in the periphery or in the core. Model 1 includes a single parameter for gender. Model 2 adds in a set of demographic characteristics. Model 3 interacts these demographic characteristics with gender to see if any traits are more predictive for being in the periphery STEM workforce for women than for men. The results from these linear probability models are presented in Table 5. The coefficients can be interpreted as the increased probability, in percentage points, of being in cell (b) rather than cell (d) in Table 1.

Across all models, gender is the most salient characteristic predicting membership in the STEM periphery among STEM job holders. The gender gap of 23 percentage points in Model 1 widens to 30 percentage points when individual characteristics are added in Model 2. We also find that being a minority increases the probability of being in the periphery substantially, while having a STEM degree decreases the probability substantially. When we additionally interact characteristics with gender (Model 3), we do not find any statistically significant interactions between gender and these demographic characteristics. However, the signs and magnitudes of the coefficients suggest that the demographic associations are even stronger for men than for women: minorities and non-STEM educated workers are less likely to be in periphery STEM jobs.

Table 4: Most Common Occupations for STEM Workers in Descending Order of Periphery STEM Prevalence, by Gender

	STEM Periphery	All others	p-value for diff.
Women			
Healthcare Support Occupations	11.1%	3.8%	0.006
Social Workers	11.0%	0.5%	<0.001
Counselors	10.7%	1.2%	<0.001
Securities, Commodities, and Financial Services	7.0%	0.0%	<0.001
Dental Hygienists	5.7%	0.0%	<0.001
Secondary School Teachers	5.5%	0.3%	<0.001
Miscellaneous Teachers and Instructors	4.4%	3.2%	0.589
Librarians	4.2%	0.2%	<0.001
Customer Service Representatives	4.1%	2.9%	0.583
Teacher Assistants	2.7%	1.3%	0.366
Men			
Driver/Sales Workers and Truck Drivers	19.2%	4.9%	0.001
Education and Library Science Teachers, Post-secondary	10.7%	0.2%	<0.001
Marketing and Sales Managers	9.1%	1.0%	<0.001
Lawyers and Judicial Law Clerks	8.0%	2.1%	0.036
Building Cleaning Workers	6.3%	1.5%	0.052
Securities, Commodities, and Financial Services	5.8%	0.1%	<0.001
Computer Control Programmers and Operators	4.8%	0.0%	<0.001
Dispatchers	4.3%	0.0%	<0.001
Customer Service Representatives	3.9%	1.5%	0.303
General and Operations Managers	3.5%	1.2%	0.263
Driver/Sales Workers and Truck Drivers	19.2%	4.9%	0.001

Source: RAND Corporation’s American Life Panel, United States
Note. Estimates weighted to approximate the 2015 Current Population Survey.

Table 5: Parameter Estimates from Linear Probability Models Predicting STEM Periphery Membership Relative to Core STEM Membership

	(1)	(2)	(3)
Male	-0.230**	0.297***	-0.259
	(0.091)	(0.075)	(0.202)
Age		-0.005	-0.005
		(0.003)	(0.005)
Highest education: BA/BS		-0.001	-0.014
		(0.097)	(0.143)
Highest education: graduate degree		0.148	0.159
		(0.096)	(0.131)
Racial minority		0.306***	0.233**
		(0.089)	(0.107)
STEM degree		0.324***	-0.263*
		(0.095)	(0.157)
Male × age			-0.001
			(0.007)
Male × highest education: BA/BS			0.023
			(0.193)
Male × highest education: graduate degree			-0.023
			(0.191)
Male × racial minority			0.124
			(0.164)
Male × STEM degree			-0.086
			(0.196)
Constant	0.609***	0.763***	0.728***
	(0.056)	(0.111)	(0.162)
Observations	267	267	267
R-squared	0.053	0.230	0.235

* $p < 0.10$ ** $p < 0.05$ ***$p < 0.01$

Source: RAND Corporation's American Life Panel, United States
Note. Estimates weighted to approximate the 2015 Current Population Survey. Robust standard errors in parentheses.

Compensation in the Periphery STEM Workforce

It is unclear the extent to which women's overrepresentation in the periphery STEM workforce should be concerning. Under our definition of STEM work, including the periphery STEM workforce as part of the broader STEM workforce significantly closes the gender gap in STEM employment at all levels of education. But the potentially good news of the equitable STEM work patterns across gender may still be concerning if women do not earn higher wages and benefits using the same skills. It is therefore important to examine how the women who closed the STEM participation gap via their acquisition of jobs within the STEM periphery are compensated for their work.

Table 6 presents the regression results of compensation from our models estimated with the Heckman corrections. For both women and men, working in the core STEM workforce (STEM job in a STEM occupation) is associated with higher earnings, higher non-wage compensation, and higher total compensation than working in the non-STEM core. Women receive a larger upgrade in wages moving from the core non-STEM workforce to the core STEM workforce, and both genders ended up equally well-off relative to the excluded group of men working in the non-STEM core (adding the coefficients on female and female core STEM). Using a standard transformation, the advantage of 0.3 log points is equivalent to about a 40 percentage-point increase in earnings accruing to core STEM workers (Kennedy, 1981).

For men, there is a significant wage increase for those working in any part of the STEM workforce, including the periphery STEM. However, this is not true for women, where there are only statistically significant gains if they work in STEM jobs in core STEM occupations. Therefore, the substantial number of periphery STEM women workers do not appear to be reaping a benefit from using their STEM skills and training in non-STEM occupations. On average, women only benefit from using their STEM skills and training if they work in traditionally classified STEM occupations.

Table 6: Parameter Estimates from OLS Models Predicting Compensation

	Log wage	Log non-wage	Log total
Female	-0.212**	-0.113	-0.233***
	(0.0827)	(0.126)	(0.0856)
Male, periphery non-STEM	0.304***	0.217	0.245*
	(0.108)	(0.221)	(0.125)
Male, periphery STEM	0.192*	0.188	0.190
	(0.103)	(0.142)	(0.118)
Male, core STEM	0.348***	0.341**	0.336***
	(0.0989)	(0.136)	(0.102)
Female, periphery non-STEM	0.129	0.188	0.156
	(0.108)	(0.151)	(0.139)
Female, periphery STEM	0.0506	0.0286	0.0284
	(0.0826)	(0.141)	(0.0938)
Female, core STEM	0.505***	0.463***	0.529***
	(0.0726)	(0.0940)	(0.0814)
Highest education: BA/BS	0.396***	0.166*	0.388***
	(0.0684)	(0.0997)	(0.0657)
Highest education: graduate degree	0.578***	0.326***	0.568***
	(0.0741)	(0.102)	(0.0715)
Racial minority	-0.258***	0.273**	-0.224**
	(0.0928)	(0.118)	(0.0941)
Potential work experience	0.0372***	0.0615***	0.0476***
	(0.0079)	(0.0151)	(0.0091)
Potential work experience squared	-0.0006***	-0.0012***	-0.0008***
	(0.0002)	(0.0003)	(0.0002)
Constant	2.317***	1.558***	2.435***
	(0.104)	(0.178)	(0.106)
Observations	1,067	794	949
R-squared	0.190	0.062	0.181

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Source: RAND Corporation's American Life Panel, United States

Note. Estimates weighted to approximate the 2015 Current Population Survey. Robust standard errors in parentheses.

DISCUSSION AND CONCLUSION

Our approach to measuring the STEM workforce takes into consideration that the economy increasingly requires workers who are proficient in the application of technology, data science, and digital communication, and who possess quantitative analysis skills and complex problem-solving skills. These workers, often from STEM educational backgrounds, can apply their STEM skills and training to a number of jobs outside of traditionally defined STEM occupations. To locate and quantify these workers, we fielded a survey to a nationally representative sample of Americans. To conclude this study, we discuss what might be driving the differences between our measurement technique and existing techniques, and what matters for understanding gender disparities in the STEM labor force.

Measuring the STEM Workforce in a Changing Economy

Each time a new measure of the STEM workforce arises, it illuminates new aspects of the economy, but comes with its own set of limitations. The Census Bureau's definition, based on expert opinion, categorically defines broad occupation categories as either STEM or not STEM. Recognizing this limitation, the Brookings Institution expanded significantly on the Census Bureau definition, classifying many more occupations as STEM. The Brookings definition used an underlying index of skills and knowledge, providing a numerical justification and a natural way to set thresholds defining additional categories such as high STEM and super STEM.

There are other complementary approaches as well. One study following the Census top-down occupation-based approach included 12 additional occupations, such as healthcare practitioners and technicians (Funk & Parker, 2018). A recent study complements the three approaches in this paper by building up a task-based definition of STEM jobs (Grinis, 2019). That study used keywords from job postings in the United Kingdom to show that around 15 percent of job postings outside STEM occupations could be classified as STEM jobs. Postings requiring STEM skills offered higher wages, regardless of whether the job was in a STEM occupation or not.

Like the United Kingdom study, we find that STEM skills used outside of STEM occupations are compensated, though primarily for men. Supporting the Brookings approach, we find that workers in periphery STEM jobs have higher Brookings STEM ratings as opposed to core non-STEM jobs, indicating they would be closer to being counted as STEM even without the information gleaned from our survey. Like the expansions to the Census approach, our periphery concept tends to include healthcare workers. Our measure is more than just another expansion of STEM, though. The size of the STEM workforce under our measure is smaller than for the Brookings measure.

Each of the measures is subject to measurement error between the imperfect categorization of real-world occupations, jobs, or tasks, and some theoretical true encapsulation of science, technology, engineering, and mathematics. Amongst the three approaches, our measure is the most subject to errors in understanding and interpretation across individuals. For example, consider a financial services agent, an occupation which accounts for seven percent of women and six percent of men in the periphery STEM workforce. Such workers may consider themselves as doing

STEM jobs because STEM seems smart and important, and so they may want to appear more favorably on a survey. Alternatively, workers could choose different thresholds for what constitutes the "STEM-like nature" while looking at the exact same job. Lastly, workers could misunderstand the prompt, somehow. For example, a financial services agent filling out the survey may quickly scan the question, see the word "math", and respond affirmatively because there is some basic math required to perform their job. A social worker might make the same mistake, steering us away from some theoretical encapsulation of STEM. These types of errors would threaten our main findings if it they are likely to occur differentially between men and women and differentially across occupations. To attenuate this error, we recommend that future research eliciting individual responses experiments with the question wording, question placement, and other prompts or instructions to infer whether respondents' understanding of the question could be driving the results.

The Brookings measure is subject to errors at three levels: in choosing how STEM-involved a broad set of tasks are, choosing how those tasks are aggregated into occupations, and choosing the cut-off for what makes an occupation STEM or not. To the extent that the decentralized errors in each level of the Brookings measure (and in our measure) average out across raters, the point estimates should be unbiased. However, the variance in small samples may be large. The Census Bureau definition, by contrast, may be biased without a clear mechanism to balance it out. For the Census measure, the measurement error is limited to a small set of decision makers, and therefore risks their opinions being out of date, being unconsciously gender-biased based on cultural norms, or being too limited by the existing set of SOC codes.

Given rapid changes in technology, STEM work will continue to be a moving target (Deming & Noray, 2018). Determinations of STEM occupations will need to be updated on regular basis. Updating the Census Bureau measure potentially faces the lowest cost, as the fewest people are involved. Either the Brookings or Census measures could be updated using existing data, by drawing different boundaries. Updating our self-reported measure requires new data collection, because there is only one boundary in the yes/no question, which cannot be redrawn without additional information.

A measure based on job postings is perhaps the most flexible and updatable, as it responds flexibly to supply and demand in the labor market: new jobs are constantly being posted, and more and more of them are being posted online (Grinis, 2019). The limitations of machine learning approaches relative to our method are that we analyze actual workers in accepted jobs, rather than postings that may represent the creation of zero (or many) job matches, and thus, may turn out to pay different wages for different tasks than the posting suggests (Grinis, 2019; Ikudo et al., 2019). Additionally, because job postings are typically written by employers and not employees, our approach is likely more sensitive to variation in the tasks, assignments, and work arrangements that workers encounter day-to-day.

Implications for Understanding Gender Gaps in STEM

Why do we observe a higher concentration of women in the STEM periphery? We speculate that there are two sets of factors: external forces acting to limit workers' choices, and internal preferences motivating workers' choices. Specifically, women might be less likely to work in core STEM jobs if they face discrimination or are less welcome in STEM job environments, or they may be less likely to work in core STEM jobs if they tend to prefer the tasks in the periphery. One study found that preferences for tasks may lead to changes in gender balance, which may be reinforced by shifts toward non-wage compensation more valued by women (Lee & Thompson, 2019). The STEM periphery may serve to create "horizontal occupational sex segregation" *within* the STEM workforce, whereby both women and men land similar STEM occupations but perform quite different tasks, with different levels of compensation. Our research adds growing evidence into how women remain disadvantaged in the labor force, even when attaining the same level of education and landing similar jobs as men.

These considerations are particularly important as efforts within the United States to improve the status of women in STEM fields, and occupations are central to improving workforce diversity and inclusion. For example, the United States has invested heavily via its National Science Foundation to promote pathways into STEM careers for young women. However, as our analysis shows, STEM careers are quite heterogenous, with varying applications of STEM skills and knowledge and consequently, unequal labor force outcomes. If the goal of these efforts is to narrow the gender wage gap, more attention needs to be paid to ensuring that young women have opportunities to acquire positions within the core STEM workforce rather than the periphery.

For proponents of policies to promote equitable outcomes across workers, our measure reduces the pressure to induce more women into STEM work, while increasing the pressure that STEM-trained women receive equal compensation in the jobs where they use their STEM skills. Policies to promote holding STEM jobs, such as tax credits and loan forgiveness, could tip the net benefit of working in STEM further toward men if these policies only reward the types of STEM jobs men choose. Alternatively, if STEM skills were more equally rewarded wherever they are used, including in the periphery, then gender wage gaps could potentially be narrowed.

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Appendix A: Discussion on the two-year gap in the two ALP surveys

We link two surveys that the same individuals answered two years apart, drawing one measure of STEM work from each. We restrict the sample to respondents who were employed in both periods, and who worked in the same broad occupation category in both periods. One risk is that the respondents changed occupations within the broad category during those two years, generating some of the mismatches we observe.

In this Appendix we use a national panel sample to estimate the proportion of people whose 2015 occupation was no longer accurate in 2017 although they remained in the same broad occupation category. We investigate occupation switches using the Survey of Income and Program Participation 2014 panel. This survey yields a large sample of individuals in a panel, so that we can observe changes over time during roughly the period of our sample. About 20 percent of individuals switch between 23 broad occupation groups across two years. This is higher than the 11 percent we find for the ALP sample. Among workers who remained in the same broad occupation group, 9 percent changed occupation. Most relevant for our paper, the percentage of those who switch STEM occupation status is between 1 and 2 percent of the sample. To the extent that our data include more stability as suggested by fewer broad occupation switches, we anticipate no more than 1 to 2 percent of our sample switched STEM occupation status from 2015 to 2017.

Table A1: Percentage of STEM switchers across two years in SIPP, overall and for subsample who remained in same broad occupation group.

	All	Same occupation group
% Switching occupation group	19.4%	-
% Switching occupation	26.6%	8.9%
% Switching Brookings high STEM classification	9.7%	2.3%
% Switching Brookings super STEM classification	7.5%	1.9%
% Switching Census STEM classification	5.6%	1.2%
SIPP person-wave observations	75,243	60,609

Note. Data based on 2014 Survey of Income and Program Participation, United States. All: workers with occupations observed across two years. Same occupation group: broad occupation group the same across two years.

Appendix B. Discussion of weighting and imputing the ALP data

In order to make comparisons with other data sets and have a nationally representative sample to make statements on the overall representation of women in the national STEM economy, we generated weights using a raking algorithm, matched against the 2015 Current Population Survey. For this study we matched on gender by race/ethnicity cell (non-Hispanic white, non-Hispanic black, Hispanic, other); gender by age in four age groups; gender by education level; household income by household size; as well as gender by U.S. Census occupation STEM definition and by Brookings Institution STEM definitions. More details on the general weighting approach in the ALP are in the technical documentation (Pollard & Baird, 2017). There are some missing observations for some demographic variables. In the regressions we use imputation to fill in these missing control variables.

Appendix C. Accounting for missing hourly wages for workers

Our calculation of the hourly wage is based on a response to the question of the annual value of earnings from their primary job, their average hours worked per week in their primary job, and their typical number of weeks worked per year in their primary job. This, in some cases, led to unreasonably small hourly wages close to zero. These typically happened by respondents reporting annual total earnings of a value less than $1,000 while still working over 30 hours a week and over 40 weeks a year. We consider these cases as mistaken responses. We set equal to missing any calculated hourly wage below $3/hour and create inverse probability weights for this missingness by doing a logistic regression of not missing (amongst those working) on gender, age, baseline family income, and highest education level. We multiply these IPWs by the sample weights based on the CPS to get the final weights for the compensation regressions. Hourly wages above $3 but below the federal minimum wage of $7.25 were set to $7.25.

Appendix D. Estimating the value of non-wage benefits

The United States' Bureau of Labor Statistics reports the results of the National Compensation Survey, wherein estimates are given about how to value fringe non-wage compensations as percentages of the wages (Bureau of Labor Statistics, 2016). We use these estimates to calculate the value of non-wage benefits of workers in our study according to their response to three questions: whether their job has paid time off, whether their job provides insurance, and whether their job provides retirement benefits. As paid time off and retirement benefits are functions of the person's pay rate, we calculate the value as 0.07 times the hourly wage for paid time off (reflecting BLS 7 percent value of the same) and 0.054 times the hourly wage for retirement benefits (reflecting BLS 5.4 percent value). For insurance, this is not typically directly a scaling of the earnings, so we use the 8.7 percent value of insurance from BLS, but we give an individual with insurance benefits a value of 0.087 times the sample average hourly wage. Some individuals get none of these three benefits, and thus they have a value of zero for non-wage benefits and an undefined value for log non-wage benefits. To address these zeros in the outcome, we use the inverse hyperbolic sine in place of the natural log, given that the inverse hyperbolic sine closely mimics the log to a scaling additive constant while being defined at an input of zero.