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Jamin D. Speer
University of Memphis and IZA

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

STEM Occupations and the Gender Gap: What Can We Learn from Job Tasks?*

Policymakers often promote the importance of STEM jobs but are concerned about the underrepresentation of women and minorities in these jobs. However, there is no agreed-upon definition of STEM jobs. I use occupation task data from O*Net to analyze the STEM task content of occupations, drawing several conclusions. First, there is no clear, robust definition of STEM occupations, even when using task data. The occupations included are highly sensitive to the cut-offs and methods used. Second, there are a number of occupations that should clearly be considered STEM by task content but are typically not, including nurse practitioners, pharmacists, and economists. Third, the gender gap in STEM jobs depends heavily on how one defines STEM. One traditional definition shows that STEM jobs are 76% male, but most task-based definitions show gender gaps only half as large (62-65% male). Racial gaps in STEM and the earnings premium for STEM occupations (35-43%) are fairly stable across definitions. The results imply that policies promoting traditionally-defined STEM jobs can unnecessarily exclude women and draw workers away from other important occupations.

JEL Classification: J01, J15, J16
Keywords: STEM, gender gaps

Corresponding author:
Jamin D. Speer
University of Memphis
Memphis, TN 38152
USA
E-mail: jspeer@memphis.edu

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1 Introduction

Both public policy and popular discourse promote the importance of STEM (science, technology, engineering, and mathematics) education and jobs. STEM jobs are considered important for economic growth and innovation (e.g., Jones 2009), and they command a large earnings premium. (Langdon et al. 2011). As a result, universities, corporations, and governments sometimes offer incentives aimed at growing the STEM workforce.

One particular concern with STEM is the underrepresentation of women and minorities. In the U.S., women made up only about one-fourth of STEM employment and one-seventh of engineers in 2009 (Beede et al. 2011). White and Asian workers are overrepresented in STEM jobs, while Black and Hispanic workers are underrepresented (NSF 2014). These gaps in STEM employment contribute to overall pay gaps (Jiang 2019, Brown and Corcoran 1997) and have led to concerns that the culture of STEM fields may be unfriendly to women and minorities (e.g., Hill, Corbett, and St. Rose 2010).

These analyses and policy initiatives require decisions about what it means to be a STEM job. Yet different government agencies (and different academic studies) use definitions of STEM that do not always agree and are not data-driven. Promoting STEM using a list of STEM jobs is likely to come at the expense of jobs left off the list, so it is important that we carefully consider how these decisions are made.

This paper asks what a STEM job is, and how the way we define STEM affects our understanding of the gender and racial gaps in these jobs. I use task data from O*Net to create data-driven definitions of STEM occupations. In my approach, STEM occupations are those that use a significant amount of science, technology, engineering, and/or mathematics in the job, regardless of occupation title, category, or required degrees. There are STEM "specialists", who use an exceptionally high amount of any STEM task, and there are STEM "generalists", who use a wide variety of STEM tasks at reasonably high levels. I compare my approaches to more traditional definitions, which tend to include full "categories" of occupations and rarely rely on actual data.

I draw several conclusions. First, there is no clear, robust definition of STEM occupations, even when using occupation task data. No task-based definition matches those used by government agencies, and the occupations included are sensitive to the cutoffs and methods used. STEM specialist jobs are quite different from STEM generalist jobs, and changing the cutoff of what counts as a specialist or a generalist also matters. The use of task data, which one can argue is a big improvement over traditional methods of defining STEM, is still limited.

Second, despite this, there are some occupations not normally considered STEM that that clearly qualify by task content, including veterinarians, pharmacists, economists, accountants, and construction managers. These jobs meet even stringent task-based definitions of STEM despite being left off the list used by the U.S. Bureau of Labor Statistics (BLS). Other medical jobs, including registered nurses, do not qualify as STEM even under the broadest task-based definitions. Conversely, there are a few traditional STEM jobs that do not use high levels of STEM tasks.

Third, the gender gap changes dramatically with the definition of STEM, while racial gaps do not. The BLS definition of STEM jobs shows that they are 76% male. Most task-based measures show a gender gap only half as large (62-65% male), largely due to the inclusion of some medical jobs. Racial gaps in STEM jobs are fairly stable across definitions: Black and Hispanic workers are underrepresented no matter the approach used. Finally, there is a large earnings premium for STEM occupations of 35-43% that is also fairly stable across definitions and is even larger for women.

The results imply that policies promoting STEM jobs that rely on traditional definitions may be unnecessarily excluding women in particular. More data-driven approaches, which pick up who is actually doing STEM-related tasks at work, are friendlier to women who are highly trained and capable in STEM fields. Further, these policies may have the unintended effect of drawing highly qualified workers away from other important occupations, particularly in the medical field. With an aging population and a growing demand for medical care, this may not be ideal.

This paper is most similar to work by Manzella, Totty and Benedetto (2019) and Rothwell (2013). Manzella et al. (2019) use factor analysis of O*Net data to create new occupational groupings based on how similar their required tasks are. They do not focus on STEM, so instead of identifying factors via factor analysis as they do, I choose tasks in science, technology, engineering, and mathematics to classify occupations.

Rothwell (2013) uses O*Net task data to define STEM occupations. He defines "high-STEM" and "super-STEM" jobs using the Knowledge subset of the task data. If an occupation requires high levels of knowledge in any single STEM area (say, biology), it qualifies as high-STEM. If an occupation requires a high level of combined knowledge of all the STEM fields, then it is a super-STEM occupation. He uses these definitions to show that many workers without a college degree work in jobs that should be considered STEM. I borrow some of his ideas here, but I show that these types of definitions are not robust, with different cutoffs and assumptions producing very different lists of jobs.

It is important to think carefully about how we define STEM jobs for several reasons. There are many examples of policy initiatives that rely on defining STEM. In the U.S., immigration policy gives preferential treatment to college students in STEM programs. Some states, including New York, offer scholarships for college students that study STEM fields. The Trump administration's initiatives for STEM education cite figures on STEM employment from the Department of Commerce. The Canadian government offers incentives to employers who hire from certain groups, including women in STEM fields. Many private corporations also offer special training and incentives to workers who enter STEM jobs. All of these require us to think carefully about what exactly we are promoting.

Any success in increasing STEM employment would naturally come at the expense of other fields not included on the list. Given my results, a definition of STEM that does not include medical professions could draw highly capable workers away from medical jobs. This is likely not the intent of such policy initiatives.

Finally, policies promoting traditional definitions of STEM may disadvantage women by excluding STEM-related jobs that are majority female. A substantial portion of the usually-reported gender gap in STEM jobs is due to women choosing science-intensive jobs that are outside the traditional STEM definitions. Surely if we are concerned about a gender gap in science capability or training, this is not a problem. However, even after my corrections, the gender gap in STEM remains substantial, confirming that there is much work to do in increasing female STEM participation.

The paper proceeds as follows. Section 2 discusses the data required for my analysis. Section 3 develops a number of task-based definitions of STEM occupations. Section 4 carries out a detailed comparison of the various measures. Section 5 looks at the gender gap and racial gaps in STEM, Section 6 offers guidance for future researchers and policymakers studying STEM, and Section 7 concludes.

2 Data

I make use of two data sources, one to classify occupations according to tasks and one to measure gender gaps and usage of STEM degrees. Data on the task content of occupations comes from O*Net, the Occupational Information Network, produced by the U.S. Department of Labor as the successor to the Dictionary of Occupational Titles. O*Net contains ratings of the importance of hundreds of "tasks" in each occupation.

The term "tasks" encompasses knowledge, skills, activities, and abilities required and used in each occupation. There are hundreds of task ratings for each occupation, allowing an occupation to be characterized as a high-dimensional vector of tasks. For each task, O*Net gives two scores: "importance" and "level". The level is designed to measure how advanced a version of that task is used. For example, an occupation might use arithmetic every day, but no calculus; that occupation would have a high importance of mathematics but a low level. In practice, the importance and level ratings are highly correlated. I use both in my analysis.

As my focus is on STEM, I proceed by finding all tasks that fit into the four categories of science, technology, engineering, or mathematics (STEM). There are five measures that clearly relate to math, four in science, three in technology, and two in engineering, giving a total of 28 STEM task scores for each occupation (one level and one importance score for each task). This turns each occupation into a 28-dimensional vector of STEM tasks. The complete list of tasks that make up each definition are found in Table 1. Full descriptions of each task are available in Appendix 1. I will use these measures to construct definitions of STEM occupations in the next section.

Table 1: O*Net Tasks Included

Mathematics	Science	Technology	Engineering
Mathematics skill	Science skill	Interacting w/computers	Engineering knowledge
Mathematics knowledge	Biology knowledge	Computer/electronics knowledge	Design knowledge
Analyzing data	Chemistry knowledge	Programming skill	
Math reasoning ability	Physics knowledge		
Number facility ability			

Note: Full descriptions of each task are available in Appendix 1. For each component task, there are two scores: an importance and a level, giving 28 total task scores for each occupation.

To see if the chosen task categories make sense, I look at two occupations whose STEM status should be obvious. Chemical engineers score at least one standard deviation above average in 27 of the 28 tasks (all but biology knowledge, where they score 0.90) and score 2.5 standard deviations or higher in 12 tasks. On the other hand, writers and authors do not meet the one standard deviation threshold on any of the 28 tasks. So at first glance, these tasks seem to be picking up what we would consider STEM content.

There are two limitations to the O*Net data that are worth mentioning. They give occupation-level averages, so they measure an individual worker's actual task usage with error (Autor and Handel 2013). Also, the task measures are not exhaustive. O*Net gives task scores for knowledge of biology, chemistry, and physics, for example, but not geology. There could be occupations which would qualify as STEM if more complete data were available.

To measure gender and racial gaps in STEM occupations as well as the earnings premium, I use the American Community Survey (ACS) from 2012 to 2017.[1] The ACS, the annual counterpart to the decennial census, contains about 3 million observations per year and includes information on demographics, employment, occupation, industry, pay, and more.

I keep workers age 30 to 50 to look at prime-age job outcomes. The reason I use 30 as the lower-bound instead of 23 or 25 is that a substantial percentage of STEM graduates attend graduate school and thus do not join the labor market until later

[1] I use the post-recession years to avoid any particular effects of the Great Recession. This does not have any real effect on the results. I obtain the ACS data via IPUMS (Ruggles et al. 2020).

than 25 (Speer 2019). This is especially true for women in STEM, who are much more likely to enter medical school than men. Using an earlier age skews the gender gap because of this. Table 2 shows summary statistics from my ACS sample.

Table 2: Summary Statistics

	Mean	St Dev
Employed	1.00	0.00
Male	0.53	0.50
Has BA	0.39	0.49
Has grad degree	0.15	0.36
BLS STEM occ	0.07	0.26
STEMM occ	0.09	0.29
O*Net STEM occ	0.17	0.38
STEM specialist narrow	0.07	0.26
STEM specialist moderate	0.10	0.30
STEM specialist broad	0.17	0.38
STEM generalist narrow	0.07	0.25
STEM generalist moderate	0.10	0.30
STEM generalist broad	0.18	0.38
Math tasks	0.04	0.83
Science tasks	-0.30	0.65
Technology tasks	0.04	0.88
Engineering tasks	-0.28	0.84
n	3,409,753	

Note: The full sample is everyone employed age 30 to 50 in the ACS from 2012 to 2017. Statistics are calculated using the ACS person weights. The STEM occupation definitions are given in the text. The task measures are taken from O*Net and are in standard deviations.

The only difficulty in matching O*Net task data to the ACS is that O*Net sometimes has more detailed occupational codes than are available in the ACS. For example, the ACS combines surveyors, cartographers, and photogrammetrists into one occupation code, while O*Net provides task data separately on surveyors and the other two occupations. In such a case, if there is not a one-to-one match between the ACS and O*Net, I assign the average task scores of the O*Net occupations to the more general ACS category. In this case, the task scores for "surveyors" and "cartographers and photogammetrists" are averaged to form the task score for "surveyors, cartographers, and photogrammetrists".

There is one other weakness of the ACS for my purposes. For those who give their occupation as "postsecondary teacher", I do not know what subject they teach. All of the traditional STEM definitions I discuss below include postsecondary teachers of STEM subjects (e.g., computer science or engineering) as STEM occupations, while excluding teachers of subjects like English and history. I cannot make this distinction, unfortunately, so I drop all postsecondary teachers from my sample.[2]

3 Defining STEM Occupations

I first present three examples of traditional STEM occupation classifications, then construct several task-based definitions to compare. This is not meant to be an exhaustive list of possible approaches. The various definitions below will show that different methods produce quite different lists and implications.

3.1 Traditional Definitions

The most basic way to construct a list of STEM occupations is to include various "categories" of occupations. In the United States, the Standard Occupational Classification (SOC) code system is used by federal agencies to classify workers into occupations and occupational categories. Codes beginning with 11 are management occupations, those beginning with 13 are business and financial operations occupations, and so on. One can go through such a list and pick the categories that seem to be STEM.

This is close to the approach used by the U.S. Bureau of Labor Statistics (BLS), the source of most labor market statistics in the U.S. In the official BLS list of STEM occupations, all of the 15 ("computer and mathematical occupations"), 17 ("architecture and engineering occupations"), and most of the 19 ("life and physical science occupations") are included in STEM.[3] It also includes all of the postsecondary teaching occupations in STEM subjects (e.g., postsecondary chemistry, math, and

[2]The ACS has field of undergraduate degree but not of graduate degrees, so this information cannot be used to proxy for the field of postsecondary teaching.

[3]The codes starting with 19 also include social science occupations, which BLS excludes from STEM. The full list of BLS STEM occupations can be found at `www.bls.gov/oes/stem_list.xlsx`.

biology teachers), two sales occupations (sales engineers and sales representatives for technical and scientific products), and three managerial occupations (managers in computer and information systems, architecture and engineering,and natural sciences)

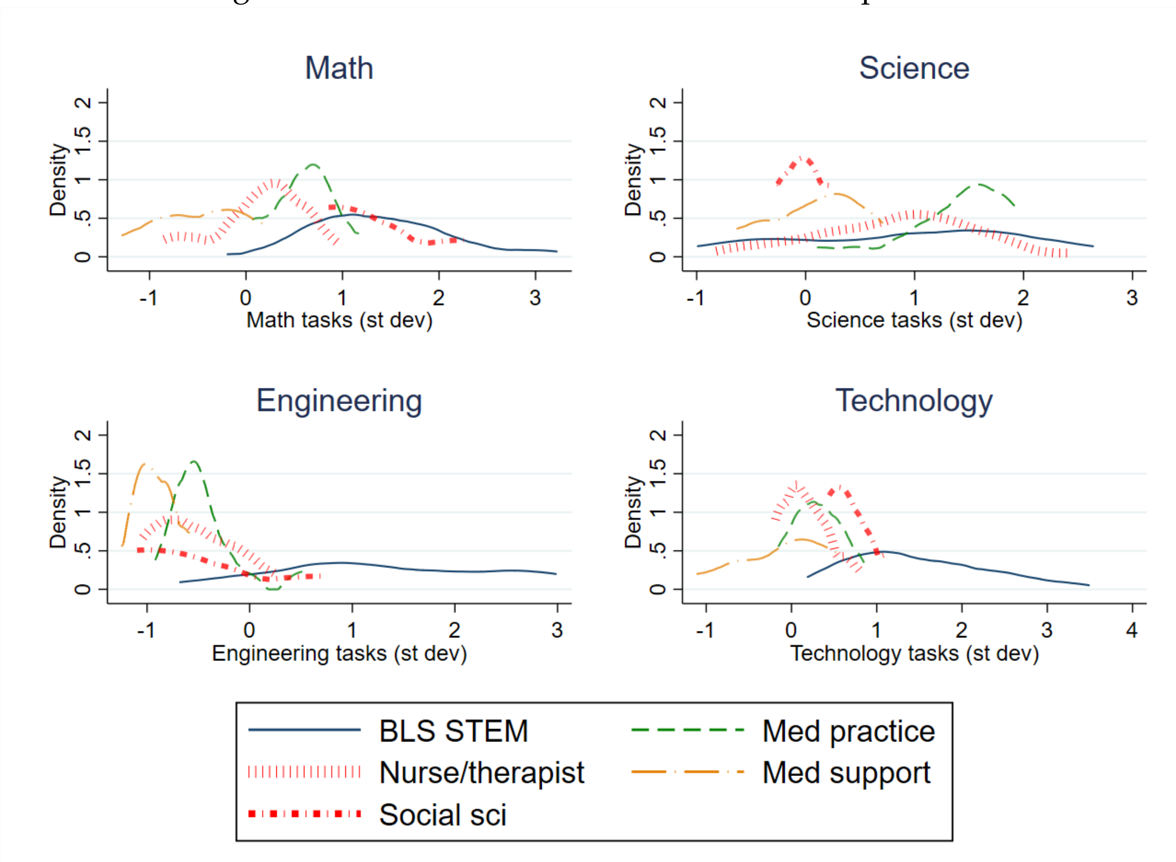
The BLS itself notes that this "is only one of many possible definitions of STEM". The list excludes medical and social science occupations, which some would consider STEM jobs. Other definitions are more inclusive, so I will refer to the BLS classification as the "traditional narrow" definition. In the ACS data, with all post-secondary teachers excluded from the sample, the BLS definition includes 49 Census occupation codes, accounting for 6.9% of all employment.

To get a first look at whether there are more occupations that should be added, Figure 1 shows the distributions of the O*Net composite task scores in the math, science, technology, and engineering tasks for five categories of occupations: the BLS STEM occupations, medical practicing and diagnosing, medical therapists and nurses, medical support, and social scientists. To keep the graphs simpler, I do not include occupations outside these groups, but they will also have a chance to be classified as STEM in my task approach below. The math task score is the occupation's average score in all of the math tasks. The others are constructed similarly.

These figures teach us several things. First, the narrowly-defined STEM occupations are higher in STEM task content than other occupations on average, and they particularly dominate in engineering and technology tasks. Second, there are clearly some BLS STEM occupations that do not score highly on some task measures, although from this figure we cannot tell if it is the same occupations scoring low on each one. Third, there are occupations not in the BLS definition (particularly in medical practice and social science) that score at least two standard deviations above the mean in science and/or math. Fourth, it does not appear that medical support occupations score highly in STEM task content.

A more inclusive definition using the same type of approach is the so-called STEMM, where the second M is for medical. There are variations of STEMM, but for the purposes of this paper, I will define STEMM to include all of the BLS STEM occupations plus medical diagnosing and treating practitioners, as well as medical/health service managers. This includes things like physicians, dentists,

Figure 1: Distributions of task content for occupations



nurse practitioners, and pharmacists, but not things like registered nurses, medical therapists, or medical technicians. This adds 12 more ACS occupations to reach a total of 61, accounting for 8.9% of total employment. I will call this the moderate traditional definition.

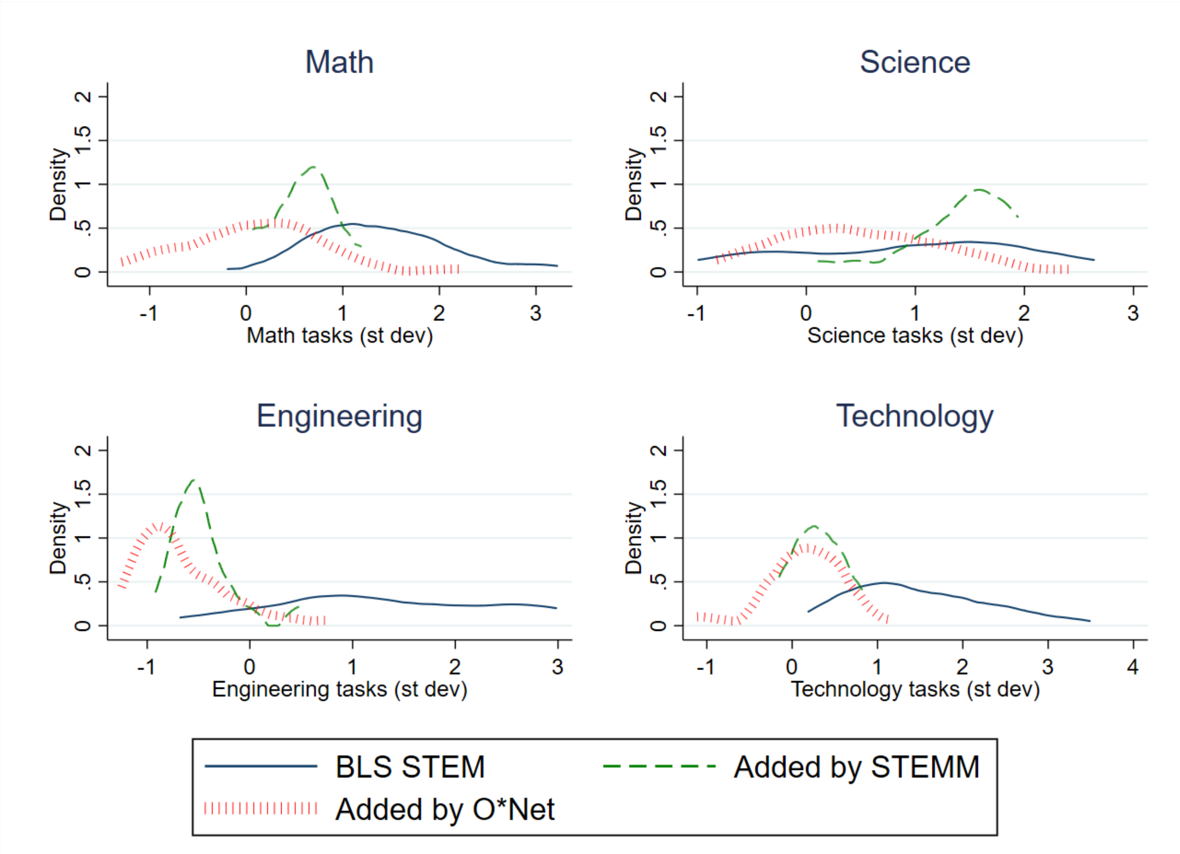
A broad definition is given by O*Net itself.[4] O*Net includes all of the STEMM occupations plus all other medical occupations (such as nurses, hygienists, and technicians) and social science occupations (such as economists and sociologists). This is considerably broader than STEMM, adding 34 occupations for a total of 95, which account for 16.5% of total employment. Table B.1 gives the full list of occupations in the ACS included under each measure.[5]

[4]See `https://www.onetonline.org/find/stem?t=0` for the full list.

[5]Of course, there are other definitions based on occupation category. The U.S. Census Bureau, for instance, has sometimes used a definition that includes social science occupations but excludes

The average task distributions of the three traditional definitions are shown in Figure 2. The solid line is the distribution for the BLS STEM occupations, the dashed line is those added by STEMM (that are not in the BLS definition), and the dash-dot line is those added by O*Net. For the most part, the BLS STEM occupations are higher in STEM-related tasks than those added by the broader definitions, particularly in math, engineering, and technology. Some STEMM occupations score highly in science, however. It appears that most occupations added by O*Net are not high in STEM task content, though some may be in science.

Figure 2: Distributions of task content for traditional definitions



medical occupations.

3.2 Using Tasks: STEM "Specialists"

The large variation within occupation category of STEM task content suggests that we should use the information for each occupation rather than including or excluding whole sets of occupations together. It may be that economists use STEM tasks much more than historians, for example. But the way to use the task information is not obvious.

Here I define the concept of STEM "specialists". These are occupations that score very high in at least one STEM task.[6] To qualify, at least one of the 28 task scores must be above a certain threshold.

This approach is in the spirit of the BLS's definition of STEM: "STEM workers use their knowledge of science, technology, engineering, or math to try to understand how the world works and to solve problems." One of the key words in that statement is "or". Being a STEM worker does not require that you do all of these things at a high level, but only one. A mathematician may not do science or engineering, but her high use of math should clearly qualify her as STEM.

To match the narrow/moderate/broad traditional definitions, I use three score thresholds to create narrow, moderate, and broad STEM specialist definitions, calibrated to account for about the same share of total employment as each of the traditional definitions. A threshold of 2.75 standard deviations accounts for 6.8% of employment, similar to the narrow BLS definition. Thresholds of 2.5 (moderate, 9.4%) and 1.95 standard deviations (broad, 17.0%) match the STEMM and O*Net employment shares.[7] Table B.2 shows the full list of occupations defined by the three measures.

Without looking at the data, it would be surprising if occupations meeting the narrow specialist definition are not already normally classified as STEM. I would expect scientists and engineers, for example, to meet the specialist thresholds. Some medical jobs may show up as specialists – perhaps they score that high in biology or chemistry – but my expectation is that they are more likely to be "generalists", as

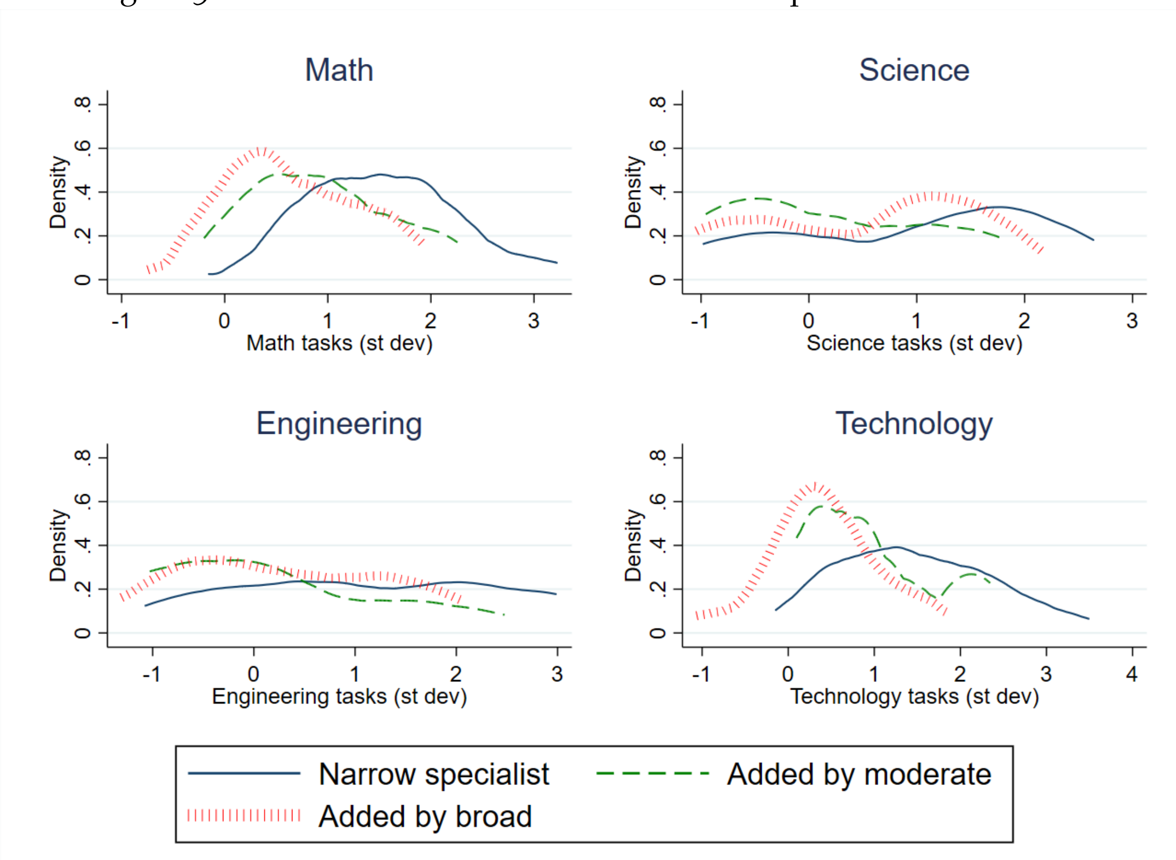
[6] Rothwell (2013) uses a similar approach, calling occupations that were at least 1.5 standard deviations above average in any STEM knowledge category "high-STEM" occupations.

[7] These match the employment shares of the traditional definitions, not the number of occupations. The narrow, moderate, and broad task definitions include 43, 56, and 95 occupations, respectively.

defined in the next section.

Figure 3 looks at the average task distributions for the narrow, moderate, and broad specialist definitions. Since the three are defined using task data, it is unsurprising that the narrow specialists are higher in STEM task content on average than occupations that are added in the moderate or broad definitions. Still, many moderate and even broad STEM specialists score highly on all four types of tasks.

Figure 3: Distributions of task content for STEM specialists definitions



3.3 Using Tasks: STEM "Generalists"

There may be occupations that use a variety of STEM tasks without being a specialist in any particular one. Here I use an alternate task-based definition, which I call STEM "generalists". While there is no perfect way to define this, I look at how many of the 28 STEM task scores are at least one standard deviation above average.

Again to match the employment shares of the narrow, moderate, and broad definitions laid out above, I define STEM occupations as those who score above the threshold in at least 12 tasks (narrow), 11 tasks (moderate), or 7 tasks (broad). Just going from 12 to 11 adds 8 occupations, which adds 2% of total employment, showing again that small changes in the threshold used can change the list considerably. Going from a threshold of 11 to 7 adds 36 more occupations. Table B.3 shows the full list of generalist occupations.

While the specialist definition may be most in line with the BLS description of STEM workers, these generalists also have a claim to be STEM workers. If one occupation requires expertise in biology and no knowledge of any other STEM subject, it is hard to argue that that occupation is more STEM-like than one which requires working knowledge (though not expertise) of math, multiple sciences, and technology.

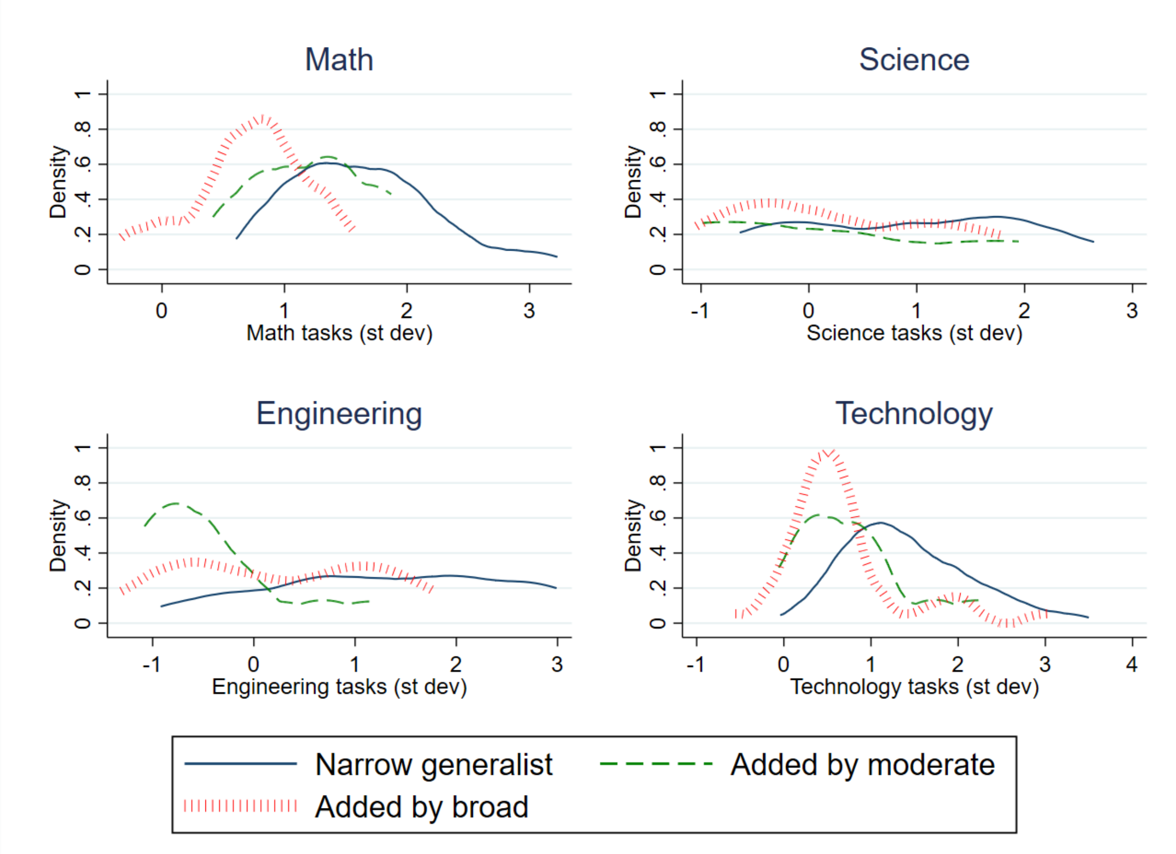
Perhaps the best example is the pre-medical curriculum at most universities in the United States. For medical school admission, students typically take one full year each of biology, organic chemistry, general chemistry, and physics, in addition to calculus and sometimes statistics. This is not enough of any single subject to achieve expertise, but few university graduates will have had more STEM education than these students. While medical jobs are excluded from the narrow BLS definition, I would expect some to show up as generalists in the O*Net data.

Figure 4 looks at the average task distributions for the narrow, moderate, and broad generalist definitions. As we saw with specialists, there are clear differences between the three groups. It does not seem that many occupations that qualify only as moderate or broad generalists score extremely high on any task category, with the possible exception of technology tasks.

4 Comparing Definitions of STEM

I now have nine definitions of STEM: a narrow, moderate, and broad categorization for each of the traditional, specialist, and generalist approaches. I compare those definitions in this section. I show that all of the definitions are quite different, that changing the cutoffs makes a substantial difference, and that the task definitions

Figure 4: Distributions of task content for STEM generalists



produce some surprising results.

4.1 Comparing the Traditional and Task Approaches

All three narrow definitions – the BLS list and the stringent task specialist and generalist approaches – account for about 7% of total employment. But the occupations included in each list are quite different, as seen in Table 3.[8] The three lists agree on 28 ACS occupations, including most scientists, engineers, and mathematical scientists. However, of the 49 ACS occupations in the BLS list, only 32 (65%) meet the task specialist definition and 37 (75%), meet the task generalist definition.

There are 8 occupations on the BLS list that meet neither task-based definition. This mostly includes technicians and support personnel in STEM industries, such

[8]The full list of occupations included under each definition of STEM is given in Tables B.1-B.3.

Table 3: Occupations Classified as STEM: Narrow Definitions

On all 3 lists	On 2 lists	On 1 list
Architectural/engineering managers	Computer systems analysts (T,S)	Information security analysts (T)
Computer/info research scientists	Web developers (T,S)	Computer support specialists (T)
Computer programmers	Network and computer systems admins (T,S)	Computer occupations, all other (T)
Software developers	Biological technicians (T,S)	Engineering technicians, except drafters (T)
Database administrators	Computer/info systems managers (T,G)	Conservation scientists/foresters (T)
Computer network architects	Natural science managers (T,G)	Ag/food science technicians (T)
Actuaries	Surveyors/cartographers (T,G)	Chemical technicians (T)
Operations research analysts	Industrial engineers (T,G)	Geological/petroleum technicians (T)
Misc. math science occupations	Drafters (T,G)	Accountants and auditors (S)
Architects, except naval	Surveyin/mapping technicians (T,G)	Budget analysts (S)
Aerospace engineers	Environmental scientists/geoscientists (T,G)	Optometrists (S)
Biomedical and agricultural engineers	Physical scientists, other (T,G)	Physician assistants (S)
Chemical engineers	Sales engineers (T,G)	Veterinarians (S)
Civil engineers	Cost estimators (S,G)	Nurse practitioners and nurse midwives (S)
Computer hardware engineers	Nurse anesthetists (S,G)	Miscellaneous office and administrative (S)
Electrical and electronics engineers	Statistical assistants (S,G)	Construction managers (G)
Environmental engineers	Computer control programmers/operators (S,G)	Financial analysts (G)
Marine engineers and naval architects		Financial specialists, all other (G)
Materials engineers		Economists (G)
Mechanical engineers		Pharmacists (G)
Petroleum/mining/geological engineers		Sales representatives, other (G)
Miscellaneous engineeers		
Agricultural/food scientists		
Biological Scientists		
Medical and life scientists		
Astronomers and physicists		
Atmospheric and space scientists		
Chemists and materials scientists		
28 occupations	Traditional and Specialist: 4 Traditional and Generalist: 9 Specialist and Generalist: 4	Traditional only: 8 Specialist only: 7 Generalist only: 6

Note: The occupations in the left column meet the definitions of the Bureau of Labor Statistics, narrow STEM specialist, and narrow STEM generalist. The occupations in the middle column meet only two of the three definitions, with which definitions they meet noted in parentheses. T=traditional (BLS), S=specialist, and G=generalist. The occupations in the right column meet only one of the three definitions, with the definition given in parentheses. The definitions of STEM occupations are given in the text.

as chemical and engineering technicians. This highlights the weakness of defining whole categories of occupations as STEM or not STEM, rather than going occupation-by-occupation.

There are also 11 occupations that meet the stringent STEM specialist criterion but are not listed by the BLS. These are mostly financial occupations (e.g., accountants and budget analysts) and medical occupations (e.g., optometrists, veterinarians, and nurse practitioners). While the latter are captured by the broader STEMM measure, financial occupations are rarely included in any traditional STEM list.

As for generalists, there are 10 occupations that qualify by tasks that are not on the BLS list. This includes some of the specialist occupations, but also economists, pharmacists, and statistical assistants. Economics qualify by scoring above one standard deviation on 14 task scores (all 10 math scores and 4 technology scores).

There are 4 occupations that qualify as both specialists *and* generalists, even under this stringent definition, yet are not listed by the BLS. This list is probably surprising: cost estimators, nurse anesthetists, statistical assistants, and computer control programmers and operators. While the last of these certainly sounds like a proper STEM occupation, it is listed under the category of "production occupations" and not included in even the broader traditional definitions.

Just from the three narrow definitions, it is obvious that tasks give us a different perspective. There are some traditional STEM occupations that may not belong on the list, and there are non-traditional STEM occupations that meet stringent task requirements to be called STEM.

Similar analyses can be done for moderate and broad categorizations, as seen in Tables B.4 and B.5. I will not discuss these as much here, but there are some things worth pointing out. Of the 12 occupations that STEMM adds to the BLS list, half qualify through either moderate task definition as well. Most of these already qualified under the narrow task measure, but now dietitians/nutritionists and physicians/surgeons (which may be too broad of a category to qualify under narrow measures) join the list. On the other hand, several occupations added by STEMM do not meet the moderate task criteria, including dentists, podiatrists, and chiropractors.

The O*Net definition appears far too broad when using the task data. Of the 34 occupations that O*Net adds to STEMM, only 10 qualify under either of the broad task measures, and only 4 (economists, clinical lab technicians, nurse anesthetists, and miscellaneous social scientists) qualify under both broad task measures. The newly added occupations that definitely do not look like STEM jobs are mostly non-diagnosing medical jobs, including dental hygienists, various types of technologists, and registered nurses (RNs), the most common type of nurse in the U.S. Nurses are not usually considered STEM (for occupations or college majors), but O*Net includes them, and Card and Payne (2017) count the nursing major as STEM in their study of college majors in Canada. The task data show that RNs will not meet a reasonable standard for STEM tasks, as they score above 1 standard deviation on only 3 of the

28 tasks, with a maximum score of 1.56 for biology knowledge.

This analysis shows that traditional definitions overlap considerably with task-based definitions, but there are many "false positives" and "false negatives". Many medical occupations are high in STEM tasks, but including them all is clearly a mistake. The O*Net definition in particular seems too broad, though it may be correct to add economists to the list. Some financial occupations, not included by any traditional definition, qualify for STEM even with narrow task definitions.

4.2 Comparing STEM Specialists and STEM Generalists

Leaving aside the traditional definitions, I can also compare the two types of task-based approaches, the STEM specialists and STEM generalists. I had expected medical jobs to mostly be picked up by the generalist measure, while jobs like economist and accountant seem more like specialists.[9]

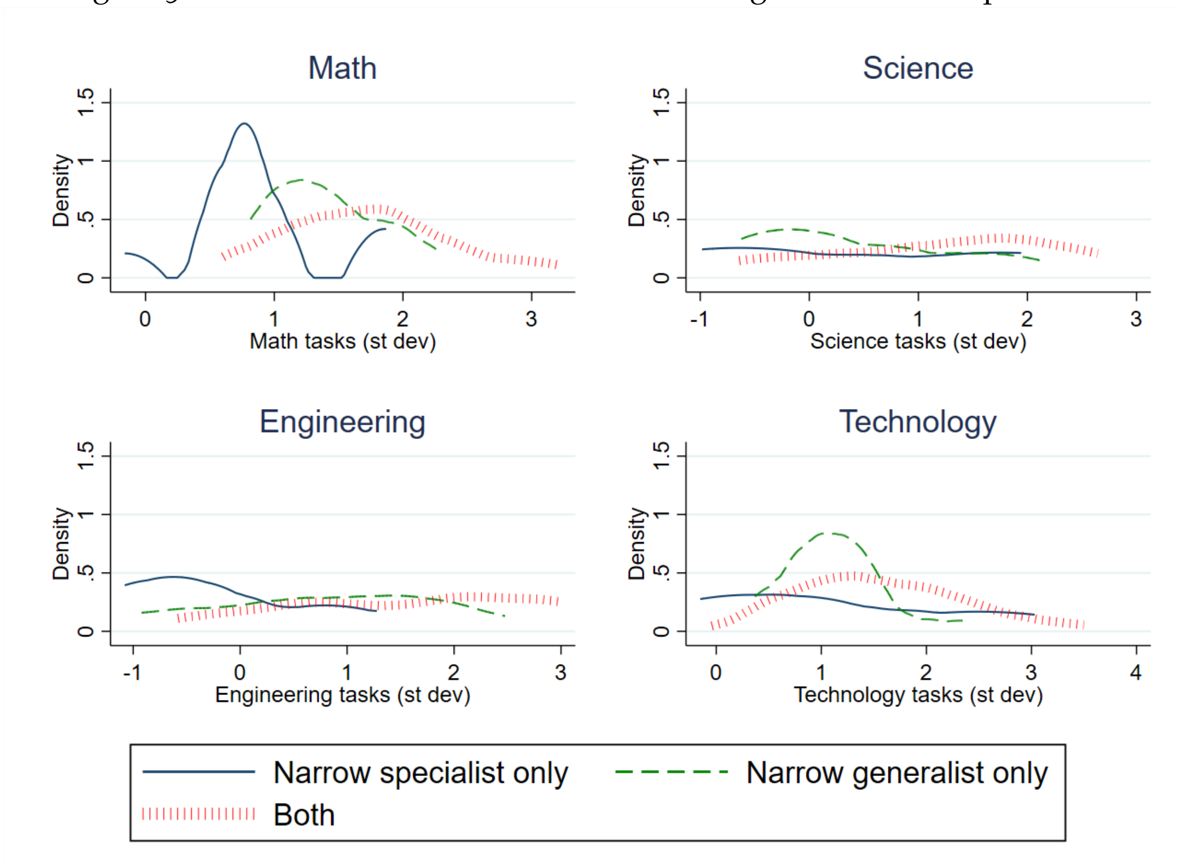
See Table 3 once again. For the narrow measures (with stringent task thresholds), the specialists include 43 ACS occupations and generalists 47. They share 32 in common. These are mostly unsurprising, as noted earlier; scientists and engineers can be considered STEM jobs without any controversy.

Looking at the occupations that are either narrowly defined specialists or generalists, but not both, my intuition was mostly not correct. Consistent with my expectations, financial jobs like accountants and budget analysts qualify as specialists. But several medical jobs also qualify only as specialists, including veterinarians, optometrists, and physician assistants. There are also some medical jobs that qualify as generalists only (e.g., pharmacists), but I did not expect to see economists here. Other generalists-only include financial analysts, drafters, and sales engineers.

Figure 5 shows the task distributions for the occupations that are narrow specialists only, narrow generalists only, and that qualify as both. The 32 occupations that qualify under both definitions are clearly highest in STEM task content; we might refer to these as "super-STEM". The only-specialists are typically higher in STEM content than the only-specialists, which makes sense given the criteria for each.

[9] The O*Net data contain more task measures for math, science, and technology than for engineering (see Table 1) This may bias both task measures away from engineering occupations, although I have not noticed this in my analysis.

Figure 5: Distributions of task content for STEM generalists and specialists



Clearly, specialists and generalist definitions are picking up different types of jobs, and there are occupations on both lists that most people would agree are high in STEM content. As I will discuss in Section 6, one good option for future researchers and government agencies might be to use the union of narrowly defined STEM specialists and generalists or perhaps some other combination of definitions.

5 Applications

The previous section makes clear that using different criteria, and different cutoffs, to define STEM makes a big difference. In this section, I ask whether there are also differences in how those definitions affect the gender gap and racial gaps in STEM jobs, as well as the earnings premium associated with these jobs.

5.1 The Gender Gap in STEM Jobs

Many discussions of STEM in the United States - in the academic literature, popular press, and policy circles - revolve around the underrepresentation of women. Literature in economics, education and other fields has documented the large gender gaps in STEM and asked when and why those gaps appear and how they might be narrowed (e.g., Seymour and Hewitt (2000), Delaney and Devereux (2019), Card and Payne (2017), Saltiel (2019), Bostwick and Weinberg (2018), Fischer (2017), Loyalka et al. (2017)). The popular press has speculated on the reasons behind the gap (e.g., Pollack (2013)), while government agencies have also identified the problem and sought solutions (e.g., White House (2012), Census Bureau (2014), Beede et al. (2011)).

The studies and articles on this topic often use different definitions of STEM. We have already seen that it is not obvious what occupations should and should not be counted as STEM, however, so it is also not clear how large the gender gap is. Given the greater inclusion of medical jobs under task criteria, I would expect tasks to generally show a smaller gender gap than traditional measures. Some of these occupations have a large female share: among workers age 30 to 50, dentists are 41% female; pharmacists, 62%; physicians and surgeons, 43%; veterinarians, 71%; and nurse practitioners, 90%. However, this may not be true when compared with the broader O*Net definition, which includes the (mostly female) medical support jobs that the task measures do not favor.[10]

In Table 4, I compare the gender gap in STEM occupations for workers age 30 to 50 across the nine different definitions of STEM job, using the ACS person weights. As defined by the BLS, STEM occupations are 76% male; the narrow generalists show the same thing. But STEM specialists look radically different, at only 62% male. All results are similar when using age 30 to 40.

Going to the moderate definitions, we see that going from narrow to moderate drastically affects the gender gap: STEMM is down to 69% male and generalists are down to 65% male. For specialists, the move to moderate does not matter much, as the male share is now 63%.

[10]Looking at college majors in Ireland, Delaney and Devereux (2019) show that the definition of STEM affects the gender gap, with the gap much smaller if nursing is included as a STEM major.

Table 4: The Gender Gap in STEM Occupations

Panel A

	Percent Male, Age 30-50		
	Traditional	STEM Specialists	STEM Generalists
Narrow	76.4	62.1	75.7
Moderate	68.5	63.4	65.2
Broad	44.6	61.7	62.4

Panel B

	Percent Male, Age 30-50
Union of narrow defs	66.3
Union of narrow tasks	64.6
Union of moderate defs	62.6
Union of moderate tasks	62.9
Intersection of broad defs	69.7
Intersection of broad tasks	62.2

Note: The sample is all employed persons age 30 to 50. Panel A shows the percentage of the sample that is male under each definition of STEM. Panel B shows the percentage of the sample that is male under alternative definitions.

The broadest measure we have – and one that does not do well by tasks – is the O*Net definition, which amazingly shows that males make up only 45% of STEM jobs. To see why O*Net comes to this conclusion, I look at the occupations that are considered STEM by O*Net and not by any other other 8 measures. Employment in these occupations, most of which are medical support jobs, is 83% female. For the task generalists, going from moderate to broad again lowers the gender gap, now to 65% male. Specialists are again at 62% male; for them, the strictness of the definition does not matter much for the gender gap.

Researchers may want to be creative with their definitions of STEM. In Panel B of the table, I show the gender gap for other combinations of occupations. Taking the union of all three narrow measures, the male share is 66%; using the narrow task measures only gives 65%. Using the intersection of the three broad measures gives a male share of 68%.

Because there is no "true" definition of STEM, we cannot say what the "true" gender gap in STEM jobs is. But it seems clear that the BLS's 76% figure is an overstatement (or at least an extreme outlier) of the gender gap in STEM. Just including medical practitioners reduces the gender gap by about one-third; using a task specialist definition reduces it by about one-half. Definitions of STEM that take account of tasks suggest a male share of employment in STEM of 62-65%.

5.2 Representation of Minorities

If the definition of STEM has such a large effect on the gender gap, it may also affect our understanding of the representation of minorities in STEM. As the National Science Foundation notes, white and Asian workers are overrepresented in STEM jobs, while Black and Hispanic workers are underrepresented (NSF 2014).

In Table 5, I perform a similar analysis as in the previous table, but this time for white, Black, Hispanic, and Asian workers, again looking at workers aged 30 to 50. For reference, of all workers in this age range who are employed, 61.0% are white, 11.6% are Black, 18.4% are Hispanic, and 6.7% are Asian.

No matter the definition, white and Asian workers are overrepresented in STEM jobs, and Black and Hispanic workers are underrepresented. While there is some variation across definitions, it is less severe than we saw with gender. For example, except for the O*Net definition, which we have already seen is an outlier and perhaps not the best approach, the Black share ranges from 5.4% to 7.6% ad the white share ranges from 63.7% to 67.7%. While these differences are worth considering, they do not fundamentally alter the picture of representation in STEM the way the gender

Table 5: Minority Representation in STEM Occupations

		Percent of Workers, Age 30-50		
		Traditional	STEM Specialists	STEM Generalists
Narrow	White:	63.7	64.4	66.4
	Black:	6.7	7.2	5.4
	Hispanic	7.7	8.0	7.8
	Asian:	19.4	18.1	18.2
Moderate	White:	64.4	64.9	66.7
	Black:	7.0	7.3	6.6
	Hispanic	7.7	8.1	8.4
	Asian:	18.5	17.4	16.2
Broad	White:	62.4	67.7	67.6
	Black:	12.0	7.2	7.6
	Hispanic	9.6	9.4	9.6
	Asian:	13.5	13.4	13.0

Note: The sample is all employed persons age 30 to 50. The table shows the percentage of the sample that is non-Hispanic white, non-Hispanic Black, non-Hispanic Asian, and Asian under each definition of STEM.

results did.

5.3 The Earnings Premium for STEM Jobs

As a third application, I look at the earnings premium for workers in STEM occupations. Jobs normally classified as STEM tend to earn more than other jobs (e.g., Langdon et al. (2011), Hanson and Slaughter (2016)). The earnings premium for STEM jobs is strongest early in the career and then declines with age (Deming and Noray 2020). The premium is strong even controlling for a worker's degree and major, and STEM majors working in STEM jobs earn more than STEM majors in non-STEM jobs (Kinsler and Pavan 2015).

As the previous exercises indicated, changing the definition of STEM jobs can change our perception of the makeup of the jobs. Here I look at the earnings premium. The regression equation is

$$logearn_{it} = X_i\beta + \gamma_1 stemocc_i + t_i + \epsilon_i$$

where the dependent variable is log annual wage and salary earnings and X_i includes race, gender, dummies for each level of education, age, and age squared. I also include year fixed effects. The variable $stemocc_i$ is an indicator for being in a STEM occupation, defined different ways, and γ_1 gives the STEM occupation premium. I again restrict to employed people age 30 to 50.

The results are in Table 6, where each cell in the table the coefficient on the STEM occupation variable from a different regression. Most definitions show an earnings premium for STEM jobs of about 30-37 log points (35-43%). The broad O*Net measure shows a smaller premium (26 log points), as does the narrow STEM specialist measure (28 log points). There is a noticeable difference between STEMM and BLS, where including medical occupations drives the premium up from 31 to 38 log points. I do not show them here, but the alternate measures I used in Table 4 (like the union of narrow task measures) give similar earnings premia to the other task-based measures.

The earnings premium does depend on the definition of STEM that is used, but the differences are smaller across measures than we saw for the gender gap. There is no "true" STEM earnings premium, but it is clear there is a strong earnings premium for STEM jobs of about 35-43% no matter the definition.

Because the gender composition changes as the definition changes, it is worth looking at the earnings premium for women specifically. The bottom panel shows that women's STEM premium is higher than the overall premium for most definitions. Women especially earn a high premium in the generalist definitions and in STEMM, reflecting high returns for women in medical professions.

The results from these three applications show that when the occupations included in STEM change considerably from definition to definition, not everything changes. Underrepresentation of minorities is common across definitions, as is the large earnings premium. The gender gap, however, is dramatically changed with

Table 6: Earnings Premium for STEM Occupations

	Dependent variable: log earnings Coefficient on "STEM Occupation" Traditional	STEM Specialists	STEM Generalists
Narrow	0.313***	0.278***	0.342***
	(0.002)	(0.002)	(0.002)
Moderate	0.378***	0.357***	0.350***
	(0.001)	(0.001)	(0.001)
Broad	0.263***	0.352***	0.386***
	(0.001)	(0.001)	(0.001)
	Women Only		
	Traditional	STEM Specialists	STEM Generalists
Narrow	0.393***	0.291***	0.414***
	(0.003)	(0.003)	(0.003)
Moderate	0.455***	0.375***	0.392***
	(0.003)	(0.002)	(0.002)
Broad	0.251***	0.357***	0.398***
	(0.002)	(0.002)	(0.002)

Note: The sample is all employed persons age 30 to 50. Each cell represents a different regression. Each cell gives the coefficient on STEM occupation (using different definitions) from a regression of log wage and salary earnings on a dummy for being in a STEM occupation, gender, race, education dummies, year dummies, age, and age squared. Robust standard errors are in parentheses. Significance: *** = 1% level, ** = 5% level, * = 10% level.

task-based approaches. This implies that the design of STEM-based policies is very important for the effects on man and women in particular.

6 Guidance for Future Researchers

There are two broad conclusions to the analysis in this paper. The first is that there is no clear best definition of STEM occupations. Changing the criteria and cutoffs changes the list of STEM jobs considerably. The second is that the definition matters.

Our understanding of the returns to working in STEM and especially of the gender gap are affected by how we define it.

These two conclusions leave researchers and government agencies in a difficult place. They often must make a choice of how to define STEM, but there is no clear right choice. Here I make a few brief suggestions for anyone studying STEM jobs in the future.[11]

First, researchers should use multiple STEM definitions to test the robustness of their conclusions. This is particularly true for studies involving gender gaps. Studies that use the BLS definition will estimate a more-than-3-to-1 male-female ratio in STEM jobs, while those using O*Net will conclude that women are the majority in STEM! If different measures can give such different estimates of the gender gap, they may also lead to different conclusions when the researcher tries to explain or decompose the gap. The best solution may be to try an array of measures for each research exercise.

Second, while traditional definitions may be the obvious starting point, incorporating task content is a clear improvement. There are many occupations that are very high in STEM content but will not show up on government lists. These, like accountant, economist, nurse practitioner, and veterinarian, must be included if the definition is to have any relationship to the task content of the jobs. If one starts with a broad traditional definition, one should certainly run some sort of task filter first; it is clear that most of the social science and medical support occupations are not very high in STEM task content. Including these will particularly skew any analysis of gender gaps.

Third, the best definition of STEM may depend on the questions being asked by the researcher or the particular concerns of the policymaker. If the interest is in workers who have advanced degrees in a science field, then the researcher may want a task specialist definition. If the question is related to a worker's flexibility to move across different types of STEM jobs, then generalists may make more sense. This logic also applies to the question of whether to use a narrower or broader measure. For a researcher particularly interested in the content of jobs held by those without

[11] A data set with all of my STEM definitions is available for download at `https://sites.google.com/site/jaminspeer/research`.

college degrees, a broader definition is likely better.

While using tasks is sensible and simple to implement, there are other valid approaches. One might be interested, for example, in STEM occupations that are high in "innovation". This is more difficult to define and measure. One could look at patents by occupation, but even then, some innovation is not patented (e.g., new recipes or new medical care approaches). The best approach to defining STEM will depend both on the questions being asked and the feasibility of answering those questions.

Finally, users should consider using a union or intersection of my task-based definitions. Unless there is a clear theoretical reason to use only specialists or generalists, for example, it seems both should qualify as STEM. The union of narrowly defined specialists and generalists is a measure that would keep the strictness of the narrow cutoffs but broaden the criteria.

Intersections can be used to identify gradients of "STEM-ness" to further differentiate occupations. The 32 occupations that are both narrow task specialists and generalists, for example, are the "most STEM" occupations, while those that make one list but not the other are a step below those. This might be useful in studies of career progression among STEM workers.

7 Conclusion

Few concepts are talked about as frequently in academia, policy, and the popular press as STEM. STEM education and jobs are considered important to future economic growth, and their health is treated as an indicator of national competitiveness and innovation. Yet for such an important concept, it is not well-defined. Even U.S. government agencies do not agree on what STEM is and is not.

I have tried to use task data to improve on traditional definitions, but even those show that there is no clear "best" measure of STEM. The task-based definitions are quite different from traditional ones, but changing the methodology and cutoffs also affect what is in and what is out. Still, it seems clear that there are some non-traditional STEM occupations that should be counted as STEM, including economists, accountants, and a number of medical professions. But the solution is not just to add all medical occupations to the BLS definition; most medical jobs, including registered nurses, do not qualify as STEM even under broad task-based definitions.

Women are outnumbered by men in STEM jobs, but the gap is seemingly not as large as is usually reported. The task definitions show that the gap is likely only about half as large (about 63% male) as the BLS definition shows (76% male). This is largely due to including some medical occupations, which are often majority female. There is a substantial earnings premium for working in a STEM job of 35-43%, which is even larger for women, especially when medical jobs are included.

These findings suggest that policies promoting STEM require careful thought about what is being promoted, and at whose expense. A policymaker using the BLS definition should ask if there is a good reason to incentivize people to be researchers instead of physicians, for example. The answer may be yes, or it may be no. My analysis also shows that certain policy incentives may unnecessarily exclude women if they leave out STEM-task-heavy occupations that are not traditionally defined as STEM. Initiatives based on certain definitions of STEM may have unintended consequences.

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A Appendix A: Task Definitions

The following O*Net tasks are included as STEM tasks, given with their descriptions from the O*Net website:

Math tasks:

- **Mathematics skill**: Using mathematics to solve problems.
- **Mathematics knowledge**: Knowledge of arithmetic, algebra, geometry, calculus, statistics, and their applications.
- **Analyzing data or information**: Identifying the underlying principles, reasons, or facts of information by breaking down information or data into separate parts.
- **Math reasoning ability**: The ability to choose the right mathematical methods or formulas to solve a problem.
- **Number facility ability**: The ability to add, subtract, multiply, or divide quickly and correctly.

Science tasks:

- **Science skill**: Using scientific rules and methods to solve problems.
- **Biology knowledge**: Knowledge of plant and animal organisms, their tissues, cells, functions, interdependencies, and interactions with each other and the environment.
- **Chemistry knowledge**: Knowledge of the chemical composition, structure, and properties of substances and of the chemical processes and transformations that they undergo. This includes uses of chemicals and their interactions, danger signs, production techniques, and disposal methods.

- **Physics knowledge**: Knowledge and prediction of physical principles, laws, their interrelationships, and applications to understanding fluid, material, and atmospheric dynamics, and mechanical, electrical, atomic and sub- atomic structures and processes.

Technology tasks:

- **Interacting with computers**: Using computers and computer systems (including hardware and software) to program, write software, set up functions, enter data, or process information.
- **Computers and electronics knowledge**: Knowledge of circuit boards, processors, chips, electronic equipment, and computer hardware and software, including applications and programming.
- **programming skill**: Writing computer programs for various purposes.

Engineering tasks:

- **Engineering and technology knowledge**: Knowledge of the practical application of engineering science and technology. This includes applying principles, techniques, procedures, and equipment to the design and production of various goods and services.
- **Design knowledge**: Knowledge of design techniques, tools, and principles involved in production of precision technical plans, blueprints, drawings, and models.

B Appendix B: Full lists of STEM occupations

Table B.1 shows the occupations considered STEM by the Bureau of Labor Statistics and then those added by the STEMM definition and by O*Net. STEMM includes all of the BLS occupations, and O*Net includes all of the STEMM occupations.

Table B.1: Occupations Classified as STEM: Traditional Measures

BLS	Added by STEMM	Added by O*Net
Computer/info systems managers	Medical/health service managers	Economists
Architectural/engineering managers	Chiropractors	Psychologists
Natural science managers	Dentists	Urban/regional planners
Computer/info systems research scientists	Dieticians/nutritionists	Misc. social scientists
Computer systems analysts	Optometrists	Occupational therapists
Information security analysts	Pharmacists	Physical therapists
Computer programmers	Physicians/surgeons	Radiation therapists
Software developers	Physician assistants	Recreational therapists
Web developers	Podiatrists	Respiratory therapists
Computer support specialists	Audiologists	Speech language pathologists
Database administrators	Veterinarians	Registered nurses
Network/computer systems admins	Nurse practitioners and midwives	Nurse anesthetists
Computer network architects		Other health diagnosing/treating occs
Computer occupations, other		Clinical laboratory techs
Actuaries		Dental hygienists
operations research analysts		Diagnostic-related techs
Misc. mathematical science occs		EMTs/paramedics
Architects, except naval		Health practitioner support techs
Surveyors and cartographers		Licensed practical/vocational nurses
Aerospace engineers		Medical records techs
Biomedical/agricultural engineers		Opticians, dispensing
Chemical engineers		Misc. health techs
Civil engineers		Other health practitioners/techs
Computer hardware engineers		Nursing/psychiatric/home health aides
Electrical and electronics engineers		Occupational therapy assistants
Environmental engineers		Physical therapist assistants
Industrial engineers		Massage therapists
Marine engineers and naval architects		Dental assistants
materials engineers		Medical assistants
mechanical engineers		Medical transcriptionists
Petroleum/mining/geol. engineers		Pharmacy aides
Misc. engineeers		Veterinary assistants and techs
Drafters		Phlebotmists
Engineering technicians		Healthcare support workers, other
Surveying and mapping technicians		
Agricultural and food scientists		
Biological scientists		
Conservation scientists and foresters		
Medical and life scientists		
Astronomers and Physicists		
Atmospheric and space scientists		
Chemists and materials scientists		
Environmental and geo-scientists		
Other physical scientists		
Agricultural/food science technicians		
Biological technicians		
Chemical technicians		
Geological/petroleum technicians		
Sales engineers		

Table B.2: Occupations Classified as STEM: Task Specialists

Narrow (2.75 threshold)	Added by moderate (≥ 2.5)	Added by broad (≥ 1.95)
Architectural/engineering managers	Computer/info systems managers manage	Chief executives/legislators
Cost estimators	Credit analysts	Financial managers
Accountants and auditors	Financial analysts	Farmers/rangers/other agriculture
Budget analysts	Personal financial advisors	Construction managers
Computer/info research scientists	Information security analysts	Natural science managers
Computer systems analysts	Computer support specialists	Market research analysts
Computer programmers	Industrial engineers	Financial examiners
Software developers	Drafters	Financial specialists, other
Web developers	Economists	Computer occupations, other
Database administrators	Chemical technicians	Engineering technicians, except drafters
Network/computer systems adminsa	Dieticians and nutritionists	Conservation scientists/foresters
Computer network architects	Physicians and surgeons	Environmental scientists and geoscientists
Actuaries	Misc. law enforcement workers	Physical scientists, other
operations research analysts		Misc. social scientists
Misc. mathematical science occupations		Agricultural/food science technicians
Architects, except naval		Artists and related workers
Aerospace engineers		Designers
Biomedical/agricultural engineers		Chiropractors
Chemical engineers		Dentists
Civil engineers		Pharmacists
Computer hardware engineers		Podiatrists
Electrical/electronics engineers		Physical therapists
Environmental engineers		Radiation therapists
Marine engineers and naval architects		Health diagnosing/treating practitioners, other
materials engineers		Clinical laboratory technologists/technicians
mechanical engineers		Other healthcare practitioners/techs
Petroleum, mining and geological engineers		Embalmers and funeral attendants
Misc. engineeers		Sales representatives, other
Agricultural and food scientists		Bookkeeping, accounting, auditing clerks
Biological scientists		Gaming cage workers
Medical and life scientists		Computer operators
Astronomers and physicists		Boilermakers
Atmospheric and space scientists		Avionics technicians
Chemists and materials scientists		Heating/AC/refrigeration mechanics/installers
Biological technicians		Misc. installation/maintenance/repair workers
Optometrists		Tool and die makers
Physician assistants		Misc. woodworkers
Veterinarians		Water treatment plant/system operators
Nurse anesthetists		Chemical processig machine setters/operators
Nurse practitioners/nurse midwives		
Statistical assistants		
Misc. office and administrative occupations		

Table B.3: Occupations Classified as STEM: Task Generalists

Narrow (at least 12)	Added by moderate (≥ 11)	Added by broad (≥ 7)
Computer/info systems managers	Financial managers	Chief executives and legislators
Construction managers	Market research analysts	Industrial production managers
Architectural/engineering managers	Accountants and auditors	Purchasing managers
Natural science managers	Budget analysts	Farmers/ranchers/other ag workers
Cost estimators	Computer systems analysts	Medical and health service managers
Financial analysts	Biological technicians	Compensation/benefits/job analysts
Financial specialists, other	Optometrists	Logisticians
Computer/info research scientists	Water treatment plant/system operators	Real estate appraisers/assessors
Computer programmers		Credit analysts
Software developers		Personal financial advisors
Database administrators		Financial examiners
Computer network architects		Information security analysts
Actuaries		Computer support specialists
operations research analysts		Nework/computer systems admins
Misc. mathematical science occs		Computer occupations, other
Architects, except naval		Engineering technicians, except drafters
Surveyors and cartographers		Urban and regional planners
Aerospace engineers		Misc. social scientists
Biomedical and agricultural engineers		Agricultural and food science technicians
Chemical engineers		Geological/petroleum technicians
Civil engineers		Dentists
Computer hardware engineers		Dieticians and nutritionists
Electrical and electronics engineers		Physicians and surgeons
Environmental engineers		Physician assistants
Industrial engineers, including health		Respiratory therapists
Marine engineers and naval architects		Nurse practitioners/nurse midwives
materials engineers		Clinical laboratory technologists/technicians
mechanical engineers		Securities/commodities/fin. services sales agents
Petroleum/mining/geological engineers		Bookkeeping/accounting/auditing clerks
Misc. engineeers		Misc. office and administrative occupations
Drafters		First-line supervisors of mechanics/installers/repair
Surveying and mapping technicians		Avionics technicians
Agricultural and food scientists		electronic home entertainment installer/repair
Biological scientists		Heating/AC/refrigeration mechanic/installer
Medical and life scientists		Industrial/refractory machinery mechanics
Astronomers and physicists		Millwrights
Atmospheric and space scientists		
Chemists and materials scientists		
Environmental scientists/geoscientists		
Physical scientists, other		
Economists		
Pharmacists		
Nurse anesthetists		
Sales representatives		
Sales engineers		
Statistical assistants		
Computer control programmers/operators		

Table B.4: Occupations Classified as STEM: Moderate Definitions

On all 3 lists	On 2 lists	On 1 list
Computer/information systems manage	Information security analysts (T,S)	Medical and health service managers (T)
Architectural /engineering managers	Web developers (T,S)	Computer occupations, other (T)
Computer/info research scientists	Computer support specialists (T,S)	Engineering technicians, except drafters (T)
Computer systems analysts	Nework/computer systems admins (T,S)	Conservation scientists and foresters (T)
Computer programmers	Chemical technicians (T,S)	Agricultural/food science technicians (T)
Software developers	Dieticians and nutritionists (T,S)	Geological/petroleum technicians (T)
Database Administrators	Physicians and surgeons (T,S)	Chiropractors (T)
Computer network architects	Physician assistants (T,S)	Dentists (T)
Actuaries	Veterinarians (T,S)	Podiatrists (T)
Operations research analysts	Nurse practitioners/nurse midwives (T,S)	Audiologists (T)
Misc. mathematical science occupations	Natural science managers (T,G)	Credit analysts (S)
Architects, except naval	Surveyors and cartographers (T,G)	Personal financial advisors (S)
Aerospace engineers	Surveying and mapping technicians (T,G)	Misc. law enforcement workers (S)
Biomedical/agricultural engineers	Environmental scientists/geoscientists (T,G)	Misc. office/administrative occupations (S)
Chemical engineers	Physical scientists, other (T,G)	Financial managers (G)
Civil engineers	Pharmacists (T,G)	Construction managers (G)
Computer hardware engineers	Sales engineers (T,G)	Market research analysts (G)
Electrical and electronics engineers	Cost estimators (S,G)	Financial specialists, other (G)
Environmental engineers	Accountants and auditors (S,G)	Sales representatives, other (G)
Industrial engineers	Budget analysts (S,G)	Water treatment plant/system operators (G)
Marine engineers and naval architects	Financial analysts (S,G)	
Materials engineers	Economists (S,G)	
Mechanical engineers	Nurse anesthetists (S,G)	
Petroleum/mining/geological engineers	Statistical assistants (S,G)	
Misc. engineeers	Computer control programmers (S,G)	
Drafters		
Agricultural and food scientists		
Biological scientists		
Medical and life scientists		
Astronomers and physicists		
Atmospheric and space scientists		
Chemists and materials scientists		
Biological technicians		
Optometrists		
34 occupations	Traditional and Specialist: 10	Ttraditional only: 10
	Traditional and Generalist: 7	Specialist only: 4
	Specialist and Generalist: 8	Generalist only: 6

Note: The occupations in the left column meet the STEMM definition, moderate STEM specialist, and moderate STEM generalist. The occupations in the middle column meet only two of the three definitions, with which definitions they meet noted in parentheses. T=traditional (STEMM), S=specialist, and G=generalist. The occupations in the right column meet only one of the three definitions, with the definition given in parentheses. The definitions of STEM occupations are given in the text.

Table B.5: Occupations Classified as STEM: Broad Definitions

On all 3 lists	On 2 lists	On 1 list
Computer/information systems managers	Web developers (T,S)	Psychologists (T)
Architectural /engineering managers	Conservation scientists and foresters (T,S)	Audiologists (T)
Natural science managers	Chemical technicians (T,S)	Occupational therapists (T)
Computer/info research scientists	Chiropractors (T,S)	Recreational therapists (T)
Computer systems analysts	Podiatrists (T,S)	Speech language pathologists (T)
Information security analysts	Physical therapists (T,S)	Registered nurses (T)
Computer programmers	Radiation therapists (T,S)	Dental hygienists (T)
Software developers	Veterinarians (T,S)	Diagnostic related technologists/technicians (T)
Computer support specialists	Health diagnosing/treating, other (T,S)	EMTs and paramedics (T)
Database administrators	Other healthcare practitioners/technicians (T,S)	Health support technologists (T)
Nework/computer systems admins	Medical/health service managers (T,G)	Licensed practical/vocational nurses
Computer network architects	Surveyors and cartographers (T,G)	Medical records technicians (T)
Computer occupations, other	Surveying and mapping technicians (T,G)	Opticians, dispensing (T)
Actuaries	Urban and regional planners (T,G)	Misc. health technologists/technicians (T)
Operations research analysts	Geological/petroleum technicians (T,G)	Nursing/psychiatric/home health aides (T)
Misc. mathematical science occs	Respiratory therapists (T,G)	Occupational therapy assistants (T)
Architects, except naval	Sales engineers (T,G)	Physical therapist assistants (T) (T)
Aerospace engineers	Chief executives and legislators (S,G)	Massage therapists (T)
Biomedical and agricultural engineers	Financial managers (S,G)	Dental assistants (T)
Chemical engineers	Farmers/ranchers/other ag workers (S,G)	Medical assistants (T)
Civil engineers	Construction managers (S,G)	Medical transcriptionists (T)
Computer hardware engineers	Cost estimators (S,G)	Pharmacy aides (T)
Electrical and electronics engineers	Market research analysts (S,G)	Veterinary assistants (T)
Environmental engineers	Accountants and auditors (S,G)	Phlebotmists (T)
Industrial engineers	Budget analysts (S,G)	Healthcare support workers, other (T)
Marine engineers/naval architects	Credit analysts (S,G)	Artists and related workers (S)
Materials engineers	Financial analysts (S,G)	Designers (S)
Mechanical engineers	Personal financial advisors (S,G)	Misc. law enforcement workers (S)
Petroleum/mining/geological engineers	Financial examiners (S,G)	Embalmers and funeral attendants (S)
Misc. engineeers	Financial specialists, other (S,G)	Gaming cage workers (S)
Drafters	Sales representatives, other (S,G)	Computer operators (S)
Engineering technicians, except drafters	Bookkeeping/accounting/auditing clerks (S,G)	Boilermakers (S)
Agricultural and food scientists	Statistical assistants (S,G)	Misc. installation/maintenance workers (S)
Biological scientists	Misc. office/administrative occupations (S,G)	Tool and die makers (S)
Medical and life scientists	Avionics technicians (S,G)	Misc. woodworkers (S)
Astronomers and physicists	Heating/AC/refrigeration mechanic/installer (S,G)	Chem. processing machine setters (S)
Atmospheric and space scientists	Computer control programmers/operators (S,G)	Industrial production managers (G)
Chemists and materials scientists	Water treatment plant/system operators (S,G)	Purchasing managers (G)
Environmental scientists/geoscientists		Compensation/benefits/job analysts (G)
Physical scientists, other		Logisticians (G)
Economists		Real estate appraisers/assessors (G)
Misc. social scientists		Securities/commodities/fin. services sales agents (G)
Agricultural/food science technicians		First-line supervisors of mechanics/installers (G)
Biological technicians		Electronic home entertainment installer/repair (G)
Dentists		Industrial/refractory machinery mechanics (G)
Dieticians and nutritionists		Millwrights (G)
Optometrists		
Pharmacists		
Physicians and surgeons		
Physician assistants		
Nurse anesthetists		
Nurse practitioners/nurse midwives		
Clinical laboratory technologists/technicians		
53 occupations	Traditional and Specialist: 10	Traditional only: 25
	Traditional and Generalist: 7	Specialist only: 11
	Specialist and Generalist: 21	Generalist only: 10

Note: The occupations in the left column meet the O*Net definition, broad STEM specialist, and broad STEM generalist. The occupations in the middle column meet only two of the three definitions, with which definitions they meet noted in parentheses. T=traditional (O*Net), S=specialist, and G=generalist. The occupations in the right column meet only one of the three definitions, with the definition given in parentheses. The definitions of STEM occupations are given in the text.