## Improving the Measurement of STEM Gender and Racial Gaps in the Workforce

Yu-Chieh Hsu NORC/University of Chicago

Janna E. Johnson University of Minnesota

Javaeria Qureshi University of Illinois Chicago

Policymakers have recently emphasized the need to improve science, technology, engineering, and math (STEM) education in the United States to ensure the future competitiveness of the country's workforce in an increasingly technology-dependent world economy. One part of this goal is to increase the number of college graduates majoring in STEM fields, particularly among women and minorities. Despite the fact that now more women graduate from college than men, the fraction of women earning degrees in STEM fields still lags far behind their male peers. Minority groups such as African-Americans and Hispanics have also increased their college graduation rates over the last few decades, but still have much lower college graduation rates than their white counterparts (National Science Foundation 2013). In order to accurately measure these gaps, precise estimates of the STEM workforce are needed. The Department of Commerce estimated there were 7.6 million STEM workers in the United States in 2010, while the National Science Foundation (NSF) estimated the number was 22 million (Langdon et al. 2011, Finamore et al. 2013). To inform policymakers of the current situation of the STEM workforce in terms of both size and diversity, more accurate population counts are essential.

We focus on one measure of the STEM workforce: the number of individuals with college majors in STEM fields. Most estimates of the number of STEM majors come from survey data. As STEM majors made up only 14% of all female bachelor degree holders and 32% of males in 2009, the entire population is relatively small.<sup>1</sup> If one is interested in the male-female or black-white difference in a specific STEM area, the population shrinks even more dramatically. When using survey data to estimate such small population sizes, large errors are possible due to sampling variation and measurement error, making it extremely difficult to accurately measure gender and racial gaps. To illustrate, the 1993 National Survey of College Graduates (NSCG) estimates there are 2,717 women in the U.S. aged 35-45 who majored in civil engineering. This number should be approximately the same in the 2003 NSCG for the same group, now aged 45-55. Instead, it is 8,832, almost three times larger. In contrast, the corresponding estimates for men are 95,501 and 108,848, a difference of only 15%.

This study remedies this problem by applying a Generalized Method of Moments (GMM) procedure (Black et al. 2012) to optimally combine data from multiple sources to produce considerably more accurate measures of the number of STEM graduates than what is possible from survey data alone. The method is based on the principle that the average of multiple noisy measures of the same population is more accurate than a single noisy measure, assuming the measurement error is random. The GMM procedure combines two periods of survey data from

<sup>&</sup>lt;sup>1</sup> Computed by the authors using the 2009 American Community Survey.

the NSCG with Vital Statistics mortality records, which are a census of all deaths occurring in the United States. Using these three sources of data, we have two measures of the population in each year: the raw survey count from that year, and the survey count in the other year combined with the deaths occurring between the two years. For example, in 1993 we have the raw survey count from the 1993 NSCG (N<sup>1993</sup>), and the 2003 NSCG count for the same population plus the deaths that occurred in that population between 1993 and 2003 (N<sup>2003</sup>+D<sup>93-03</sup>, also known as the "backward estimator" in demography). The GMM procedure computes an estimate for 1993 using these two measures, assigning the optimal weight to each. By combining information from these three sources of data in an optimal fashion, we are able to compute more accurate measures of small populations than what are possible using the survey alone.

Before we turn to our estimates of gender and racial gaps, we first demonstrate how the GMM estimator improves the accuracy of the counts of individuals with specific STEM majors.<sup>2</sup> As we do not observe the true population count for each college major, we can never know the true improvement. However, we can indirectly measure the improvement by computing census death rates. If one considers a specific birth cohort, the only difference between two censuses of this cohort should be a decrease due to deaths that occur between the two censuses. Therefore, one can compute a census death rate by calculating the difference between two censuses. To illustrate, we consider non-Hispanic white men born in the United States over the period 1948-1958. The overall ten year census death rate for this population between 1990 and 2000 was approximately 0.02, as shown in the bottom panel of Table 1. When we do the same calculation for this population for our 58 STEM majors in the NSCG, the median death rate among these majors is -0.26, meaning we observed a 26% increase in the population who had this college major, impossible as we are considering the same age cohort.<sup>3</sup> The observed raw death rates for these majors range from -158 to over 0.90, highlighting the inaccuracy of the raw counts. The death rate computed using our GMM measures of the population in 1993 and 2003 are much closer to the total population rate, with a median of 0.03 and a range of only 0.001 to 0.09. This convergence of the death rate using our GMM measure for these college majors to the overall population death rate shows that indeed our procedure is improving the measurement of the STEM population.<sup>4</sup>

Table 1:	Ten-	Year (	Census	Death	Rates	for	<b>US-Born</b>	White	Men,	Birth
Cohorts	1948-	1958,	, 1993-2	2003						

STEM Majors	Median	Min	Max
Raw Death Rate	-0.256	-157.900	0.909
GMM Death Rate	0.033	0.001	0.087
Total Population			
Census Death Rate	0.020		
M D d - 1	(a 12003 a 1993) (a 1993 (m)	OTTEND ' ' I NICO	G O 11 G

Note: Death rates computed as  $(N^{2003}-N^{1993})/N^{1993}$ . There are 58 STEM majors in the NSCG. Overall Census death rate computed using same formula but using population measures in 1990 and 2000.

 $<sup>^{2}</sup>$  We use the NSF definition of STEM and calculate counts for college majors meeting this definition that can be identified in the NSCG (58 majors).

<sup>&</sup>lt;sup>3</sup> This assumes that no one in this age cohort receives a bachelor's degree in STEM between 1993 and 2003. As the cohort we consider is aged 35-45 in 1993, we believe this to be a reasonable assumption.

<sup>&</sup>lt;sup>4</sup> We have also computed these numbers for other racial and gender groups (Hispanic, black, and Asian men, as well as women) and observe similar differences between the GMM and raw measures.

We now turn to how our improved measures of STEM college majors affect the measured gender and racial gaps in the science and technology workforce. We first consider the gender gap among non-Hispanic whites in 1993, again focusing on birth cohorts 1948-1958. We computed the gender gap for each of the 58 majors in our sample<sup>5</sup> using the raw 1993 NSCG counts and our GMM counts. Note that the direction of the change in the gap between the two measures depends on the relative size of the measurement error for men and women, and we cannot predict whether the GMM estimate should reduce or increase the gap relative to the raw counts. We calculated the gap as the number of men in each major for each woman. If there were an equal number of men and woman with a specific major, this number would be equal to 1. For 17 of the majors, the gender gap between the raw counts was smaller than that between the GMM estimates, and for 40 majors the GMM gender gap was smaller than the raw gap. For the majors for which the GMM gap exceeds the raw gap, the GMM gap was on average 61% larger than that measured with the raw counts. To consider a specific example, the major of nuclear engineering had approximately 6 men for every woman when measured with the raw counts, but this increased to 16 men per woman with the GMM estimates, an increase of 186%. For the 40 majors that had a smaller GMM gap, the gender gap measured with the raw counts was over three times larger on average than that using our GMM estimate. For the ecology major, there were 41 men for every woman using the raw counts, and just 3 using the GMM estimates. For physics, the gender gap is 15 men per woman using the raw counts, and 10 using GMM.

Looking at the black-white gap for men, we also see large differences between the gap calculated with the raw counts and that using the GMM estimates. We measure the black-white gap using number of white men per one black man in each major. For the 26 majors where the GMM gap exceeded the raw gap, the difference was 72% on average. The environmental engineering gap was 9 men per one black man using the raw counts, and using GMM it was 20:1. Twenty-two majors had the GMM gap less than the raw gap, and on average the GMM gap was half the size of the raw gap. Computer science had a raw gap of 63 whites per one black major, and the GMM gap was only 24:1.

The large differences between the gender and racial gaps measured using the raw and GMM estimates highlight the difficulty of measuring small populations using national-level surveys. Accurately measuring these populations using survey methods would require much larger sample sizes and/or specifically targeted surveys, and would therefore be enormously expensive. The GMM method improves the measurement of these populations using data already collected, imposing no extra cost. The importance of accurate measures of the STEM workforce in designing policies targeting STEM education and training cannot be overemphasized.

The preliminary results discussed here only cover estimates for one cohort (birth years 1948-1958) and the 1993 and 2003 NSCG. In addition, we will use our GMM estimation method to look at older and younger cohorts in both years, as well as other races, enabling us to accurately measure the change in the composition and size of the STEM workforce over time. The 2013

<sup>&</sup>lt;sup>5</sup> We were unable to compute the gender gap for 2 and 10 majors for the gender and black-white gaps, respectively, as there was at least one category (black men, white women, etc.) in these majors with a count of zero in either the 1993 or 2003 NSCG.

edition of the NSCG will be released in the coming months, meaning we will be able to expand our analysis to cover two decades. Our results will inform policymakers about which specific areas of STEM to target when designing their policies on STEM education in the United States.

## References

Black, Dan A., Yu-Chieh Hsu, Seth G. Sanders, and Lowell J. Taylor, 2012. "Combining Forward and Backward Estimates of Mortality," Manuscript, Carnegie Mellon University.

Finamore, John, Daniel J. Foley, Flora Lan, Lynn M. Milan, Steven L. Proudfoot, Emilda B. Rivers, and Lance Selfa, 2013. "Employment and Educational Characteristics of Scientists and Engineers", National Center for Science and Engineering Statistics Info Brief NSF 13-311.

Langdon, David, George McKittrick, David Beede, Beethika Khan, and Mark Doms, 2011. "STEM: Good Jobs Now and for the Future", US Department of Commerce Economics and Statistics Administration Issue Brief #03-11.

National Science Foundation, National Center for Science and Engineering Statistics, 2013. *Women, Minorities, and Persons with Disabilities in Science and Engineering: 2013.* Special Report NSF 13-304. Arlington, VA. Available at <u>http://www.nsf.gov/statistics/wmpd/</u>.