Stemming the tide of inequality? Immigration, gender, and spatial income disparities in today's leading technological sectors

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Abstract: Income inequality in the United States is at an all-time high. The rise of inequality between people and places is being fueled by technological changes that heavily favor workers with college degrees, particularly those in fields related to Science, Technology, Engineering and Mathematics (STEM). But among workers in these leading technological sectors, who exactly is reaping the rewards? We answer this question through detailed analysis of nativity- and gender-based income disparities within STEM occupations, areas of work known to be disproportionately male and foreign born. After establishing that women earn around 15 percent less than men in STEM, we attempt to explain the income differentials in STEM through differences in the educational attainment, labor-force participation, occupational holding, and labor market contexts of US- and foreign-born, men and women. Contrary to expectations, we find that these adjustments actually *widen* the income deficit for women in STEM, and particularly so for foreign-born women. Women do earn significantly more when employed in the leading STEM labor markets, but the earnings gap relative to men is remarkably persistent across locations. Our findings confirm that the growth of the STEM work favors men, not only because they are more likely to work in these high-paying occupations, but because they also tend to get paid more within these occupations.

Keywords: STEM, immigration, inequality, gender, wage, labor market

1. Introduction

Technological change has been a key force behind the rise of inequality in the United States (Kemeny and Storper, 2020a). These changes have been fueled by the creation of new work in the areas of Science, Technology, Engineering and Mathematics (STEM). In the United States, STEM work now accounts for around 40 percent of GDP and 8.1 million workers. While the STEM labor force has doubled in size since 1990, participation has not been evenly distributed by gender or nativity. Foreign-born workers account for about 17 percent of the US labor force, but more than 24 percent of workers in STEM (American Association for the Advancement of Science, 2020; American Immigration Council, 2017). In many STEM fields, there are also more than three men to every woman. These compositional imbalances mean that the economic rewards generated in STEM are distributed unequally.

While the representational issues in STEM have been extensively documented, much less is known of the earnings disparities *within* STEM occupations (van Veelen et al., 2019). We ask, how large are these gender- and nativity-earnings differences within STEM occupations, and what forces might account for these disparities? We answer these questions by measuring earnings differences within STEM occupations by gender and nativity, and then examine the degree to which these outcomes can be explained by observable differences in individual's education, experience, occupation and location. To do so, we rely on information on STEM workers from the 2014-2018 American Community Survey Public-Use Microdata Samples (ACS PUMS) (Ruggles, 2021). We examine these data within an Oaxaca-Blinder decomposition framework.

There are many potential sources of earnings disparities by nativity and gender. Recent work suggests that spatial income inequality is being exacerbated by the concentration of "Big Tech" firms and the very high relative earnings of college educated workers living in "superstar cities" such as San Francisco and New York (Autor, 2019; M. Feldman et al., 2021; M. P. Feldman et al., 2021; Kemeny and Osman, 2018; Kemeny and Storper, 2020b). This is directly relevant to STEM work, which is often highly selective, skill-biased, and disproportionately concentrated in these high-income cities. Earnings disparities by gender and nativity could therefore reflect group-level differences in education and experience levels (Alegria and Branch, 2015; O'Keeffe, 2013; Wang and Lysenko, 2014), occupational holding (Colakoglu et al., 2018; Hanson and Slaughter, 2016), or place of residence (Grogger and Hanson, 2015, 2011). Our decomposition framework enables assessment of the role of these confounders in driving earnings disparities within STEM.

After accounting for confounders, our analysis reveals highly persistent earnings disparities within STEM occupations. We first document that foreign-born men in STEM earn more than their US-born counterparts. This difference can, however, be explained almost entirely by the fact that foreign-born men tend to hold higher education levels and are more likely to live in the leading STEM labor markets. This finding is consistent with the hypothesis that immigrants benefit from their greater propensity to settle in high-wage labor markets and gateway regions (Abramitzky et al., 2021).

Our analysis of gender tells a different story. While location, education and occupation explain most of the difference between men, these attributes explain very little of the difference between men and women. In fact, the adjustment for these observed differences widens the estimated earnings disparity by gender. Compared to men within the same occupations, locations and with similar levels of education, women earn 30 to 40 percent less than men on average. This difference is particularly pronounced for foreign-born women, who earn 18 percent less than even US-born women. Our analysis thus points to the rigid persistence of the gender earnings gap within STEM, and with a particularly large deficit for foreign-born women. In some respects, the earnings deficit associated with being a foreign-born woman resembles the “double disadvantage” that has been noted in other inequality contexts (Donato et al., 2014, 2006)

We conclude our analysis by assessing the role of geography and local labor market context in shaping these earnings disparities. Contrary to recent findings that document strong geographic effects on economic outcomes (Cavanaugh and Breau, 2019; Chetty et al., 2014; Connor and Storper, 2020; Eriksson and Hane-Weijman, 2017; Goodwin-White, 2018; Haus-Reve et al., 2021; Rothwell and Massey, 2015), we present a picture more of geographic similarity than of difference. While men and women both earn more on average when they work in leading STEM labor markets, the *relative* earnings gaps between US- and foreign-born men and women in STEM is surprisingly stable across urban contexts. These low levels of variation in gender-based disparities suggest that their underlying roots are pervasive across the US urban system.

2. Inequality in STEM

Our focus on STEM aims to capture areas of work that are highly specialized, relatively well remunerated, and at the technological frontier of the economy. Although there is no agreed-upon definition of STEM, STEM work is generally considered to rely on professional knowledge and quantitative analytical skills, directed toward information and problem solving in the context of rapid technology advancement (Bureau of Labor Statistics, 2014; U.S. Department of Education, 2022). STEM is regularly cited as the “future of the work” in expanding scientific frontiers, developing new products, and is portrayed as essential to America’s global leadership in innovation, economics and national security (Executive Office of the President of the United States, 2021). Our concern here is thus not only with the current situation of workers in STEM occupations, but potentially broadly toward work that is at the frontier of the economy and which may be a harbinger of what is to come.

2.1. Gender and nativity

The emergence of STEM work as a driving force behind the economy has had large and uneven impacts. STEM work tends to be rewarding for highly skilled workers and has substantially steepened the educational gradient in earnings (Kemeny and Osman, 2018; Kemeny and Storper, 2020a). While there has been much investigation into how these changes have affected inequality by educational attainment, much less is known about the source of disparities among workers with high levels of education. Furthermore, STEM work has also traditionally been conceptualized as a “pipeline”, in which women and minorities are disproportionately left out or left behind (Alegria and Branch, 2015). Less is known however about the economic outcomes and career trajectories of women and minorities who have successfully made into STEM occupations.

STEM provides a particularly interesting context for examining the economic attainment of immigrants. We know that when compared to immigrants in non-STEM sectors, foreign-born STEM workers tend to have smaller wage gaps and more quickly reach parity with their US-born counterparts (Hanson and Slaughter, 2016). This may be because foreign-born workers in STEM tend to be highly positively selected into STEM occupations due to their younger age profiles, their high levels of educational attainment, and requirements associated with H-1B visa sponsorship from tech firms (Hanson and Slaughter 2016). The relatively favorable position of immigrants in STEM could thus reflect their positive selection across a range of attributes.

We also know however that US-based employers tend to discount credentials that have been earned overseas (Wang and Lysenko, 2014). The positive selection of foreign-born STEM workers could therefore be dampened by an undervaluing of foreign-earned credentials and employers preference for domestic degree holders. There is also evidence that the overrepresentation of immigrant men in the information, communication and technology sector has led to saturation in some contexts, often leaving immigrants facing unusually competitive local labor market conditions (Wang and Lysenko 2014). We still however have a far from complete understanding of the exact position and circumstances faced by foreign-born STEM workers.

While nativity-based inequality in STEM is yet to be fully explored, we know more about gender-based inequalities in STEM (Raghuram, 2008). We know that women are underrepresented in STEM education and employment, and they earn less than men with similar qualifications (Beede et al., 2011; Xu, 2015). This could partly reflect the negative stereotyping and lack of role models for women in STEM (Griffith, 2010; van Veelen et al., 2019). Scholars also observe that women are also positively selected into STEM education and labor market, which might ameliorate the gender-based earnings disparity in STEM. However, despite the positive selection at the entry of STEM, women are also found lacking career persistency in STEM due to less favorable wage, lack of peer mentorship and networks, and family duties (Hardey, 2019; Hunt, 2016). However, we still know surprisingly little about the wage disparities at the intersection of gender and nativity in STEM occupations. Our work provides new insight on these economic disparities in STEM within a framework that addresses the interaction of gender and nativity (see Kofman and Raghuram 2006; Raghuram 2008; United Nations 2018; UN Women Headquarters 2018).

2.2. Spatial inequality

The unique and changing geography of STEM work may also influence earnings disparities among the highly educated. The economic and technological changes associated with the rise of STEM have been shown to have sizeable geographic effects, with serious consequences for intergenerational and interpersonal inequalities (Chetty et al., 2014; Connor and Storper, 2020). The rise of new work in fields related to STEM has depressed the wages of non-college workers, and sharply elevated the wages of highly-skilled workers, particularly those in the leading agglomerations (Autor, 2019). These agglomerations not only include superstar cities such as San Francisco and Boston, but also notable mid-size cities in the Research Triangle and the Pacific Northwest (Wright et al., 2017; Wright and Ellis, 2018). Locational differences between men and women or between the foreign- and US-born could plausibly exacerbate intergroup inequalities.

At the same time, labor markets specialized in STEM may also be conducive to lower levels of inequality. Large cities with high average levels of education tend to be highly conducive to skill acquisition and more rapid career advancement (Roca and Puga, 2017). It has been claimed that knowledge-based economies are more welcoming to immigrants and women because workers in these labor markets tend to hold more progressive values and are more open to cultural diversity (Florida, 2002; Florida and Mellander, 2016; Storper and Scott, 2009; van der Waal, 2012). Historical evidence shows that high levels of immigrant economic mobility has been a long running feature of the Pacific cities of the US, particularly those that are specialized in STEM today (Abramitzky et al., 2020; Connor, 2018).

There are also reasons to be skeptical about the role of STEM focused labor markets in attenuating intergroup inequalities. Wright et al. (2017) for example found that STEM agglomerations tend to disproportionately benefit white men in terms of qualification-based job matching. Goodwin-White (2018) also discovered that gender pay gaps tend to be declining more quickly in less economically dynamic regions, but this seems to mainly reflect the declining economic fortunes of men in these labor markets. These varying perspectives thus point to the high levels of uncertainty over the contribution of local labor market contexts to intergroup inequality.

3. Data and method

This research analyzes the annual wage differentials of STEM workers of different nativity and gender groups in the US using samples pooled from 2014-2018 American Community Survey Public Use Microdata Samples (ACS PUMS) dataset. We split the STEM workers into four nativity-gender groups including US-born and foreign-born men and women. As we are primarily interested in workers within the STEM fields, we restrict our sample to STEM workers (categorized by 2018 Bureau of Labor Statistics (BLS) Standard Occupational Classification (SOC) code) who are in civilian employment and aged between 25-65.[1] As there is no strict definition of how to classify occupations as "STEM", we adopt the broad definition provided by the Bureau of Labor Statistics (Bureau of Labor Statistics, 2014) and also examine heterogeneity across various STEM occupational groups. We exclude health-related occupations from this analysis because they often require different credentials and job duties than those of the "core" science and engineering related occupations in the STEM fields (National Science Foundation and National Science Board, 2022).

We should be cautious about quickly drawing conclusions from observed earnings differences by gender and nativity, because these groups also differ with respect to occupation, education, experience, and location. To appropriately investigate the role of these interpersonal differences in driving earnings disparities, we undertake an Oaxaca-Blinder decomposition. The Oaxaca-Blinder decomposition is a well-established method for studying wage differentials, as it facilitates group-level comparisons that adjust for confounding attributes (Blau and Kahn 2017, Goodwin-White 2018, Broyles and Fenner 2010). This approach enables us to calculate the persistence and

[1] This study choses population age 25+ as it will allow us to capture full college education because all US Census Bureau data count only those age 25 and above in educational attainment measures.

size of wage penalties by nativity and gender beyond differences in human capital, occupational holding or location across subpopulations.

We follow a three-fold decomposition structure. This technique decomposes the wage differential between two components, an “endowment” and a “coefficient”. The “endowment” component reflects the group differences in our dependent variable (wages) that be attributes to observables, such as education or work experience. The “coefficient” component is the residual group-level difference that cannot be unaccounted for by these observed (endowment) attributes. This residual or unexplained component captures the two groups’ difference in the effect of the independent variables, such as the differences in the earnings associated with education for men and women. A third “interaction” component is also included in the decomposition models: this measures the interaction of the endowment and coefficient components, such as the joint effect of women’s underrepresentation in high-paying occupations and their less favorable wages within those occupations.

Our three-fold approach relies on the estimation and comparison of 4 separate regression models. These models are estimated as a series of subsets for each of our *k* population categories of interest (foreign-born men, foreign-born women, US-born men, US-born women). While we are aware of the influence of foreign-earned credentials and visa status on the labor market outcome of foreign-born workers, we included all the Foreign-born as the ACS dataset doesn’t allow us to differentiate visa status or where the STEM workers obtain their education. For each group *k*, we estimate two models, presented in Equation 1 and Equation 2 below. Equation 1 estimates the wage differential between foreign-born men, the reference group, and the remaining three groups: foreign-born women, US-born men, and US-born women. This first model adjusts for differences across the four groups in terms of their age, race, ethnicity, education level and occupation. The second model, depicted in Equation 2, is identical to the first model but also considers the workers' metropolitan statistical areas (MSA) of residence. These models can be described as:

$$Y_{i,k} = \beta_{1,k}TIME_{i,k} + \beta_2 AGE_{i,k} + \beta_3 RACE_{i,k} + \beta_4 HISPANIC_{i,k} + \beta_5 EDUCATION_{i,k} + \beta_6 OCCUPATION_{i,k} + \mu_{i,k} \tag{1}$$

$$Y_{i,k} = \beta_1 TIME_{i,k} + \beta_2 AGE_{i,k} + \beta_3 RACE_{i,k} + \beta_4 HISPANIC_{i,k} + \beta_5 EDUCATION_{i,k} + \beta_6 OCCUPATION_{i,k} + \beta_7 MSA_{i,k} + \mu_{i,k} \tag{2}$$

where Y_i is the natural logarithm of the annual wage for individual *i* in group *k*, and these wages are estimated as a function of a range of individual-level characteristics. $TIME_i$ adjusts for the annual weeks and usual weekly hours worked in the previous year, *AGE* proxies for experience, highest degree attained is captured by *EDUCATION*, and we include indicators for race and ethnicity. *OCCUPATION* refers to a set of 34 STEM occupational categories per BLS's 6-digit SOC code to measure occupational selectivity, with Architectural and Engineering management occupations as the omitted reference group (highest average wage). We adopted the 34 STEM occupational categories as they are the most detailed SOC code found in the ACS datasets[2].

Standard errors are calculated using a non-parametric bootstrapping approach with 20,000 sampling replicates. The calculation and visualization are both conducted in statistical software R using the *Oaxaca* package (Hlavac, 2014).

[2] We adopted BLS's 6-digit SOC code, which contains 101 STEM occupations. However, due to the data compression in the ACS PUMS datasets, there are only 34 6-digit STEM SOC codes available.

4. Describing the personal and geographic profiles of STEM workers

Table 1. Wage, education and racial profiles of STEM workers in the US by nativity and gender.

		Total in Non-STEM	Total in STEM
All	N	79054253	3835154
	Share	100%	100%
	Wage	57569.23	90389.59
	Bachelor	23.73%	43.98%
	Master's	12.58%	24.34%
	Doctorate	0.91%	4.36%
	Weekly hour	40.6	43.0
	% White	56.60%	64.68%
Foreign-born men	n	10457535	676082
	Share	13.23	17.63%
	Wage	27413	102052.8
	Bachelor	16.84%	39.60%
	Master's	11.10%	35.72%
	Doctorate	1.30%	9.64%
	Weekly hour	41.9	42.6
	% White	16.78%	23.28%
Foreign-born women	n	8115595	253317
	Share	10.27%	6.61%
	Wage	39917	77079
	Bachelor	20.94%	39.33%
	Master's	12.18%	38.83%
	Doctorate	1.02%	10.35%
	Weekly hour	37.4	42.0
	% White	17.30 %	21.00%
US-born men	n	31488600	2162493
	Share	39.83	56.39%
	Wage	71268	93950.24
	Bachelor	24.47%	45.88%
	Master's	11.22%	19.36%
	Doctorate	0.84%	2.45%
	Weekly hour	42.0	43.1
	% White	70.32%	80.00%
US-born women	n	28992523	743262
	Share	36.67%	19.38%
	Wage	47687	73957.49
	Bachelor	26.19%	44.00%
	Master's	14.69%	23.52%
	Doctorate	0.82%	3.08%
	Weekly hour	38.29	41.7
	% White	67.06%	74.08%

Note: Annual wage in US$ adjusted to 2018 value. These values are derived from the weighted estimates from the 2014-2018 ACS PUMS datasets. Samples are selected from the 100 largest MSAs in the US, aged 25-65 years old.

4.1. Personal attributes

We begin by introducing some broad descriptive features of economic inequality within STEM. **Table 1** provides summary statistics from the PUMS dataset on the earnings and educational profiles of workers in and outside of STEM. For each of our four categories of worker, we provide the total and share of workers, their annual wage, educational profile, and weekly hours worked. These statistics provide direct insight into the composition of STEM, differential selectivity on education, and also earnings disparities by group.

The distributional statistics reconfirm the well-known gender imbalance in STEM and non-STEM occupational holding. The share of US- and foreign-born women working outside of STEM is almost twice as high as the share of women working within STEM. US-born men, in contrast, are the most overrepresented group within STEM occupations. While roughly 56 percent of STEM workers are US-born men, who contribute just under 40 percent to the non-STEM labor force. Foreign-born men, in contrast, are the most balanced group across the two sectors, making up 13.23 percent of workers in non-STEM occupations and 17.63 percent of workers in STEM occupations. It is worth noting, however, that the average wage for all four groups is substantially higher for those that work in STEM.

There are two notable features of the wage differences across the four groups working in STEM. Firstly, men earn substantially more than women. US-born men earn around 27 percent more than US-born women, and foreign-born men earn 32 percent more than foreign-born women. The earnings gap is thus quite similar for both immigrants and the US-born. These gender-based earnings gaps are narrower in percentage terms than what is observed outside of STEM.

The wage gaps by nativity are somewhat more surprising. Outside of STEM, US-born workers earn more on average than the foreign-born. The advantage for the US-born is such that US-born women actually earn more than do foreign-born men. Within STEM occupations, however, the situation is reversed. Foreign-born workers in STEM earn more than their US-born counterparts, by about four percent for women and by eight percent for men. This foreign-born earnings advantage is thus something of an unusual feature of the STEM sector.

The educational distributions provide a strong clue as to what could account for these earnings patterns by gender and nativity within STEM. While foreign-born men earn significantly more than US-born men, they are also much more likely to hold an advanced degree. Compared to their US-born counterparts, foreign-born men are around twice as likely to possess a Master’s degree and around four times more likely to hold a doctorate. Similar disparities are evident between US- and foreign-born women. What is not explained by these distributions however is why US- and foreign-born women have higher educations than their male counterparts, but still earn substantially less.

4.2. Occupational differences

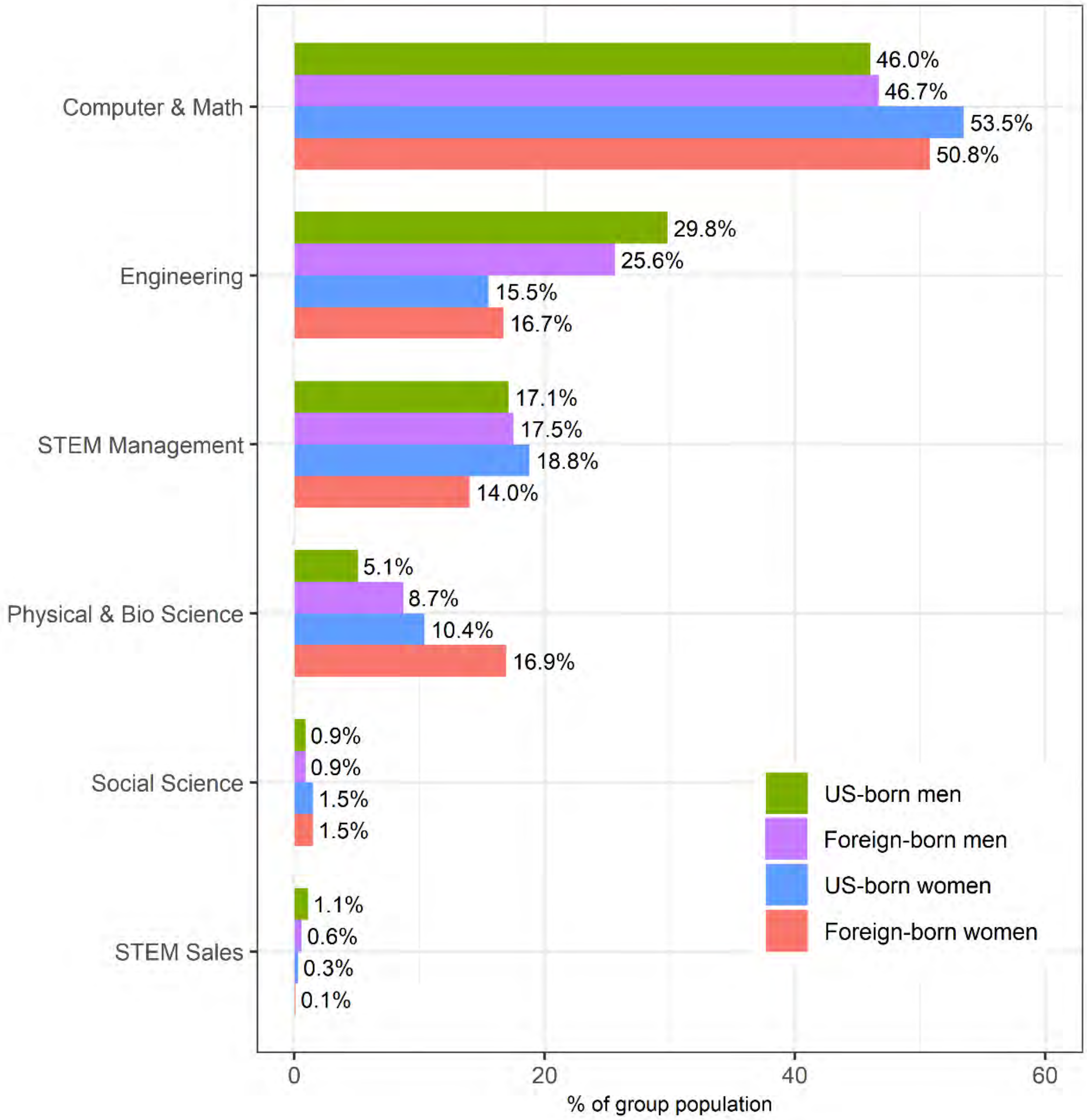


Figure 1 Share of each nativity-gender group employed in different STEM occupations. These 6 categories are derived from BLS's 6 STEM broad groups SOC code. See Appendix.A for detailed occupational distributions across the four groups.

We also observe highly uneven distributions of the groups across different STEM occupations. **Figure 1** show the distribution of each of our four color-coded categories of workers across six broad STEM occupational categories. Each bar represents the share of STEM workers from a particular nativity-gender group that is employed in the corresponding occupation category. This means that for any given group, (e.g., foreign-born women), their bars will sum to 100 percent.

Perhaps counter to expectations, women within STEM are more likely than men to work in occupations associated with computers and math. Almost 54 percent of US-born women work in these fields, while that value is only 46 percent for US-born men. To clarify, this does not mean that 54 percent of workers in computers and math are women, it means that 54 percent of the women in STEM overall work in this fields. In fact, women make up only 29 percent of workers in the fields of computers and math. A similar, albeit smaller, difference is evident among the foreign-born. Women, US- and foreign-born, are also substantially more likely to be found in the physical and biological sciences, and in the social sciences. Note, these statistics do not imply that women make up the majority of workers in these areas, because there are far fewer women in STEM overall and so they are actually a minority in all fields.

The main area of over concentration for men is in the field of engineering. Compared to women, men in STEM are from 10 to 15 percentage points more likely to work in engineering. This gap makes men around twice as likely to be found in the engineering field than women. Men are also more likely to work in sales occupations, but as can be seen from the small percentages, these occupations make up a relatively small share of jobs in the STEM sector.

4.3. Geographic differences

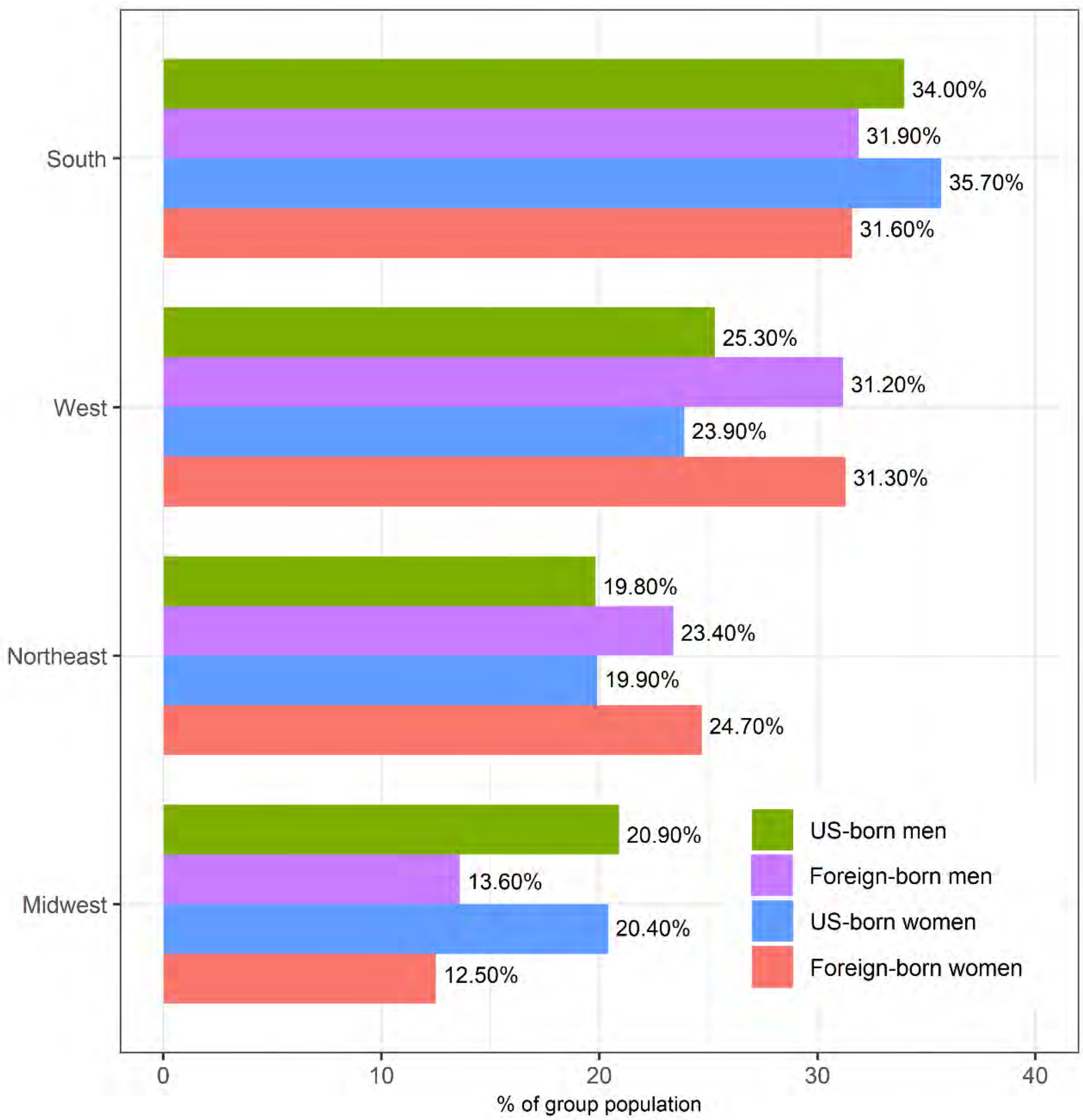


Figure 2. Share of each nativity-gender group reside in different regions. See Appendix.B for group population distribution across census divisions

We also note that US- and foreign-born men and women live in different places, and these places are characterized by different contexts with respect to inequality. **Figure 2** presents the regional distribution of our four worker categories within STEM. Similar to Figure 1, the color-coded bars represent share of workers from each group that reside in a given region. While we know that four census regions are a coarse geographic aggregation, we present it here to illustrate our point in the simplest fashion.

The primary differences in the regional geography of our four groups are by nativity, and not by gender. US-born workers in STEM are more likely to live in the South and the Midwest than are foreign-born workers. In contrast, foreign-born workers are much more likely to live in the West and the Northeast. This is not surprising given that the West and the Northeast are home to many of the major immigrant gateway regions. This is a point of particular significance as these regions also contain many of the most dynamic STEM labor markets, such as San Francisco, Boston, Seattle and Los Angeles. The disproportionate residence of the foreign-born in these regions could help explain their higher average wages. It is also worth noting that, overall, men and women tend to live in similar places when grouped according to their place of birth. That is, US-born men and women tend to be similarly distributed across regions, as are foreign-born men and women.

Our final descriptive figure provides insight into the geography of inequality across the groups. For the 100 largest Metropolitan Statistical Areas (MSAs) we calculated the GINI index for all STEM workers and decomposed this GINI index by the four nativity-gender groups. **Figure 3** maps this measure as a means of describing the geography of intergroup inequality. Places with higher values on the GINI index (higher inequality) are labeled with larger red circles, and places with lower values (lower inequality) are colored blue.

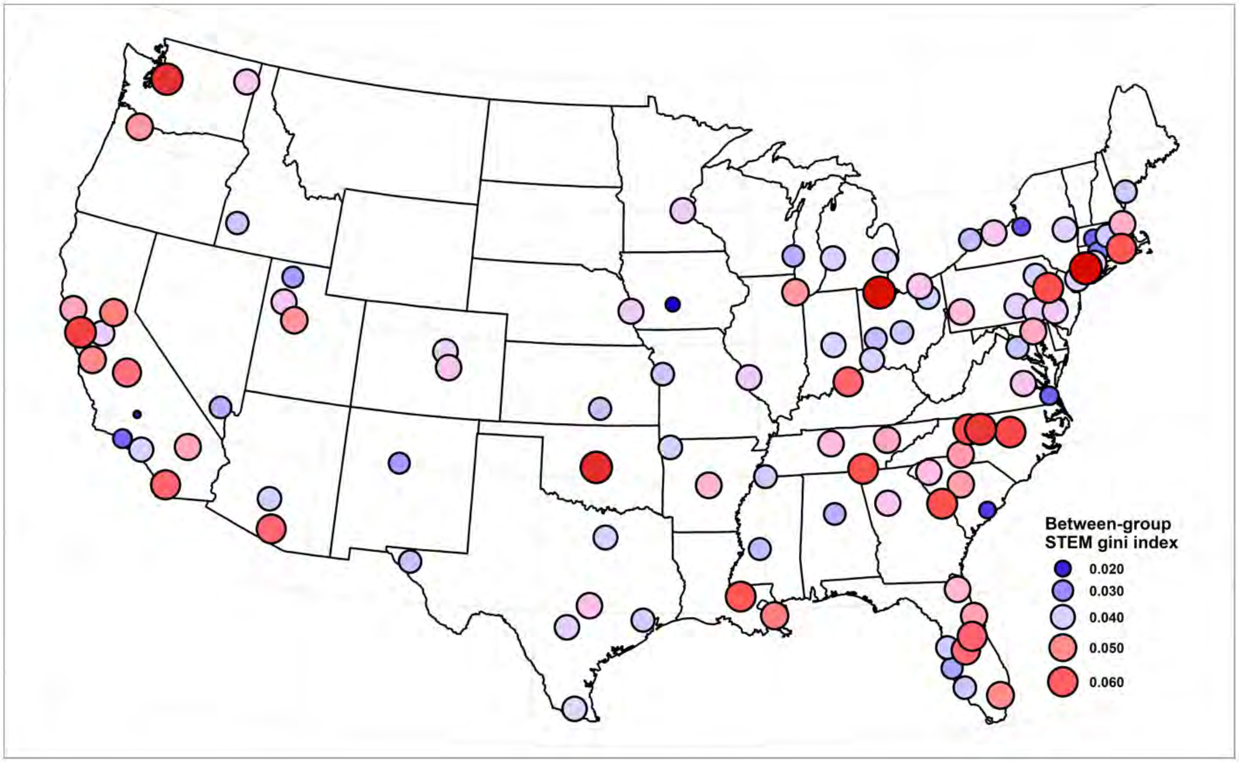


Figure 3. Between-group GINI index among STEM workers in the 100 largest MSAs in the US. These estimates are calculated from the group-wise decomposition of the GINI index among the STEM worker sample by the 4 nativity-gender groups. See Allanson(2014) for more details.

Figure 3 reveals a very striking pattern in that many of the largest intergroup earnings disparities among STEM workers also tend to be in the most economically dynamic regions of the country. The Bay Area in California, San Diego and Seattle all stand out as high inequality contexts. Elsewhere in the country, the Northeast, Florida, and the Research Triangle of North Carolina are also places of high inequality. Interestingly, inequality is far weaker in the interior states, the Midwest, and Texas. Recall that this map only shows the 100 largest metropolitan regions, so these differences are not a reflection of urban and rural places. Instead, they appear to be capturing the fact that the most dynamic STEM labor markets also tend to exhibit the highest levels of inequality.

Taken together, our descriptive geographic patterns thus suggest that the leading STEM labor markets and regions are characterized by high levels of inequality, but also disproportionate shares of the foreign-born. The analysis that follows thus tries to decompose and explain earnings inequality within our more formal statistical framework.

5. Results

5.1. Summary of main results

Before exploring the fine details of our analysis, we begin by previewing our key results and specifications in **Figure 4**. The intuition of our analysis is that we first want to measure the earnings differences across our four groups, and then attempt to explain these differences based on the broad range of factors discussed above. **Figure 4** plots the differences in the natural log of wages for three of our four groups. The omitted reference group are foreign-born men, who are highest earners at baseline. We represent this group with the vertical zero line.

Model I presents the average differences between our four groups with no additional controls. These baseline estimates are simply a recalculation of the average earnings differences that we showed earlier in the descriptive statistics. The highest earners at baseline are foreign-born men. Foreign-born earn substantially more than US-born men and foreign-born women, and both of these groups earn substantially more than US-born women. As we have documented, however, these groups vary across many other dimensions, and so it is unclear to what extent these differences are an accurate picture of economic inequity and to what degree these differences mainly reflect underlying differences in attributes like education or location across these groups.

Model II adjusts our estimates for a large batch of control variables including average working hours, weeks worked, age, race and ethnicity, educational attainment, and occupational holding.

Adjustments for these variables produce very substantial changes in the estimated wage disparities across the four groups. The first notable change is that the difference between US- and foreign-born men almost disappears, and if anything, now US-born men are now estimated to hold a slight earnings advantage. This means that the earnings difference between US- and foreign-born men can be explained almost entirely by the differences in the observed attributes of the two groups. Worded differently, if we took a US-born man and a foreign-born man who held the same occupation, and who were of the same age and education level, we could expect to find minimal differences in earnings.

While the adjustments in Model II narrow the difference among men, the gap between men and women is a very different picture. From Model I to Model II we see a very substantial divergence in earnings by gender, with men earning substantially more. This change partly reflects the fact that the average woman in STEM has a higher level of educational attainment than the average man, but still earns less at baseline. Thus, when we consider a man and a woman in the same occupation, with the same educational and personal characteristics, we find a significant earnings penalty for woman. Furthermore, we note that this penalty is particularly pronounced for foreign-born women, even relative to US-born women.

In Model III, we make one final adjustment for the different distribution of workers across metropolitan areas. This entails adding a fixed effect to remove the variation in wages that can be attributed to different local labor market contexts. This adjustment results in no substantial change in the earnings differentials between the four groups. The earnings gap between men and women further widens, and the difference among men remains relatively small.

The change estimates across the three models lend themselves to a very simple interpretation. Observable attributes can explain almost all of the earnings differences among men, but these same attributes actually lead to an underestimation of the true gap between men and women, a deficit that is particularly heavily felt by foreign-born women. Our overall story thus points to an enduring gender-based disparity in wages, and negative interaction between gender and nativity on the earnings of foreign-born women. The remainder of the results discusses the specifics of this analysis in greater detail, before concluding with further examination of the role of local labor market contexts.

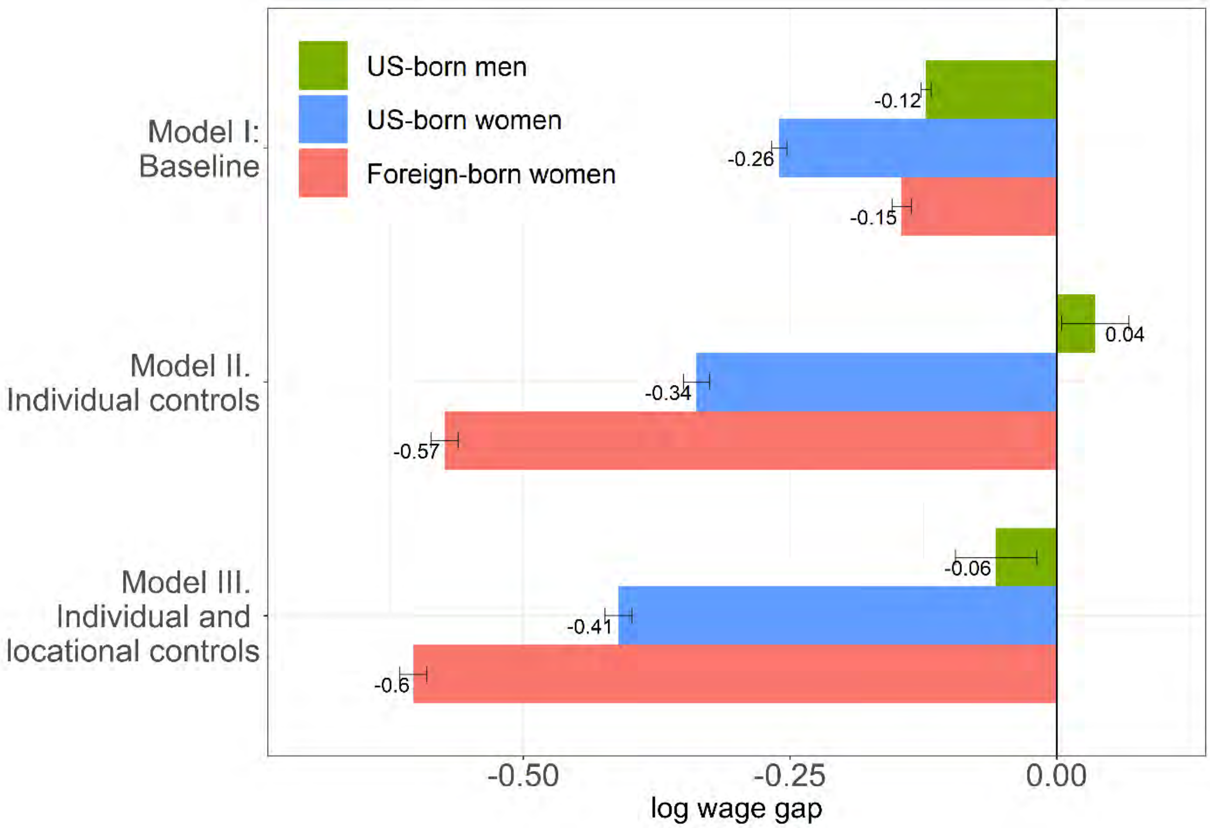


Figure 4. (log)Wage gap comparison, before and after individual endowment characteristics and location adjustment. Foreign-born men's average log-transformed wage (11.39587) is the reference group. Confidence intervals are constructed at 95% level. Model II controlled for working time, and personal attributes including age, race and ethnicity, education and occupations. Model III adds locations to Model II's controls.

5.2. Detailed decomposition of wage disparities

Table 2. percentage of wage gap explained by group differences in each decomposition components

	US-born Men	Foreign-born Women	US-born Women
	(Ref = Foreign-born Men)		
Baseline			
Wage gap	-6123	-26752	-28154
Log wage gap	-0.124	-0.145	-0.258
Model II. Individual controls			
Endowment	**67.6%**	**13.1%**	**35.1%**
Working hour & week	3.6%	-0.1%	0.1%
Age	2.4%	6.7%	0.4%
Race and ethnicity	-22%	0.3%	0.1%
Education	75.3%	-8.3%	29.2%
Occupation	8.3%	14.5%	5.3%
Coefficient	**29.4%**	**83.5%**	**55.6%**
Interaction	**-3.0%**	**-3.4%**	**9.2%**
Model III. Individual & locational controls			
Endowment	**99.6%**	**11.5%**	**46.0%**
Working hour & week	5.4%	0.1%	0.4%
Age	-8.6%	8.6%	-2.9%
Race and ethnicity	-5.1%	1.1%	1.7%
Education	65.2%	-8.1%	26.6%
Occupation	6.3%	13.1%	3.8%
Metropolitan Area	36.4%	-3.2%	16.4%
Coefficient	**43.0%**	**81.7%**	**60.3%**
Interaction	**-42.6%**	**5.7%**	**-4.8%**

Note: The Working hour & week variables contain 2 sets of variables controlling for weeks worked in the previous year and average hours worked per week. The week variables contain 6 groups including 50-52 weeks (reference), 1-13, 14-26, 27-39, 40-47 and 48-49 weeks. The hour variables range from 1 to 80, with 40 hours per week as reference. Age variables contain 4 age groups including 25-34 (reference), 35-44, 45-54 and 55-65. The Race and ethnicity variables included contain 5 groups including non-Hispanic white (reference), Asian, Black, Hispanic and Others. The Education variable contain 5 different levels including bachelor's (reference), no college education, some college education, master's, and doctoral degrees. The Occupation variables contain 34 different STEM occupations in accordance with BLS's 2018 SOC codes, with engineering management as the reference category. The Metropolitan Area variables contains the largest 100 Metropolitan Statistical Areas in the US, with San Jose-Sunnyvale-Santa Clara MSA was set as the reference category. See appendix E – G for detailed coefficients.

We begin our description of the specific results with the first decomposition analysis (Model II). **Table 2** provides a detailed breakdown of the share of the (log) wage differentials that can be attributed to group differences in personal attributes (endowment), the differing effects of the independent variables on different groups (coefficient), and the compounding influence of the endowment and the coefficient terms (interaction). Column 1-3 summarizes the decomposition results for each group relative to foreign-born men. For completeness, we supplemented two models comparing the wage differentials between foreign-born women (reference) and US-born women, and the wage differentials between US-born men (reference) and women[3]. The percentages in each row can be interpreted as the share of the wage differential that is attributable to a given set of independent variables.

The percentage associated with the endowment describes the share of variation in wages that is explained by the observed independent variables. As discussed above, personal attributes explain 68 percent of the earnings differences between foreign-born men and US-born men, 35 percent of the gap with US-born women, but only 13 percent of the difference with foreign-born women. These estimates confirm the earlier finding that observed characteristics explain much of the difference between foreign- and US-born men, but far less of the difference between men and women.

Below the endowment values, we also provide a detailed breakdown of the relative contribution of different groups of variables. These statistics highlight the salience of different attributes depending on the comparison in question. Notably, for the comparison between US-born men and foreign-born men, education is by far the most important difference, explaining 75 percent of the variation between the two. While occupational differences matter between US- and foreign-born men, occupational differences contribute only 8 percent. This provides quite strong

[3] See appendix C

evidence that the higher average educational attainment of foreign-born men provides much of the explanation for why they earn more than US-born men.

The contributions to the differences between US-born women and foreign-born men follows a somewhat similar pattern. While the overall contribution of the endowment in the model for US-born women (35.1 percent) is substantially smaller than it is for US-born men (67.6 percent), similar factors seem to be at play. The only factors that make a major contribution in explaining these differences are educational attainment (29.2 percent) and occupational holding (5.3 percent). This means that the main difference in the models for US-born men and women is that endowment characteristics explain only about half the earnings gap for US-born women as they do for US-born men.

The story for foreign-born men and foreign-born women is qualitatively different. Age, a proxy for experience, explains 6.7 percent of the earnings difference between these groups and occupation explains around 14.5 percent. The negative coefficient on the educational component for foreign-born women implies that the higher educational attainment of foreign-born women means that the true earnings difference is actual underestimated in the baseline comparison of earnings means. Overall, the contribution of the endowment to the gap between foreign-born men and women is small, but the factors that do matter appear to be mainly career focused (experience and occupational holding).

Our second decomposition model adds the extra adjustment for metropolitan area of residence (Model III). The main finding from this analysis is that metropolitan area of residence makes a significant contribution to the endowment term. Compared to foreign-born men, metropolitan area of residence explains about 36.4 percent of the earnings difference for US-born men and 16.4 percent of the difference for US-born women. For foreign-born women, the contribution is negligible and slightly negative. This implies that a substantial share of the earnings gap between foreign-born men and US-born men and women can be explained by the disproportionate residence of foreign-born men in high-income labor markets. Foreign-born women tend to live in similar locations to foreign-born men, so location explains none of the gap between these two groups.[4]

Finally, while race and ethnicity are important factors in explaining within group wage differentials, they make a relatively small contribution to the expected earnings gaps across these four groups. Only among foreign-born and US-born men do we find a substantial contribution (-22 percent), and the value is negative. This reflects the fact that US-born men are more likely to be white, and because whites tend to earn more, racial differences across groups are not a plausible explanation for the gaps that we observe here.

5.3. Differential effects of personal characteristics on earnings

On the whole, our decomposition models reveal that observable characteristics (education, age, occupation, etc.) explain surprisingly little of the earnings differences between men and women. This is evident in low contributions of the "endowment" values for women and the relative high contributions of the "coefficient" values. Recall that the coefficient values indicate the degree to which the earnings associated with the independent variables differs across groups. In this section, we explore this possibility in detail. This enables us to explore, for example, the extent to which women with PhDs or women working as engineers get paid less than men who work in the same fields or who hold the same qualifications.

[4] Our location-only models show that the location difference and location effect both play significant role in determining nativity-based wage differentials. See appendix.D for detail

We begin with two figures, one showing the varying effects of education and race (**Figure 5**) and another that examines differences across occupations (**Figure 6**). The color-coded bars refer to the exponentiated values of the expected log-transformed wage of foreign-born and US-born men and women. **Figure 5** summarizes the effects of race and ethnicity (non-Hispanic White as reference group) and education (Bachelor's as reference group), and **Figure 6** summarizes the average effect of the 34 STEM occupations, grouped in 6 broad occupation groups.

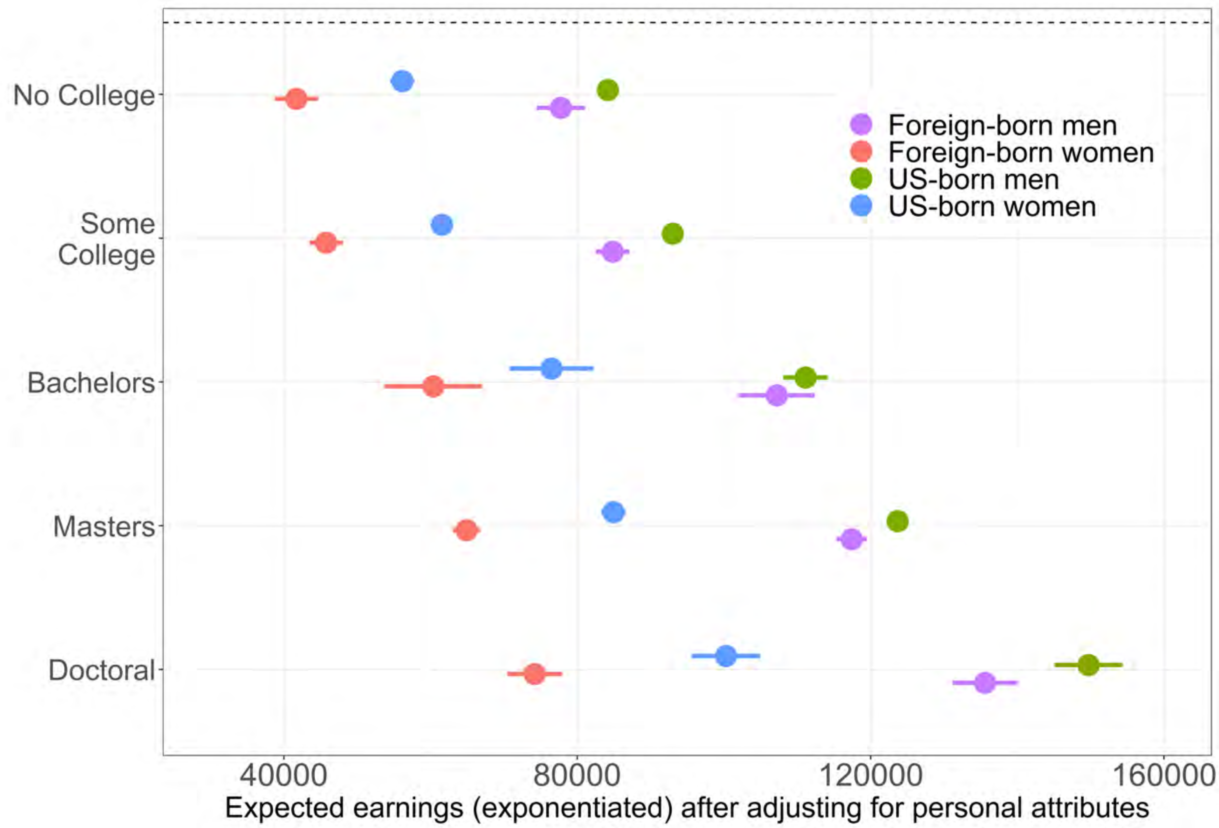


Figure 5. Expected earnings derived from the estimates in Model II, effects of Race, ethnicity, and education. These estimates are exponentiated fitted values derived from the three sets of decompositions from model 1, analyzing the working time adjusted (log)wage gaps between Foreign-born women, US-born men and women, and the reference group: foreign-born men, 25-35 years old, bachelor's degree, engineering management occupation. The confidence intervals are constructed at 95 percent level. See Appendix.E for detailed coefficients and fitted values of race, ethnicity and education.

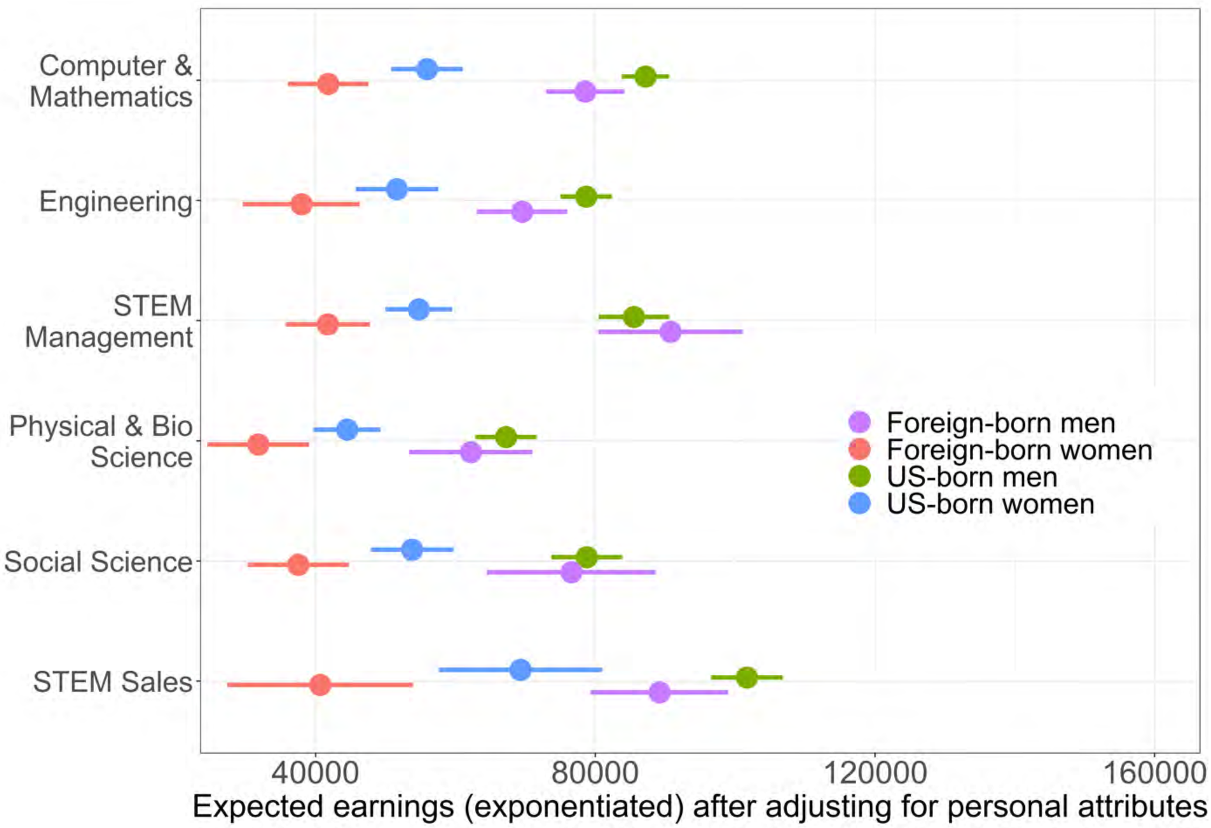


Figure 6. Expected earnings derived from the estimates in Model II, Average effects of STEM occupations. These estimates are derived from the average effect of STEM occupations under BLS's 6 broad STEM occupation categories. See Appendix.F for detailed occupational effects. Engineering management is the omitted reference category.

5.3.1. Education attainment effect

Figure 5 demonstrates two notable features as to the earnings gaps by educational attainment. Firstly, at all levels of education, the relative ordering of the groups is highly stable. US-born men earn the most, followed closely by foreign-born men, then US-born women and finally foreign-born women. Irrespective of educational level, this broader earning disparity structure is stable.

The second notable feature with respect to education is that the between-group disparities widen with higher levels of education. There is a relatively narrow range of earnings across the four groups in the “no college” and “some college” categories. At the bachelor’s and Master’s degree levels, the gaps widen somewhat, and finally among PhDs, we see by father largest gap between the lowest earning group (foreign-born women) and the highest earning group (US-born men).

5.3.2. Occupational effect

Figure 6 presents the estimated earnings gaps across the major occupational categories. As mentioned above, these estimates are derived from 34 major STEM occupations, but we aggregate these estimates up to the six broad categories shown here. Once again, women earn less than men across the board, and foreign-born women are the lowest earners in each occupation. There are some notable differences across occupational areas though. The earnings gaps in the social, physical and biological sciences for the four groups are relatively small, which is notable give that these occupations also tend to have lower average levels of earnings. Contrastingly, the earnings gaps are substantially larger in the fields of engineering, computers, mathematics, and management. While US-born women seem to do relatively well in sales compared to other occupations, it is worth nothing that this is by far the smallest of the occupational classes.

5.4. Geographic influences on earnings

Our final set of results examine the extent to which local labor market context shapes intergroup inequality. We begin by examining whether the size of the earnings disparities across groups varies with the local STEM labor market. For example, is the earnings disadvantage higher for women in STEM labor markets that are more specialized in computers and math? For the 100 largest metropolitan areas, we explore these relationships based on the average wage in STEM, the share of STEM workers in the local labor force, the share of STEM workers with a master’s degree or PhD, and the share of STEM workers in computer and math. We visualize these relationships in **Figure 7**, which uses four sets of local regression models to fit a set of non-linear curves.

Stability is the overarching feature of these graphs. For the most part, the relative differences in earnings levels between each of the four groups remains largely similar irrespective of how the labor markets differ. In general, the more STEM concentrated the labor market is, the higher the average earnings for all four groups. This holds for metropolitan areas with higher average wages, higher STEM shares and more educated STEM labor forces. Furthermore, the relationships appear to become less noisy and more precisely defined the more that the metropolitan area is focused on STEM. This is evident in that as the fitted lines slope upwards, the curves become increasingly stable.

The final panel of **Figure 7** does not capture the local scale of the STEM labor market, but rather its specialization in the largest class of STEM occupations, computers and math. We find relatively stable associations between specialization in these areas and the average wages across the four groups. For the most part, we do not find an obvious change in either the average wages of groups, or the wage differentials across groups, based on whether the labor market is specialized in computers and math.

The differences presented in these graphs do not lend themselves to strong claims regarding geographically varying inequality. Once we adjust for differences in the attributes of workers across locales, we actually find a great deal of consistency in the higher earnings of men relative to women. This consistent also holds for the relatively large earnings deficit for foreign-born women. Our findings thus suggest that whatever the source of these intergroup disparities in earnings within STEM, they are widely pervasive across the major labor markets.

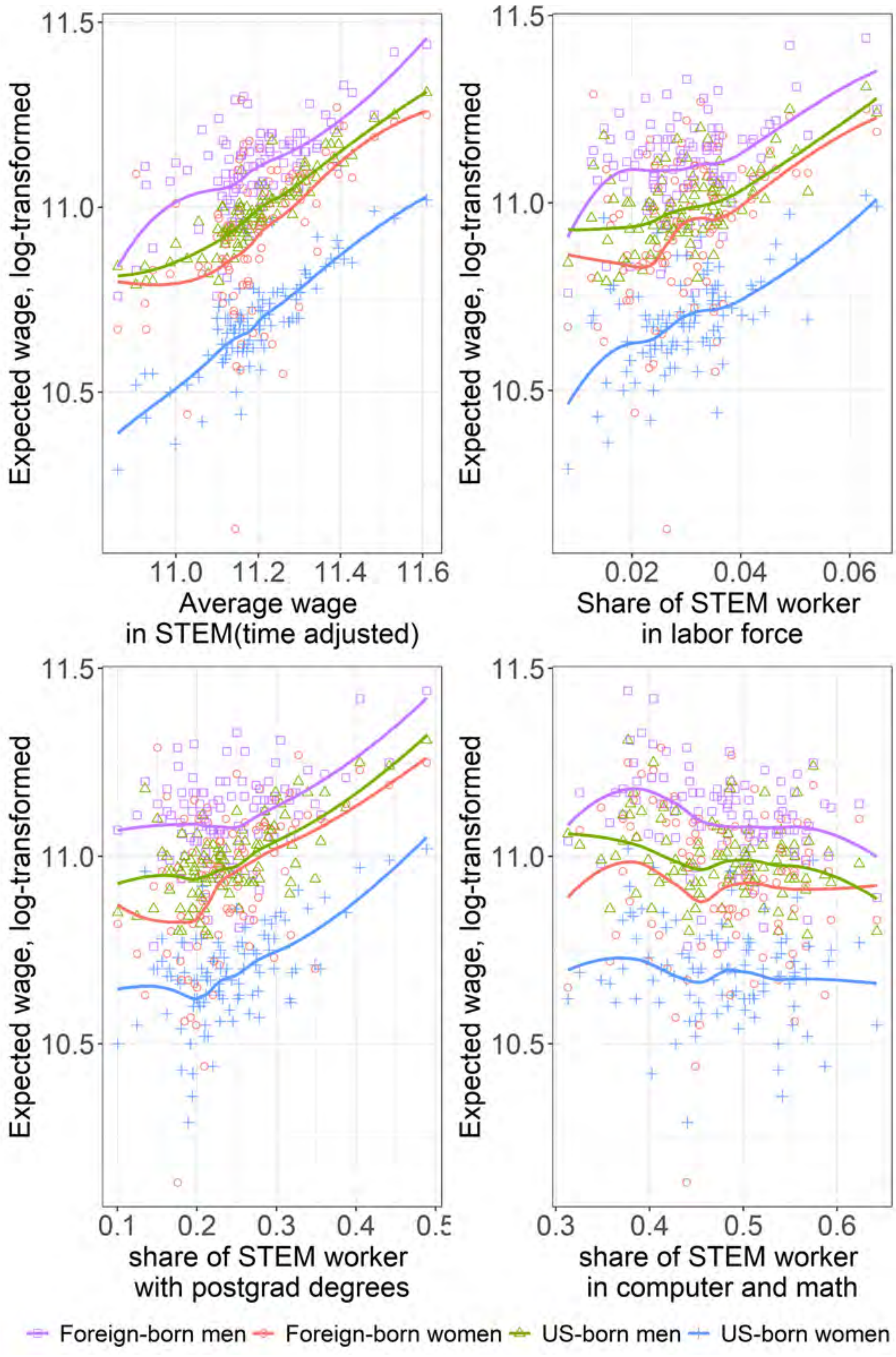


Figure 7. Local regression models between expected earnings in STEM and regional features. These estimates are derived from the fitted values of the 4 nativity-gender groups from Decomposition 2, model 1. The four models summarize the effect of time-adjusted average wage in STEM, the share of STEM workers in the labor force, the share of STEM workers with postgraduate degrees, and the share of STEM workers in computer and mathematics occupations across the largest 100 MSAs in the US.

6. Conclusion

The industries and fields associated with Science, Technology, Engineering and Mathematics have taken center stage in American economy, but relatively little is known about who is reaping the rewards of the current technological revolution. This paper examines how inequality within STEM along the axes of gender and nativity. We applied a decomposition analysis to the American Community Survey to measure the nature of earnings disparities within STEM and then try to account for these differences using personal and locational attributes.

Our first major findings document a reasonably rigid structure of earnings inequality within STEM, with US- and foreign-born men earning the most, and women earning the least. Earnings disparities observed among US- and foreign-born men can largely be attributed to differences in standard observable confounders such as educational attainment, experience, and location. There are thus relatively straightforward explanations for the observed earnings disparities among men.

The differences between men and women are much more difficult to explain. Although women are underrepresented in STEM, they are well educated relative to men. This means that women are highly positively selected into STEM on education. Once we account for women's education levels, occupations, and locations, however, they hold an even larger earnings deficits relative to men than what is implied by the raw data. After adjusting for personal differences, the gender-based earnings disparity widens from 15-20 percent to between 30 and 40 percent. This wage penalty is especially strong for foreign-born women, who earn almost 20 percent less than even US-born women. This is all to say that women's relatively high baseline level of education partly disguises to true size of gender-based earnings disparities within STEM.

Our final finding highlights the rigidity of these disparities across urban labor markets. Social scientists have recently been documenting strong geographical effects on personal outcomes

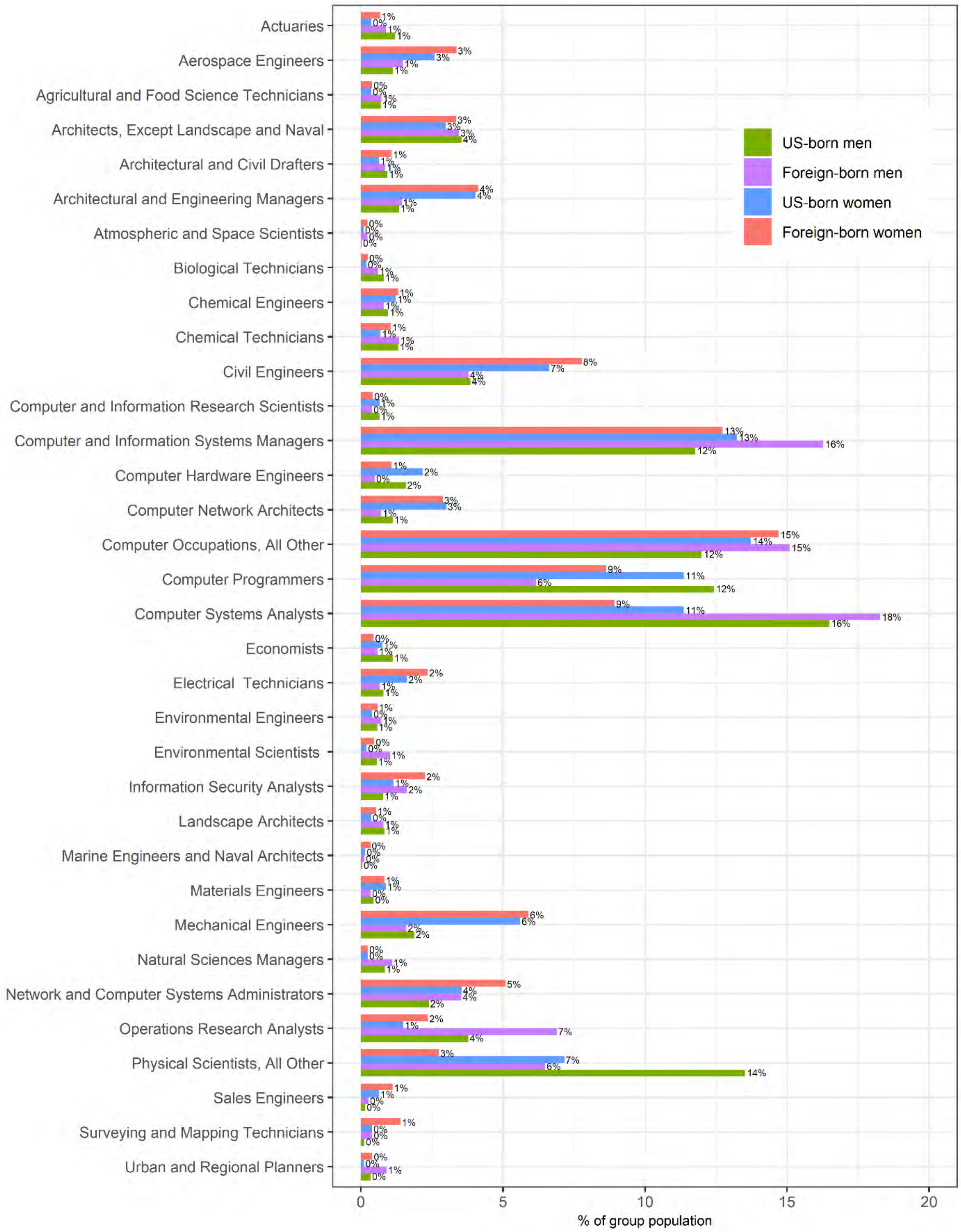
(Cavanaugh and Breau, 2019; Chetty et al., 2014; Connor and Storper, 2020; Eriksson and Hane-Weijman, 2017; Goodwin-White, 2018; Haus-Reve et al., 2021; Rothwell and Massey, 2015), but our analysis reveals something different. The relative earnings disparities between US- and foreign-born men and women in STEM is remarkably stable across space. Worded differently, while all four groups earn more on average in the leading STEM labor markets, the relative gaps between the groups are highly resilient. This finding closely aligns with recent work highlighting the surprising persistence of place-based structural inequalities in major metropolitan areas (Wright et al., 2017). The main takeaway from this finding is that whichever forces are driving these disparities, they are very deeply rooted.

Overall, our findings point to large earnings deficits for women, particularly foreign-born women. The situation of foreign-born women resembles the double disadvantage observed by other scholars (Donato et al., 2014; van Veelen et al., 2019). We cannot provide conclusive evidence on why exactly foreign-born women experience such a disadvantage, but we have provided strong evidence that it is not due to their age, occupation, educational attainment, or location within the United States. This means that unobserved factors such as discrimination, immigration status, or non-cognitive skills, could be at work here (Alegria and Branch, 2015; Grove et al., 2011; United Nations, 2018).

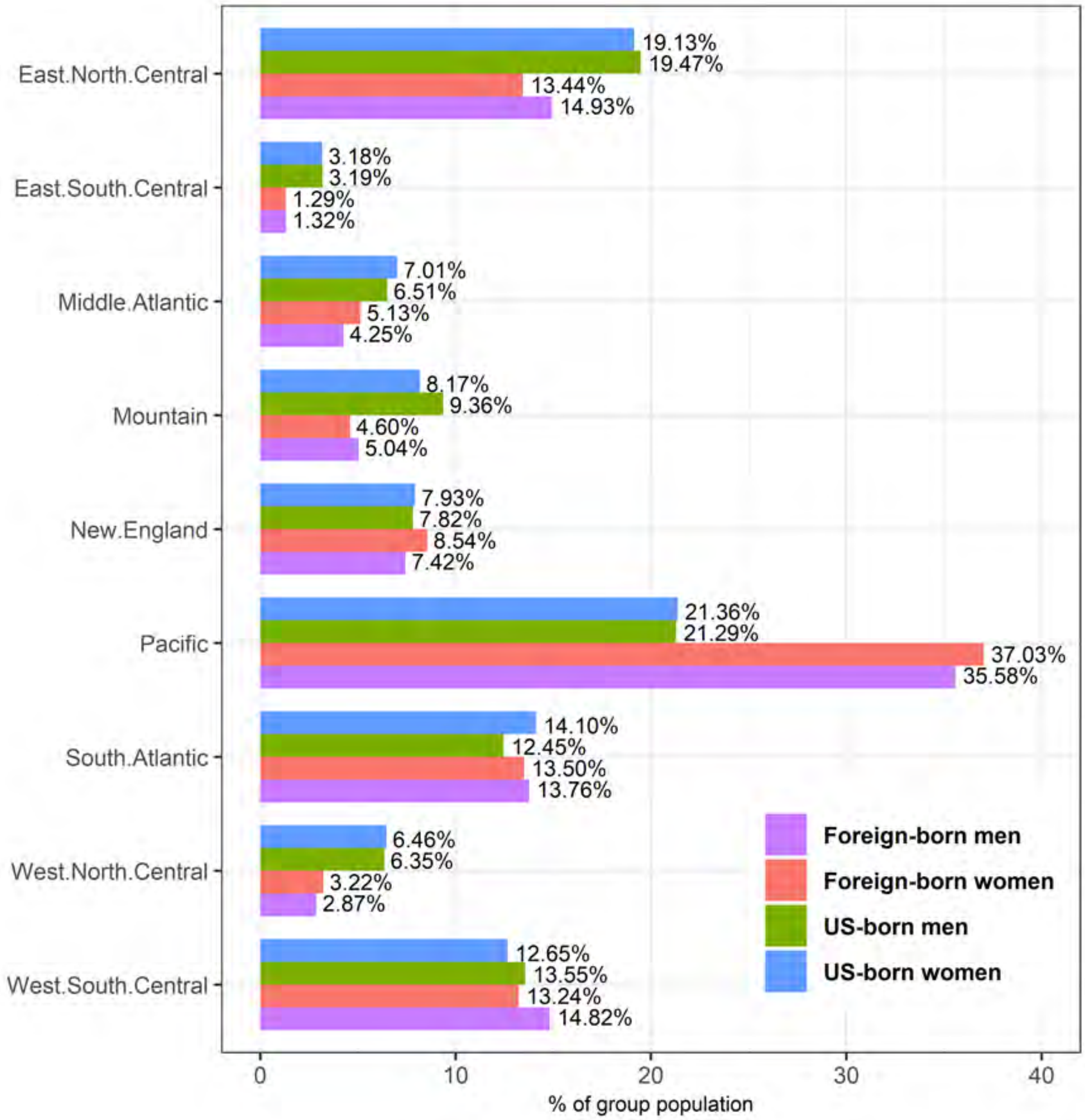
Our analysis is constrained in that we are confined to relatively coarse classifications of education and occupation, and we do not observe personal emplyoemnt histories. Our analysis relies on only 34 occupational codes, and we would likely explain more variation if we had more detailed information on these occupations and their task focus, which could potentially affect our measures of gender-based inequality in STEM (Speer, 2020). We are also aware that women are more likely to move out of STEM occupation for a variety of reasons (Hunt, 2016), but we are unable to incorporate this fact within our modelling strategy. If women who face larger penalties are more likely to leave STEM occupations, we may actually be underestimating the gender-based earnings gap. We also do not observe much information on the highest degree attained. We do know whether this degree was a doctorate, a master's degree and so on, but we know nothing of the institution for which these degrees were obtained. Incorporating this information could improve our ability to better explain the gender and nativity disparities that we observe in STEM. Advancing along these lines will require different data sources and future work.

Additionally, although we are not entirely sure about the mechanism, we do find in our regional models the possibilities that the interactions between regional context and personal attributes playing some roles in shaping the nativity-based wage differentials. Our future studies will focus on this possibility and further investigate how highly skilled workers in different gender and nativity groups fare under different labor market context, or how different individual characteristics acted as mediator in respond to regional features and macro-level factors (international) and local policies/institutions (Kemeny and Cooke, 2017; Li and Park, 2006; McDaniel et al., 2019; Storper and Scott, 2009).

7. Appendix



Appendix A. Share of each nativity-gender group employed in different STEM occupations. These estimates are derived from the 34 6-digit BLS STEM SOC code.



Appendix B. Share of each nativity-gender group reside in different regions

	Model 2 USW (Ref = FBW)	Model 3 USW (Ref = USM)
Baseline		
Wage gap	-3852	-19747
Log wage gap	-0.120	-0.140
Model II. Individual controls		
Endowment	**86.2%**	**10.2%**
Working hour & week	3.5%	-0.1%
Age	-5.6%	1.0%
Race and ethnicity	23.2%	6.0%
Education	68.2%	-8.5%
Occupation	-3.1%	11.8%
Coefficient	**23.8%**	**90.3%**
Interaction	**-12.8%**	**-3.5%**
Model III. Individual & locational controls		
Endowment	**123.3%**	**14.1%**
Working hour & week	4.8%	-0.2%
Age	-16.4%	3.0%
Race and ethnicity	26.7%	6.7%
Education	67.4%	-6.8%
Occupation	-2.5%	14.0%
Metropolitan Area	43.3%	-2.6%
Coefficient	**28.2%**	**85.3%**
Interaction	**-51.5%**	**0.6%**

Appendix C. supplement models. Column 1 compares the wage differentials between foreign-born women (reference) and US-born women. Column 2 compares the wage differentials between US-born men (reference) and women

	Model 1			Model 2	Model 3
	A: USM	B: FBW (Ref = FBM)	C: USW	USW (Ref = FBW)	USW (Ref = USM)
Endowment (Different Occupations)	40%	-4%	17%	49%	-3%
Coefficient	57%	104%	83%	53%	104%
Interactions	2%	1%	0%	-2%	-1%

Appendix D. Location-only decomposition estimates. These models only controlled for annual weeks and weekly hours worked, and locations (with San Jose-Sunnyvale-Santa Clara, CA as reference)

	Foreign-born Men		Foreign-born Women		US-born Men		US-born Women	
	Coefficient	Fitted value	Coefficient	Fitted value	Coefficient	Fitted value	Coefficient	Fitted value
Asian	-0.003	11.58	0.041	11.05	-0.024	11.22	0.002	11.62
Black	-0.201	11.38	-0.153	10.86	-0.125	11.12	-0.08	11.54
Hispanic	-0.153	11.43	-0.16	10.85	-0.065	11.18	-0.056	11.56
Other	-0.032	11.55	0.026	11.03	-0.021	11.22	0.024	11.64
Non-Hispanic White	-	11.58	-	11.01	-	11.24	-	11.61
No College	-0.321	11.26	-0.370	10.64	-0.278	10.97	-0.309	11.31
Some College	-0.234	11.35	-0.277	10.73	-0.178	11.07	-0.217	11.40
Bachelor’s	-	11.58	-	11.01	-	11.24	-	11.62
Master’s	0.091	11.67	0.072	11.08	0.107	11.35	0.105	11.72
Doctoral	0.235	11.81	0.206	11.21	0.298	11.54	0.271	11.89

Appendix E. Coefficients and fitted values from Model II. Effect of Race, Ethnicity and Education

.

	Foreign-born Men fitted value	Foreign-born Women fitted value	US-born Men fitted value	US-born Women fitted value
Engineering Management (Ref)	11.58	11.01	11.24	11.62
Actuaries	11.54	10.76	11.30	11.62
Computer.and.Information.Research.Scientists	11.27	10.78	11.01	11.26
Computer.Network.Architects	11.37	10.81	11.10	11.43
Computer.Occupations..All.Other	11.14	10.48	10.81	11.10
Computer.Programmers	11.26	10.60	10.98	11.28
Computer.Systems.Analysts	11.21	10.57	10.92	11.24
Information.Security.Analysts	11.30	10.70	11.07	11.38
Network.and.Computer.Systems.Administrators	11.17	10.51	10.89	11.17
Operations.Research.Analysts	11.17	10.55	10.93	11.28
Aerospace.Engineers	11.31	10.67	11.12	11.49
Architects..Except.Landscape.and.Naval	11.19	10.42	10.80	11.12
Architectural.and.Civil.Drafters	10.98	10.30	10.66	10.92
Chemical.Engineers	11.30	10.70	11.13	11.52
Civil.Engineers	11.17	10.57	10.98	11.33
Computer.Hardware.Engineers	11.33	10.77	11.07	11.28
Electrical.and.Electronic.Engineering.Technologists.and.Technicians	10.85	10.17	10.71	11.03
Environmental.Engineers	11.11	10.49	10.91	11.28
Landscape.Architects	11.20	10.55	10.79	11.10
Marine.Engineers.and.Naval.Architects	11.20	10.97	10.96	11.29
Materials.Engineers	11.18	10.68	10.99	11.29
Mechanical.Engineers	11.14	10.63	10.97	11.31
Surveying.and.Mapping.Technicians	10.97	10.16	10.60	10.97
Computer.and.Information.Systems.Managers	11.41	10.73	11.07	11.36
Natural.Sciences.Managers	11.42	10.55	10.90	11.20
Agricultural.and.Food.Science.Technicians	10.85	10.24	10.48	10.93
Atmospheric.and.Space.Scientists	11.10	10.59	11.04	11.18
Biological.Technicians	11.05	10.32	10.61	11.05
Chemical.Technicians	10.83	10.23	10.64	11.01
Environmental.Scientists.and.Specialists..Including.Health	11.36	10.41	10.84	11.17
Physical.Scientists..All.Other	11.02	10.40	10.84	11.12
Sales.Engineers	11.40	10.61	11.16	11.52
Economists	11.40	10.61	11.06	11.42
Urban.and.Regional.Planners	11.08	10.45	10.74	11.11

Appendix F. Fitted values from model II, effects of STEM occupations

MSA	Foreign-born Men fitted value	Foreign-born Women fitted value	US-born Men fitted value	US-born Women fitted value
San Jose-Sunnyvale-Santa Clara, CA (Ref)	11.44	10.84	11.38	11.03
Worcester, MA-CT	11.28	10.67	11.12	10.81
Winston-Salem, NC	10.94	10.43	11.03	10.55
Wichita, KS	11.09	10.30	10.93	10.67
Washington-Arlington-Alexandria, DC-VA-MD-WV	11.25	10.77	11.32	10.99
Virginia Beach-Norfolk-Newport News, VA-NC	11.06	10.52	11.06	10.74
Urban Honolulu, HI	11.11	10.53	11.05	10.79
Tucson, AZ	11.05	10.37	11.00	10.61
Toledo, OH	11.21	10.40	10.93	10.42
Tampa-St. Petersburg-Clearwater, FL	11.01	10.53	11.02	10.69
Syracuse, NY	11.08	10.68	10.98	10.62
Stockton-Lodi, CA	11.2	10.21	11.26	10.97
Springfield, MA	11.28	10.44	11.02	10.71
Spokane-Spokane Valley, WA	11.24	10.55	10.87	10.74
Seattle-Tacoma-Bellevue, WA	11.31	10.66	11.21	10.85
Scranton--Wilkes-Barre--Hazleton, PA	11.07	10.40	10.92	10.50
Santa Rosa, CA	11.17	10.46	11.18	10.93
San Francisco-Oakland-Hayward, CA	11.42	10.81	11.32	10.97
San Diego-Carlsbad, CA	11.18	10.54	11.18	10.84
San Antonio-New Braunfels, TX	11.07	10.56	11.02	10.67
Salt Lake City, UT	10.96	10.51	11.01	10.63
St. Louis, MO-IL	11.06	10.47	11.05	10.65
Sacramento--Roseville--Arden-Arcade, CA	11.07	10.55	11.10	10.72
Rochester, NY	10.94	10.62	10.99	10.64
Riverside-San Bernardino-Ontario, CA	11.17	10.52	11.14	10.78
Richmond, VA	11.08	10.60	11.11	10.77
Raleigh, NC	11.18	10.67	11.10	10.69
Provo-Orem, UT	11.14	10.21	11.03	10.44
Providence-Warwick, RI-MA	11.12	10.62	11.11	10.70
Portland-Vancouver-Hillsboro, OR-WA	11.2	10.63	11.12	10.79
Portland-South Portland, ME	11.3	10.73	11.03	10.68
Pittsburgh, PA	10.95	10.44	11.00	10.63
Phoenix-Mesa-Scottsdale, AZ	11.13	10.62	11.08	10.71
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	11.15	10.65	11.14	10.82
Oxnard-Thousand Oaks-Ventura, CA	11.33	10.80	11.19	10.87
Orlando-Kissimmee-Sanford, FL	11.06	10.42	11.00	10.70
Omaha-Council Bluffs, NE-IA	11.07	10.29	11.02	10.67
Oklahoma City, OK	11.04	10.24	11.05	10.63
Ogden-Clearfield, UT	11.17	10.13	11.08	10.79
North Port-Sarasota-Bradenton, FL	11.1	10.02	10.93	10.53
New York-Newark-Jersey City, NY-NJ-PA	11.23	10.70	11.24	10.86
New Orleans-Metairie, LA	10.98	10.72	11.06	10.68
New Haven-Milford, CT	11.11	10.68	11.11	10.71
Nashville-Davidson--Murfreesboro--Franklin, TN	11.09	10.48	11.00	10.64
Minneapolis-St. Paul-Bloomington, MN-WI	11.06	10.55	11.10	10.78
Milwaukee-Waukesha-West Allis, WI	11.08	10.57	10.97	10.71
Miami-Fort Lauderdale-West Palm Beach, FL	11.03	10.45	11.07	10.64
Memphis, TN-MS-AR	11.13	10.41	11.01	10.75
McAllen-Edinburg-Mission, TX	10.76	10.25	10.91	10.29
Louisville/Jefferson County, KY-IN	11.17	10.45	11.01	10.61
Los Angeles-Long Beach-Anaheim, CA	11.15	10.67	11.19	10.83
Little Rock-North Little Rock-Conway, AR	10.99	10.50	10.99	10.70
Las Vegas-Henderson-Paradise, NV	11.1	10.54	11.08	10.79
Lancaster, PA	11.18	10.33	11.07	10.58
Lakeland-Winter Haven, FL	11.12	10.59	10.97	10.37
Knoxville, TN	11.15	10.75	10.97	10.62
Kansas City, MO-KS	11.15	10.38	11.05	10.64
Jacksonville, FL	11.04	10.34	11.02	10.68
Jackson, MS	10.83	10.34	11.00	10.58
Indianapolis-Carmel-Anderson, IN	11.16	10.44	11.02	10.68
Houston-The Woodlands-Sugar Land, TX	11.25	10.73	11.24	10.85
Hartford-West Hartford-East Hartford, CT	11.16	10.59	11.15	10.78
Harrisburg-Carlisle, PA	11.14	10.69	11.06	10.77
Greenville-Anderson-Mauldin, SC	11.17	10.37	11.07	10.61
Greensboro-High Point, NC	11.14	10.43	10.89	10.60
Grand Rapids-Wyoming, MI	11.12	10.74	11.03	10.68
Fresno, CA	11.11	10.38	11.03	10.69
Fayetteville-Springdale-Rogers, AR-MO	10.89	10.41	10.87	10.56

El Paso, TX	10.83	10.67	10.87	10.53
Detroit-Warren-Dearborn, MI	11.17	10.65	11.11	10.69
Des Moines-West Des Moines, IA	11	10.54	11.08	10.72
Denver-Aurora-Lakewood, CO	11.12	10.66	11.16	10.80
Deltona-Daytona Beach-Ormond Beach, FL	11.11	10.32	10.91	10.55
Dayton, OH	10.91	10.76	11.02	10.58
Dallas-Fort Worth-Arlington, TX	11.2	10.60	11.15	10.77
Columbus, OH	11.07	10.55	11.07	10.75
Columbia, SC	10.81	10.53	10.94	10.67
Colorado Springs, CO	11.05	10.31	11.11	10.70
Cleveland-Elyria, OH	11.02	10.53	10.99	10.63
Cincinnati, OH-KY-IN	11.16	10.59	11.03	10.74
Chicago-Naperville-Elgin, IL-IN-WI	11.15	10.64	11.14	10.76
Chattanooga, TN-GA	11.05	10.15	11.06	10.51
Charlotte-Concord-Gastonia, NC-SC	11.2	10.68	11.10	10.69
Charleston-North Charleston, SC	11.06	10.30	11.06	10.73
Cape Coral-Fort Myers, FL	11.06	10.25	10.87	10.44
Buffalo-Cheektowaga-Niagara Falls, NY	10.99	10.43	10.97	10.60
Bridgeport-Stamford-Norwalk, CT	11.11	10.85	11.27	10.92
Boston-Cambridge-Newton, MA-NH	11.21	10.72	11.21	10.86
Boise City, ID	10.76	10.50	10.93	10.70
Birmingham-Hoover, AL	11	10.14	11.07	10.69
Baton Rouge, LA	11.04	10.23	11.14	10.62
Baltimore-Columbia-Towson, MD	11.22	10.67	11.25	10.90
Bakersfield, CA	11.14	10.87	11.18	10.71
Austin-Round Rock, TX	11.19	10.65	11.09	10.71
Augusta-Richmond County, GA-SC	11.29	9.71	11.04	10.68
Atlanta-Sandy Springs-Roswell, GA	11.15	10.54	11.10	10.74
Allentown-Bethlehem-Easton, PA-NJ	11.2	10.58	11.06	10.56
Albuquerque, NM	11.14	10.28	11.01	10.71
Albany-Schenectady-Troy, NY	11.17	10.67	11.06	10.70
Akron, OH	10.97	10.64	11.00	10.57

Appendix G. Fitted values from model III, the effects of Metropolitan Area

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