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Causes and Consequences of Inequality in the STEM: Diversity and its Discontents

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ABSTRACT
Social Science research on science careers tends to focus on gender as the primary mechanism affecting which people enter and succeed in science. Despite the often narrow focus on gender, the demographic composition of many science fields in the US has changed considerably as the US workforce incorporated more women, people of color, and non-US born workers following important legal changes in the 1960s. Using data from the Integrated Public Use Microdata Series (IPUMS) (1% samples for 1960 and 1970, 5% samples from 1980, 1990 and 2000) as well as the American Community Survey from 2009, we show how a narrow focus on gender oversimplifies the racial and increasingly global dynamics of the scientific labor force. We further examine the factors that produce and constrain the scientific labor force sustaining the complex inequality we see when we disaggregate the demographic profiles of two exemplary science fields, Computing and Life Science.

KEYWORDS
Gender; race; immigrant; science; occupations; computing; life sciences

Causes and Consequences of Inequality in the STEM: Diversity and its Discontents

Studies of women in science as well as studies of immigration and science have been growing since 1970. Yet both streams of research tend to oversimplify the causes and consequences of inequality in the Science, Technology, Engineering, and Mathematics (STEM) disciplines. Research on women in science often treats gender as the primary mechanism affecting which people enter and succeed in science. By and large, the literature on women in science regards all women as White, American, and middle class, to the exclusion of race/ethnicity or citizenship status. Few studies examine how socially relevant identities, such as race or migration status, may change or complicate our understanding of scientific fields as sex segregated occupations.

Choo and Ferree (2010) urge researchers to expand understandings of inequality arguing that "dynamic analyses would consider how national and transnational structures of inequality are produced and reproduced in multisited processes such as gendering, racialization, labor exploitation, and generational succession" (p. 147). Acker (2006) encourages researchers to look "at specific organizations and the local, ongoing practical activities of organizing work that, at the same time, reproduce complex inequalities "(p. 442). While some researchers do look at intersections of gender and race (Ong 2005; Leggon 2010; Varma and Hahn 2008) or gender and migration (Doquier, Lowell, and Marfouk 2009) these studies do not look at the intersections of all three. Moreover the studies that do consider gender and race use small samples and qualitative methods that add context and bring the experiences of underrepresented groups to light, but cannot provide macro-level views of employment across different scientific disciplines (e.g. Leggon 2010, Ong 2005).

Finally, many studies rely on the "pipeline" metaphor, which assumes that there is a single path from early education to a scientific career and from which women and minorities tend to "leak" out. Yet, closer examination shows that women are not underrepresented in all sciences, not all minorities are underrepresented, and representation is not the same for US-born and Non-US born people of color. While scientific fields, in general, are moving in the direction of more diversity, there are vast differences in individual fields necessitating field level analyses. Thus, the pipeline metaphor oversimplifies the racial and gender dynamics of scientific fields while presenting the fields as overly homogeneous.

Take for example, the growth of Life Science and Computing, both of these fields have been central to the US economy over the last three decades and continue to be central in the future "innovation economy" imagined by current political leaders. The pipeline metaphor would lead us to expect similar patterns of gender and minority representation in both fields. However, women are a growing proportion of Life Science workers, but a shrinking proportion of Computing workers, while the representation of underrepresented minorities in both fields has been relatively stagnant. This divergent pattern suggests more than a passive path accommodating women and minorities within scientific fields, rather fields themselves have different orientations to men, women, and minorities that encourage or discourage their persistence. In addition, the growth of both Life Science and Computing fields has been fueled, in large part, by changes to immigration law to ensure a supply of skilled workers, whose experiences are entirely unaccounted for in the pipeline.

In this paper we examine the shift in the size and demography of the Computing and Life Science workforces. We aim to answer two questions. 1) How did the gender composition of the scientific labor force in Life Science and Computing change over time? 2) How does our understanding of scientific labor force in these fields change when we disaggregate by gender, race, and nationality over time? We begin by reviewing the literature to show how a focus on women or immigrants oversimplifies the racial and increasingly global dynamics of the scientific labor force. We use the decennial US census from 1960-2000 and the 2009 American Community Survey. The shifts in the composition of the science and technology workforce happened in the context of broad changes to equal employment and immigration law. Thus we examine these changes to better understand what broadening participation has meant, what groups have been newly included, and what groups should be better targeted for increased participation. This analytic strategy allows us to demonstrate, how our understanding of what it means to "broaden participation in STEM" might change when we consider multiple axes of identity.

GROWTH OF COMPUTING AND LIFE SCIENCE IN HISTORICAL CONTEXT

Two important labor market changes had lasting and far-reaching effects on the size and composition of the US labor force that must be considered when making sense of the growth of the scientific labor force. First, Title VII of the Civil Rights Act of 1964 prohibited employment discrimination based on race or sex, opening new doors to education and employment for White women and Americans of color. While Title VII may have opened doors to science and technology jobs, these jobs still required access to higher education that many men and women of color had been denied, through legal segregation for those of working age in the 1960s and through subtler means thereafter.

Haigh (2010) argues that when the Computing field was first taking off, before it was clear that the field would provide high status, managerial jobs, women were actively recruited. Particularly from among the mostly White and female ranks of keypunch operators who already possessed the skills needed for programming. Once it became clear that Computing jobs would be good jobs, women were all but barred. Many White women who worked as keypunch operators had a path, though unrealized, into Computing, while black women who were essentially barred from entering clerical work due to their race had no path at all (Branch, 2010). Unfortunately, the moment of promise for equal opportunity, particularly for education and employment, was not fully realized as the science and technology workforce grew.

Second, the Immigration Act of 1965 provided non-family based paths to immigration for skilled professionals and marked the beginning of a new normal in US immigration policy. While the US government has placed more immigration restrictions on poor immigrants, it has also changed laws allowing more highly educated immigrants to enter the country. Information, ideas, and capital flow nearly instantly between global cities facilitated by coveted skilled professionals (Sassen 1998:p XXVII). The US now heavily relies on this labor stream to keep pace with the demand for STEM workers and has gone to great lengths to maintain it.

OVERSIMPLIFYING THE CAUSE OF INEQUALITY IN STEM WORK

There is a massive body of research on participation in STEM work that demonstrates emphatically that women are underrepresented in STEM fields. This literature identifies gender socialization, desires for work and family balance, and lack of mentors as barriers for women. Gender socialization, especially socialization that occurs in schools, is often cited as a cause for the prevalence of women in certain occupations (Blickenstaff, 2005; Simpkins, Davis-Kean, & Eccles, 2006). Teachers, observers, and girls themselves tend to believe that they are less capable than their male classmates even when objective measures would suggest otherwise (Correll, 2001; Hyde et al. 2008).

In schools women suffer from a lack of female mentors in STEM disciplines (Sonnert, Fox, and Adkins, 2007). Even when they do enter and succeed in engineering majors, Cech et al. (2011) find that they are not confident in their ability to be professional engineers. Similarly, international research shows that women have lower self-evaluations of their abilities with computers than their male peers (Vekiri, 2013; Meelissen and Drent, 2008; Robnett, 2013). For example, in a survey of 5th grade students in Greece, Vekiri (2013) found that boys used computers more and were more confident in their computer competence.

If women do pursue a STEM field and believe they are capable, researchers argue that they still have to reconcile desires for family life and workplace success. Blackwell and Glover (2008) find that women in the UK with degrees in science, engineering, or technology are less likely to work in those fields than men with similar degrees and more likely than women with degrees in health related fields to leave the workforce if they become mothers. Ceci, Williams and Barnett (2009) and Frome, Alfeld, Eccles and Barber (2006) argue that the desire to balance work and family life presents an additional barrier for women. Eccles (2005) argues that for many women the value of learning Computing does not outweigh the value of a more feminine-typed course of study that they believe will better allow them to both pursue a career and care for children. Eccles and colleagues further argue that science careers are time consuming and male dominated (Eccles, 1994; Frome, Alfeld, Eccles & Barber, 2006). This literature suggests women are less likely to be able to balance work and family, and more likely to experience discrimination, hence in their view it should not be surprising that women are underrepresented.

This literature contributes a sophisticated gendered analysis but tends to regard all women as the same, as if race, class, citizenship, ethnicity or sexual orientation do not matter and all women have the same response to the pressure to conform to heteronormative femininity. In contrast to earlier findings Cech et al. (2011) find that concerns about balancing work and family do not have a significant effect on college women's decision to pursue engineering. The difference between Cech and colleagues' findings and earlier findings may be due to cohort effects or selectivity bias that drew women who were less family- oriented to the schools where their research was conducted. No matter the source of the difference, this contrast shows that desires for work and family balance are not the same barriers for all women.

Even when researchers are attentive to race in shaping the experience of men and women in science, gender often becomes the dominant theme. For example, Varma and Hahn (2008) surveyed 150 students who were either computer science or engineering majors at minority serving institutions (historically black colleges and universities, Native American serving and Hispanic serving colleges) to learn where along the pipeline these students are more likely to leave. While the researchers carefully selected a racially diverse sample, and present descriptive statistics for the racial breakdown of their sample, all of the statistical comparisons are between men and women only.

The idea of one "pipeline" carrying all future scientists along their career paths is woefully inadequate. This metaphor assumes all women from all schools and backgrounds experience the same science "pipeline" carrying future scientists equally to all science fields. School conditions, family background, access to science education, and science-related extracurricular activities, are not the same for all students and may not operate the same way for all students in all contexts. Not only do women in different schools across a variety of social contexts experience different pathways to science careers, not all women in US science careers received their science education in the US.

There are a handful of studies that do examine gender, race, migration, and/or class intersectionally and thus demonstrate that the path into STEM work is not the same for everyone. O'Keefe (2013) studies the importance of "exceptional" popular science fiction characters, particularly Star Trek's Lieutenant Uhura (a black female communications officer), for underrepresented minorities in STEM fields. She finds that these characters, despite their small numbers, were inspirational to her interviewees. Ong (2005) conducted longitudinal interviews with 36 undergraduate physics students and found that the women of color in particular engaged in "body projects", to help them manage the mismatch between their appearance and the stereotypical image of a physicist. These studies deal with multiple identities and help us understand how people who do not match the stereotypical scientist find inspirations and alternative paths. The current study builds on this work by deepening our understanding of what underrepresentation looks like in different scientific fields.

STEM, WORK, AND MIGRATION

The STEM workforce in the US is not made up of only American born workers and the laws and politics around migration provide important additional context necessary for understanding who STEM workers are and who is underrepresented. In the 1990s, scientific fields experienced an immigration boom, particularly among the highest educated workers. Thanks, in large part, to the H1B Visa program passed by Congress. H1B visas provided additional paths to migration for highly skilled immigrants and are the primary visa used for workers in the tech industry. Upwards of 57% of Computer Science and Electrical Engineering doctorate holders in 2003 were Non-US born (Regets, 2007).

US lawmakers and science policy advisors and analysts are seeking even more ways to attract immigrant workers with world-class STEM skills. The National Academy of Sciences (National Research Council 2010) and senators Charles Schumer and Lindsey Graham (2010), ideological opposites on many issues, describe attracting Non-US born scientists as a matter of national economic security. More opportunities are becoming available in the countries that send the most immigrant workers to the US, larger proportions of highly- skilled migrants are receiving only temporary visas, fueling fears that more of these workers may return home (National Research Council 2010; Regets 2007; Favell, Feldblum and Smith 2007). The idea that the highly educated from outside the US may stop immigrating to the US has led organizations such as the National Academy of Science to push for new immigration measures (National Research Council, 2010). The National Academy of Sciences has authored two reports, *Rising Above the Gathering Storm: Energizing and Employing America for a Brighter Economic Future* (2007) and Rising Above the Gathering Storm*, Revisited: Rapidly Approaching Category 5* (2010), warning of national economic disaster if the US fails to provide easier access and more incentives for highly- skilled immigrants to come to the US.

Framing the demographics of scientific fields as a gendered “pipeline problem” or even part of the culture or organizational practice of the field misses the important global and racial factors that have the potential to transform how gender operates in the context of each field. It is important to remember that migrant science and technology workers are coming from places with different gender regimes and consequently different understandings of what constitutes appropriately gendered work. Immigrant STEM workers also live with different kinds of relationships to their employers than do American workers. An employer must sponsor the H1B visa and while it can be transferred between employers, a period of unemployment can jeopardize visa status. This is a particular problem for workers contracted for specific projects who are compelled to find new assignments or jeopardize their immigration status (Banerjee, 2006). Banerjee (2006) interviewed Indian men in the US Computing workforce and found that despite high pay they navigate a complex set of immigration laws that puts their legal status in the US in the hands of their employer. Many of her interviews experienced periods in-between contracts when their visas were technically not valid and they could have been subject to deportation – a threat that American workers do not face.

Science and technology workers are enacting multiple identities and doing so across institutional, organizational, legal, and cultural contexts. They have different kinds of pressures to participate or not participate in the US STEM workforce and those pressures are not even the same across all science and technology fields. In the analysis that follows we demonstrate how the demographics of the Computing and Life Science fields changed over time. Rather than examining only gender we demonstrate that our understanding of how gender may affect participation may change when we examine gender, race, and migration together.

DATA AND METHODS

The data for this study are drawn from the Integrated Public Use Microdata Series (IPUMS) using 1% samples for 1960 and 1970, 5% samples from 1980, 1990 and 2000, as well as the American Community Survey from 2009, which replaced the 1% long form census (Ruggles et al., 2010). Ten year intervals are less than ideal, since change in computing happened very quickly in the 1990s. It is likely that much of the dot-com boom and bust are masked by the length of the interval during this period. Combining these samples provides a representative random sample of workers in the US that spans the 50-year period of dramatic growth in the scientific workforce.

IPUMS data provide the most comprehensive set of quantitative information on long-term changes in the US population, including immigration, earnings, and occupation. In addition, IPUMS integrates the data samples across years to allow for uniformity in variable names and meaning including harmonized occupational titles, permitting an analysis of occupations over time. Since IPUMS is based on the decennial census it does not trace changes in individuals across years, instead we will examine trends cross-sectionally. We limit the sample to individuals employed at least part time with at least a bachelor's degree. These workers are more likely to intend to have careers in the sciences rather than casual employment and have pursued education related to their chosen occupational field. In other words, they have traversed some version of the metaphorical "pipeline".

First, we show the demographics of the two fields over the fifty year period separated by only gender, then disaggregated as fully as sample size allows by race and region of origin. We examine only men and women to show the picture upon which most previous research relies. Next, we disaggregate to show the differences *among* women and men. This approach allows us to show how much we are missing with a focus on gender alone. By highlighting two STEM occupations with opposite patterns for women's participation we demonstrate that research lamenting women's low rates of participation in STEM fails to take account of differences across STEM fields, even if all women did experience the same conditions. The strategy of simple descriptive disaggregation allows us to highlight racial and national differences that have consequences for paths into or away from STEM careers. We believe the strength of this approach lies in its simplicity. No complex or sophisticated statistical modeling is needed to see that the pipeline metaphor does not stand up to the differences *among* men and women and across STEM fields.

We take our analysis a step further, using binary logistic regression to predict the likelihood of working in Computing or Life Science. We estimate the effects of race, gender, and migration, while controlling for age, education, and US citizenship. The multivariate analysis is especially important for small groups, whose under or over representation is relative to their representation in the larger workforce. The logistic regression results in coefficients (which we present as odds ratios) that can be compared across groups more directly. For example, in 2009 US-born Asian women are only .83% of the US workforce with at least a Bachelor's degree but 1.69% of the Life Science workforce, and they were 81% more likely to work in Life Science than US-born White men. While US-born Asian women represent only a tiny fraction of the Life Science workforce they are not underrepresented. The combination of descriptive statistics and logistic regression allows us to more fully understand representation in scientific fields by gender, race, and migration.

Variables

The disaggregated analysis examines White men and women, underrepresented minority men and women, US-born Asian men and women, Non-US born Asian men and women, Non-US born Western men and women, and Other Non-US born men and women. White men and women include only white men and women born in the US or abroad to American parents. Underrepresented minority men and women were born in the US or abroad to American parents and identify their race as Black, Hispanic, Native American, or any other race that is not white or Asian. Since Asians are not underrepresented in STEM fields they are separated from other minority groups for this analysis.

US-born Asian men and women were born in the US or abroad to American parents and identify their race as Asian. Non-US born Asian men and women are those born on the Asian continent, Indian subcontinent, Japan, or the Philippines. Since entrance into the US was severely restricted for Asians prior to 1965, the majority of Asians in the US, particularly those of working age were born outside the US (Xie & Goyette, 2004). Most Asians in our analysis are Non-US born (87%). Asian immigrants are the majority of Non-US born workers in both Life Science and Computing, 54% and 65% respectively. China, India, and the Philippines each send about one quarter of all workers from Asia with the remaining quarter coming from other countries.

Non-US born Western men and women include those born in Europe, Canada, Australia, and New Zealand. Canada, Germany, and Russia each sending 10-15% of Non-US born Western workers. Other Non-US born men and women include those born in Africa, South and Central America, the Middle East, the West Indies, and the Caribbean. Slightly more than 20% of other Non-US born workers come from South America, slightly less than 20% come from Africa, Mexico and the West Indies each send roughly 15% and an additional 12% come from Cuba.

Even though US understandings of race do not apply in all countries from which workers emigrate, in US terms most of those in the Asian group would be thought of as Asian, most of those in the Non-US West group would be thought of as White, and most of those in the Other Non-US born group would be thought of as Black or Hispanic. Since US understandings of race cannot be directly applied to Non-US born workers, and nation of origin is not a reliable proxy for race, we do not extend US-based understandings of race to the Non-US born workforce. For example, 89% of US workers born in Egypt identify their race as White as do 88% of South Africans. To regard these groups as black because they are African would mis-categorize many workers who would indeed be considered White in the US, yet to regard them all as White would miss the differences in how race is understood in these countries relative to the US.

We used the IPUMS 1990 occupation codes to determine occupational categories. IPUMS 1990 occupations codes are harmonized over time so that occupations are coded as they would have been coded in 1990, regardless of the occupational categories that existed at the time of the census. This means that occupations are coded as consistently as possible over the fifty year period. The Computing occupation titles are electrical engineer, computer systems analyst, computer scientist, computer software developer, and electrical engineering technician (census codes 55, 64, 65, 213, 229). The Life Science occupation titles are biological scientist, medical scientist and biological technician; importantly people in these occupations are not health care providers (census codes 78, 83, 223). We do include technicians in both fields with at least a bachelor's degree since in these fields technicians require specialized knowledge and often work as assistants to scientists designing, testing, and implementing scientific innovation and technologies. We exclude health care providers and teachers in order to focus on occupations where workers are expected to innovate and participate in the development of new technologies. While there are certainly Computing or Life Science professionals with job titles that do not clearly mark them as such, these occupations unambiguously approximate the scientific labor force we aim to study.

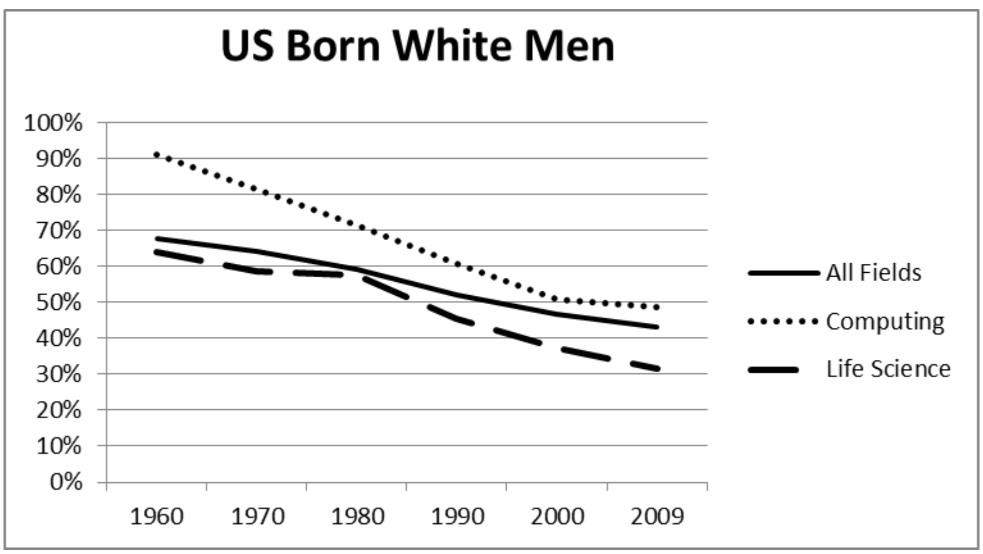
We include controls for education, age and US citizenship in the logistic regression. Education is the number of years of education completed; since our analysis is limited to workers with at least a bachelor's degree (at least 16 years) this distribution is abbreviated. On average the Life Science and Computing workforces are younger than the rest of the US workforce with at least a bachelor's degree ($p<.01$). Computing workers have significantly less education while Life Science workers have significantly more in every observation year ($p<.01$). Both groups are also significantly less likely to be US citizens ($p<.01$).

Ideally we would be able to measure social class, sexual orientation, and other aspects of identity that may intersect with gender however the data do not allow for such a fine-grained approach. While this dataset does have limitations it is the best data available for comparing non-US born and US-born workers. The approach we take allows us to better capture and understand changes in the scientific workforce that stem from the dramatic shift in the makeup of the labor force post-1960. Disaggregating White women, underrepresented minority women, US-born Asian women and Non-US born women enables us to examine differences in the participation of these groups that may suggest complex gender dynamics not identified by the literature on women in science. Similarly, disaggregating Whites, underrepresented minorities, US-born Asians and Non-US born workers enables us to distinguish increasing racial diversity driven by immigration as opposed to increased participation of historically underrepresented groups. Further, the paths to enter the American scientific workforce are not the same for immigrant workers, who must navigate complex legal frameworks to come and work in the US, and underrepresented minorities who face a legacy of oppression and exclusion from education and employment opportunities.

RESULTS

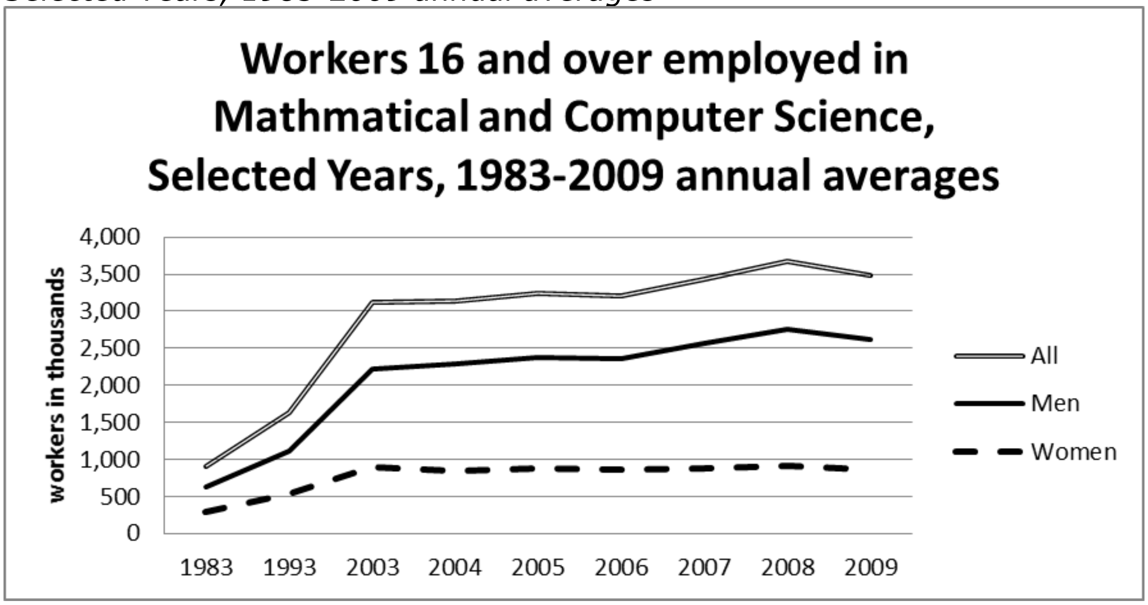
White men have steadily decreased as a percentage of science workers (see Figure 1). This change, however, does not reflect an exodus of White men. In fact, the absolute number of men, regardless of race or birthplace, in the scientific workforce generally has increased from roughly 625,000 in 1983 to 2,618,000 in 2009 (see Figure 2). The total civilian labor force has more than doubled between 1960 and 2009 fundamentally shifting its demographic composition (Lee & Mather, 2008). Women increasingly entered the workforce and the easing of immigration restrictions in the mid-1960s, particularly for skilled Non-US born workers, spurred an immigration boom.

Figure 1: Percent US-Born White Men Among Workers with at Least a Bachelor's Degree in Select Fields



Source: Integrated Public Use Microdata Series, version 5

Figure 2: Workers 16 and over employed in Mathematical and Computer Science, Selected Years, 1983-2009 annual averages



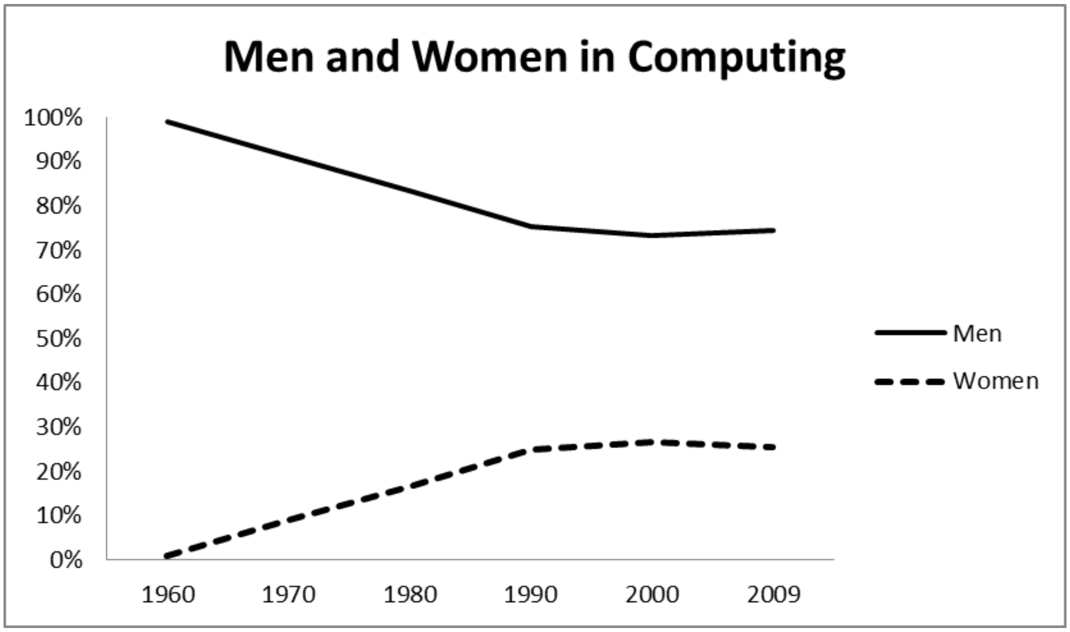
Source: National Science Foundation (2011) Division of Science Resources Statistics

In 1960, nearly 90% of scientists and engineers were White men, but this number fell sharply, roughly 10% each decade, until 2000 when the percentage of Computing workers who are White men begins to level off at about 50% (see Figure 1). Life Science, on the other hand, had a lower percentage of White men all along, 64% in 1960, lower even than the percentage in all occupations. The percentage of White men employed as Life Science workers decreased slightly between 1960 and 1970, remained stable through 1980 before steadily declining over the next 30 years. In 2009, White men were 43% of all workers, just under 49% of Computing workers and 32% of Life Science workers.

Figures 3 and 4 represent the gender-only labor force breakdown common in the literature on the STEM pipeline. Figure 3 shows the gender breakdown for the Computing workforce and figure 4 shows the Life Science workforce. Since figure 1 showed that White men are slightly less than 50% of workers in Computing but men are roughly 80% of Computing workers it is clear from these charts alone that a significant portion of men in Computing are either underrepresented minorities, US-born Asians, or Non-US born workers. Similarly White men are 32% of Life Science workers but men in general are roughly 50%. Women, regardless of race or birthplace, account for about 50% of Life Science workers but only about 25% of Computing workers.

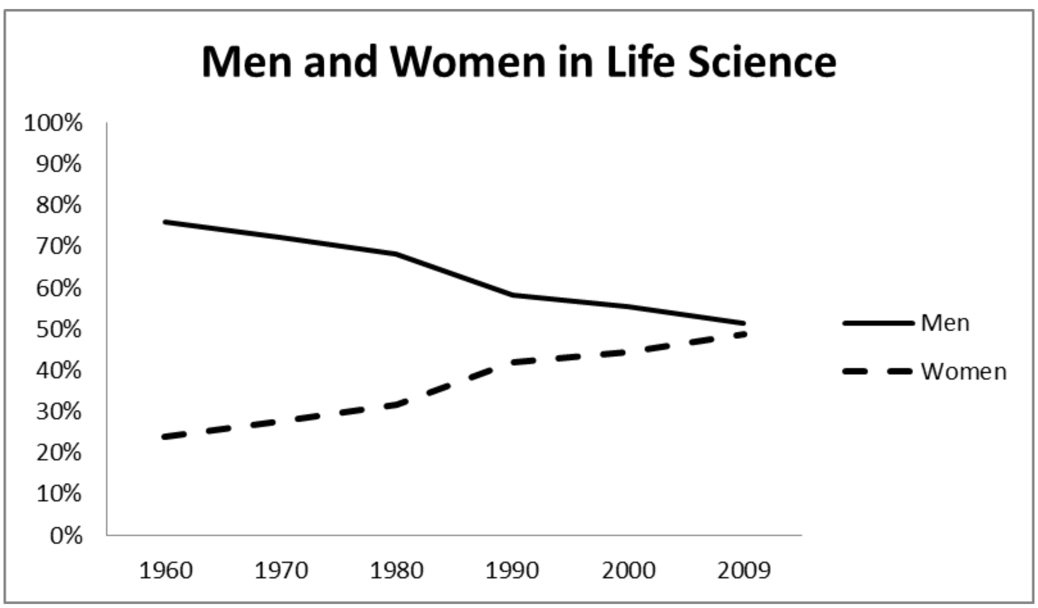
Figures 5 and 6 show the percentage of Whites, underrepresented minorities, US-born Asians, as well as non-US born Asians, Western, and other non-US born men and women in Life Science and Computing.

Figure 3: Percent of Men and Women with at Least a Bachelor's Degree Working in IT Fields



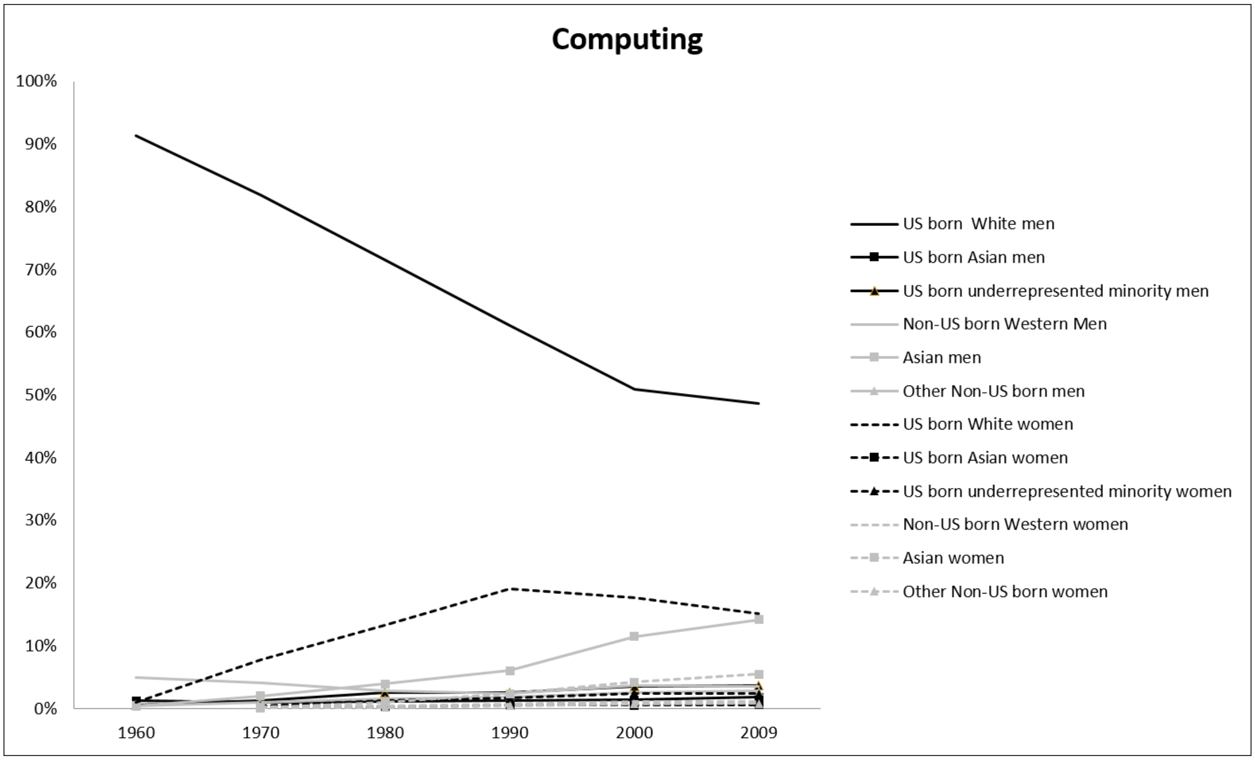
Source: Integrated Public Use Microdata Series, version 5

Figure 4: Percent of Men and Women with at Least a Bachelor's Degree in Life Science, 1960-2009



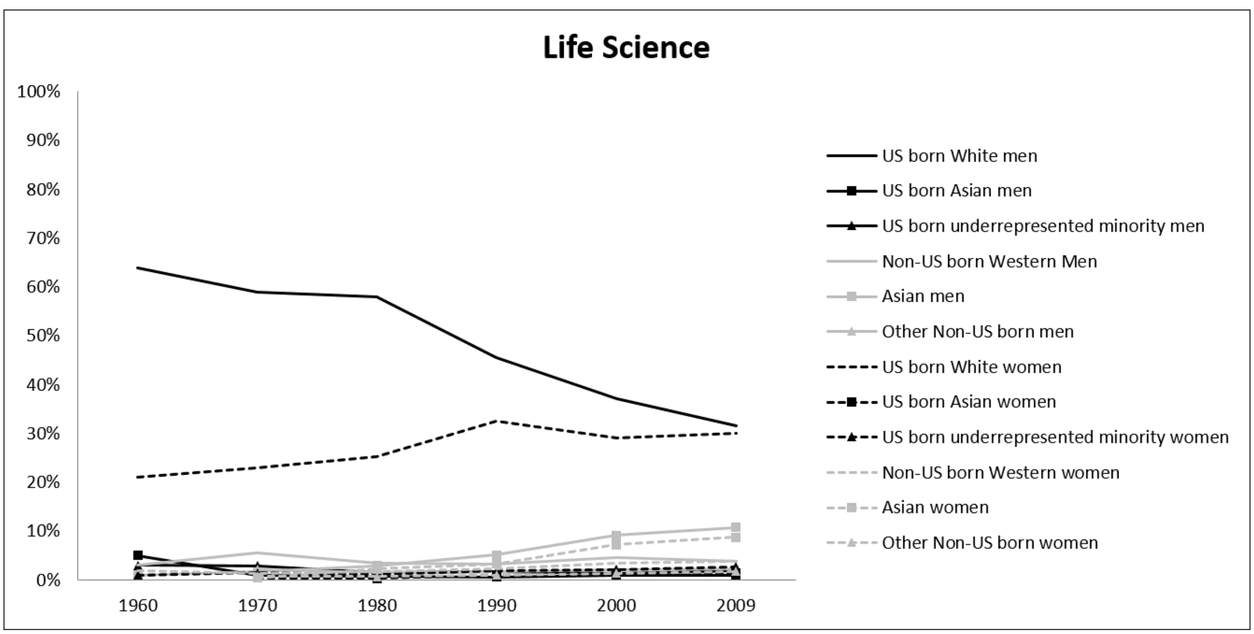
Source: Integrated Public Use Microdata Series, version 5

Figure 5. Full disaggregation of Computing occupations 1960-2009.



Source: Integrated Public Use Microdata Series, version 5. Originally published on-line in Alegria, 2014

Figure 6. Full disaggregation of Life Science occupations, 1960-2009.



Source: Integrated Public Use Microdata Series, version 5. Originally published on-line in Alegria, 2014

From these graphs it is clear that White men are still the largest group of workers in both fields, however White women are likely to outnumber their male counterparts in the near future in Life Science. No other group is poised to come close to White men in Computing. While White women are still the second largest demographic, if current trends continue they are likely to be outnumbered by non-US born Asian men in the near future. Non-US born Asian men dramatically outnumber their US-born Asian male counterparts as well. In 1960, they made up less than half a percent (.48%) of the Computing workforce, by 2009 their representation soared to 14.14%. In contrast, US-born Asian men composed 1.25% of the Computing workforce in 1960 and underwent little growth in the intervening decades. In 2009, they still made up only 1.82% of the Computing labor force.

The pattern of representation for US-born and Non-US born Asian women is similar to their male counterparts. While there were too few US and Non-US born Asian women to count in the 1960 they diverge dramatically by 2009. US-born Asian women slowly but steadily increase through 2009 composing .56% of the Computing workforce. Whereas Non-US born Asian women increase astronomically making up 5.49% of Computing workers in 2009, just over three times the representation of US-born Asian men. While US-born Asian women are better represented in Life Science, reaching 1.39% in 2009, 8.76% of Life Science workers were Non-US born Asian women. Not only are Non-US born Asian workers unlike US-born Asians, their participation in Life Science and Computing fields far outpaces the representation of all other groups (men and women) from around the world, who represent only 8.15% of Computing and 11.62% of Life Science workers combined.

Underrepresented minority men were better represented in Life Science in 1960 composing 3% of the workforce, than in 2009 when they fell to just under 2%. However, this trend of declining representation does not extend to Computing. Underrepresented minority men were only .58% of Computing workers in 1960 but grew, almost six-fold, to 3.62% in 2009. There were too few underrepresented minority women in Computing to count in 1960, but by 2009 they composed 2.33% of Computing workers, more than four times the representation of US-born Asian women. Similarly, they were 1% of Life Science workers in 1960 and grew to 2.77% in 2009 (nearly twice the representation of US-born Asian women). These descriptive statistics clearly illustrate the importance of disaggregating trends in representation. We now turn to the binary logistic regression to better account for the influence of relative group size on representation.

Likelihood of working in life science or Computing

We use binary logistic regression to estimate the likelihood of employment in Life Science and Computing by race, gender, and migration status controlling for age, education, and US citizenship from 1980-2009. Unfortunately, the small size of these fields prior to 1980 does not allow for a disaggregated analysis. White men are the reference group in the logistic models. In the 1980 sample there was not sufficient variation in education among workers with at least a bachelor's degree for education to be a meaningful control variable, thus it was omitted in the 1980 models.

Results from the logistic regression are presented as odds ratios for ease of interpretation. Odds ratios are interpreted as probabilities above or below 1.00 where an odds ratio of 1.00 would indicate that a group is equally likely to work in the Life Science or Computing field as White men. Odds below 1.00 indicate a group is less likely, and odds above 1.00 indicate a group is more likely. A non-significant finding indicates that there is no significant difference in the likelihood of working in these fields between a group and White men.

White women were significantly less likely to work in Life Science than their male counterparts in 1980 but from 1990 onward that was no longer the case and there was no significant difference in their representation in Life Science. Underrepresented minority men were also significantly less likely than White men to work in Life Science in 1980 and this did not change until 2009, almost 30 years after White women made inroads. Underrepresented minority women follow the same general trend as their male counterparts and White women, although they were the least likely to work in Life Science in 1980.
The statistics for US-born Asian men and women do not look like other people of color or White women. US-born Asian men began the period significantly more likely than White men to work in Life Science, although the significance of this difference fluctuated from 1990 to 2009. In contrast, there was no significant difference between US-born Asian women and White men in 1980, but from 1990 onward they were significantly (ranging from 2 to 1.8 times) more likely than White men to work in Life Science.

Non-US born Asian men and women are even more likely than their US-born Asian counterparts to work in Life Science and this difference remained significant for both groups throughout the study period. In 2009, Non-US born Asian men were more than twice as likely to work in Life Science as White men; while Non-US born Asian women were 2.7 times as likely. Non-US born Western men and women follow a trend similar to Non-US born Asians. They are significantly more likely than White men to work in Life Science throughout the period and Non-US born women are even more likely their male counterparts, 2.4 compared to 1.7 times, respectively.

Other Non-US born men and women (which mostly represents African and South American workers) are unlike other groups because trends for men and women are virtually identical. Other Non-US born men were significantly more likely than White men to work in Life Science in 1980 (but not in 1990), though there was no significant difference for Other Non-US born women in either year. In 2000 both Other Non-US born men and women were significantly less likely than White men to work in Life Science, but by 2009 this had reversed, and there was again no significant difference between Other Non-US born workers and White men.

Table 1.Odds ratios from logistic regression predicting working in a Life Science or Computing job, 1980-2009

	Life Science				Computing			
Variable	1980	1990	2000	2009	1980	1990	2000	2009
White Women	.762***	.997	.964	1.047	.307***	.366***	.351***	.290***
Underrepresented Minority Men	.622***	.791*	.565***	.909	.762***	.781***	.852***	.942
Underrepresented Minority Women	.387***	.660***	.628***	.801	.293***	.365***	.399***	.355***
US-born Asian men	1.674**	1.281	1.632***	1.256	1.761***	1.730***	1.84***	1.684***
US-born Asian Women	.804	2.243***	1.830***	1.810*	.602***	.687***	.648***	.422***
Non-US born Asian Men	1.743***	1.711***	1.619***	2.0516***	2.065***	2.745***	2.976***	3.358***
Non-US born Asian Women	2.260***	1.866***	2.166***	2.761***	.823**	1.220***	1.193***	1.204***
Non-US born Western Men	1.991***	1.734**	1.335***	1.709***	1.438***	1.863***	1.641***	1.568***
Non-US born Western Women	2.164***	2.202***	1.666***	2.428***	.468***	.708***	.597***	.514***
Other Non-US born Men	1.403*	.923	.651***	.910	1.166**	1.259***	.915***	.822***
Other Non-US born women	1.426	1.010	.670***	.966	.278***	.459***	.321***	.240***
US Citizen	1.0180	.718***	.483***	.649***	1.105*	1.368***	.698***	.723***
Years of Education		1.398***	1.681***	1.761***		.822***	.854***	.848***
Age	.981***	.966***	.968***	.9741***	.973***	.964***	.969***	.983***
constant	.008***	.000***	.000***	.000***	.096***	4.468***	5.330***	3.480***
BIC	44031	58657	92887	2527950	232429	432854	679063	17502225
Log Likelihood	-21919	-29223	-46336	-1263877	-116119	-216322	-339424	-8751015
N	914232	1299424	1671512	452905	914232	1299424	1671512	452905

* Significant at p<.05 level
** Significant at p<.01 level
*** Significant at p<.001 level

The trend in Life Science seems to be toward racial integration and eventual feminization, but Computing took an entirely different path. White women were significantly less likely (1 -. 307 = .69, 69%) than White men to work in Computing in 1980. Their odds increased in 1990, but decreased in 2000 and by 2009 they were less likely to work in Computing (71%) than they had been in 1980. Underrepresented minority men were also significantly less likely to work in Computing than White men in 1980 but their odds increased substantially over the period and by 2009 there was no significant difference between underrepresented minority men and White. The story for underrepresented minority women more closely mirrors that of White women than their male counterparts. They were significantly less likely (71%) than White men to work in Computing throughout the period, but unlike White women, their odds of working in Computing in 2009 (.355 or 65%) were higher than in 1980.

US-born Asian men are significantly (76%) more likely than White men to work in Computing throughout the period, although their odds decreased by 2009 (1.684 or 68%). US-born Asian women, on the other hand, are significantly (40%) less likely than White men to work in Computing in 1980 but their odds also decrease over time (58%). Non-US born Asian men are significantly (106%) more likely than White men to work in Computing in 1980 and their dominance in the field grows throughout the period. By 2009, Non-US born Asian men are 3.4 times or 240% more likely than White men to work in Computing. Non-US born Asian women, in contrast, are significantly (18%) less likely to work in Computing than White men in 1980, but this reverses in 1990 and by 2009 they are 20% more likely to work in Computing than White men.

Non-US born Western men are significantly more likely than White men to work in Computing throughout the period, and their likelihood increases from 1.4 times more likely than White men in 1980 to 1.6 in 2009. Non-US born Western women, in contrast, are significantly (53%) less likely than White men to work in Computing in 1980, although their likelihood fluctuates dramatically over the period (29%-1990, 40%-2000, 49%-2009). Other Non-US born men are the only group who reversed from more likely (26%) than White men to work in Computing to less likely (18%) in 2009. Other Non-US born women follow a similar pattern as Non-US born Western women; they are significantly less likely than White men to work in Computing in 1980 (72%) but their likelihood fluctuates dramatically over the period (54%-1990, 68%-2000, 76%-2009).

DISCUSSION

In this paper we examined the shift in the size and demography of the Computing and Life Science workforce. We aimed to answer two questions. 1) How did the gender composition of the scientific labor force in Life Science and Computing change over time? 2) How does our understanding of scientific labor force in these fields change when we disaggregate by gender, race, and nationality over time?

Let us first consider gender composition, the decrease in the percentage of White men in Life Science and Computing points to considerable diversification (see

Figures 3 and 4). In Life Science the percentage of men decreases as the percentage of women increase, by 2009 there is near equity of representation. On the other hand, men are still the vast majority of Computing workers. Women were 1% of Computing workers in 1960 and 25% in 1990. The contemporary Computing labor force is highly sex segregated, composed largely of White American and Non-US born men (National Science Foundation, 2011) despite numerous "broadening participation" initiatives by government and private interests to increase women's representation.

By focusing only on the gender breakdown of these fields we miss the substantial changes that took place in the scientific workforce over this period, of which gender parity is only a part. While men clearly dominate Computing, Whites dominate Life Science. There is near gender parity in this field but clear stratification between Whites, immigrants and underrepresented minorities. White men and women are equally represented in the Life Science workforce, as are Non-US born men and women, and underrepresented minority men and women. But underrepresented minority men were actually better represented in Life Science in 1960 (8%) than they were in 2009 (3%). Underrepresented minority men do not fare much better in Computing where they compose only 6% of the workforce. Underrepresented minority men and women make up more than 30% of the US population yet they are a small fraction of the Life Science and Computing workforces.

White workers are an increasingly small proportion of the Life Science and Computing workforce. Non-US born Asians and Westerners (men and women) were much more likely (ranging from 1.7 to 2.7 times in 2009) than White men to work in Life Science. In 2009, Non-US born Asian men were 3.4 times as likely as White men to work in Computing. However, the representation of other Non-US born groups is more uneven. While Non-US born Asian women and Non-US born Western men both outpace White men by 1.2 and 1.6 times, respectively, in 2009 this is substantially less than Non-US born Asian men. In addition, Non-US born Western women as well as Other Non-US born men and women are less likely than White men to work in Computing by a significant margin. These findings point clearly to the need for intersectional analysis, by focusing on gender, race, *or* nativity we miss the important ways in which these identities intersect.

Finally, without a careful field level comparison of Life Science and Computing, we would have drawn erroneous conclusions about the roles that race, gender, and nativity played in shaping fields. Although scientific fields in the aggregate are moving towards gender parity and increasing diversity, there are vast differences within individual fields. The business of advancing innovation in Life Science and Computing is a global undertaking and the workforces in these fields increasingly reflect that reality. By observing the demographic trends in Life Science and Computing in the second half of the 20th century we can see that focusing on the gender composition alone is insufficient to grasp the magnitude of changes in the scientific labor force. Disaggregating by gender, race, and nativity offered insights into new and enduring inequalities in the labor force shaped by the intersection of workers' identities.

CONCLUSION

Diversity remains a spoken mission but not an achieved goal. As of 2010 the National Science Foundation, a critical funding source for a wide variety of scientific research, operated 19 different programs specifically focused on broadening participation in science and an additional 19 programs that emphasized broadening participation among several goals. Such initiatives have the potential to increase both the diversity and the raw number of talented people STEM. Despite these investments, access to STEM jobs remains unequal. Underrepresented minorities and White women (in Computing) still compose only a fraction of these growing and lucrative fields.

Policy at the national level looks to a larger and more diverse pool of scientists to renew the economy through innovation, without addressing the complex and intersecting factors that shape the demographics of the scientific workforce, such as the quality of elementary and secondary education and the cultural orientations of scientific fields. Initiatives aimed at broadening participation in the science and technology workforce have not been coupled with concerted efforts to improve the quality of education in the public schools that primarily serve underrepresented minorities. Hence, access to the good jobs that science and technology provide are largely reserved for those privileged enough to receive a high quality math and science education. Consequently, these fields are plagued with the old, familiar race and class inequalities only on a new scale that simultaneously reflects both the race and class dynamics of the US and the countries that send migrant science and technology workers.

While immigrants are highly successful in entering the American scientific workforce, they do so with severe restrictions that bind their legal status in the country to the good faith of their employers. These highly sought-after employees face precarious legal situations due to their immigration status that require extreme compliance to their employers (Banerjee, 2006). The dependent relationships that Non-US born workers often have with their employers reflect a new form of inequality in a scientific labor force already plagued with race, gender, and class dynamics endemic to the US context.

The academic literature has failed to fully examine the complex and intersecting race, gender, nationality and field specific factors that shape the scientific workforce. Studying why women generally are underrepresented in science and technology requires an assumption that all women are underrepresented equally and across all sciences and this is simply not the case. The narrow focus on gender in the literature has resulted in misunderstanding of even the most basic demographic profile of the scientific workforce. Men and women have roughly equal representation in Life Science, yet we were able to demonstrate persistent stratification by race and nationality. The racial stratification in Life Science is so severe that underrepresented minority men were better represented before the Civil Rights movement when racial segregation was legal. In Computing, women's participation has decreased slightly but this reflects a decrease in White women's participation as Non-US born women and women of color have increased slightly but represent only a small portion of workers. White men's decline in participation is sharper than White women's because their decline was driven by the rapid growth in the field. That growth was fueled first by White women then immigrant workers whose access to these jobs had been limited.

Insomuch as the goal of research is to understand the causes and consequences of inequality in science and technology, work that narrowly focuses on gender or immigration must be abandoned in favor of an approach that disentangles the complex inequality that undergirds the scientific labor force. This study demonstrates that our understanding of inequality in the science and technology workforce is incomplete because it is not attentive to multiple and intersecting inequalities. Our intersectional analysis sheds light on key shortfalls in the existing literature on women in science. Further, it helps us to better understand the trends and divergences in groups' labor market representation over time as well as the factors that produce and constrain access and opportunity in the scientific workforce.

The US has invested considerable resources to ensure a steady and diverse supply of highly skilled labor, taking steps ranging from changing immigration laws to funding programs to attract women and minorities to science and technology. These measures have dramatically increased both the size and diversity of the scientific workforce but enduring inequalities remain and new inequalities have emerged.

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