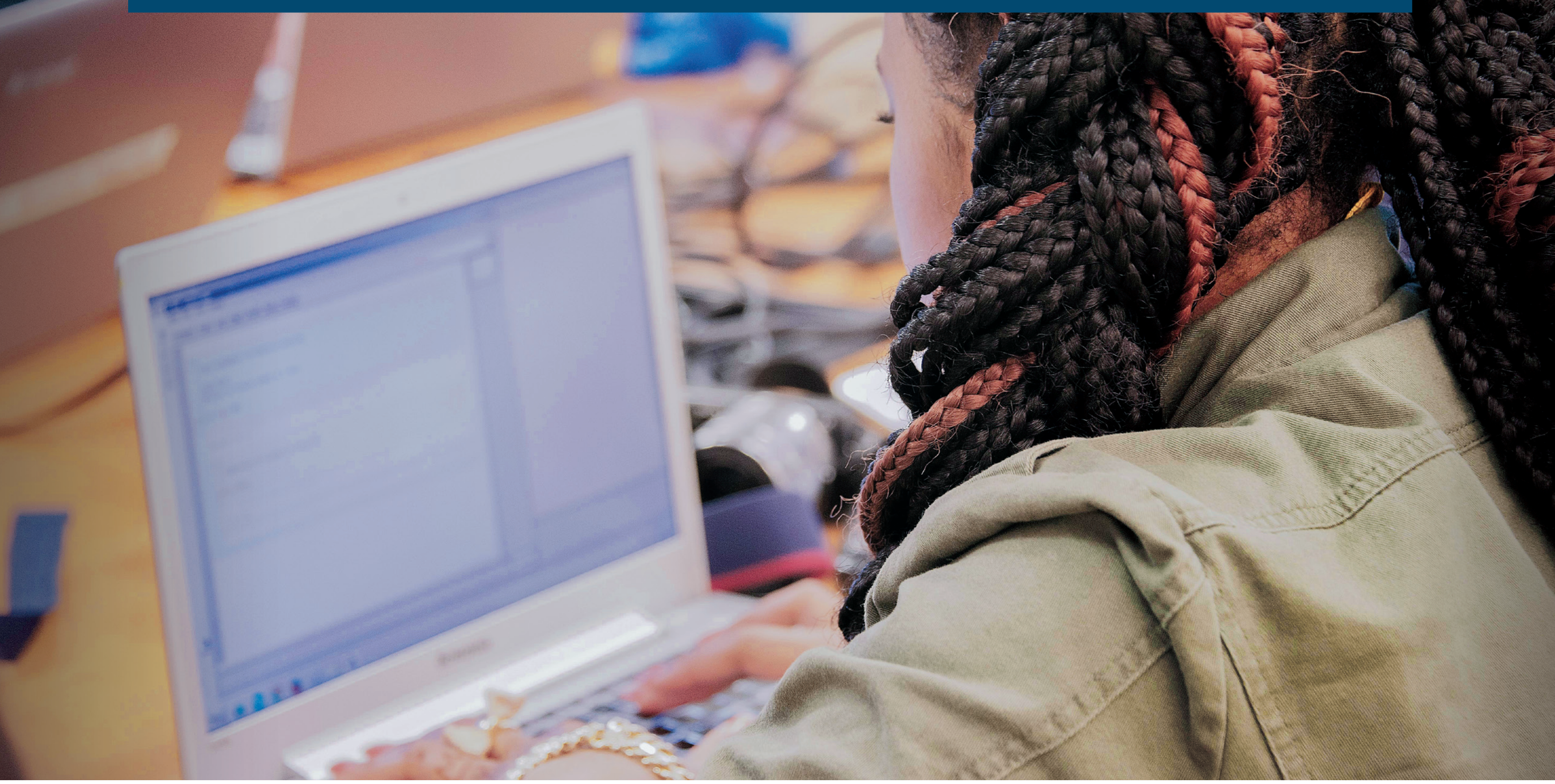
THE LEAKY TECH PIPELINE:

A Comprehensive Framework for Understanding and Addressing the Lack of Diversity across the Tech Ecosystem



KAPOR CENTER
FOR SOCIAL IMPACT

Date: 2/28/18

AUTHORS:
Allison Scott, Ph.D.
Freada Kapor Klein, Ph.D.
Frieda McAlear, M.Res.
Alexis Martin, Ph.D.
Sonia Koshy, Ph.D.

www.leakytechpipeline.com

KAPOR CENTER
FOR SOCIAL IMPACT

The Kapor Center for Social Impact (KCSI) aims to enhance diversity and inclusion in the technology and entrepreneurship ecosystem through increasing access to tech and STEM education programs, conducting research on access and opportunity in computing, investing in community organizations and gap-closing social ventures, and increasing access to capital among diverse entrepreneurs.

EXECUTIVE SUMMARY

Increasing diversity in the technology ecosystem is an urgent national priority.

Despite being one of the largest drivers of the United States economy, the technology ecosystem has remained stubbornly homogenous by race and gender, with women, Black, Latinx, and Native American individuals vastly underrepresented. This persistent underrepresentation has very real consequences. Without a diverse workforce, the innovative potential of technology will be stymied. Without access to high-income jobs and opportunities for wealth creation through tech entrepreneurship and investment, wealth inequality will worsen. And, without preparing a much broader segment of the population for the future technology workforce, our nation's future global competitiveness will suffer.

To remain competitive in the global technology economy, the United States will need to develop a robust future technology workforce, build companies with diverse talent to enhance innovation, foster welcoming and inclusive work environments to retain diverse talent, and address growing wealth inequality.

Despite increasing recognition of the importance of diversity, well-intentioned commitments to diversity, and the investment of hundreds of millions on diversity-related initiatives, there has been little progress. Why? We believe that this stagnation is not the result of individual companies lacking commitment or individual practices being ineffective; instead we believe that there is a lack of shared understanding about the complex nature of the problem necessary to drive effective solutions.

Common explanations have included the belief that universities don't produce enough computer science graduates who are women and underrepresented people of color — blaming the lack of a sufficient pipeline of talent. Or that bias in hiring prevents qualified candidates from being employed — blaming tech company hiring practices. Or that harassment, discrimination, and lack of inclusive company culture drives underrepresented employees to leave — blaming the company culture. While each of these are true, we believe that they represent a partial. but incomplete framing of the problem that then inform one-off solutions which fail to significantly move the needle.

In reality, the tech pipeline begins early, in elementary school, and continues through higher education and extends into the workplace and entrepreneurship. There are leaks and barriers throughout the length of the pipeline that syphon off talent, particularly talent from underrepresented backgrounds.

In this paper, we present a comprehensive framework for understanding and addressing the racial and gender underrepresentation in the technology ecosystem: The Leaky Tech Pipeline Framework.

The Leaky Tech Pipeline Framework draws upon social science research and data, as well as the experiences and insights of tech professionals, to describe the lack of diversity as a result of a complex set of structural and social/psychological barriers, or "leaks," which occur across the length of the technology pipeline.

We use this framework to map out the leaks and barriers which occur across four stages of the technology pipeline, beginning from preschool to high school, and continuing through higher education, the tech workforce, entrepreneurship, and venture capital.

❶ **PREK-12 EDUCATION:** From preschool through high school, underrepresented students of color disproportionately lack access to high-quality schools and teachers to develop fundamental knowledge, peers and role models to develop interest in computing, and computer science courses to prepare for college. By the end of high school, just 16% of students who participate in AP Computer Science are Black, Latinx, or Native American/Alaskan Native, affecting participation in computing in higher education.

❷ **HIGHER EDUCATION:** Wealth gaps affect college preparation, choice, admission, and time to degree completion, while the lack of diverse peers and role models, unwelcoming campus and classroom climates, and stereotype threat affect the pursuit and persistence of computing in higher education for women and underrepresented students of color. Just 21% of all Bachelor's degrees in computing are earned by Latinx, Black and Native American/Alaskan Native students, while just 18% are earned by women, limiting opportunities to enter the technical and computing workforce.

❸ **TECH WORKFORCE:** Biases in recruiting and hiring exclude women and underrepresented people of color from entering the tech workforce, while negative workplace cultures, harassment, inequitable pay, and bias in promotion contribute to decreased satisfaction and turnover. Although 21% of computer science degree earners are Black or Latinx, they comprise just 10% of technical employees in the tech workforce, limiting access to high-wage, high-growth occupations and limiting the benefits of a diverse workforce.

❹ **ENTREPRENEURSHIP & VC:** Without access to social networks, social and financial capital, and facing bias in investment decisions, women and underrepresented people of color encounter significant obstacles to launching tech startup ventures, gaining venture capital investment, or becoming tech investors. Nearly 98% of venture-backed technology startup founders are White or Asian, and 83% are male. Of the gatekeepers to capital investments, 97% are white or Asian, demonstrating the homogeneity in technology creation and investment, which can exacerbate economic inequality and neglect to solve pressing societal challenges.

This complex set of leaks individually and cumulatively contributes to the opportunities and outcomes for women and underrepresented people of color to participate in the technology ecosystem.

Creating a Diverse Technology Ecosystem: A Comprehensive Solution

The technology sector has a unique opportunity to demonstrate leadership in providing the innovation, problem-solving, product development, and capital to implement comprehensive solutions to diversify technology and improve the sustainability of the country's future technology-driven economy. So where do we start?

By introducing a framework describing the barriers across the pipeline which produce disparities, the Leaky Tech Pipeline Framework provides a roadmap for comprehensive interventions and solutions to increase racial and gender diversity across the tech ecosystem.

A comprehensive approach will require visionary and strategic initiatives, leadership from tech companies, government, philanthropic organizations, nonprofits, and educators; collaboration across stakeholder groups; significant human and capital resources; and continuous assessment of impact and efficacy of interventions.

Below we outline recommendations in 6 critical areas across the pipeline as a place to start:

- Increase Equity in K-12 Education.
- Expand Computer Science Education.
- Enhance Pathways into Technology Careers.
- Implement Comprehensive D&I Strategies within Companies.
- Increase the Prevalence of Diverse Computing Role Models.
- Create Public-Private Partnerships to Develop the Future Computing Workforce.

Challenging? Absolutely. But if we accept that addressing disparities in technology is an economic imperative, and we work from a shared understanding of the complexity of the problem, then we can begin to develop and implement comprehensive and effective solutions.

We believe that the Leaky Tech Pipeline Framework can provide a place for us to start, so that we can collectively work towards improving racial, gender and other forms of diversity in the technology sector, thereby strengthening the workforce of the future.

The Leaky Tech Pipeline website provides a tool for stakeholders to use to explore research and data on barriers to diversity. We look to stakeholders and collaborators across the tech ecosystem to share new research, provide feedback on innovative ways to share data, so that the website continues to be a useful tool for the field.

It is our hope that this paper, along with the accompanying website, will provide data and research to stakeholders, and that collaboratively, we can continue to build upon the framework and contribute to the development and scaling of effective solutions.

BACKGROUND

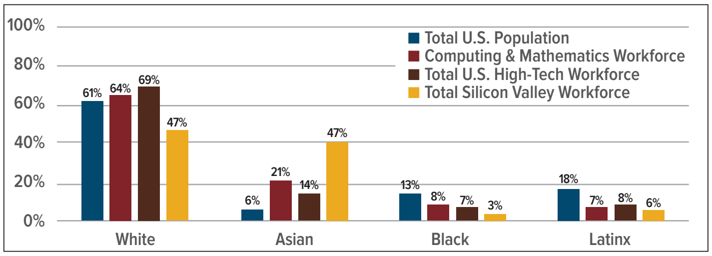
Across the globe, technology is the backbone of the rapid transformation and innovation occurring across all sectors of the economy, from healthcare and education to transportation, energy, and defense. This technology-driven transformation has fundamentally altered access to knowledge, increased connectivity, productivity, and access to goods and services and has the capacity to improve health outcomes, and address deeply-entrenched social challenges (Baller, et al. 2016; Dutta, Geiger, & Lanvin, 2015). As we enter the Fourth Industrial Revolution, a stage of predicted exponential technological transformation, economists indicate that the growth and prosperity of global economies will be based on their ability to innovate, adapt to technology-driven disruption, and counteract negative consequences of digitization (Manyika, 2017; Schwab, 2016).

The critical role of computing in the United States economy is evident in the current national labor market trends and future projections (Bureau of Labor Statistics, 2017a; Dutta, Geiger, & Lanvin, 2015; West, 2011). Science, Technology, Engineering and Mathematics (STEM) occupations currently account for nearly 8.6 million jobs in the United States and high-tech industries produce nearly one-quarter of all economic output ($7.4T in 2014; Bureau of Labor Statistics, 2016, 2017). Seven of the top 20 most profitable companies in the United States are technology companies (Fortune 500, 2016). Between 2009 and 2015, STEM occupations grew twice as fast as non-STEM occupations (10.5% compared with 5.2%), with computer and information technology occupations projected to grow 13%, add nearly 550,000 new jobs and see over 1 million job openings in the U.S. economy over the next 10 years (Bureau of Labor Statistics, 2017). In addition to rapid job growth, computer and information technology occupations are also among the highest paying, with an average annual wage of $82,860, more than two times higher than the median wage for all other occupations ($36,200; BLS, 2015). Given the critical role that computing plays in the national economy and the continued projected economic growth in STEM and computing occupations, developing a robust, skilled national workforce will be essential to the future economic prosperity of the United States.

The Demographics of the Technology Workforce

Despite the economic growth of the technology sector and the U.S. economy as a whole, a significant challenge exists in the lack of diversity and vast underrepresentation by race and gender within its technology workforce. The technology sector nationwide is overwhelmingly male (74%), White (69%), and Asian (21%), while female, Black, Latinx, and Native American/Alaskan Native professionals are underrepresented in the technology workforce relative to their proportion of the labor force and the United States population (BLS, 2015; U.S. Census Bureau, 2016). Black and Latinx adults comprise roughly 30% of the United States population, yet only between 7% and 8% each of individuals employed across all computing and mathematical occupations (BLS, 2015) and across the high-tech sector (EEOC, 2016). Women make up half of the nation's population but are just 26% of those employed in computer and mathematical occupations (BLS, 2015) and only 36% of those employed in the high-tech workforce (EEOC, 2016).

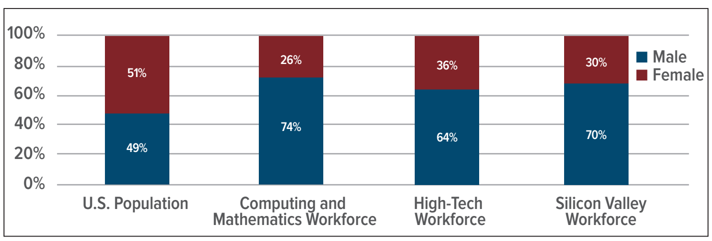
Figure 1. U.S. Population Demographics and the Computer/ Mathematics, High-Tech, and Silicon Valley Workforce, by Race/Ethnicity



Sources: U.S. Census Bureau (2016), Bureau of Labor Statistics (2016), EEOC (2016).

In Silicon Valley, home to one of the world's largest tech economies, the percentage of Black and Latinx employees is much lower: between 3-6% of the workforce (EEOC, 2016; Kotkin, 2017; Figure 1). When examining the intersection of race and gender, women of color comprise 1% or less of all employees across many Silicon Valley tech companies (Evans & Rangarajan, 2017). Further, among the largest and most profitable technology companies, including Google and Facebook, the percentage of Black and Latinx employees is as low as 2-4% (Google EEO-1 data, 2016; Facebook EEO-1 data, 2017).

Figure 2. U.S. Population Demographics and the Computer/ Mathematics, High-Tech, and Silicon Valley Workforce, by Gender.



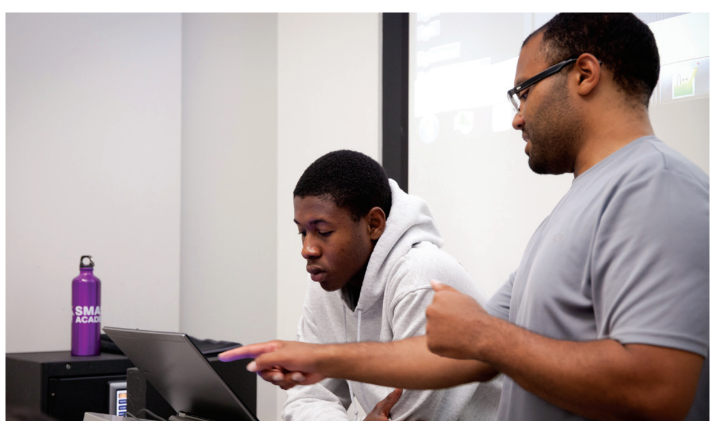
Sources: U.S. Census Bureau (2016), Bureau of Labor Statistics (2016), EEOC (2016)

Race and gender disparities also exist in: (1) Non-technical positions within technology companies, including HR, Marketing, and Sales (relative to the percentage of women, Black, and Latinx professionals in the labor force), (2) Technical positions, including Engineering, Software Development (relative to the percentage of women, Black, and Latinx CS/Engineering degree earners), and (3) Leadership positions, where women, Black and Latinx employees are less likely to be in leadership positions overall, and Asian women are least likely to be represented among technology executives (EEOC, 2016; Evans & Rangarajan, 2017; Gee & Peck, 2017; OpenMic, 2017).

By comparison, women, Black and Latinx professionals are represented across other industries at much higher rates, consistent with their proportion of the overall U.S. population. These disparities indicate that there are unique and pervasive challenges in diversifying the technology industry (EEOC, 2016).

The technology workforce in the United States is 90% White or Asian, and 75% male.

In technology-based entrepreneurship and venture capital, both technology investors and company founders are decidedly lacking in diversity. Ninety-seven percent of investment professionals are White or Asian, while just 2% are Black and 1% are Latinx (Kerby, 2016). Women make up just 11% of investment professionals (Kerby, 2016). Technology startup entrepreneurs are overwhelmingly White (87%) and male (83%), while just 1% of all entrepreneurs launching VC-backed companies are Black (CB Insights, 2010). Thus, opportunities to both invest in and lead companies poised to earn large financial returns are largely limited to a small and homogenous portion of the U.S. population. Women of color comprise less than 1% of all founders receiving venture capital funding (Finney, 2016).



Why Addressing Underrepresentation in Technology is an Urgent Priority

While data on underrepresentation are essential to understand the lack of diversity across the tech sector, this issue is far more complex and consequential than a simple discussion of representation and parity. The underrepresentation by race and gender across the technology ecosystem is of significant concern for three main reasons:

❶ The growing diversity of the U.S. population and need for a robust future workforce,

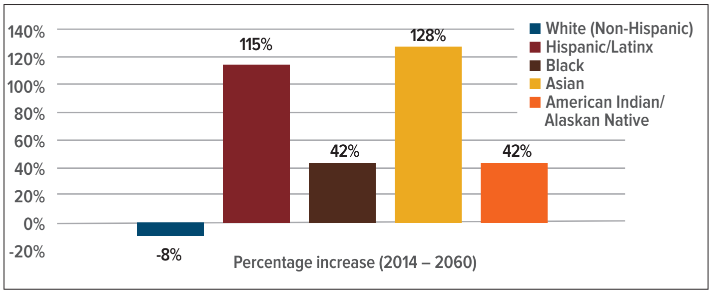
❷ The benefits associated with having a diverse workforce, and

❸ The detrimental impact of underrepresentation on exacerbating economic inequality for diverse communities.

Future Workforce Needs. Two important trends are converging: the rapid pace of growth in computing-related occupations and need for a skilled workforce, and the increasing racial diversity of the U.S. population. Economic projections indicate continual job growth and vacancies in computing-related fields will outpace the supply of skilled professionals within the U.S. workforce, which can ultimately challenge the global competitiveness of the United States in science and technology (BLS, 2015; National Academies, 2007; National Science Board, 2015). The Department of Labor predicts that there will be more than 1.3 million job openings in computer and mathematical occupations by 2022 (BLS, 2015a). In 2018, the United States is estimated to experience a shortage of 190,000 skilled data scientists (Lund et al., 2013), and by 2024, this number could increase to a shortage of 250,000 (Henke et al, 2016). One study found that for every 7 computing job openings, there was one graduate with a computing degree (Rothwell, 2012) and in cybersecurity, there are an estimated 285,000 current job openings (Cyberseek, 2017). More than half of Ph.D. earners in computer and engineering are not U.S. citizens, which leads to shortages of doctoral-level scientists in government sector positions (due to citizenship requirements) and the potential export of talent to the home country and reliance on H1-B visas to fill open positions (BLS, 2015; NSF, 2016; Wakabayashi & Schwartz, 2017).

Simultaneously, groups that are the most underrepresented in the technology and computing workforce are also among the fastest growing segments of the population, and the technology sector has not adapted to these changing demographics. Over 50% of the newest generation of children (under age 1) and over half of the K-12 student population in the United States are students of color (NCES, 2013; U.S. Census Bureau, 2015, 2017). One-quarter of the current U.S. population under the age of 18 is Latinx (U.S. Census Bureau, 2016), and one in five workers will be of Hispanic/Latinx descent by 2026 (BLS, 2017). From 2016 to 2017, Latinx, Asian, and Black individuals accounted for 91% of all population growth (Pew Research Center, 2017). Further, from 2014 to 2060, the non-Hispanic/White population will be the only group to decrease (by 8%), while the Hispanic/Latinx, Asian, and multiracial populations are projected to increase by 115-128% (Colby & Ortman, 2015). These converging trends present a major challenge for the technology sector and create urgency for enhancing diversity in the current and future tech workforce. Thus, in order to keep pace with the workforce demands required to maintain economic growth, maintaining the current participation rates among racial/gender groups will be insufficient. The United States must develop talent beyond the groups who have traditionally participated in computing and technology.

Figure 3. Projected Growth of the U.S. Population by Racial/Ethnic Group, through 2060.



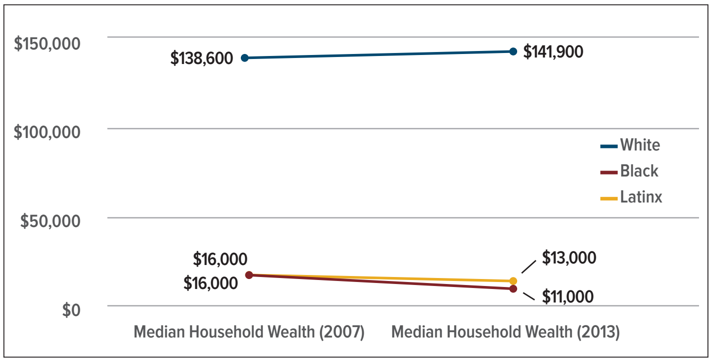
Source: Colby & Ortman (2015).

Benefits of a Diverse Workforce. Beyond the future workforce needs which must increasingly include diverse populations, research has demonstrated that workforce diversity positively impacts everything from revenue and profits to hiring and satisfaction/engagement of employees. According to a report by Dalberg and Intel (2016), increasing racial and gender diversity in the U.S. technology workforce can add $470-570Bn in new value to the tech industry and over 1.5% to the national GDP. McKinsey also found that across 366 companies and a range of industries, companies in the top quartile for employee race and gender diversity demonstrated greater financial returns than industry medians (Hunt et al., 2015). Research studies have also found that companies with greater racial and gender diversity demonstrate a larger customer base, increased sales revenue, and higher market value than more homogenous companies (Dalberg/Intel, 2016, Herring, 2009, Hunt et al., 2015, Page, 2007, Roberson & Park, 2006). Diverse companies and teams have demonstrated a stronger orientation towards innovation and have a greater likelihood of introducing new innovations into the market (Diaz-Garcia et al., 2013; Galia & Zenou, 2012; Talke, Salomo & Kock, 2011; Miller & Triana, 2009). Research has demonstrated that diverse companies also have an advantage in investor perceptions (Roberson & Park, 2006), employee morale (Jehn, Northcraft & Neale, 2009), talent recruitment and employee satisfaction (Hunt et al., 2015), increased deal flow from entrepreneurs who value diversity (Kapor Center, 2017), and the development, launch, and investment in innovative products to solve societal challenges facing diverse communities (Godwyn & Stoddard, 2011).

Conversely, the lack of diversity on teams can negatively affect companies in product ideation, algorithm development, and marketing of products, thus alienating customers and risking reputational damage. There are numerous recent examples of tech products which faced negative backlash from customers: (a) Google launching a photo algorithm which enabled racial stereotypes (Schupak, 2016), (b) Snapchat launching a new image filter which utilized insensitive caricatures of Asian and Black features (King, 2016), (c) Nextdoor and AirBnb receiving criticism for their platforms enabling of racial profiling and discrimination (Edelman, Luca & Svirsky, 2016; Medina, 2016), (d) Beauty.AI's launching of a beauty algorithm biased against people of color (Levin, 2016), (e) Microsoft's millennial chatbot using abusive language (Hern, 2016), and (f) Facebook's insensitive launch of new VR product soon after Puerto Rico's hurricane destruction (Kharpal, 2017). Beyond the development, launch, and marketing of products themselves, there is also a presumed relationship between the lack of a diverse workplace and the preponderance of complaints and lawsuits about tech workplace culture, discrimination, and sexual harassment, which have dominated the media in recent years. These incidents can then have an effect on company reputation, consumer satisfaction, and, in some cases, profits.

Detrimental Impact on Underrepresented Communities. While diversity in the technology workforce has economic benefits for the nation and for individual companies, the lack of access, opportunity, and inclusion in occupations with the highest wages and job security also has dire consequences for the economic future of communities of color. Computing-related jobs are among the fastest-growing and highest-paying occupational category, in addition to having low unemployment rates and high job security (BLS, 2015). Yet, tracing back to historical policies and practices of discrimination, women and underrepresented people of color have the highest rates of poverty and unemployment (BLS, 2017; Census, 2015), with nearly 1 in 4 Black or Latinx families living in poverty. Underrepresented people of color also have significantly lower household income and household wealth than their counterparts, with economic inequality along racial lines having grown much wider in the past 30 years (Pew Research Center, 2016; Figure 4). Income gaps by gender are also persistent, and most acutely affect Black and Latinx women who earn only between 50-63% of what White men earn (Pew Research Center, 2017; AAUW, 2016). The lack of opportunity to participate in the technology sector in meaningful numbers reduces opportunities for economic mobility for women and underrepresented people of color (PolicyLink, 2015). These disparities in economic opportunities have the potential to further exacerbate economic inequality by race and gender (Manyika et al., 2015). Beyond the income disparities associated with low rates of participation in computing jobs, women and underrepresented people of color lack opportunities to amass wealth through equity in early-stage tech startups and through investing in companies which go on to be successful through acquisition or IPO. The biggest beneficiaries in the technology sector have been investors, shareholders, and innovators, each of which have significant barriers to entry for underrepresented populations, and which have served to build and recreate wealth in select communities (Schwab, 2016). In addition, underrepresented communities risk being detrimentally affected by the byproducts of both technological shifts in the global economy and the burgeoning tech ecosystem, including gentrification, displacement, and concentrated poverty (Schwab, 2016; PolicyLink, 2015).

Figure 4. Median Net Worth of Households, by Race (2007-2013)

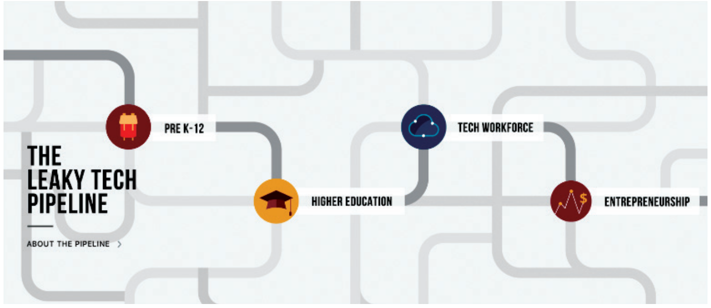


Source: Pew Research Center (2016)

While the evolution of technology has already demonstrated a significant impact on society, the future of work and trend towards automation of jobs has the potential to further exacerbate disparities. Predictions suggest that automation can accelerate the displacement of 2 times as many jobs between 2015 and 2025, as the previous decade (McKinsey, 2016). The jobs of the future will allow highly-skilled workers greater opportunities, while there will be significant displacement among lower-skilled workers, women, and Black and Latinx individuals (Manyika, 2017; Manyika et al., 2015; Pew Research Center, 2016; WEF, 2016). Finally, since technological innovations have the potential to disrupt ineffective or stagnant systems and practices, having talent from all background can increase opportunities to create tech-driven solutions to challenges particularly affecting diverse communities.

THE LEAKY TECH PIPELINE FRAMEWORK

A fundamental challenge to effectively addressing racial and gender underrepresentation in the technology ecosystem has been the absence of a shared comprehensive understanding of the underlying causes of disparities. Without accurately framing the problem and identifying the complex causes of underrepresentation, the development and implementation of initiatives to increase diversity in computing will not be comprehensive and risk being ineffective. For example, framing underrepresentation as a result of an insufficient supply of computer science college graduates from diverse backgrounds or as a result of unconscious biases and negative tech workplace culture, each presents a partial, but incomplete explanation of the problem. Accordingly, despite hundreds of millions of dollars being invested in initiatives to improve workforce diversity (Google: $265M in 2014 and 2015; Intel: $300M for 5 years; Apple $50M in 2015), the percentage of women and underrepresented people of color employed by some of the largest tech companies has barely budged, improving by up to 1 percentage point or remaining stagnant from year to year (Cakebread, 2017; Donnelly, 2017; EEOC, 2016; Google, 2016; Guynn, 2015). In fact, a trend analysis of the racial and gender diversity of Silicon Valley's tech workforce indicated that the number of Black and Latinx professionals has actually declined over the past 8 years (Gee & Peck, 2017).



In response, this paper addresses this fundamental challenge facing the technology sector by presenting a comprehensive framework for understanding and addressing the underlying causes of racial and gender underrepresentation in technology: The Leaky Tech Pipeline Framework. The Leaky Tech Pipeline framework situates the experiences and opportunities of individuals within the broader societal context of economic, educational, and social policies, practices, and systems which have historically led to disproportionate access to quality education, employment, wealth, healthcare, and physical environments, especially among communities of color (Coates, 2014; Grusky & Hill, 2017; Jencks & Phillips, 2011; Oliver & Shapiro, 2006; Institute of Medicine et al., 2003; Tate, 1997). The framework draws upon a large body of social science research to describe the lack of diversity in the technology sector as the result of a complex set of interrelated (and often cumulative) structural and social/psychological barriers.

The Leaky Tech Pipeline framework is organized into four stages in the technology and entrepreneurship pipeline: (1) Pre K-12 Education, (2) Post-Secondary Education, (3) Tech Workforce, and (4) Entrepreneurship and Venture Capital. In each of the four stages of the pipeline, this framework: (a) synthesizes the research on the barriers and obstacles that affect opportunities for women and underrepresented people of color to participate in the technology and entrepreneurship ecosystem, and (b) summarizes the data on current participation among women and underrepresented people of color at 4 critical junctures across the pipeline, including participation in AP computer science, completion of computing degrees, participation in the tech workforce, and participation in entrepreneurship and venture capital. This comprehensive framework is intended to provide a synthesis of the root causes of underrepresentation for a broad range of stakeholders in order to inform strategic interventions capable of rapidly and effectively increasing the racial and gender diversity across the technology ecosystem.

PREK-12 EDUCATION

The Barriers:

Access and Participation in Early Computing Education

Despite the aspirational view of education as an equalizer, which provides opportunities for students from all backgrounds to be successful (Mann, 1846), decades of research have demonstrated that while all students have access to public education, the quality and rigor of their educational experience vary dramatically by demographic factors including race, gender, and socioeconomic status (Darling-Hammond, 2004; Kozol, 1992; Oakes, 1985; Skiba et al., 2002;). As a result, not all students have equal opportunities to succeed in their educational pursuits, particularly in computing.

In pre K-12 public education, numerous structural barriers exist in access to high-quality preschool, school funding and resources, qualified teachers, internet and technology, and rigorous and advanced courses, by race and socioeconomic status. In computing education specifically, structural barriers exist in access to extracurricular opportunities (such as robotics and coding camps) and introductory and advanced computing courses, by both race and socioeconomic status. In addition to the lack of opportunity to develop early computing skills and knowledge, numerous social/psychological barriers affect the interest, engagement, and motivation of girls and underrepresented students of color in the participation and pursuit of computing.

- **Access to Preschool.** Black, Latinx, and low-income children are much less likely to be enrolled in preschool and less likely to attend high-quality preschool programs than white children and children from higher socioeconomic backgrounds. The lack of access to high-quality preschool places Black, Latinx, and low-income children at a disadvantage in literacy, language, and socio-emotional development and contributes to achievement gaps prior to the start of Kindergarten (U.S. Dept. of Education, 2015).
- **School Funding and Resources.** School districts serving large percentages of students from low-income backgrounds (high-poverty) and from underrepresented racial backgrounds (high-minority) receive between 10-15% less in school funding from state and local taxes than low-poverty, low-minority districts. A calculation by Education Trust (2015) indicates that this disparity in school funding results in approximately $1,200 less per student per year in high-poverty schools, and for an average high school with 1,000 students, this translates to $1.2M less per year to spend on teacher salaries, equipment, science labs, technology, extracurricular activities like art, music and sports, and teacher professional development (Ushormisky & Williams, 2015; WestEd, 2011; Williams v. State of CA, 2000).
- **Qualified Teachers.** Students who attend high-poverty schools are less likely to have teachers with classroom teaching experience and degrees, credentials, or authorizations in their teaching subject — two key indicators of effective STEM teachers and the strongest correlates of student achievement in mathematics (Adamson & Darling-Hammond, 2011; Darling-Hammond, 2000, 2004; Education Trust, 2010). According to an analysis of math teachers in California's schools, just 30% of math teachers in high-poverty schools have credentials or authorizations to teach mathematics, compared to 80% of math teachers in low-poverty schools (Education Trust-West, 2015).
- **Internet and Technology.** Despite increasing reliance on access to home internet and computers for traditional and extracurricular education, Black, Latinx, and low-income families are less likely to have access to broadband wireless and personal computers at home than their counterparts (Pew, 2012, 2015). Approximately 50% of households making under $30K per year have access to the internet at home, compared to nearly 90% of households making over $75K per year. White families are almost 2 times more likely to own personal computers than Black families, and higher income families own personal computers at almost twice the rate of lower income families (Pew, 2012, 2015).

The availability of AP Computer Science courses in public high schools is directly correlated to the race and SES of students attending the school, with low-income students and students of color much less likely to have access to these critical courses.

- **Advanced STEM Courses.** Low-income students, underrepresented students of color, and rural students are far less likely to attend schools that offer Advanced Placement courses, limiting the opportunity to take these courses, and in turn affecting college application competitiveness and preparation (Handwerk et al., 2008; Mattern, Shaw & Ewing, 2011). In STEM subjects, Black, Latinx, and Native American students are much less likely to have access to the full range of math and science courses (Algebra I, Geometry, Algebra II and Calculus; Biology, Chemistry, Physics) and Advanced Placement math and science courses than their peers (Education Commission of the States, 2017). For instance, just 33% of schools with high-minority student populations offer Calculus, compared to nearly 60% of low-minority schools (U.S. Dept. of Education, 2016) and just 1 in 10 Black students attend a high school that offers Physics (Education Commission of the States, 2017).

- **Access to Computing Courses.** Access to computer science courses is highly correlated to student racial background and socioeconomic status. Underrepresented students of color are much less likely to attend high schools that offer any computer science courses than their peers, with only 34% of Black students nationwide attending high schools offering computer science courses (Change the Equation, 2015). Low-income students are also much less likely to have access to computer science courses in their schools (Google & Gallup, 2015). Disparities in access to Advanced Placement Computer Science courses, which are strong predictors of majoring in computer science, are even more striking. Across the state of California, high-poverty and high-minority schools are twelve times less likely to offer AP Computer Science than low-poverty and low-minority schools (Martin et al., 2015).

- **Extracurricular Computing Activities.** Extracurricular activities can stimulate interest and skill development in computing and related subjects (robotics, engineering, web design) and can also provide enrichment during out-of-school time to continue stimulating academic development, yet students with limited financial resources or living in regions without access to these programs lack the opportunity to participate in these activities (Locke, 2015; Snellman, Silva & Putnam, 2015; Zaff et al., 2003).

- **Computing Stereotypes and Stereotype Threat.** Gender and racial stereotypes about math, science, and computing abilities are shaped by media and popular culture and appear as early as second grade (Cvencek et al., 2011). Stereotypes about computer scientists are pervasive and include, being male with "nerdy" attributes, a lack of interpersonal skills, a hyperfocus on computers, and incompatibility with communal and societal goals (Cheryan et al., 2015; Cheryan et al., 2013; Mercier et al., 2006). Stereotypes and associated low expectations for girls and students of color in math and computing can be reinforced by peers, parents and teachers and negatively affect interest self-efficacy, and aspirations in computing (Cimpian et al., 2016; Gunderson et al., 2011; Papageorge et al., 2016). Stereotype threat, or the fear of confirming a negative stereotype about one's group identity can decrease academic performance and lead to dis-identification and disengagement in the stereotyped domain, as studies have shown with women and people of color in STEM fields (Shapiro & Williams, 2012; Steele & Aronson, 1995).

- **Environmental Cues.** The computing classroom environment can also signal belonging or exclusion for different groups of students through subtle and overt cues. The unbalanced racial and gender representation in computing classrooms can activate negative stereotypes among underrepresented groups, and reinforce negative stereotypes about the ability of girls and students of color to succeed (Cheryan et al., 2009; Master et al., 2016; Murphy et al, 2007). Traditional and non-culturally relevant curriculum and pedagogy can also be exclusionary for students who don't see connections between the curriculum and their background, culture, experience or interests (Martin et al., unpublished).

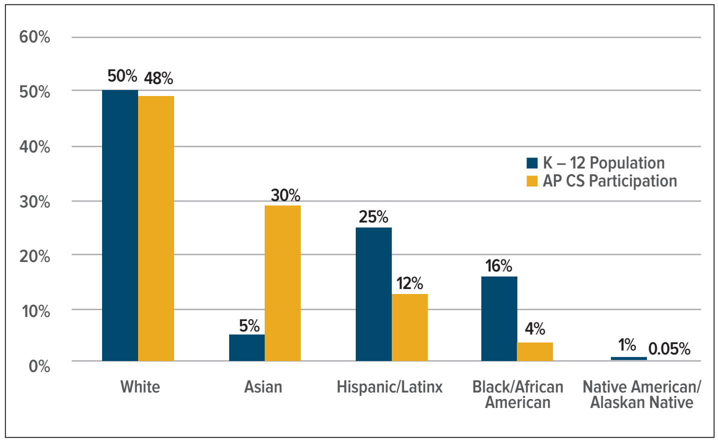
- **Role Models and Mentors.** Role models and mentors provide both inspiration and guidance for educational and workforce pathways in computing. Given the lack of women and underrepresented people of color in the technology workforce, however, there is an associated lack of diverse role models and mentors for girls and students of color, which can detrimentally affect exposure to careers in computing and interest in pursuing computing (Price, 2010; Cheryan et al., 2012). Exposure to stereotypical (e.g., male, white/Asian) examples of computing professionals in media and classrooms can reinforce misperceptions about the field of computing and reinforce perceived disconnects between computing and the interests and passions of students from diverse backgrounds (Carter, 2006).

By the Numbers:

Disparities in Participation in AP Computer Science

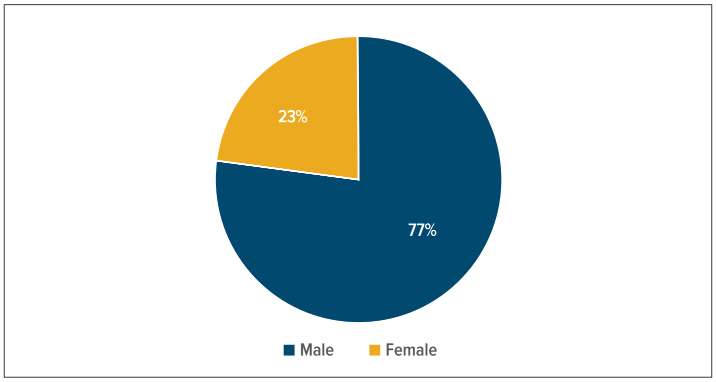
By the end of high school, structural barriers in access to quality education and social/psychological barriers in the stereotypes, expectations, and environments of computing have caused the loss of a large proportion of potential tech talent in students from diverse racial and gender backgrounds. White students participate in Advanced Placement math and science courses at 5x the rate of Latinx students and 9x the rate of Black students (College Board, 2016). Black and Latinx students comprise just 16% of the students taking AP Computer Science (College Board, 2017; Figure 5), with 70% of the Black or Latinx students taking AP CS A being male. Only 23% of all AP CS A test-takers are female (Figure 6), and nearly 85% of these female students are White or Asian (College Board, 2017). In 24 states, less than 10 Black students took the AP CS A exam, and 15 states had less than 10 Latinx students take the AP CS A exam (Ericson, 2016).

Figure 5. AP CS A Test-takers, by Race/Ethnicity



Source: College Board, 2017

Figure 6. AP CS A Test-takers, by Gender



Source: College Board (2017)

Since taking AP CS in high school is a strong predictor of majoring in computer science in higher education, these disparities place girls and underrepresented students of color at a significant disadvantage for pursuing computing education and careers by the end of high school.

The Barriers:

Enrollment and Completion of Computing Degrees in Higher Education

Contrary to the assumption that all students have equal opportunity to pursue the post-secondary degree of their choosing, high school quality, preparation and coursework (all of which are correlated to race and income) are greatly predictive of the type of college and field of study students are able to pursue. Structural barriers in teaching quality, resources and access to advanced coursework affect underrepresented high school students' preparation for college; wealth gaps affect college choice, affordability, and degree completion time; and constraints on universities affect the rigor of curriculum offered to students. These barriers are then compounded by additional social and psychological barriers including classroom and campus climate, stereotype threat, and the lack of role models, mentors, and peers, all of which affect the enrollment, persistence, and completion of computing-related degrees among students from underrepresented backgrounds.

- **Academic Preparation.** Students who do not take AP Computer Science in high school — who are most likely to be Black, Latinx, low-income, and/or female — are 8x less likely to pursue college degrees in computer science (Mattern, Ewing & Shaw, 2011). Even when computer science courses are available in the high schools attended by underrepresented students of color and low-income students, they are less likely to receive passing scores needed to count towards major admissions, earn college credit towards introductory courses, and be prepared for the rigor of post-secondary computing courses (Handwerk et al., 2008). Given that computer science at many universities is an oversubscribed and highly selective choice of major, it further limits opportunities for students from diverse backgrounds to enroll in computing majors (Nager & Atkinson, 2016).

- **Wealth and Income Inequality.** The median wealth of white households ($141,900) is 13x higher than the median wealth of Black households ($11,000) and 10x higher than Latinx households ($13,700; Kochhar & Fry, 2014). Racial disparities in family income affect college preparation, college choice, the ability to finance higher education, the ability to attend school full-time versus working part-time, the number of years to degree completion, and the amount of debt accrued by the time of graduation (Scott-Clayton & Li, 2016). As a result of family income alone, low-income students and underrepresented students of color face significant non-academic obstacles to completing computing degrees.

- **Curriculum Alignment and Offerings.** While there is a need for all universities to adapt and update curriculum content and courses to prepare students for the workforce, there is some preliminary evidence that universities with smaller endowments (including state schools, Historically Black Colleges and Universities, Hispanic Serving Institutions, and Tribal Colleges) have fewer resources to update their computing curriculum and less overall access to large tech industry partners to ensure alignment in curriculum (Nager & Atkinson, 2016; Vara, 2016). While this lack of alignment might not affect completion of computing degrees, it has a detrimental effect on academic preparation and student matriculation into the workforce.

- **Campus and Classroom Climate.** The experiences of students from underrepresented backgrounds on college campuses, particularly in majors in which there is little racial and gender diversity, differ from their peers in the subtle biases in classroom environments and micro-aggressions from peers and instructors. The experience of micro-aggressions, ranging from questioning about ability or background, having lower expectations, overlooking contributions, and differential treatment by professors and advisors can all negatively impactthe self-efficacy, engagement, and academic performance of underrepresented students (Chang et al., 2011; Harwood et al., 2015; Malcom et al., 1975; Solorzano et al., 2000). The classroom environment, including the lack of racial and gender diversity among students, and stereotypical cues in posters, curriculum, and other supplemental materials is related to decreased belonging, retention, and career aspirations among women and underrepresented students of color (Cheryan et al., 2009; Master et al., 2016; Murphy et al., 2007).

- **Stereotypes and Stereotype Threat.** Both conscious and unconscious stereotypes and biases held by faculty and other gatekeepers affect both attitudes and behavior towards underrepresented students and the behavioral and psychological responses of students. Studies estimate that up to 25% of White adults view Black adults as less intelligent than Whites, and over 70% of adults across 35 countries hold implicit stereotypes associating men and masculinity with STEM fields (Associated Press, 2012; Nosek et al., 2009). These stereotypes affect both the performance evaluation and faculty recommendations of underrepresented groups (Dutt et al., 2016). Stereotype threat affects the performance of women and underrepresented students of color in STEM courses and contributes to a reduced sense of belonging, disengagement, and decreased career aspirations in stereotyped domains (including computing; Major et al., 1998; Shapiro & Williams, 2012; Walton & Spencer, 2009; Steele & Aronson, 1995).

- **Role Models, Mentors, and Peer Networks.** The underrepresentation of women and students of color in computing education and careers limits the exposure of girls and students of color to teachers and role models from similar race and gender backgrounds — exposure that is associated with increased identification, self-efficacy and aspirations in STEM fields (Stout et al., 2011). Underrepresentation also limits the size of peer networks of same-race and same-gender peers, which can contribute to decreases in motivation, self-efficacy and academic and social support (Hurtado et al., 2009; Figueroa et al., 2015; Palmer et al., 2011; Price, 2010; Stout et al, 2011). Same-gender mentors can have a significant positive effect on women in science and engineering, while women without mentors are less likely to persist to degree completion (Dennehy & Dasgupta, 2017).

- **Internships and Workforce Pathways.** Students from underrepresented racial and gender backgrounds who pursue computing degrees, also face an additional obstacle to computing careers: access to internships and on-the-job skill development opportunities. At many tech companies, an internship is a foot in the door and companies often convert interns into full-time employees. Yet the reliance on informal social networks for referrals and recruitment from elite universities, coupled with the differences in preparation for interview processes by universities and programs can limit opportunities for students attending less competitive universities, which are often attended by underrepresented students of color and students from low-income backgrounds (Bambenek, 2016; Vara, 2016). While emerging innovative approaches, including bootcamps and apprenticeship programs, hold some promise for increasing pathways into tech jobs, their overall long-term efficacy has not been established.

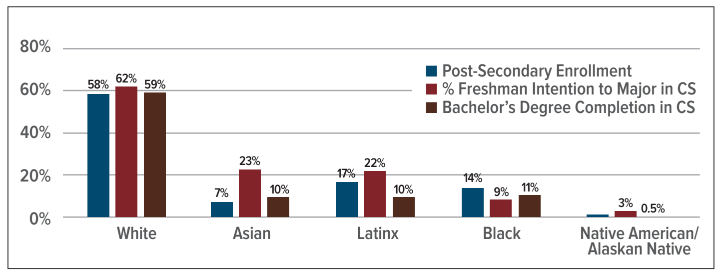
The median wealth of white households is 13x higher than Black households and 10x higher than Latinx households, with wealth disparities affecting college preparation, choice, financing, attendance, time to degree completion, and debt upon graduation.

By the Numbers:

Disparities in the Pursuit and Completion of Computing Degrees

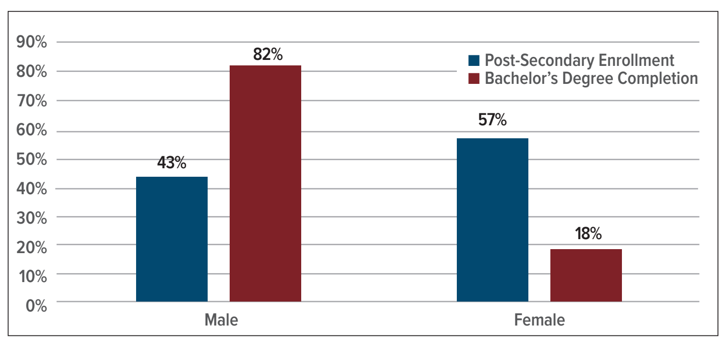
Barriers affecting entry into college and persistence and completion of computing degrees cause another significant reduction in the pool of potential tech talent among students from diverse racial and gender backgrounds. In the cohort of freshmen entering college each year intending to major in computer science, White and Asian students comprise the majority of intended computing majors (62% and 23%, respectively), with Black students in particular intending to major in computing at rates lower than their peers (NSF, 2016). By the time of degree completion, Latinx, Black and Native American/Alaskan Native students combined earn just 21% of all Bachelor's degrees in computing, while Asian and White students earn 69%. Latinx, Black and Native American/Alaskan Native students are both underrepresented compared to other racial groups and when compared to their percentage of the student population enrolled in college (Figure 7). Women earn just 18% of all Bachelor's degrees in computing, with 75% of those degrees being completed by White or Asian women, and only 24% by Black or Latinx women (NSF, 2016; Figure 8). While the four-year college degree is not the only route into tech careers, and numerous alternative pathways including bootcamps and apprenticeship programs have emerged, there is little data on their efficacy.

Figure 7. Post-Secondary Enrollment, Freshman CS Intentions, and CS Bachelor's Degree Completion, by Race



Source: National Science Foundation (2016). Appendix Table 2-19. National Center for Education Statistics (2016). Note: Figures for freshman intentions add up to more than 100% since Hispanic/ Latinx can be across multiple race categories.

Figure 8. Post-Secondary Enrollment and CS Bachelor's Degree Completion, by Gender



Source: National Science Foundation (2016). Appendix Table 2-19. National Center for Education Statistics (2016). Note: Figures for freshman intentions not available by gender

Since completion of a computer science degree is typically required to become a software engineer or developer, the disparities in computer science degree entry and completion limit opportunities for women and underrepresented people of color to participate in one of the highest-paying and fastest-growing jobs in the sector and across the economy.

TECH WORKFORCE

The Barriers:

Entry, Participation, Retention, and Advancement in the Tech Workforce

Despite the significant loss of potential tech talent during K-12 and post-secondary education, is it not solely the lack of availability of talent that is driving disparities in the tech workforce. Instead, data indicate that the tech workforce is failing to hire and retain women and underrepresented people of color at rates proportional to degree completion and workforce participation rates (NSF, 2016, EEOC, 2016), and specific barriers prevent underrepresented individuals from entering or remaining in these occupations. Biases in the recruitment, interviewing, and hiring processes prevent professionals from underrepresented backgrounds from being hired into technical and non-technical roles within tech companies. Professionals from underrepresented racial and gender backgrounds who do enter the tech workforce face negative workplace culture, harassment, biases in promotion and advancement, and pay inequality. Individually and cumulatively, these barriers contribute to the lack of satisfaction, turnover, and depressed rates of participation across the tech sector among women and underrepresented people of color.

- **Bias in Recruitment, Interviewing, and Hiring.** Numerous conscious and unconscious biases impact the hiring process, which cumulatively affect the likelihood of professionals from underrepresented backgrounds to be recruited, interviewed, and hired at tech companies. Recruiting and hiring alumni from top-ranking universities, including U.C. Berkeley and Stanford, limits the geographic, racial and economic diversity in the recruitment pool (Robinson, 2017). Insular peer social networks, which are highly segregated by race, socioeconomic status, and geography, limit knowledge-sharing about job opportunities across groups and influence hiring decisions (Cox et al, 2016; Lin, 2001; McPherson et al., 2001). Bias in the review of resumes results in candidates with ethnic-sounding names and female candidates being rated less positively, receiving fewer call-backs, and being less likely to advance to the interview round (Bertrand & Mullainathan, 2004; Goldin & Rouse, 2000; Moss-Racusin, et al., 2002). Racial bias in hiring, specifically for Black job applicants, has remained unchanged and persistent since the 1980's (Quillian et al., 2017). In the interviewing process, candidates with accents, people of color, women, and working mothers are all rated less favorably than their peers in competence and hiring recommendations and subjective assessments of "cultural fit" disadvantages candidates from diverse backgrounds (Biernat & Kobrynowicz, 1997; Correll et al., 2007; Rivera, 2012; Segrest Purkiss et al., 2006; Steele, 1997).

74% of women in computing jobs report experiencing gender discrimination in their workplace.

- **Stereotype Threat.** Racial and gender stereotypes can restrict interest among underrepresented professionals in pursuing occupations where they could be susceptible to stereotype threat (Davies et al., 2002), potentially limiting the appeal of certain tech jobs and companies among candidates from diverse backgrounds. In workplace settings where racial or gender groups are a numerical minority (including many tech companies and workplace settings), race and gender stereotypes can be activated and produce stereotype threat responses (Eagly & Carli, 2008), affecting the performance, engagement, satisfaction, and turnover intentions of employees from underrepresented racial and gender backgrounds (Steele, 1997; VonHippel et al., 2011).

- **Workplace Culture and Harassment.** Women and underrepresented people of color experience stereotyping, bullying, harassment, and other experiences of unfairness and discrimination at rates significantly higher than their peers (Fowler, 2017; Kolhatkar, 2017; Miley, 2015; Scott et al., 2017; Snyder, 2014; Women Who Tech, 2017). Seventy-four percent of women in computing jobs report experiencing gender discrimination at work, and 42% indicate that sexual harassment is a problem in their workplace (Funk & Parker, 2018, 2018). Data from three studies indicate that between 50% and 60% of women experienced harassment while working at a tech company (compared to 16% of men), and 1 in 10 experienced sexual harassment in their previous company (Elephant in the Valley, 2015; Scott et al., 2017; Women Who Tech, 2017). Sixty-two percent of Black employees in STEM jobs report experiencing racial discrimination, and are significantly more likely to experience stereotyping and negative assumptions about their background and ability than other groups (Funk & Parker, 2018; Scott et al., 2017). This negative workplace culture, which disproportionately affects women and underrepresented people of color, is significantly related to increased rates of turnover and lower retention rates (Scott et al., 2017) and at least partially related to the higher rates of Black and Latinx computer science and engineering degree-earners opting-out of tech jobs, compared with their peers (Beasley, 2011). Further, the lack of diversity within tech workplaces and lack of employee satisfaction with company diversity efforts also contributes to decreased satisfaction and increased turnover (Hunt et al., 2015), thus contributing to the lack of diversity by creating a revolving door for underrepresented groups.

- **Bias in Promotion and Advancement.** In the performance evaluation process, conscious and unconscious biases disadvantage women and people of color in tech, with performance ratings being much higher when there is a match between the race and gender of managers and employees (Kraiger & Ford, 1985). Women, working mothers, and underrepresented people of color are also rated lower on average in promotion potential when compared to their peers (Correll et al., 2007; Landau, 1995), and despite equal performance ratings receive less in compensation increases than their peers (Castilla, 2008). In addition, biases in day-to-day workplace experiences restrict access for women to challenging assignments and relationships with mentors and senior leaders that play a critical role in advancement to leadership positions (Correll & Simard, 2016; Eagly & Carli, 2007; LeanIn.org & McKinsey, 2015). Companies with male-dominated leadership are less likely to promote women into leadership positions than companies with a high proportion of female leaders (Tharenou, 1999). Specifically, underrepresented women of color are most likely to experience being passed over for promotion (Scott et al., 2017) and Asian women are the least likely to advance to executive positions in tech (Gee & Peck, 2017). The lack of equity in review and promotion processes negatively impacts satisfaction and retention, further exacerbating pay gaps, and contributing to turnover among underrepresented groups.

- **Pay Inequality.** Across nearly all occupational categories, and despite identical education, experience, and job titles, women and people of color receive substantially lower salaries than their male counterparts, and this is no different in technical occupations. Female software engineers on average earn 83% of the salary that male software engineers earn (Hegewisch & Williams-Baron, 2017). Compensation disparities are also pronounced at the intersection of race and gender, with women of color facing the starkest pay disparities. For example, Asian male professionals across occupations earn nearly twice as much as Black female professionals (AAUW, 2017). While a variety of factors contribute to the size and pervasiveness of the gender pay gap, pay inequity is a barrier to diversity and inclusion in tech, as evidenced by recent Department of Labor lawsuits against Google, Oracle, and Palantir (Fiegerman, 2017).

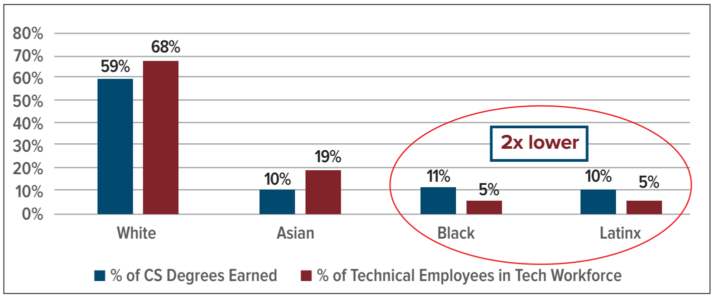
- **External Stressors & Work-Life Balance.** In addition to barriers to participation and advancement within tech workplaces, women and underrepresented people of color are more likely to face external economic, family, and environmental stressors, all of which can impact engagement and retention in the workplace. Women are more likely to be custodial parents and caretakers for elderly parents than men, but working mothers are less likely to be rated as competent and perceived as committed to work as men with children and women without children with equal qualifications (Kmec, 2010). Underrepresented people of color are more likely to graduate college with higher amounts of debt and to have lower generational wealth, which affects job choices, risk-taking, and retention/turnover decisions. Finally, underrepresented people of color are more likely to experience racial discrimination, poverty, violence and health disparities, creating unique stressors for women and people of color outside of the workplace, which then impacts participation and retention in the workplace (Census, 2016; Gee & Ford, 2011; Jones et al., 2018; Pew Research Center, 2016).

By the Numbers:

Disparities in Participation and Advancement in the Tech Workforce

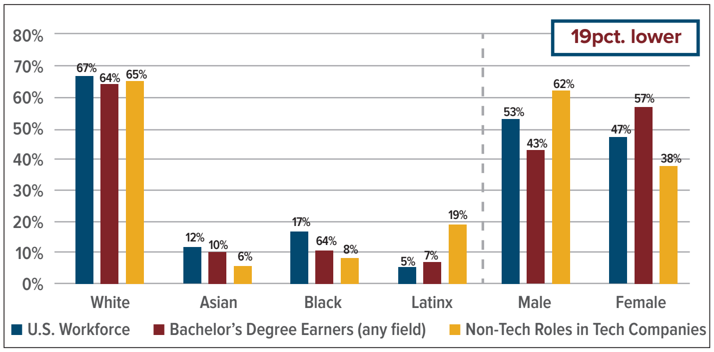
Despite earning 20% of Bachelor's degrees in computing, just 10% of the technical computing workforce is Black or Latinx. These data indicate that nearly twice the amount of talent from diverse racial and gender backgrounds complete computer science degrees each year, than are employed in the technical computing workforce (EEOC, 2016; NSF, 2016; Figure 9). Among the non-technical jobs within tech companies (including sales, marketing, human resources, and operations), women and underrepresented people of color are employed in non-technical positions at rates nearly 1.5 times lower than their representation among Bachelor's degree earners (Kapor Center, 2016; NSF, 2016). Despite earning 57% of all Bachelor's degrees, women comprise only 38% of non-technical employees (Figure 10). At the tech leadership and executive level, the disparities are even starker: 94% of tech leadership positions are held by White or Asian professionals, and 80% are held by men (Figure 11).

Figure 9. Employment in Technical Positions in Tech Companies, by Race



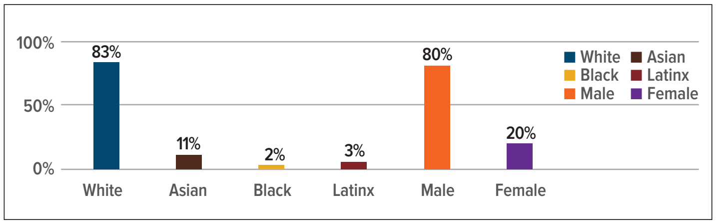
Source: NSF (2016). Science and Engineering Indicators, 2016; EEOC (2016). Analysis of professional occupations in the high-tech sector, with professional occupations including: computer programmers, software developers, web developers, and database administrators.

Figure 9. Employment in Non-Technical Positions in Tech, by Race and Gender



Source: Kapor Center (2016). Analysis of EE0-1 Reports from 20 Top-Grossing Tech Companies, which includes 11 hardware, software, and internet companies with available data; Non-technical positions include Sales, Marketing, HR, Operations, among others. National Science Foundation: Science and Engineering Indicators (2016, Table 2-18), Bureau of Labor Statistics: Labor Force Characteristics by Race and Ethnicity (2015).

Figure 11. Employment in Leadership Positions in Tech, by Race and Gender



Source: EEOC (2016). Diversity in High Tech; Leadership positions include: Executives, Senior Officials, and Managers.

Without the opportunity to enter, participate and advance in the tech workplace, a significant number of talented women and people of color are excluded from high-income jobs, upward economic mobility, and access to the valuable experience, capital, and networks necessary to launch and invest in tech startups.

ENTREPRENEURSHIP AND VENTURE CAPITAL

The Barriers:

Launching and Investing in Venture-Backed Technology Enterprises

The tech entrepreneurship ecosystem in the United States is an intricately related, far more exclusive tier of the broader tech ecosystem, with nearly insurmountable obstacles for large portions of the population. There are even greater obstacles to pursuing tech entrepreneurship for individuals from racial and gender backgrounds underrepresented in tech. Significant educational, economic, and social barriers exist to launching a startup venture, and subsequent biases and barriers in the investment process, restrict the number of underrepresented entrepreneurs launching ventures, having access to networks of power and influence, and gaining venture capital investment. In addition, venture capitalists and investors who act as gatekeepers capable of restricting or providing access to capital are largely homogenous and have homogenous social networks, which reinforces and replicates existing disparities in tech entrepreneurship.

- **Education and Career Pathways.** Due to cumulative educational, social, and economic barriers, underrepresented students of color (particularly from low-income backgrounds) are far less likely to attend highly-selective public and private universities and Ivy League schools than their peers (NCES, 2008), less likely to major in STEM or computer science (Carnevale et al., 2016), and less likely to participate in the tech workforce and venture-backed startups (EEOC, 2016). Since investors prioritize founders who attended top-tier universities or have startup/tech experience, founders from underrepresented racial and gender backgrounds with non-stereotypical educational and careers pathways face obstacles when launching tech startups (Stanford et al., 2017; Wadhwa et al., 2008). Additionally, the lack of access to peers, mentors, and associates from university alumni networks and professional networks from the tech industry prevent underrepresented groups from gaining access to referrals, introductions and recommendations from gatekeepers necessary to launch and fund tech startups.

- **Generational Wealth.** The historical economic exclusion of people of color from education, homeownership, and business ownership has created pervasive racial wealth gaps with the median wealth of White families being 13x higher than Black families and 10x higher than Latino families (Kocchar & Fry, 2014). As a result, underrepresented students of color are more likely to incur greater college loan debt and spend more years burdened by loan debt than White students (Scott-Clayton & Li, 2016). In addition, in the absence of generational wealth transfer, underrepresented professionals have less access to financial capital to finance early stage ventures, experience greater economic stress, and have more aversion to taking the financial risks often necessary to pursue tech entrepreneurship (Kan & Tsai, 2005; Traub et al., 2017). Thus, wealth is directly related to the decision to pursue entrepreneurship and financial constraints exclude those without sufficient financial means, which disproportionately affects people of color.

- **Social Networks and Social Capital.** Social networks are highly segregated by race and gender (Cox et al., 2016; McPherson et al., 2001), thus restricting access for women and underrepresented people of color to social capital in venture capital through alertness to new opportunities, endorsements/recommendations, and access to networks with financial capital (Lin, 2001; Stuart & Sorenson, 2005). Social networks, including direct personal relationships and indirect relationships through shared connections or experiences, are directly tied to the ability of entrepreneurs to acquire VC funding. Many top-tier VC firms rely on “warm intros” from someone within their network before startup founders have an opportunity to pitch their companies and investors are more likely to invest in companies that they are introduced to within their social network or companies that have secured a prominent investor (Shane & Cable, 2002; Stuart & Sorenson, 2005; Stuart, Hoang, and Hybels, 1999). Without access to social networks within venture capital, entrepreneurs from diverse backgrounds have less opportunity to launch companies, develop new products, grow successful ventures, and create their own venture funds.

- **Bias in Investment Decisions.** In the investment decision-making process, from the company pitch to the close of term sheets, evidence reveals that implicit and explicit biases negatively affect women and underrepresented people of color. Regardless of the quality of a company, VCs are more likely to invest when they share the same racial/ethnic background as the company's executive (Hegde & Tumlinson, 2014). When presented identical pitches, venture capitalists are twice as likely to invest in a startup when the pitch is narrated by a male versus female entrepreneur (Brooks et al., 2014), and the questions that investors pose to men and women differ dramatically and affect funding decisions (Kanze et al., 2017). The practice of pattern-matching (or looking for future entrepreneurs that fit demographic profiles of past successful founders), and preferences for specific educational pedigrees or startup industry experience put women and underrepresented people of color, who are not well-represented in the tech workforce, at a disadvantage (Morrill, 2014; Tinkler et al., 2014).

- **Stereotype Threat.** Through the stereotype threat mechanism, the societal stereotypes about the race and gender groups which excel in technical pursuits and entrepreneurial ventures can impact both the interest and performance of underrepresented groups in entrepreneurship and venture capital. Stereotype threat can be activated in situations where there is evaluative scrutiny and where an individual is the sole representative of their group (Steele & Aronson, 1995; Stroessner & Good, 2011). This threat can play out in pitches, board meetings, and informal networking settings where women and people of color are vastly underrepresented. Similar to the broader tech ecosystem, stereotypes about the technical and entrepreneurial potential of individuals from underrepresented racial and gender backgrounds can affect interest in pursuing entrepreneurship, launching a company, and performance in evaluative settings. Women are less likely to indicate interest and intention in pursuing entrepreneurship, particularly when it is associated with stereotypically masculine characteristics (Gupta et al., 2008), and women of color are particularly impacted given their dual marginalized identities in STEM fields (Ong et al., 2010).

- **Culture and Climate.** Similar to the culture of larger tech companies, women and underrepresented people of color often experience the workplace culture of tech startup companies and venture capital firms as filled with bias, harassment, and discrimination (Fairchild, 2016; LPFI, 2011; Scott et al., 2017; Women Who Tech, 2017). In one survey, 80% of female investors reported witnessing sexism and nearly 50% of investors of color reported witnessing racism in venture capital and the tech industry; 43% of founders witnessed racism in the process of raising capital (Fairchild, 2016). Another study found over 50% of women working in tech experienced some form of sexual harassment, including being propositioned in exchange for funding, a job or a promotion (Women Who Tech, 2017). In the past year, a number of women have stepped forward to shed light on the culture of sexual harassment in venture capital, entrepreneurship, and tech more broadly (O'Brien, 2017), providing evidence of a culture which negatively affects both the day-to-day satisfaction and the career trajectories of women and underrepresented people of color.

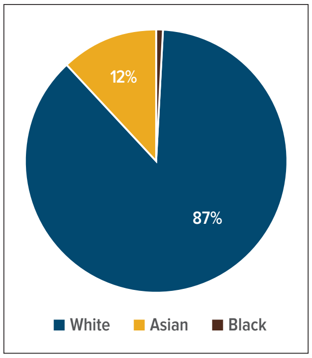
When presented identical pitches, venture capitalists are twice as likely to invest in a startup when the pitch is narrated by a male versus female entrepreneur.

By the Numbers:

Disparities in Tech Entrepreneurship and Venture Capital.

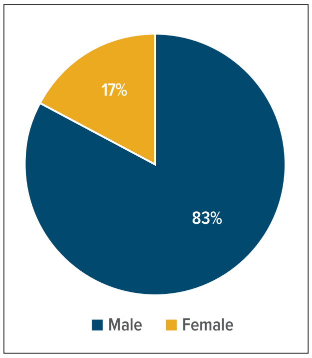
The lack of critical access to generational wealth or social networks of power and capital, coupled with the bias and harassment within the culture of venture capital, ensures the number of women and underrepresented people of color launching and investing in tech startup companies is shockingly low. According to the most recent data, nearly 99% of the founders of companies completing internet-seed and Series A rounds were White or Asian and less than 1% were Black (CB Insights, 2010; Figure 12). Female founders make up just 17% of all venture-backed startups receiving seed-stage funding, with women of color comprising less than 1% (Finney, 2017; Teare, 2017; Figure 13). Large discrepancies are also seen in the amount of money invested in companies, by founder race: the median amount raised by all-Asian founding teams is more than 2 times the amount that all-Black founding teams raise ($4M versus $1.3M) and women-led companies raise one-tenth of the amount of capital as male-led companies ($10B versus $90B in 2016, Teare, 2017). Of the venture capitalists who act as gatekeepers by providing capital investments, 89% of VCs are male and 74% are white (with African American and Latinos representing just 1% each of all venture capitalists; Kerby, 2016, Figures 14 and 15).

Figure 12. Venture-Backed Founders, by Race/Ethnicity



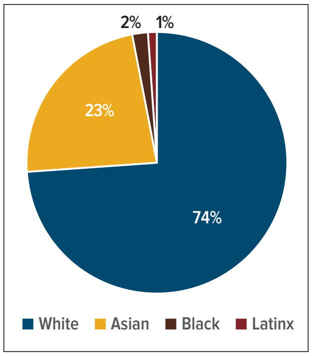
Source: CB Insights (2010). Includes Internet Seed and Series A, Jan-June 2010

Figure 13. Venture-Backed Founders, by Gender



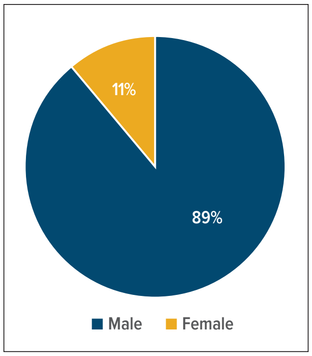
Source: Teare (2017)

Figure 14. Venture Capitalists, by Race/Ethnicity



Source: Kerby (2016)

Figure 15. Venture Capitalists, by Gender



Source: Kerby (2016)

Without the participation of women and people of color in the creation of new technology enterprises and solutions and the investment in wealth-creating ventures, tech will replicate and exacerbate trends of wealth inequality and neglect to solve critical challenges facing diverse communities.

CREATING A DIVERSE TECHNOLOGY ECOSYSTEM: A COMPREHENSIVE SOLUTION

Decades of education and social science research demonstrate that racial and gender disparities in the technology ecosystem result from a complex set of intertwined structural and social/psychological barriers which restrict access and opportunities for women and underrepresented people of color throughout PreK-12 education, higher education, the tech workforce, tech entrepreneurship, and venture capital. These cumulative and compounding barriers exclude women and underrepresented people of color at each major stage in the pipeline, from participating in early computing courses, completing computing degrees, entering the tech workforce, ascending to leadership positions, and launching and investing in tech startups. This disproportionate exclusion of women and underrepresented people of color across the tech workforce limits the robustness of our national technical workforce, hampers future national economic growth and competitiveness, restricts access to high-opportunity jobs for a large portion of the population, and exacerbates economic inequality.

While technological advancement has presented the opportunity to address deeply-entrenched patterns of social, educational, and economic inequality in the United States, without racial and gender diversity across the workforce, and among entrepreneurs, investors, and shareholders, technology has instead exacerbated existing inequality (Schwab, 2016). As advancement in technology continues to accelerate, innovation and automation is predicted to continue to have a disproportionately negative impact on the displacement of low-skill workers, women, and Black and Latinx professionals (Manyika, 2017; Manyika et al., 2015; WEF, 2017; Pew Research Center, 2016). At this critical moment, the technology sector has a unique opportunity to demonstrate leadership in providing the innovation, problem-solving, product development, and capital to implement comprehensive solutions to diversify technology and improve the sustainability of the country's future economy.

In order to rapidly and effectively increase racial and gender diversity across the tech ecosystem, a comprehensive approach is needed to address each of the underlying structural and social/psychological barriers which cause underrepresentation across each stage of the pipeline. A comprehensive approach will require visionary and strategic initiatives, leadership from tech executives and government officials, collaboration across stakeholder groups, significant human and capital resources, and continuous assessment of impact and efficacy of interventions.

Below we outline recommendations in 6 critical areas across the pipeline as a place to start:

❶ **Increase Equity in K-12 Education.** Significant national, state, and local education reform efforts are needed to improve access to quality pre-school, provide school funding for facilities and activities (including technology, science labs, etc.), and provide highly-qualified and experienced teachers in all classrooms to ensure all students have the opportunity to develop foundational knowledge, skills, and interest. Reform is also needed at the high school level to ensure students have equitable access to rigorous coursework, including Advanced Placement math and science courses, to prepare them for entry and success in post-secondary education.

❷ **Expand Computer Science Education.** In K-12 public education, policy changes, education reform and financial investments are needed to develop rigorous standards for computing education, increase the availability of computer science courses, provide training and certification pathways for teachers, and ensure computer science courses are incentivized via graduation requirements and college credits. These changes are needed to ensure that all students have the opportunity to participate in rigorous, engaging, and relevant computing instruction. It is critical that these educational opportunities provide not just access to introductory courses, but provide opportunities for repeated exposure including computing pathways (e.g., Cybersecurity, Networking, Web Design, etc.) and Advanced Placement computer science courses, in order to prepare students for college and career readiness.

❸ **Enhance Pathways into Technology Careers.** Pathways into the tech workforce need further development and expansion to reduce barriers to entry for job seekers, expand the pool of technical and non-technical talent, and provide sustainable talent pipelines for tech employers. Workforce development initiatives can include revamping community college curricula and programming to better align with emerging technology needs, bootcamps which provide skill development in specific areas, and apprenticeship and internship programs where young professionals develop skills and social capital by working on discrete projects within companies while gaining access to critical networks. These programs should be developed in collaboration with industry leaders to ensure that curriculum aligns with the needs of tech companies, while prioritizing the development of talent in local communities to ensure companies reflect the communities in which they are situated. Additionally, in entrepreneurship and venture capital, initiatives are needed to inspire underrepresented entrepreneurs, provide programming for emerging entrepreneurs and companies, and make connections between entrepreneurs from diverse backgrounds and the social networks of power within the technology sector.

❹ **Implement Comprehensive Diversity and Inclusion Strategies.** Within higher education institutions, tech companies, and venture capital firms, comprehensive organization-wide diversity and inclusion strategies must be implemented and prioritized in order to create authentically diverse and inclusive workplace environments. These efforts should start with a strong commitment to diversity and inclusion from the highest levels of executive leadership, and include an articulation of core organizational values, specific diversity goals, and consistent data collection and reporting on employee demographics and satisfaction. A comprehensive strategy for diversity and inclusion must be implemented, which includes all aspects of the company, and not one-off trainings or workshops. Recruitment, interviewing, compensation, performance management, and promotion processes and practices should be audited to examine potential biases, and overhauled as needed to ensure fair and effective processes at each stage in the employment lifecycle. Investment decision-making processes should similarly be examined for bias along with trends in referrals, pitches, and investments. Specific strategies for creating inclusion must also be implemented, including creating harassment and bias-free work environments, supporting employee affinity groups and networks (e.g., ERGs), providing flexibility for parents and caregivers, and supporting work-life balance.

❺ **Increase the Prevalence of Diverse Computing Role Models.** To counteract racial and gender stereotypes about computing ability and the characteristics of computing professionals, exposure to computing professionals from diverse backgrounds can be extremely effective in reducing stereotype threat and increasing computing aspirations among underrepresented students from kindergarten through college and the workplace. Exposure can occur in media through movies, TV shows, and commercials, and social media campaigns and can also occur through direct interactions including classroom visits, field trips, career fairs, conferences, mentorship programs, and networking events. Increased diversity among instructors, professors, tech leaders, investors, and board members will also serve to counteract stereotypes and provide aspirational examples for students, early career employees, and entrepreneurs. Access to diverse role models can also reduce misconceptions about what computing professionals do and demonstrate the variety of careers that computing skills can be applicable for, and additionally, how technology can be used as a tool to solve social challenges.

❻ **Create Public-Private Partnerships to Develop the Future Computing Workforce.** Given the deeply-entrenched societal inequities which underlie the root causes of underrepresentation in the technology sector, large scale public-private partnerships are also needed to bring nonprofit organizations, education, government, philanthropy and industry together to work collaboratively towards collective impact goals. These goals can include increasing mathematics competency, increasing the availability and rigor of computer science education, increasing college accessibility and affordability, building city-wide entrepreneurship ecosystems, and investing in social impact ventures aiming to narrow gaps of equity and opportunity.

While there are no easy solutions, the Leaky Tech Pipeline Framework gives us a comprehensive understanding of the problem, so that we can work collectively towards improving the racial and gender diversity of the technology sector and strengthening the workforce of the future.

DEFINITIONS & LIMITATIONS

TERMINOLOGY & DEFINITIONS

- **Technology Ecosystem.** Within this report, we attempt to discuss the challenges and barriers to diversity across the technology ecosystem, and utilize "tech ecosystem" as a broad term to define the environment which prepares students for technology careers, produces and utilizes technology and technology-driven products, and creates and invests in tech companies.

- **Technology Sector, Technology Industry, and High-Tech.** The industries and occupations associated with technology are challenging to define, and evolving rapidly, given the integration of technology and technical positions across all sectors of the workforce. Throughout the report, we use the terms technology sector, technology industry, and high-tech loosely and interchangeably to describe a cluster of companies which produce innovative technology, introduce new products and processes, and emphasize technology (EEOC, 2016). For the purposes of this report, we examine and utilize data from four different sources to explore the technology sector: (1) the Bureau of Labor Statistics occupational category for computing and mathematical occupations," (2) the Equal Employment Opportunity Commission (EEOC)'s high-tech companies, and (3) the EEOC's Silicon Valley high-tech companies, and (4) a Kapor Center analysis of EEO-1 reports from the 25 top-grossing hardware, software, and internet technology companies (with available data).

- **Technology Workforce.** We use the term "technology workforce" to describe both individuals employed in technical occupations, and those in non-technical occupations within technology companies.

- **Computing Workforce.** Within the technology sector and industry, we define the computing workforce as individuals with technical occupations, including: (1) the occupations comprised within the Bureau of Labor Statistics category for computing and mathematical occupations, (2) the occupations listed as professional or technical in the public EEO-1 reports of tech companies (understanding the limitations in the EEO-1 reporting mechanisms).

- **Computer Science.** We use the term "computer science" to describe the "study of computers and algorithmic processes, including their principles, their hardware and software designs, their implementation, and their impact on society." This definition is adapted from the definition utilized by the Association for Computing Machinery and used in the K-12 Computer Science Standards Framework. We use the terms computing and computer science interchangeably.

- **Diversity and Underrepresentation.** This paper intentionally focuses on race, gender, and socioeconomic disparities in access and opportunity across the tech ecosystem. Underrepresentation is defined as the lack of representation in computing education, degree completion, the tech workforce, and entrepreneurship/ VC, in comparison to representation in the U.S. population and representation among potential pools of candidates (e.g., the total labor force, CS degree-earners). Underrepresented people of color include: Black, Latinx, and Native American/Alaskan Native individuals. Women include those defining their gender identity as female. Given the importance of examining intersectional barriers, we report on the experiences and outcomes of women of color, whenever possible, which include women from underrepresented backgrounds (Black, Latinx, Native American/Alaskan Native). Low-income students include students whose families meet the federal criteria for receiving Free/Reduced Price Lunch. The focus on racial, gender, and SES disparities is due in part to the availability of data (while comprehensive data is not readily available on other demographic variables). This focus on race, gender, and SES is not intended overlook other forms of diversity; and is instead intended to inform and bolster discussions of diversity in tech in all forms, including gender identity, sexual orientation, age, (dis)ability, parenting status, religion, immigration status, schooling background, parenting/caregiving status, language, and veteran status, among others.

LIMITATIONS:

In this paper, we attempted to synthesize a broad and robust amount of literature on barriers for underrepresented populations, bias in schools and workplaces, and data on the technology ecosystem into a coherent framework. Within the scope of this work, we have identified the following limitations to highlight:

- **Non-Linear Stages:** The four stages of the technology pipeline are intended to provide a structure for understanding barriers and disparities at various points in time. The stages are not intended to solely be linear, and our use of the pipeline metaphor is not intended to suggest that all students and professionals follow a linear trajectory from preschool through entrepreneurship. While many follow a traditional pathway, there is ample evidence that there are many points of entry to the tech workforce and entrepreneurship, and also many points of exit and re-entry. The use of the stages attempts to capture the experiences and obstacles that are faced at each of these key points in time.

- **Barriers:** The barriers outlined in each of the stages are intended to synthesize findings into categories to simplify concepts and provide opportunities for clearer understanding of the barriers. We believe that this attempt to comprehensively summarize and simplify barriers is an important, but undoubtedly not all-inclusive, review. For simplification purposes, and to identify the key 5-8 barriers per stage, some obstacles are not mentioned in detail due either to a lack of research on the topic or due to being combined into a larger category.

- The literature on diversity across the tech ecosystem, and related research on social, economic and educational inequality, is extensive. We intended to provide a robust and comprehensive summary of existing research on each topic, while acknowledging that we have not included all relevant research articles, citations, or findings. Conversely, in some areas there were a lack of empirical research findings, but we included relevant newspaper articles from reputable news outlets, which provided insights not yet available in peer-reviewed research.

- While synthesizing the research findings, some of the research was conducted with women, while other studies were conducted with people of color. We attempt to specify which groups the research was conducted with, while also suggesting, in some cases, that given that both women and people of color are underrepresented in tech, some of the findings may be extrapolated to have similar impact on other marginalized groups. Additional research is needed to fully build out the body of research on women, women of color, and people of color across the technology ecosystem.

We hope that this research paper, including the barriers, the data, and the cited research, will serve as a starting place for the field, and that collaboratively, we can continue to build on the framework, add citations, and identify new barriers in an ongoing process of updating content.

REFERENCES

AAUW (2017). The Simple Truth about the Gender Pay Gap.

Adamson, F. & Darling-Hammond, L. (2011). Addressing the Inequitable Distribution of Teachers: What it Will Take to get Qualified Effective Teachers in All Communities

Baller, Di Battista, Dutta & Lanvin (2016). World Economic Forum: Global Information Technology Report. The Networked Readiness Index, 2016.

Bambenek, C. (2016). We talked to interns at Google, Microsoft, and Uber about what it's like to work at the world's biggest tech companies. Business Insider (August 19, 2016).

Beasley, M. (2011). Opting-out: Losing the Potential of America's Young Black Elite.

Bertrand, M. & Mullainathan, S. (2004). "Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination." *American Economic Review,* 94(4), 991-1013.

Biernat, M., & Kobrynowicz, D. (1997). Gender- and race-based standards of competence: Lower minimum standards but higher ability standards for devalued groups. *Journal of Personality and Social Psychology,* 72(3), 544-557.

Brooks, A.W., Huang, L., Kearney, S., & Murray, F. (2014). Investors prefer entrepreneurial ventures pitched by attractive men. PNAS, 111(12), 4427-4431.

Bureau of Labor Statistics (2017). Unemployment Rates by Age, Sex, Race, and Ethnicity

Bureau of Labor Statistics (2017). Occupational Employment Projections: 2016-26.

Bureau of Labor Statistics (2017). STEM Occupations: Past, Present, and Future.

Bureau of Labor Statistics (2016). High-Tech Industry: What it is and why it matters to our economic future.

Bureau of Labor Statistics (2016). Labor Force Statistics from the Current Population Survey: Employed Persons by Detailed Occupation, Sex, Race, and Ethnicity.

Bureau of Labor Statistics (2015). Occupational Outlook Handbook: Computer and Information Technology Occupations.

Bureau of Labor Statistics (2015). STEM Crisis or STEM Surplus? Yes and Yes.

Bureau of Labor Statistics (2013). Occupational Employment Projections to 2022.

Cakebread, C. (2017). Apple reiterated its commitment to diversity and inclusion, but it made little progress in the last year and is still predominantly white and male. Business Insider (November 9, 2017)

Carnevale, A. P., Jayasundera, T., & Gulish, A. (2016). *America's divided recovery: College haves and have-nots.* Washington, DC: Georgetown University, Center on Education and the Workforce. Retrieved from https://cew.georgetown.edu/wpcontent/uploads/Americas-Divided-Recovery-web.pdf

Carter, L. (2006). Why students with an apparent aptitude for computer science don't choose to major in computer science. *Proceedings of the 37th SIGCSE Technical Symposium on Computer Science Education.* pp. 27–31.

CB Insights (2010). Venture Capital Human Capital Report.

Chang, M.J., Eagan, M.K., Lin, M.H., & Hurtado, S. (2011). Considering the impact of racial stigmas and science identity: Persistence among biomedical and behavioral science aspirants, *J. High. Educ., 82* (5), 564–596.

Change the Equation (2017). New Vital Signs Data: Access to Challenging STEM Courses.

Cheryan, S., Master, A., & Meltzoff, A. (2015). Cultural stereotypes as gatekeepers: increasing girls' interest in computer science and engineering by diversifying stereotypes. Frontiers in Psychology, 6 (49).

Cheryan, S., Davies, P.G., Plaut, V.C., Steele, C.M. (2009). Ambient belonging: How stereotypical cues impact gender participation in computer science. *Journal of Personality and Social Psychology,* 97(6), pp. 1045-1060.

Cheryan, S., Drury, B., & Vichayapai, M. (2012). Enduring Influence of Stereotypical Computer Science Role Models on Women's Academic Aspirations. *Psychology of Women Quarterly,* 37 (1), 72-79.

Cheryan, S., Plaut, V., Handron, C., & Hudson, L. (2013). The stereotypical computer scientist: Gendered media representations as a barrier to inclusion for women. *Sex Roles,* 69(1) 58-71.

Cimpian, J., Lubienski, S., Timmer, J., Makowski, M., & Miller, E. (2016). Have Gender Gaps in Math Closed? Achievement, Teacher Perceptions, and Learning Behaviors across Two ECLS-K Cohorts. AERA Open, 2 (4), 1-19.

Coates, T.H. (2014). The Case for Reparations. The Atlantic (June 2014).

Colby, S., & Ortman, J. (2015). Projections of the Size and Composition of the U.S. Population: 2014 to 2060. U.S. Census Bureau.

College Board (2017). AP Program Participation and Performance Data, 2017.

Correll, S., Benard, S., & Paik, I. (2007)Getting a Job: Is There a Motherhood Penalty? American Journal of Sociology, 112 (5), 1297-1339.

Correll, S. & Simard, C. (2016). Vague Feedback is Holding Women Back. Harvard Business Review, April 29, 2016.

Cox, D., Navarro-Rivera, J., Jones, R. (2016). Race, Religion, and Political Affiliation of Americans' Core Social Networks. PRRI, April 3, 2016.

Cvencek, D., Meltzoff, A. N. and Greenwald, A. G. (2011). Math–Gender Stereotypes in Elementary School Children. Child Development, 82 (3), 766-779.

Cyberseek (2017). Cybersecurity Supply/Demand Heat Map. Retrieved from: http://cyberseek.org/heatmap.html.

Dalberg & Intel (2016). Decoding Diversity: The Financial and Economic Returns in Tech.

Darling-Hammond (2004). Inequality and the Right to Learn: Access to Qualified Teachers in California's Public Schools. Teachers College Record, 106 (10), 1936-1966.

Darling-Hammond, L. (2000). Teacher Quality and Student Achievement: A Review of State Policy Evidence. Education Policy Analysis Archives, 8 (1), 1-44.

Davies, P. G., Spencer, S. J., Quinn, D. M., & Gerhardstein, R. (2002). Consuming images: How television commercials that elicit stereotype threat can restrain women academically and professionally. *Personality and Social Psychology Bulletin,* 28(12), 1615-1628.

Dennehy, T. & Dasgupta, N. (2017). Female peer mentors early in college increase women's positive academic experiences and retention in engineering. PNAS, April 14, 2017.

Diaz-Garcia, C., Gonzalez-Moreno, A., & Saez-Martinez, F.J. (2013). Gender Diversity within R&D Teams: Its Impact on Radicalness of Innovation. Journal of Innovation, Organization & Management, 15 (2).

Donnelly, G. (2017). Google's 2017 Diversity Report Shows Progress in Hiring Women, Little Change for Minority Workers. Fortune (June 29, 2017).

Dutt, K., Pfaff, D. L., Bernstein, A. F., Dillard, J. S., & Block, C. J. (2016). Gender differences in recommendation letters for postdoctoral fellowships in geoscience. *Nature Geoscience,* 9(11), 805+.

Dutta, S., Geiger, T., & Lanvin, B. (2015). World Economic Forum: Global Information Technology Report. ICTs for Inclusive Growth.

Eagly, A. H., & Carli, L. L. (2007). *Leadership for the common good. Through the labyrinth: The truth about how women become leaders. Boston,* MA, US: Harvard Business School Press.

Edelman, B., Luca, M. & Svirsky, D. (2016). Racial Discrimination in the Sharing Economy: Evidence from a Field Experiment. American Economic Journal, Applied Economics, 9 (2), 1-22.

Education Commission of the States (2017). Percentage of students in high schools which do not offer challenging math and science, by race/ethnicity, 2013-2014.

Education Trust-West (2015). The STEM Teacher Drought: Cracks and Disparities in California's Math and Science Teacher Pipeline.

Elephant in the Valley (2015). Survey of Women in Silicon Valley (April-May 2015).

Equal Employment Opportunity Commission (2016). Diversity in High Tech.

Ericson, B. (2016). AP Data for the United States: 1998-2016.

Evans, W. & Rangarajan, S. (2017). Hidden figures: How Silicon Valley keeps diversity data secret. Reveal News (October 26, 2017).

Facebook (2017). EEO-1 Report, 2017.

Fairchild, C. (2016). Investors and startup founders think tech's diversity problem will fix itself.

Fiegerman, S. (2017). Labor Department Goes After Big Tech for Discrimination. CNN Money (April 10, 2017).

Figueroa, T., Wilkins, A., & Hurtado, S. (May 2015). Black STEM Students and the Opportunity Structure. Paper presented at the annual forum for the Association for Institutional Research, Denver, CO.

Finney, K. (2016). The Real Unicorns of Tech: Black Women Founders. The #ProjectDiane Report.

Fortune (2016). Fortune Global 500, 2016.

Fowler, S. (2017). *Reflecting on one very, very strange year at Uber.* [online] Susan J. Fowler. Retrieved from: https://www.susanjfowler.com/blog/2017/2/19/reflecting-on-one-very-strange-year-at-uber.

Funk, C. & Parker, K. (2018). Women and Men in STEM Often At Odds over Workplace Equity. Pew Social Trends.

Galia, F. & Zenou, E. (2012).Board composition and forms of innovation: Does diversity make a difference? European Journal of International Management, 6(6), 630-650.

Gee, B. & Peck, D. (2017). The Illusion of Asian Success: Scant Progress for Minorities in Cracking the Glass Ceiling from 2007–2015.

Godwyn, M. & Stoddard, D. (2011). Minority Women Entrepreneurs: How Outsider Status Can Lead to Better Business Practices.

Goldin, C., & Rouse, C. (2000). Orchestrating impartiality: The impact of" blind" auditions on female musicians. *American Economic Review,* 90(4), 715-741.

Google & Gallup (2015). Searching for Computer Science: Access and Barriers in K-12 Education.

Google (2016). EEO-1 Report, 2016.

Griswold, A. (2014) Google's Workforce is Mostly White and Male. Slate (May 28, 2014).

Grusky, D. & Hill, J (2017). Inequality in the 21st Century. Avalon Publishing.

Gupta, V.K., Turban, D.B., & Bhawe, N. (2008). The effect of gender stereotype activation on entrepreneurial intentions. Journal of Applied Psychology, 93 (5), 1053-61.

Gunderson, E., Ramirez, G., Levine, S., & Beilock, S. (2011). The Role of Parents and Teachers in the Development of Gender-Related Math Attitudes. *Sex Roles* (2012) 66:153–166.

Guynn, J. (2015). Exclusive: Google Raising Stakes on Diversity. USA Today (May 5, 2015).

Handwerk, P., Tognatta, N., Coley, R., & Gitomer, D. (2008). Access to Success: Patterns of Advanced Placement Participation in U.S. High Schools. Educational Testing Service.

Harwood, S. A., Choi, S., Orozco, M., Browne Huntt, M., & Mendenhall, R. (2015). Racial microaggressions at the University of Illinois at Urbana-Champaign: Voices of students of color in the classroom. University of Illinois at Urbana-Champaign.

Hegde, R. & Tumlinson, J. (2014). Does Social Proximity Enhance Business Partnership? Theory and Evidence from Ethnicity's Role in U.S. Venture Capital. Management Science (May 21, 2014).

Hegewisch, A. & Williams-Baron, E.. (2017). "The Gender Wage Gap and Work-Family Supports: Women's Choices or Policy Choices?" *Saint Louis University Public Law Review* 36 (July). Retrieved from: http://law.slu.edu/sites/default/files/Journals/ariane_hegewisch-and-emma_williams-baron-article.pdf

Henke, N., Bughin, J., Chui, M., Manyika, J., Saleh, T., Wiseman, B. & Sethupathy, G. (2015). The Age of Analytics: Competing in a Data-Driven World. McKinsey Global Institute.

Hern, A. (2016). Microsoft Scrambles to Limit PR Damage Over Abusive AI Bot Tay. The Guardian (March 24, 2016).

Herring, C (2009). Does Diversity Pay? Race, Gender, and the Business Case for Diversity. American Sociological Review, 74(2), 208-224.

Hewlett, S., Marshall, M. & Sherbin, L. (2013) How Diversity Can Drive Innovation. Harvard Business Review (December 2013).

Hunt, V., Layton, D., & Prince, S. (2015). Why Diversity Matters. McKinsey & Co.

Hurtado, S., Cabrera, N. L., Lin, M. H., Arellano, L., & Espinosa, L. L. (2009). Diversifying science: Underrepresented student experiences in structured research programs. *Research in Higher Education,* 50(2), 189–214.

Institute of Medicine (2003) Unequal Treatment: Confronting Racial and Ethnic Disparities in Healthcare. Washington, DC: The National Academies Press.

Jehn, K., Northcraft, G., & Neale, M. (2009). Why Differences Make A Difference: A Field Study of Diversity, Conflict, and Performance in Workgroups. Administrative Sciences Quarterly, 44(4), 741-763.

Jenks, C. & Phillips, M. (2011). The Black-White Test Score Gap. Brookings Institution Press.

Jones, R., Cox, D., Fisch-Friedman, M. & Vandermaas-Peeler, A. (2018). Diversity, Division, Discrimination: The State of Young America. Public Religion Research Institute.

Kan, K. and Tsai, W. (2005). Parenting practices and children's education outcomes, *Economics of Education Review,* 24, issue 1, p. 29-43. Retrieved from: https://EconPapers.repec.org/RePEc:eee:ecoedu:v:24:y:2005:i:1:p:29-43.

Kanze, D., Huang, L., Conley, M., & Higgins, E.T. (2017). Male and Female Entrepreneurs Get Asked Different Questions by VC's and it Affects How Much Funding they Get. Harvard Business Review (June 27, 2017).

Kapor Center (2017). Dear Investors (Part 2): What Kind of Impact Investor Are You? Medium, April 28, 2016.

Kmec, J. A., & Gorman, E. H. (2010). Gender and discretionary work effort: Evidence from the United States and Britain. *Work and Occupations,* 37(1), 3–36

Kolhatkar, S. (2017). What Hollywood Could Learn from Wall Street's Sexual Harassment Reckoning. *The New Yorker* (November 15, 2017).

Kotkin, J. & Schill, M. (2017). The Cities Producing the Most Tech Jobs: 2017. Forbes (March 16, 2017).

Kozol, J. (1992). Savage Inequalities: Children in America's Schools. Harper Perennial.

Kerby, R. (2016). Who is a VC? TechCrunch (February 10, 2016).

Kharpal, A. (2017). Mark Zuckerberg Apologizes after Critics Slam His "Magical" Virtual Reality Tour of Puerto Rico Devastation. CNBC (October 10, 2017)

King, H. (2016). Snapchat Under Fire For Another 'Racist' Filter. CNN Tech (August 10, 2016).

Kochhar, R. & Fry, R. (2014). Wealth inequality has widened along racial, ethnic lines since the end of the Great Recession. Pew Research Center.

Kraiger K., Ford JK (1985) A meta-analysis of ratee race effects in performance ratings . Journal of Applied Psychology 70(1): 56-65.

LeanIn.Org & McKinsey. (2016). Women in the Workplace. Retrieved from: https://womenintheworkplace.com/

Level Playing Field Institute (2011). The Tilted Playing Field: Hidden Bias in Information Technology Workplaces.

Levin, S. (2016). A Beauty Contest Was Judged by AI and the Robots Didn't Like Dark Skin. The Guardian (September 8, 2016).

Lin, N. (2001). Social Capital: A Theory of Social Structure and Action. Cambridge: Cambridge University Press.

Locke, C. (2015). Choosing a Summer Coding Camp That's Right for Your Kids. Retrieved from: https://www.edsurge.com/news/2015-03-26-choosing-a-summer-coding-camp.

Lund, S., Manyika, J., Nyquist, S., Mendonca, L., & Ramaswamy, S. (2013). Game Changes: Five Opportunities for U.S. Growth and Renewal. McKinsey Global Institute.

Major, B., Spencer, S., Wolfe, C., Crocker, J. (1998). Coping with negative stereotypes about intellectual performance: The role of psychological disengagement. *Personality and Social Psychology Bulletin,* 24, 34–50.

Malcom, S., Hall, P., & Brown, J. (1975). *The double bind: The price of being a minority woman in science.* Washington, DC: American Association for the Advancement of Science.

Mangalindan, J.P. (2014) How Tech Companies Compare in Employee Diversity. Fortune (August 29, 2014).

Mann, H. (1846). Twelfth Annual Report to the Secretary of the Massachusetts State Board of Education.

Manyika, J. (2017). Technology, Jobs, and the Future of Work. McKinsey Global Institute.

Manyika, J., Ramaswamy, S., Khanna, S., Sarrazin, H., Pinkus, G., Sethupathy, G., Yaffe, A. (2015). Digital America: A Tale of the Haves and Have Mores. McKinsey Global Institute.

Martin, A., McAlear, F. & Scott, A. (2015). Path Not Found: Disparities in Access to Computer Science Courses in California High Schools.

Martin, A., Scott, A., Ryoo, J., Madkins, T., Goode, J., Scott, K., & McAlear, F. (2017). *Culturally Relevant Computer Science Pedagogy: From Theory to Practice.* Manuscript under review.

Master, A., Cheryan, S., & Meltzoff, A. N. (2016). Computing whether she belongs: Stereotypes undermine girls' interest and sense of belonging in computer science. *Journal of Educational Psychology,* 108, 424-437.

Mattern, K. D., Shaw, E.J. & Ewing, M. (2011). Is AP Exam Participation and Performance Related to Choice of College Major? New York: The College Board. Retrieved from: http://research.collegeboard.org/sites/default/files/info2go/2012/8/infotogo-2011- 6-ap- participation-performance-major- choice.pdf

McKinsey (2016). "Haves" and "have mores": The Accelerating Digitization of the U.S. Economy.

McPherson, M., Smith-Lovin, L., & Cook, J.M. (2001). Birds of a Feather: Homophily in Social Networks. Annual Review of Sociology, 27, 415-444.

Medina, J. (2016). Website Meant to Connect Neighbors Hears Complaints of Racial Profiling New York Times (May 16, 2016).

Mercier, E. M., Barron, B. and O'Connor, K. M. (2006). Images of self and others as computer users: the role of gender and experience. *Journal of Computer Assisted Learning,* 22: 335–348.

Miley, L. (2015). Thoughts on Diversity Part 2. Why Diversity is Difficult. Medium.com (November 3, 2015). Retrieved from: https://medium.com/tech-diversity-files/thought-on-diversity-part-2-why-diversity-is-difficult-3dfd552fa1f7

Miller T., Triana M. (2009). Demographic Diversity in the Boardroom: Mediators of the Board Diversity–Firm Performance Relationship. Journal of Management Studies, 46(5), 755-786.

Morrill, D. (2014). How Mattermark Teamed Up With Bloomberg Beta to Predict Who Will Start Companies Next. Mattermark (March 26, 2014)

Moss-Racusin, C. A., Dovidio, J. F., Brescoll, V. L., Graham, M. J., & Handelsman, J. (2012). Science faculty's subtle gender biases favor male students. *Proceedings of the National Academy of Sciences,* 109(41), 16474 LP-16479.

Murphy, M. C., Steele, C. M., & Gross, J. J. (2007). Signaling threat: How situational cues affect women in math, science, and engineering settings. *Psychological Science,* 18(10), 879-885.

Nager, A. & Atkinson, R. (2017). *The Case for Improving U.S. Computer Science Education.* Information Technology and Innovation Foundation. Accessed at: www.itif.org

National Academies (2007). Rising Above the Gathering Storm: Energizing and Employing America for a Brighter Future.

National Center for Education Statistics (2016) Total Enrollment in Degree-Granting Post-Secondary Institutions (Table 303.10).

National Center for Education Statistics (2013). Enrollment and percentage distribution of enrollment in public elementary and secondary schools by race/ethnicity and region: Selected years, fall 1995 through fall 2023 (Table 203.50).

National Center for Education Statistics (2008). Education Longitudinal Study of 2002 (ELS:2002). Percentage of spring 2002 high school sophomores by the selectivity of the first postsecondary institution attended and select student characteristics (Table 4).

National Science Board (2015). Revisiting the STEM Workforce.

National Science Foundation (2016). Science and Engineering Indicators, 2016. Freshman intending to major in S&E fields by sex, race, and ethnicity (Table 2-16).

Nosek, B. A., Smyth, F. L., Sriram, N., Lindner, N. M., Devos, T., Ayala, A., & Greenwald, A. G. (2009). National differences in gender–science stereotypes predict national sex differences in science and math achievement. *Proceedings of the National Academy of Sciences of the United States of America,* 106(26), 10593–10597.

Oakes, J. (1985). Keeping Track: How Schools Structure Inequality. Yale University Press.

O'Brien, S. (2017). Months after sexual harassment allegations rock the tech world, not much has changed. CNN Tech (October 27, 2017).

Oliver, M. & Shapiro, T. (2006). Black Wealth, White Wealth: A New Perspective on Racial Inequality. Routledge.

Ong, M., Wright, C., Espinosa, L., Orfield, G (2011). Inside the Double Bind: A Synthesis of Empirical Research on Undergraduate and Graduate Women of Color in Science, Technology, Engineering, and Mathematics. Harvard Educational Review, 81(2), 172-209.

OpenMic (2017). Breaking the Mold: Investing in Racial Diversity in Tech.

Page, S. E. (2008). The Difference: How the Power of Diversity Creates Better Groups, Firms, Schools, and Societies.

Palmer, R. T., Maramba, D. C., & Dancy, T. E.. (2011). A Qualitative Investigation of Factors Promoting the Retention and Persistence of Students of Color in STEM. *The Journal of Negro Education,* 80(4), 491–504.

Papageorge, N. W., Gershenson, S., & Kang, K. (2016). Teacher Expectations Matter (IZA Discussion Papers No. 10165). Bonn. Accessed at: https://www.econstor.eu/bitstream/10419/147851/1/dp10165.pdf

Pew Research Center (2017). The Narrowing, but Persistent Gender Gap in Pay.

Pew Research Center (2017). U.S. Hispanic Population Growth Has Leveled Off.

Pew Research Center (2016). On Views of Race and Inequality, Blacks and Whites are Worlds Apart. Chapter 1: Demographic Trends and Economic Well-Being.

Pew Research Center (2015). The Demographics of Device Ownership. Pew Research Center, Internet and Technology.

Pew Research Center (2012). Digital Differences. Pew Research Center's Internet & American Life Project (2012).

PolicyLink & PERE (2015). An Equity Profile of the San Francisco Bay Area Region.

Price, J. (2010). The effect of instructor race and gender of student persistence in STEM fields. *Economics of Education Review,* 29(6), 901-910.

Quillian, L., Pager, D., Hexel, O., Midtboen, A. (2017). Meta-analysis of Field Experiments Shows No Change in Racial Discrimination in Hiring Over Time. PNAS, 114 (41), 10870-10875.

Rivera, L. A. (2012). Hiring as Cultural Matching. *American Sociological Review,* 77(6), 999–1022.

Roberson, Q. & Park, H. (2006). Examining the Link Between Diversity and Firm Performance: The Effects of Diversity Reputation and Leader Racial Diversity. Cornell University: Working Paper.

Robinson, M. (2017). A public university sends more grads to Silicon Valley's tech giants than any Ivy League school. *Business Insider.* May 2, 2017.

Rothwell, J. (2012). The Need for More STEM Workers. Brookings (June 1, 2012).

Sallomi, P. (2017). 2017 Technology Industry Outlook. Deloitte.

Schupak, A. (2015). Google Apologizes for Mis-tagging Photos of African Americans. CBS News (July 1, 2015).

Schwab, K. (2016). The Fourth Industrial Revolution: What it means, how to respond. World Economic Forum.

Scott, A., Klein, F.K., & Onovakpuri, U. (2017). The Tech Leavers Study.

Scott-Clayton & Li, (2016). Black-white disparity in student loan debt more than triples after graduation. Brookings Center on Children and Families. *Evidence Speaks Reports,* 2(3).

Segrest Purkiss, S. L., Perrewé, P. L., Gillespie, T. L., Mayes, B. T., & Ferris, G. R. (2006). Implicit sources of bias in employment interview judgments and decisions. *Organizational Behavior and Human Decision Processes,* 101(2), 152–167.

Shapiro, J. & Williams, A. (2012) The role of stereotype threats in undermining girls' and women's performance and interest in STEM fields. *Sex Roles.* 66(3-4), 175-183.

Skiba, R., Michael, R., Nardo, A., Peterson, R. (2002). The Color of Discipline: Sources of Racial and Gender Disproportionality in School Punishment. The Urban Review, 34 (4), 317-342.

Snellman, K, Silva, J. & Putnam, R. (2015). Inequity outside the classroom: Growing class differences in participation and extracurricular activities. Voices in Urban Education, 40, 7-13.

Snyder, K. (2014). The abrasiveness trap: High-achieving men and women are described differently in reviews. Fortune, Retrieved from: http://fortune.com/2014/08/26/performance-review-gender-bias/

Solorzano, D., Ceja, M., & Yosso, T. (2000). Critical Race Theory, Racial Microaggressions, and Campus Racial Climate: The Experiences of African American College Students. Journal of Negro Education, 69(1/2), 60

Steele, C. M., & Aronson, J. (1995). Stereotype threat and the intellectual test performance of African Americans. *Journal of Personality and Social Psychology,* 69(5), 797–811.

Steele, C. M. (1997). A threat in the air: How stereotypes shape intellectual identity and performance. *American Psychologist,* 52(6), 613-629.

Stroessner, S. & Good, C (2011). Stereotype Threat: An Overview. Excerpts and adaptations from reducingstereotypethreat.org.

Stout, J., Dasgupta, N., Hunsinger, M., & McManus, M. (2011). STEMing the tide: Using ingroup experts to inoculate women's self-concept in Science, Technology, Engineering and Mathematics (STEM). *Journal of Personality and Social Psychology,* 100(2), 255-270.

Stuart, T. E., & Sorenson, O. (2005). Social networks and entrepreneurship. In *Handbook of entrepreneurship research* (pp. 233-252). Springer, Boston, MA.

Stuart, T. E., Hoang, H., & Hybels, R. C. (1999). Interorganizational endorsements and the performance of entrepreneurial ventures. *Administrative science quarterly,* 44(2), 315-349.

Swift, M. (2010). Five Silicon Valley Companies Fought the Release of Employment Data and Won. San Jose Mercury News (February 11, 2010).

Talke, K., Salomo, S., & Kock, A. (2011). Top Management Team Diversity and Strategic Innovation Orientation: The Relationship and Consequences for Innovativeness and Performance. Journal of Product Innovation Management, 28(6), 819-832.

Tate IV, W. (1997). Critical Race Theory and Education: History, Theory, and Implications. Review of Research in Education, 22, 195-247.

Teare, G. (2017) In 2017, Only 17% of Startups Have A Female Founder. TechCrunch (April 19, 2017).

Tharenou, P. (1999). Gender differences in advancing to the top. *International Journal of Management Reviews,* 1(2), 111–132.

Tinkler, J., Bunker Whittington, K., Ku, MC, & Davies, A.R. (2015). Gender and venture capital decision-making: the effects of technical background and social capital on entrepreneurial evaluations. Social Science Research, 51, 1-16.

Traube, A., Sullivan, L., Meschede, T., Shapiro, T. (2017). *The Asset Value of Whiteness: Understanding the Racial Wealth Gap.* Demos/Institute on Assets and Social Policy.

U.S. Census Bureau (2017). The Nation's Older Population is Still Growing, The Nation's Population is Becoming More Diverse.

U.S. Census Bureau (2016). QuickFacts: Population Estimate, by Race and Hispanic Origin (July 1, 2016) and Gender (Female persons, percent, July 1, 2016).

U.S. Census Bureau (2016). Custodial Mothers and Fathers and Their Child Support: 2013.

U.S. Census Bureau (2015). Income, Poverty, and Health Insurance Coverage in the United States. Retrieved from: https://www.census.gov/newsroom/press-releases/2015/cb15-157.html

U.S. Dept. of Education (2016). Persistent Disparities Found Through Comprehensive Civil Rights Survey Underscore Need for Continued Focus on Equity. Retrieved from: https://www.ed.gov/news/press-releases/persistent-disparities-found-through-comprehensive-civil-rights-survey-underscore-need-continued-focus-equity-king-says .

U.S. Department of Education (2015). A Matter of Equity: Preschool in America. Retrieved from: https://www2.ed.gov/documents/early-learning/matter-equity-preschool-america.pdf

Vara, V. (2016). Why Doesn't Silicon Valley Hire Black Coders? Howard University Fights to Join the Tech Boom. Bloomberg (January 21, 2016)

von Hippel, E., Ogawa, S., de Jong, J.P.J. (2011). The age of the consumer-innovator. *MIT Sloan Management Review,* 53 (1) (2011), pp. 27-35.

Wakabayashi, D. & Schwartz, N. (2017). Not Everyone in Tech Cheers Visa Program for Foreign Workers. NY Times (February 5, 2017).

Walton, G. M., & Spencer, S. J. (2009). Latent ability: Grades and test scores systematically underestimate the intellectual ability of negatively stereotyped students. Psychological Science, 20(9), 1132-1139.

West, D.M. (2011). Technology and the Innovation Economy. Brookings Institution Report (October 19, 2011).

WestEd Center for Teaching and Learning (2011). High Hopes, Few Opportunities: The Status of Elementary Science Education in California. Retrieved from: https://wested.org/wp-content/uploads/2016/11/139932337432088StrengtheningScience_summ-3.pdf

Williams et al., v. The State of California (2000).

Women Who Tech (2017). Tech and Startup Culture Survey.

World Economic Forum (2016). The Future of Jobs: Employment, Skills and Workforce Strategy for the Fourth Industrial Revolution.

Zaff, J., Moore, K., Papillo, A., & Williams, S. (2003). Implications of Extracurricular Activity Participation During Adolescence on Positive Outcomes. Journal of Adolescent Research, 18 (6), 599-630.