WORKING PAPER

# Who Gets Counted as Part of America's STEM Workforce?

## The Implications of Different Classification Approaches for Understanding the Gender Gap in STEM

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**Abstract**

The STEM (science, technology, engineering, and math) economy has been defined by top-down categorizations of occupations by experts. This study takes a bottom-up approach, directly asking a national sample of workers to self-classify their jobs as STEM or not. We identify a sizeable group of workers in what we call the "periphery STEM workforce," who report working STEM jobs outside of traditional STEM occupations. Women are more likely than men to be in the periphery STEM workforce, but they do not receive significantly higher wages than do non-STEM workers. This aspect of the gender pay gap is invisible using the current classification schemes.

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## I. Introduction

Science, technology, engineering, and mathematics majors and fields have been grouped together and branded collectively as "STEM." The general concept has grown in importance, 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, Smith, and Melton 2011; 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 (National Academy of Sciences, National Academy of Engineering, and Institute of Medicine 2007). Workers with degrees in STEM are more likely to be employed, and to earn more than their peers with degrees in other subjects (Baird, Bozick, and Harris 2017; Carnevale, Smith, and Melton 2011). The validity of these conclusions depends on how exactly STEM is defined, and it is a concept that is changing constantly as new jobs and technologies emerge. This paper revisits and refines the definition of STEM employment using a new national survey of workers.

Any attempt to define the boundaries of STEM learning and work is somewhat arbitrary, but the consequences of these definitions are not. For example, research in the 1990s and early 2000s documenting the United States' mediocre international standing with respect to STEM education and innovation led to massive investments by the federal government in STEM training and STEM research (National Academy of Sciences, National Academy of Engineering, and Institute of Medicine 2007). Immigration policymakers have attempted to incorporate allocations for visas based on STEM degrees and the needs of STEM employers via the controversial STEM Jobs Act of the 114$^{th}$ Congress (which did not become law). Moreover, in 2018 the U.S. News and World Report began using the proportion of degrees granted in STEM as a factor in determining their rankings of universities (Morse and Brooks 2017). Therefore, defining STEM is not simply an esoteric academic exercise, but one that has real consequences for how policymakers, educators, and employers structure and support the school-to-work pipeline in the United States.

The concept of STEM is also useful for identifying gender gaps in education and work. Women and men work in STEM occupations at different rates, with notably greater shares of men in the STEM workforce than women (Baird, Bozick, and Harris 2017; Carnevale, Smith, and Melton 2011; U.S. Equal Employment Opportunity Commission 2016). The gap between genders begins early, when young girls and boys are first introduced to STEM subjects in elementary school, and compounds over time (Fryer and Levitt, 2010; Hill, Corbett, and St. Rose, 2010; Jaeger at al. 2017). In Canada, much of the gender gap in choosing STEM can be traced to differences in STEM preparation in high school (Card and Payne 2017). As college students, women are less likely than men to choose majors in STEM fields and conditional on registering as STEM majors, women are less likely than men to stay in the program and graduate as STEM majors (Arcidiacono et al. 2016; Baird, Buchinsky, and Sovero 2017; Chapa and De La Rosa 2006; Chesler et al. 2010). Conditional on graduating with a bachelor's degree in STEM, women are less likely than men to work in a STEM occupation (Baird, Bozick, and Harris 2017). As a result, the STEM workforce remains disproportionately male (Gonzalez et al. 2016; 2017).

These gender differences in the workforce have persisted even as long-standing gender disparities in 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 more likely to enroll in and complete college (National Center for Education Statistics 2016, National Student Clearinghouse Research Center 2018). Women earn higher grades and have higher postsecondary aspirations (Fortin, Oreopoulos, and Phipps 2015). Further, 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 2017). Men have however maintained an advantage in physics, computer science, engineering, and math, across all levels and selectivity of colleges (Schneider et al. 2015).

Clearly women's advancement in STEM education and in STEM employment has been uneven, and we lack definitive explanations for this phenomenon and its consequences. Concerns about gender equity in STEM have intensified with warnings about a shortage of STEM workers in the United States (President's Council of Advisors on Science and Technology 2012), as well as the potential role STEM jobs can play in closing the gender pay gap.

In this paper, we put forth the hypothesis that a significant proportion of women's participation in the STEM workforce is obscured by how the STEM workforce is operationally defined. To date, measurement of the STEM workforce by the federal government and think tanks has relied on top-down classifications of occupations by federal agencies. These definitions are based on what typical workers do in each occupation, and thus ignore potential variation across workers within an occupation as well as recent developments and newly emerging jobs.

Consider an occupation where 90 percent of the workers within that occupation are not involved in STEM-specific tasks. In this case, all workers in this occupation would be classified as non-STEM. However, this leaves 10 percent of the workers who are doing STEM tasks but are nonetheless excluded from official determinations of the size of the STEM workforce. Many healthcare workers, technicians, and teachers (particularly those of STEM subjects) apply STEM skills and concepts in their daily jobs but are classified per their occupation as non-STEM. If women are differentially located in STEM jobs within non-STEM occupations, then measuring the STEM workforce by occupation codes will underrepresent women's presence and potentially misdiagnose policy problems.

To address this limitation, we measured STEM jobs from the bottom up, by asking workers directly whether they consider the work they do on a daily basis to be STEM. These questions were included in a new 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.

Figure 1 provides an illustration of the concordance or discordance between the traditional top-down classifications and our new bottom-up classification.

**Figure 1. Two-dimensional measurement of the STEM workforce**

| | | **Bottom-up approach (Self-Reported Jobs)** | |
|---|---|---|---|
| | | **Non-STEM** | **STEM** |
| **Top-down approach (Expert Classified Occupations)** | **Non-STEM** | **(a)** Core non-STEM workforce | **(b)** Periphery STEM workforce |
| | **STEM** | **(c)** Periphery non-STEM workforce | **(d)** Core STEM workforce |

In the figure, cells (c) and (d) on the second row form the official estimate of the STEM workforce produced by the federal government and think tanks, based on occupational classifications. This ignores the shaded cell (b), containing STEM workers whose jobs use STEM skills and knowledge outside STEM-classified occupations. We call workers in cell (b) the "periphery STEM workforce." We investigate whether ignoring the periphery STEM workforce creates a distorted view of supply and demand in an economy that increasingly blends STEM skills and knowledge into many occupations.

To preview our survey results, we estimate that the periphery STEM workforce (cell b) contains 10 to 12 percent of all workers. Most of these periphery STEM workers are women. For example, when using the U.S. Census Bureau's occupation-based classification, 22 percent of men with STEM bachelor's degrees work in a STEM occupation, compared to only 15 percent of women with STEM bachelor's degrees. These differences are even more pronounced when using the Brookings Institution's task-based classification of STEM occupations (both definitions are described in detail later), where 58 percent of men with a STEM bachelor's degree work in a high STEM or super STEM occupation, compared to only 34 percent of women. However, when using self-reports of STEM jobs from our survey, the rates of remaining in STEM jobs among STEM graduates are much higher and nearly equal across genders: 71 percent for men and 72 percent for women.

We also explore whether there are wage differences among workers who occupy different classifications in the workforce (i.e. different cells in Figure 1). We find that men earn more if working in any form of STEM work, particularly cells (c) and (d) in Figure 1, but that this is not true for women in cell (b), the periphery STEM workforce. We do not attempt to fully account for selection into types of work. We simply model wages using a Heckman selection model to account for selection into employment.

The paper proceeds as follows. Section II provides more precise definitions used throughout the paper and describes the methods we will employ to measure the periphery STEM workforce. Section III describes the data from the American Life Panel. Section IV presents the results, which we discuss in the concluding Section V.

## II. Methods

### *A. Defining the STEM Workforce*

Available documentation indicates that the STEM acronym originated within the National Science Foundation in the 1990s, where it was initially coined as “SMET” before the order was rearranged to become STEM (Lund and Schenk 2010). This change foreshadowed additional efforts to refine and strengthen the concept of STEM, including this paper. We compare and contrast two existing methods of classifying STEM employment before introducing a third, new method. The three methods have subtle differences that turn out to have major implications for who is and who is not considered part of the STEM workforce.

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” (BLS 2018). We define a *job* as the specific work arrangement of a given individual, including the exact tasks they perform. Two persons in the *same occupation* could have *different jobs* if they perform different tasks, or view their tasks differently. For example, consider two workers employed as computer support specialists for a large accounting firm. One spends most of their time in management, monitoring equipment inventory and dispatching staff to deal with technical support requests from employees. The other spends most of their time writing and debugging code for the firm’s proprietary database software. While both hold the same occupation, their daily jobs are quite different in their substance and in their objectives.

The two existing methods of identifying the STEM workforce assess STEM qualities at different levels, by considering an occupation holistically or by considering tasks and skills which then are combined with varying weights into different occupations. Our approach is slightly different from either one, asking individuals to look holistically at the tasks and skills they personally perform. Thus, respondents to our survey do not assess the tasks they do one by one, and they do not average over all the people that are in their occupation. Most important, our approach allows for some individuals within an occupation, or who perform certain combinations of tasks and skills, to self-define as using STEM, while others in that occupation, or using a similar combination of tasks and skills, to self-define their work as not using STEM.

The remainder of this section discusses the three methods in turn. The U.S. Census Bureau holistically classifies occupations based on the input of government officials (holistic occupation approach); the Brookings Institution categorizes tasks based on the input of researchers and then rates occupations according to their component tasks (task-based occupation approach); and our approach classifies jobs based on the input of workers (holistic job approach).

*A.1 Holistic Occupation Classification: U.S. Census Bureau Approach*

The U.S. Census Bureau has inventoried and classified each of 539 total occupations to determine whether or not they should be considered STEM. The classification comes from the Standard Occupational Classification Policy Committee, a consortium of nine federal agencies charged with standardizing occupational definitions. In April 2012 the Committee issued a recommended STEM occupation classification based on expert consensus. Per this consortium, workers in 62 occupations were defined as comprising the STEM workforce. More expansive versions of the holistic occupation approach have been developed. For example, Funk and Parker (2018) include 12 additional occupations, such as healthcare practitioners and technicians. However, the Census classification is used throughout federal agencies and by many researchers to officially measure the size of the STEM workforce for policy purposes.

*A.2 Task-Based Occupation Classification: The Brookings Institution Approach*

In response to criticisms that the U.S. Census Bureau's approach does not consider variation in the extent to which STEM skills and concepts are utilized on the job, and overly relies on the subjective beliefs of the rating task forces, the Brookings Institution created a classification system (Rothwell 2013). Their approach uses the Department of Labor's Occupational Information Network (O*NET), which includes ratings of the types of knowledge required for a given occupation based on its component tasks. For each occupation and for each of the four STEM fields (i.e. science, technology, engineering, and mathematics), Brookings created a 7-point score indicating the level of knowledge required from that STEM field for that occupation. Occupations with a knowledge score 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. Averaging the scores across all four fields, occupations with an average knowledge score at least 1.5 standard deviations above the mean were classified as "super STEM occupations."

In comparison to the U.S. Census Bureau's approach, the Brookings Institution's method results in a broader definition of STEM, uncovering what Rothwell (2013) called the "hidden STEM economy" of blue-collar 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, health care, and construction industries (Rothwell 2013). A task-based approach has the potential to reduce traditional biases regarding what occupations or work activities are considered to be STEM, especially as they relate to gender, and indeed this approach classifies slightly greater proportion of women as STEM workers (we examine differences in more detail below).

### *A.3 Holistic Job Classification: RAND ALP Approach*

The third approach to classifying the STEM workforce is to directly survey workers and ask if their jobs are STEM. We execute this approach by administering a survey to a nationally-representative random sample of adults in the United States as part of the RAND Corporation's American Life Panel (ALP). Our bottom-up approach 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 occupations outside of the traditionally-defined STEM workforce (per Census and Brookings Institution approaches). To identify these workers, we provided definitions and examples of STEM work, and then directly asked the survey respondents whether their job was in STEM.

This approach allows for individuals to reply about the nature of their job as they experience it each day. Respondents also provided their occupation from among the 539 Census occupations, allowing us to classify them by both the Census and Brookings approaches. Even if the occupation they work in rises above the threshold for a STEM classification for the typical worker, the respondent may do fewer STEM-related tasks, and vice versa for non-STEM occupations. These types of disagreements may vary by gender, and our approach allows us not only to measure the occupations where men and women are working, but which jobs they take within occupations.

*B. Research questions and empirical approach*

Given these three approaches, we investigate the following questions.

1. How does self-reported STEM job classification differ from the existing occupation-based classifications? (size of the periphery STEM workforce)
2. Are women and men differentially sorted into the periphery STEM workforce? (composition of the periphery STEM workforce)
3. Conditional on worker and job characteristics, is there any observed wage benefit or a wage penalty for working in the periphery STEM workforce? (validating the market importance of the periphery versus core STEM workforce concept)

To answer the first questions, we display cross-tabulations and descriptive figures from our survey data. To answer the second question, we display descriptive statistics as well as multiple regression results weighing the characteristics associated with working in the periphery STEM workforce. To answer the third question, we model earnings using a simple regression of wages on observable characteristics of workers and jobs, as well as on STEM classifications.

## III. Data

The RAND American Life Panel (ALP) is a nationally sampled internet panel (with non-internet users provided with a computer and internet connection) 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. There are approximately 6,000 panel participants overall; however, not all are invited to participate in each survey. In our analysis we focus on a subset of respondents who were randomly sampled for recruitment into the panel. Pollard and Baird (2017) provide additional information on the ALP sample and data collection methods.

This paper relies primarily on two questions from two different surveys. The first question asked whether the respondent works in a STEM job. This question was included in ALP survey MS480, developed and administered by the authors in the summer of 2017 to 3,569 sample members. The wording of the question was as follows:

> *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.*

The second question comes from ALP survey MS436, administered in the summer of 2015 to the entire panel, which asked individuals about their occupation. The occupation question used a dropdown menu populated by the Standard Occupation Codes (SOC), which prompted the respondent to choose the occupation that best resembled their own. There were 3,131 respondents to the occupation question. Given our focus on the employed workforce, we limited the sample to adults under the age of 65. Of the remaining 2,707 respondents, 1,898 were employed, and of these, 1,694 reported an occupation. We merged responses from MS436 and MS480, yielding 1,494 respondents in the focal demographic group who both had a reported an occupation in MS436 and answered the question about STEM job in MS480. Note that we also draw respondent demographic data from ALP MS480.

We constructed this sample in order to measure STEM job classifications in three distinct ways for the same workers at the same point in time. However, because these two surveys were administered two years apart, mismatches in classifications could be driven respondents changing jobs between surveys. To limit the effects of these changes, we limited the sample further. A broadly defined measure of occupation was observed in both MS436 and MS480, comprised of 23 major Census occupation codes rather than the 539 we use in the analysis. We excluded 439 more workers who changed broad occupations between surveys. Our final sample size for the analysis was 1,055. We believe our 2015 STEM occupation classification for the final sample is likely to be accurate for up to 98% of the respondents. This estimate comes from a parallel analysis we conducted using the Survey of Income and Program Participation (SIPP) across the same time period (shown in Appendix A). In this analysis of the SIPP, we found that just 1 to 2 percent of workers whose broad occupation group was constant between 2015 and 2017 changed STEM occupation status between those two years.

The final 1,055 respondents are weighted to match the Current Population Survey (CPS). Appendix B describes the weighting procedure, and our procedures to account for some item-wise missing data.

Table 1 presents the summary statistics for our analytic sample. Listed at the bottom of the table are the different classifications of the STEM workforce. Recall that the Brookings Institution uses two definitions, one that indicates a concentration in one of the four STEM fields (high) and a more restrictive one that indicates a concentration across all four STEM fields (super). In our analysis, we sometimes present these two options, and at other times for simplicity, we present an option which is inclusive of either high STEM or super STEM, and label this simply Brookings STEM.

**Table 1: Summary statistics for American Life Panel (ALP) sample**

| | Percent | | | |
|---|---|---|---|---|
| Women | 45.7 | | | |
| Racial minority | 30.1 | | | |
| Highest education: BA | 20.3 | | | |
| Highest education: post-BA | 17.3 | | | |
| Boss same gender | 54.4 | | | |
| 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 | | | |
| | Mean | Std. dev. | Min. | Max. |
| Age | 42.6 | 11.7 | 21 | 64 |
| Family income ($1,000s) | 90.3 | 60.4 | 2.5 | 250.0 |
| Years working for current employer | 8.3 | 8.4 | 0 | 50 |
| Hourly wage ($) | 35.6 | 99.2 | 0 | 1,302 |

*Estimates weighted to match CPS 2015. Based on analysis sample of 1,055 survey respondents.*

Table 1 gives us our first look at the size of the STEM workforce, which ranged from 6 percent of workers using the Census approach to 27 percent of workers using Brookings' approach. Meanwhile, our approach using self-reports yielded an estimate in between the two, at around 20 percent. Thus, in our data we have a sample of a few hundred STEM workers to examine differences in classifications, and how these differences relate to individual characteristics and employment outcomes.

## IV. Results

### *A. How does self-reported STEM job classification differ from the existing occupation-based classifications?*

To address our first research question, we used our ALP sample to cross-tabulate multiple approaches in Table 1. The rows identify the two existing approaches, and the columns identify our approach. The four cells within each of the two panels sum to 100%. The periphery STEM workforce is shaded in gray.

The total size of the periphery STEM workforce (shaded) missed by traditional approaches was 15.8% of all workers by the Census approach and 9.4% of all workers by the Brookings approach. These are substantial proportions of workers, and particularly of STEM workers. Contrasting our approach with the Census approach, there were almost four times as many workers in the STEM periphery than in the core STEM (bottom right cell, 4.0 percent) and far more even the total official STEM (bottom row, 4.0 percent plus an additional 1.7 percent in the other off-diagonal). And contrasting our approach with the Brookings approach, the STEM periphery was estimated to be approximately the same size as the core STEM workforce.

**Table 2. The periphery STEM workforce**

| | | Our Approach (Holistic Job-Based) | |
|---|---|---|---|
| | | Non-STEM | STEM |
| Census Approach (Holistic Occupation-Based) | Non-STEM | 78.5% | 15.8% |
| | STEM | 1.7% | 4.0% |
| Brookings Approach (Task Occupation-Based) | Non-STEM | 64.0% | 9.4% |
| | STEM (High, Super) | 16.2% (8.3%, 7.9%) | 10.3% (6.4%, 3.9%) |

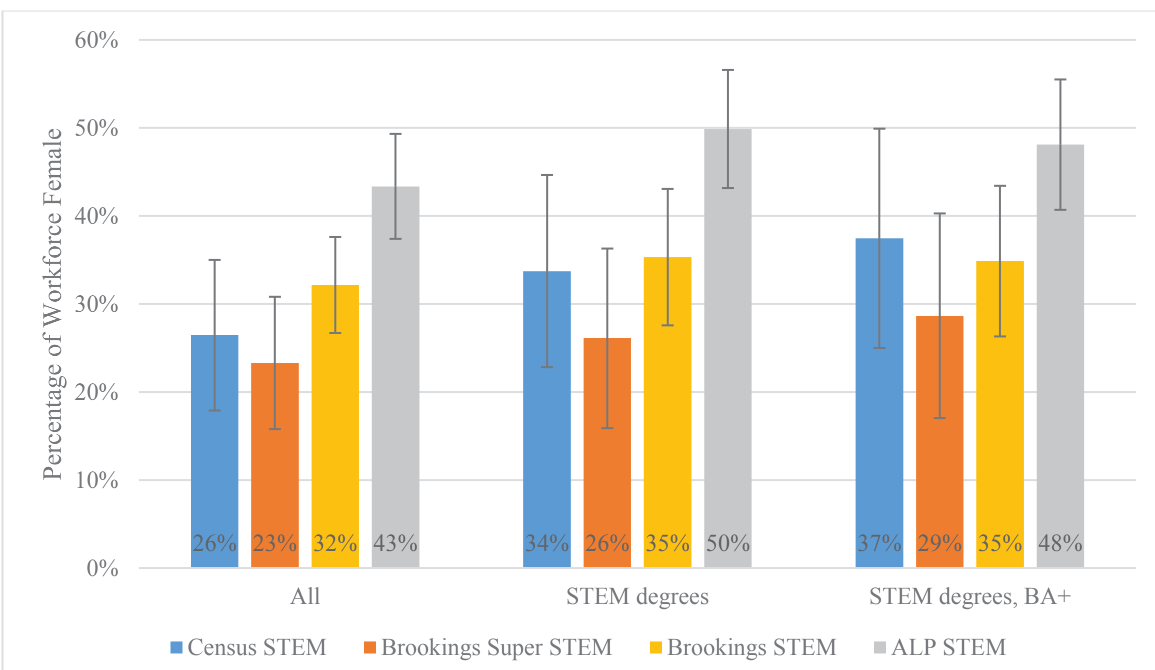
*Estimates weighted to match CPS 2015. The gray cells indicate the periphery STEM workforce. Percentages sum to 100%.*

### *B. Are women and men differentially sorted into the periphery STEM workforce?*

To analyze gender balance, we calculated the proportion of women in the STEM workforce using the three classification approaches in Figure 2. We evaluated these proportions for three different populations of workers: all workers, workers with any postsecondary credential in a STEM field (including associate's degrees, certificates, and bachelor's degrees), and workers with a bachelor's degree or higher in a STEM field.

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 (see Figure 2). Using our bottom-up approach, we see there was near parity between the genders, especially for those with STEM postsecondary credentials, where confidence intervals indicate balance between men and women. When using the Census definition or either of the Brookings' definitions, there were significantly more men in STEM at all education levels, with about a three-to-one ratio for all workers and around a two-to-one ratio for post-secondary STEM degree holders. By all measures, the bars rise from left to right, showing that women are better represented in the STEM workforce as education increases, reflecting the overall trend that women are advancing in some fields and earning more high-level degrees than men.

**Figure 2: Gender composition of STEM workforce by level of education and classification approach**



*Estimates weighted to match CPS 2015. Whiskers denote 95% confidence interval around the estimates.*

Next, we performed cross-tabulations of the STEM and non-STEM classifications reported in Table 2 by gender. The size of the periphery STEM workforce was larger for women than for men, especially when using the Brookings classification, where 11.4% of women were estimated to be in the periphery STEM workforce, compared to 7.8% of men. This difference became even more pronounced as a percentage of all workers reporting being in a STEM job. For men in the Brookings classification, about 38 percent of all STEM job holders were in the periphery, whereas for women, about 61 percent of all STEM job holders were in the periphery. While not of primary focus, we also note in Table 3 that not only were men much less likely to be in periphery STEM economy, they were much more likely to be in the periphery non-STEM economy, that is, on the other off-diagonal working non-STEM jobs in STEM occupations.

**Table 3: STEM job and occupation classification comparison by gender**

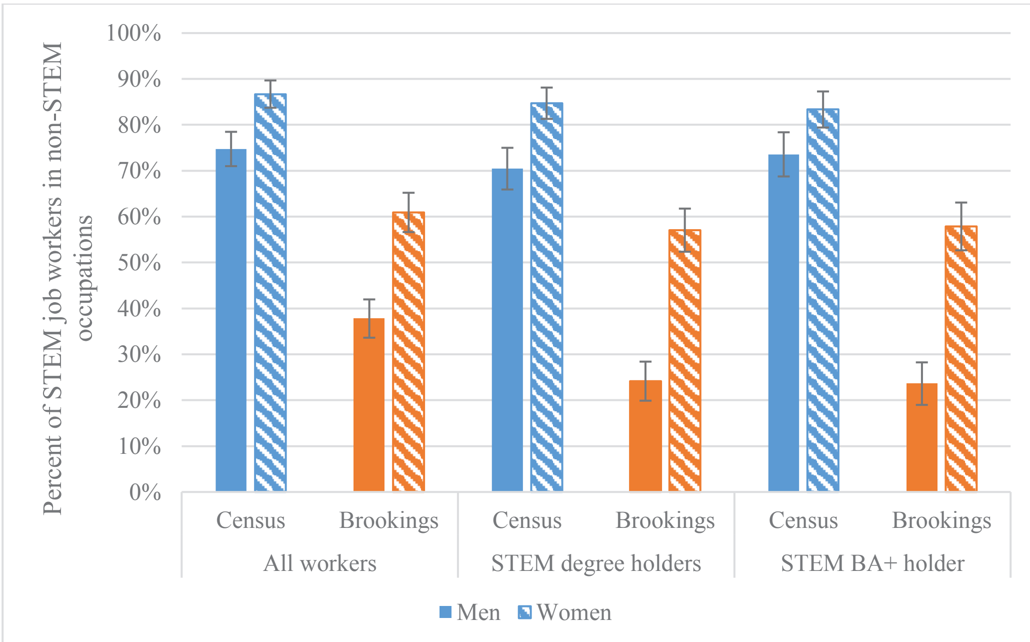
| | | Our Approach (Holistic Job-Based) | | | |
|---|---|---|---|---|---|
| | | Men | | Women | |
| | | Non-STEM | STEM | Non-STEM | STEM |
| Census Approach (Holistic Occupation-Based) | Non-STEM | 76.9% | 15.4% | 80.5% | 16.2% |
| | STEM | 2.5% | 5.2% | 0.8% | 2.5% |
| Brookings Approach (Task Occupation-Based) | Non-STEM | 59.0% | 7.8% | 69.9% | 11.4% |
| | STEM (High, Super) | 20.4% (8.9%, 11.5%) | 12.8% (7.6%, 5.2%) | 11.3% (7.7%, 3.6%) | 7.3% (4.9%, 2.4%) |

*Estimates weighted to match CPS 2015. The gray cells indicate the periphery STEM workforce.*

Figure 3 shows the percentage of STEM job workers who were in the periphery STEM workforce (based on the columns of Table 3) by level of education. The figure presents these same trends, and across several groups. Overall, the contrast of our approach with the (more restrictive) Census approach (blue bars) yields the highest proportion of workers who worked in STEM jobs but who did not work in STEM occupations. However, regardless of classification approach or level of education, a greater proportion of women who reported working in STEM jobs did so in the periphery STEM workforce.

These findings are consistent with the findings of Baird, Bozick, and Harris (2017), who found that among STEM degree holders, and even among non-STEM degree holders, men were more likely to end up working in STEM occupations. Our analysis shows that many of the women with STEM degrees who did not end up working in STEM occupations still classified themselves as working in STEM jobs.

**Figure 3: Periphery STEM workforce as a percent of STEM job workers**




*Estimates weighted to match CPS 2015. "Census" and "Brookings" labels refer to periphery STEM workforce estimates created by contrasting RAND ALP with either Census or Brookings estimates.*

To give concrete examples of the sources of these discrepancies, Table 3 reports the 15 most common occupations for men and women in the periphery STEM workforce, contrasted with the Brookings STEM classification only. For example, we found that 11 percent of all women in the periphery STEM economy were working in "Miscellaneous Healthcare Support Occupations", which Brookings classifies as non-STEM. Only 4.6 percent of all women in the sample worked in this occupation group, which supports that we are not just identifying the more common occupations but producing a new and meaningful definition of jobs within occupations.

For women, the industries that contributed most to discordance across classification schemes were healthcare and education. Health care support workers, social workers, counselors, educators, dental hygienists, and librarians all appeared in the periphery. For men, the occupations most represented in the periphery seem to be comprised of a different set: occupations such as managers, postsecondary instructors, law clerks, and salespersons.

The occupations here that stand out as less traditionally STEM-related (truck drivers for men, customer service for women) serve to emphasize that individuals perform (or perceive that they perform) STEM jobs across a wide array of occupations.

**Table 3: Most common occupations for individuals classified as in a non-STEM occupation (Brookings approach) but reporting being in a STEM job (RAND ALP approach)**

| Women | | | Men | | |
|---|---|---|---|---|---|
| | Periphery | Overall | | Periphery | Overall |
| Miscellaneous Healthcare Support Occupations | 11.1% | 4.6% | Driver/Sales Workers and Truck Drivers | 19.2% | 6.0% |
| Social Workers | 11.0% | 1.7% | Education and Library Science Teachers, Postsecondary | 10.7% | 1.0% |
| Counselors | 10.7% | 2.3% | Marketing and Sales Managers | 9.1% | 1.7% |
| Securities, Commodities, and Financial Services Sales Agents | 7.0% | 0.8% | Lawyers and Judicial Law Clerks | 8.0% | 2.6% |
| Dental Hygienists | 5.7% | 0.7% | Building Cleaning Workers | 6.3% | 1.9% |
| Secondary School Teachers | 5.5% | 0.9% | Securities, Commodities, and Financial Services Sales Agents | 5.8% | 0.6% |
| Miscellaneous Teachers and Instructors | 4.4% | 3.3% | Computer Control Programmers and Operators | 4.8% | 0.4% |
| Librarians | 4.2% | 0.7% | Dispatchers | 4.3% | 0.3% |
| Customer Service Representatives | 4.1% | 3.1% | Customer Service Representatives | 3.9% | 1.7% |
| Teacher Assistants | 2.7% | 1.5% | General and Operations Managers | 3.5% | 1.4% |
| Administrative Services Managers | 2.5% | 0.9% | Law, Criminal Justice, and Social Work Teachers, Postsecondary | 2.3% | 0.5% |
| Medical and Health Services Managers | 2.4% | 1.5% | Miscellaneous Entertainers and Performers, Sports and Related Workers | 2.3% | 0.2% |
| Miscellaneous Education, Training, and Library Workers | 2.4% | 0.8% | Miscellaneous Assemblers and Fabricators | 2.1% | 0.2% |
| Social Science Research Assistants | 2.3% | 0.3% | First-Line Supervisors of Sales Workers | 2.0% | 1.6% |

*Estimates weighted to match CPS 2015.*

To complete our analysis of gender differences, we estimated regression models predicting membership in the periphery STEM workforce. The results from these linear probability models are presented in Table 4. We limited the sample to those who reported being in STEM jobs, and then we created an indicator for being outside a Brookings STEM occupation. The model reports the increased probability of being in cell (b) rather than cell (d) in Figure 1, associated with various characteristics. This was strictly an exploratory analysis, and so we had no specific hypotheses about our covariates. Model 1 included only a parameter for gender. Model 2 added in a set of other demographic characteristics. Model 3 included an interaction of gender and the additional demographic characteristics to determine whether any traits are more predictive for being in the periphery STEM workforce for women than for men.

Across all models, gender was a salient characteristic predicting membership in the STEM periphery among STEM job holders. The gender gap of 23 percentage points widened to 30 percentage points when other characteristics were added (Model 2). We also found that being a minority increased the probability of being in the periphery substantially, while having a STEM degree decreased the probability substantially. Interactions of gender with other demographic characteristics (Model 3) did not show any statistically significant interactions between gender and these demographic characteristics, meaning that the gender gaps are relatively consistent across demographic groups. However the signs and magnitudes of the coefficients suggest that men were even more likely to follow the large demographic shifts away from the periphery, denoted by non-minority status and STEM degree holding, than were women.

**Table 4: Coefficients from linear probability models predicting being classified as a non-STEM occupation, among those reporting holding a STEM job**

| | (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 | -0.0142 |
| | | (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* |
| | | (0.0951) | (0.157) |
| Male * age | | | -0.001 |
| | | | (0.007) |
| Male * highest education: BA/BS | | | 0.0228 |
| | | | (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 |

*Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*
*Estimates weighted to match CPS 2015.*

*C. Is there a wage difference for working in the periphery STEM workforce?*

It is unclear whether women's overrepresentation in the periphery STEM workforce should be concerning. One concern is if women's STEM skills are poorly compensated relative to men's skills, and this is not attributable to differences in preferences for types of work. Our data do not give much purchase on removing bias from selection into jobs, but we investigate differences in wages more broadly, in the periphery versus non-periphery STEM workforce.

We estimated regressions predicting log wages, controlling for individual and job characteristics, and included indicators for STEM classifications of different types. The base reference group for each gender was workers in the core non-STEM workforce. We present the findings without controls, then with controls added, and with controls plus a Heckman correction for selection into the paid labor market. The Heckman selection regression uses as additional selection variables: number of dependents and the interaction of number of dependents with gender. This is a common choice for the 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 perhaps 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. Table 5 presents the regression results.

For both women and men, working in the core STEM workforce (STEM job in STEM occupation) was associated with greater wages. This was especially true for women. For example, in the two-state Heckman selection model (Model 3), the core STEM workforce participation coefficient is 0.725 in log wages for women and 0.536 for men. Using Kennedy's (1981) transformation, this is equivalent to 105 percentage points, or about a doubling of earnings for women comparing core non-STEM workforce to core STEM workforce, and about a 69 percent increase for men.

For men, there was a significant increase in wages when working in the periphery non-STEM workforce. This did not appear to be the case for women, although we cannot reject equality of the coefficient for women and for men on periphery non-STEM work.

**Table 5: Coefficients from regression models predicting log wages**

| | (1) | (2) | (3) |
|---|---|---|---|
| Female | -0.165 | -0.159* | -0.162* |
| | (0.113) | (0.0838) | (0.083) |
| Male, non-STEM job in STEM occupation | 0.300* | 0.217** | 0.217** |
| | (0.177) | (0.0968) | (0.096) |
| Male, STEM job in non-STEM occupation | -0.0125 | 0.123 | 0.123 |
| | (0.225) | (0.252) | (0.252) |
| Male, STEM job in STEM occupation | 0.615*** | 0.537*** | 0.536*** |
| | (0.131) | (0.134) | (0.134) |
| Female, non-STEM job in STEM occupation | 0.297* | 0.200 | 0.200 |
| | (0.162) | (0.194) | (0.194) |
| Female, STEM job in non-STEM occupation | 0.137 | 0.0742 | 0.074 |
| | (0.141) | (0.172) | (0.171) |
| Female, STEM job in STEM occupation | 0.703*** | 0.725*** | 0.725*** |
| | (0.149) | (0.128) | (0.128) |
| Highest education: BA/BS | | 0.340*** | 0.341*** |
| | | (0.077) | (0.077) |
| Highest education: graduate degree | | 0.498*** | 0.499*** |
| | | (0.082) | (0.082) |
| Racial minority | | -0.028 | -0.032 |
| | | (0.082) | (0.082) |
| Potential work experience | | 0.072*** | 0.072*** |
| | | (0.022) | (0.022) |
| Potential work experience squared | | -0.001*** | -0.001*** |
| | | (0.0003) | (0.0003) |
| More than one job | | 0.111 | 0.111 |
| | | (0.082) | (0.082) |
| STEM degree | | -0.113 | -0.112 |
| | | (0.090) | (0.090) |
| Constant | 2.920*** | 1.430*** | 1.423*** |
| | (0.096) | (0.374) | (0.378) |
| Heckman selection | | | Yes |
| Observations | 1,067 | 794 | 949 |

*Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*
*Estimates weighted to match CPS 2015. Multiple imputation used for missing values in more*

*than one job variable and number of dependents. Heckman selection on number of dependents, highest education, racial minority, and STEM degree, and each of those interacted with gender.*

For women, there were statistically significant gains over non-STEM workers only if they work in STEM jobs in STEM occupations. The increase in wages was also statistically different from being in either periphery workforce. There were no observable wage increases for working in the periphery STEM workforce over working in the core non-STEM workforce, either for men or for women. Therefore, the substantial number of periphery STEM workers, who are predominantly women, do not appear to be reaping a benefit from using their STEM skills and training in non-STEM occupations. Women benefit from their STEM skills and training only if they pursue traditionally-classified STEM occupations.

## 5. Conclusion

The increasing demand for workers with the skills to undertake quantitative analysis and complex problem-solving across all parts of the economy has elevated the focus on STEM education and STEM employment in the United States. Because a core policy focus is the expansion and promotion of STEM education and training to meet this demand, it is essential to understand the broader contours of the STEM workforce both in terms of its size and composition. This paper pursues that goal using a new approach to determine who is in the STEM workforce. In contrast to traditional top-down classification approaches that emphasize occupations, we created a bottom-up approach based on how workers appraise the application of STEM skills and concepts to their own jobs.

Our approach is more sensitive to variation across workers, though it would be possible to dig deeper by measuring on the level of each task rather than the job as a whole. It is also up-to-the-minute, reflecting the status of STEM work in 2017 without requiring reclassification of new occupations by boards of experts. Given the rapid changes in technology, STEM work will continue to be a moving target (Deming and Noray 2018; Ikudo et al. 2018).

Our survey yielded three new insights into the STEM workforce. Summarizing our three core findings, we first discovered that there is a sizeable group of workers (ranging from 10% to 15% of the workforce) in what we call the "periphery STEM workforce." Second, we found that women are more likely than men to be in this periphery STEM workforce. When determining the size of the STEM workforce using self-reports from the RAND ALP, men and women were *equally likely* to be in the STEM workforce. Third, we found that the most marked wage increases accrue to workers in the core STEM workforce. Outside the core, we found that women with a background in STEM who work in the STEM periphery earn about the same as women with a background in STEM who work in non-STEM occupations.

While there exists a rich body of literature documenting gender disparities in pay, even for the same jobs, our research elucidates this phenomenon in the context of one of the most high-demand segments of the economy, accounting for the types of jobs individuals take. Our findings suggest that policies aimed at providing more STEM education opportunities for women will not necessarily reduce the STEM wage gap if women with STEM degrees continue to take jobs in the periphery instead of the core once they finish their education.

The question of why workers take these jobs remains open. There are several approaches to answering the question, which must decompose several supply and demand factors. In a companion paper to follow this study, using the same ALP data, we take a bottom-up approach to answering this question by asking workers directly why they do or do not work in STEM, with a particular focus on those who have STEM degrees.

A key limitation to this study is that in using self-reported, subjective appraisals of jobs, our classification of the STEM workforce is inherently influenced by differences across individuals in beliefs and interpretations of what is and what is not STEM. Even with the instructions provided to sample members, we anticipate that variation in familiarity with and a conceptual understanding of STEM will yield heterogeneity in subjective appraisals of whether or not one's job is in fact STEM. This is affected by the general societal emphasis on STEM and could change over time. Heterogeneity in interpretation of our prompt could be a partial explanation for the observed gender differences, if women are more likely than men to consider the same job in a non-STEM occupation as STEM. Separating out whether the change in the gender gap comes from heterogeneity in beliefs, a desire to self-classify as STEM because it is emphasized in society, or simply from uncovering STEM jobs missed by top-down classifications, has important policy implications.

In closing, as the economy becomes increasingly reliant on workers with strong quantitative and analytical skills, there is a growing need for workers, educators, employers, and policymakers to identify the most efficient ways to engage the school-to-work pipeline of STEM talent that can support an expanding, innovative STEM economy. Our study has highlighted one key difference between men and women, and overall has highlighted the phenomenon that STEM skills and training are applied in an array of occupations that fall outside the traditional boundaries of STEM. Given that women are more concentrated in these peripheral occupations, any effort to close the gender gap in STEM employment needs to consider variation in the ways that men and women sort into STEM training and employment.

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

We linked two surveys that occurred two years apart, drawing one measure of STEM work from each. We restricted the sample to those who were employed in both periods and worked in the same broad occupation category in both periods. In this Appendix, we use a national panel sample to bound the number of people for whom their 2015 occupation was no longer accurate in 2017, although they remained in the same broad occupation category. Such occupation switches add noise to our analysis and potentially lead us to misidentify the periphery STEM workforce. This exercise bounds the misidentification to be small in magnitude.

We investigated occupation switches using the Survey of Income and Program Participation (SIPP) 2014 panel. The SIPP 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 switched between those 23 broad occupation groups across two years. This was higher than the 11 percent we found for the ALP sample. Among workers who remained in the same broad occupation group, 9 percent changed occupations. Most relevant for our paper, the percentage of those who switched STEM occupation status was 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 occ. 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 |

*Data based on 2014 SIPP, sample of individuals that have occupations recorded across two years .All: all workers with occupations across two years. Group stayers: all with 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 (CPS). For this study we matched on gender by race/ethnicity cell (non-Hispanic white, non-Hispanic black, and Hispanic as well as all other race/ethnic groups), gender by age in four bins, 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 reported in Pollard and Baird (2017).

There were some missing observations for some demographic variables in the ALP sample. In the regression models, we use multiple imputation, chained predictions using 10 imputations.