Mapping the Regions, Organizations and Individuals that Drive Inclusion in the Innovation Economy*

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Version June 5, 2021

Abstract. Innovation is essential for economic growth, prosperity and social progress. However, there is strong evidence of persistent inequality and exclusion of women in the U.S. innovation economy. We develop a framework to map the inventor (patentee) gender gap and identify contexts and catalysts for inclusion. Our approach has three main goals: First, to build inventor inclusivity metrics that capture the presence of women in the flow of new inventors, allowing comparisons across regions, organizations, and individuals. Second, to identify the overall gap between the rate of female new STEM graduates and the rate of female new inventors, emphasizing that the inventor gender gap is more than a supply problem. Third, to understand the variation in inventor inclusivity across top patenting regions, organizations and individuals, providing a window into policy and regional and organizational catalysts for change.

Keywords: Innovation economy; inventor gender gap; inclusivity metrics; STEM talent; inclusive regions, firms, and universities.

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1. Introduction.

The current focus on gender inclusion in the innovation economy serves as a reminder of the importance of gender diversity for social progress (e.g., the United Nations Sustainable Development Goal (SDG) 5: Gender Equality), but also emphasizes the fact that missing female inventors reduce innovation and economic growth (e.g., Romer, 1990; Acemoglu, Akcigit, and Celik, 2020; Cook, 2020). Still, there is strong evidence of persistent inequality and exclusion of women in our innovation economy.

A simple review of female representation across the innovation pipeline, from idea to impact, illustrates the on-going challenge of accomplishing both equity and inclusion for women in STEM and beyond.

It is well documented that *inequality exists for women in academic STEM training and related activities*. Female PhD students and postdocs are less likely to participate in elite labs and to be trained by top inventors (Sheltzer and Smith, 2014; Delgado and Murray, 2020). Women represent only 9 to 31% of STEM faculty in U.S. universities (depending upon discipline) and remain under-represented in tenure track roles (Thursby and Thursby, 2005; Freeman et al., 2009; Wolfinger, Mason, and Goulden, 2008; Li and Koedel, 2017) and in many leadership roles (Madsen, 2012).[1]

There is also *gender inequality in knowledge production and commercialization*. Women, and under-represented minorities as well as those from lower socio-economic categories, are systematically missing from patenting (Cook and Kongcharoen, 2010; Milli et al., 2016; Lax Martínez, Raffo, and Saito, 2016; Jensen, Kovács, and Sorenson, 2018; Bell et al., 2019; Cook, 2020; USPTO, 2020). Within academia, female faculty in the life sciences patent at 40% the rate of males (Ding, Murray, and Stuart, 2006) and represent only a small percentage of the founders of life science enterprises (Stuart and Ding, 2006). Women with similar education levels to men also are less likely to become innovation-driven entrepreneurs (Roberts, Murray and Kim, 2015) and they receive less than 10% of venture capital flows (Brush et al., 2018).

[1] Prior studies offer a variety of explanations for the leaky academic pipeline, including motherhood and worse access to resources (e.g., Zuckerman, Cole, and Bruer, 1991; Sonnert and Holton, 1995; Fox, 2005; Ding, Murray, and Stuart, 2006, 2013; Mairesse and Pezzoni, 2015).

Prior work also has found *gender inequality in innovation governance*. Women represent a small fraction of scientific advisory boards (Ding, Murray, and Stuart, 2013), and only 10% of Chief Technical Officers (CTOs) and Chief Information Officers (CIOs) in the technology sector in 2019 according to a study by firm Korn Ferry.[2]

Resolving this lack of inclusion in the innovation economy will affect both economic and social performance. First, it is inefficient to use only part of the talent pool (Bell et al., 2019; Cook, 2020): we have 'missing Einsteins' or more appropriately missing Curies and Lovelaces, Knights and Donovans. Second, diverse inventors and researchers are more likely to search the solution space more widely and to emphasize different problem domains, including those that could be particularly relevant for women (Koning, Samila, and Ferguson, 2020; Hofstra et al., 2020). Third, more diverse teams might incorporate more distributed sources of information, with higher 'collective intelligence' (Woolley et al., 2010) and better outcomes (Apesteguia, Azmat, Iriberri, 2012; Joshi, 2014; Joshi and Knight, 2015). Finally, more diverse senior leadership within firms may lead to better governance and higher performance, but the evidence for that is mixed (e.g., Post and Byron, 2015; Adams and Ferreira, 2009; McKinsey & Company, 2020).

Against this reality of continued exclusion from the innovation economy, we focus on the inventor (patentee) gender gap in the U.S. economy where women constitute only 10% of inventors in 2015 U.S. granted utility patents. Patenting is an especially important arena for inclusion because it cuts across a wide range of organizational settings, from the public to the private sector, and from individuals to teams. It is also a context where arguments for low inventor inclusion – the lack of STEM talent and role models growing up and early in careers (Bell et al., 2019; Cook and Kongcharoen, 2010; Cook, 2020) – seem especially challenging and suggest that a deeper examination is warranted. The STEM pipeline data illustrate significant aggregate improvement in the presence of women (especially for PhDs), but this improvement is not reflected in overall inventor inclusion (Delgado and Murray, 2020). Specifically, female participation in STEM PhD degrees is about 35% among 2010-2015 U.S. graduates, but women represent only 14% of new (first patent) inventors in 2015 (Figure 1). This gap provides the backdrop to our more fine-grained

[2] See Business Wire (2019), "Korn Ferry Analysis of Largest U.S. Companies Shows Percentage of Women in C-Suite Roles Inches Up from Previous Year".

analysis; one that emphasizes variation across STEM and invention fields, across regions, and across organizations.

We are motivated by the notion that technological (i.e., field), organizational and locational factors play an important role in the inventor gender gap. Women's participation in innovation varies widely by technology field and application domain (Koning et al., 2020). Women's inclusion in innovation also varies by type of organization – university versus firms (Whittington and Smith-Doer, 2008), and across organizations as a result of differing innovation and managerial practices (e.g., Eaton, 1999; Stuart and Ding, 2006; Castilla, 2011). It also changes by region due to different cultures, economic specialization and knowledge networks (Florida 2002; Rosenthal and Strange, 2012; Delgado et al., 2018). As a result, a comprehensive analysis of gender inclusion in innovation through the lens of patenting must consider how different regions, organizations and individuals use their pipeline of STEM trained women to a greater or lesser extent across technological fields in support of the wider innovation economy.

2. Methodology: Mapping Inventor Inclusivity across Regions, Organizations, and Individuals.

We develop a novel empirical framework for mapping the inventor gender gap and identifying settings (regions, organizations and individuals) that serve as catalysts for inclusion. This empirical approach has three main goals. First, to build metrics for female inventor inclusivity that capture participation in patenting by technological field (specifically the presence of women in the stock of inventors and in the flow of new inventors, as well as women's contribution to patenting taking into account team size). Second, to identify the gap between the rate of female new STEM graduates and the rate of female new inventors by field in order to quantify the nature of the invention gender gap. These two types of analysis allow for comparisons of gender participation in patenting across regions, organizations, and individuals while also accounting for different levels of female STEM talent and for the patent composition of these different contexts. Such comparisons serve our third main goal: to build an understanding of the variation in inventor inclusivity across top patenting contexts recognizing that by identifying and understanding those settings with high rates of female participation, we can drive and accelerate inclusion. We explain our empirical framework next.

2.1. Inventors and STEM Talent by Gender.

We identify all U.S. inventors (patentees located in the United States) in the utility patents of U.S. origin granted to organizations during 2000-2015 (USPTO PatentsView data). Our first task is to assign the probable gender of each of the inventors on a patent using our name-gender match algorithm (Delgado and Murray, 2020).[3] Then we can define inventor-level inclusion (*% Female Inventors*) within a selected pool of inventors, rather than taking the more "token woman" approach of simply counting patents with 'at least one woman'. We are especially interested in the flow of new inventors (those with their first-ever utility patent granted in a given period): this allows us to capture the potential for cumulative advantage and long-term change in inventors' career dynamics that might be enabled by increasing the flow of new inventors into the economy at any given point in time (Merton, 1968; Allison and Stewart, 1974; Allison, Long, and Krauze, 1982; David, 1993; DiPrete and Eirich, 2006). In that way, increases in women in STEM training might be clearly translated into the innovation economy.

To connect inventor data with STEM supply at an aggregate level, we use the Integrated Postsecondary Education Data System (IPEDS) data to measure the flow of STEM Bachelor's and PhD graduates by gender in the U.S. economy (See Appendix). We can also disaggregate this by region and by university to compare the presence of women in the training pipeline with the presence of female new inventors in patents. While we are not able to match this STEM supply data at the firm level, this provides an important avenue for future work.

2.2. Female Inventor Inclusivity Metrics.

We compute three main Female Inventor Inclusivity scores for the regions, organizations and individuals in our sample. First, the *% Female Inventors* (FIs) of total inventors (i.e., the number of FIs divided by all gender-matched inventors). This captures the presence of women in the pool of inventors. Second, the *% Female New Inventors* (FNIs) of total new inventors (i.e., the number of new (first-ever utility patent) FIs divided by all gender-matched new inventors). As noted, this novel score of inclusivity captures the presence of women in the flow of inventors and is the focus of our analysis. Building on our work, the USPTO has recently started to report the *% Female New*

[3] We estimate an inventor gender only when 80% or more of the individuals with that first name are of a single gender. Using this approach about 93% of the U.S. inventors and 88% of university inventors were matched to one gender.

Inventors as a key metric for understanding inclusion (USPTO, 2020). Third, the *% Female Patents* (FPs) of total patents (i.e., the number of patents by women divided by the number of gender-matched patents). This variable is based on the proportional allocation of each patent across its female and male co-inventors, and captures women's contribution to patenting.[4]

We note that the *% Patents with a Female Inventor* (i.e., the number of patents with at least one woman divided by all patents) has been the focus of many studies. This measure captures whether women are part of a team of inventors, but does not take into account that patents tend to have multiple co-inventors. Inclusion and equity considerations are not necessarily met by having one woman on a large team of otherwise male inventors.

Importantly, we move beyond inclusivity scores and develop *inclusivity indices* to account for variation in patent composition across technology classes in different sets of patents (e.g., universities versus firms). Both inclusivity scores and female talent availability vary across technological fields, as represented by patent technology classes: e.g., Computers & Communications versus Drugs & Medical patents. Thus, we compute the inclusivity scores (*% Female New Inventors*) by technology class –using the six classes identified by Hall, Jaffe, and Trajtenberg (2001). We then build an 'inclusivity index': a weighted average of the technology-class inclusivity sub-scores (See the Appendix). This allows for better comparison of different sets of patents in multiple contexts: e.g., one region to another, universities versus firms, or comparing one firm to another, such as IBM versus Medtronic patents. Our inclusivity index along with the inclusivity scores by technology class allow for a more fine-grained mapping of STEM talent into particular technological fields and provides for a more systematic understanding of the link between STEM talent supply and patent inclusion.

2.3. Mapping Context: Catalysts for Inclusion.

We map variations in our inclusivity metrics –score and index– across top patenting regions, organizations and individuals to uncover catalysts for inclusion. These three levels of analysis are

[4] For example, if a patent has 1 woman and 3 men out of 4 inventors, then the contribution of women to this patent is 0.25 and the contribution of men is 0.75. When a patent has some inventors without gender estimate, their proportion of the patent is allocated to 'unmatched' patents and not used to compute the *% FPs* score.

each extremely salient as we explore ways to shape and improve inclusion in innovation. At the regional level, policies, culture, and innovation ecosystems can shape inclusive innovation (Florida 2002, 2010; Rosenthal and Strange, 2012; Delgado et al., 2018). At the organization level, practices, climate and culture influence inclusive outcomes (Ding, Murray and Stuart, 2006, 2013; Settles et al., 2006; Bhaskarabhatla and Hegde, 2014). At the individual level, there is evidence that key individuals, for example faculty, influence graduate students' research and invention outcomes (NASEM Report, 2018; Settles et al., 2006; Sheltzer and Smith, 2014; Moss-Racusin et al., 2012; Pezzoni et al., 2016; Delgado and Murray, 2020). Likewise, managers and CEOs can influence inclusion (Castilla, 2011; Rocha and Van Praag, 2020).

Part of our analysis is done with the full U.S. sample. However, patenting is a highly skewed activity (O'Neale and Hendy, 2012). This serves as a reminder that a small number of regions, organizations and individuals may serve as critical catalysts and contexts for change in inclusion. We exploit this to understand the settings where inclusion is particularly high, and to identify those where change may be catalyzed to great effect.

3. The Persistent Inventor Gender Gap in the Economy is not just a STEM Skills Problem.

Across each of our inclusivity scores we observe the large inventor gender gap in the U.S. economy (Table 1). For 2015 U.S. patents, only 10% of all inventors are women. Similar gaps in the *% Female Inventors* have been identified in other countries (Lax Martínez, Raffo, and Saito, 2016; Hoisl and Mariani, 2017). The *% Female New Inventors*, while higher, is still only 14.3%. The contribution of women to patenting is also very low with a *% Female Patents* score of 7.8%. These scores contrast with the *% Patents with a Female Inventor* which is 18.9% in 2015. This indicator is both over-optimistic and 'tokenistic', while the focus of many studies, it masks low female participation given that patents tend to have multiple co-inventors (three on average; Table 5).

The inventor gender gap is persistent: at the current rate of improvement (since 2000), it will take 139 years to reach parity in *% Female New Inventors* and 266 years for *Female Inventors* (Table 1 and Figure 1). This raises the question: *Is the STEM pipeline limiting female new inventors?*

Our data show that the low presence of female new inventors is not simply a STEM skills problem (Figure 1). Building on Delgado and Murray (2020), we quantify trends in the gender gap in STEM graduates (1995-2015) versus inventors in the 2000-2015 period. To capture graduates at risk of patenting, we compare inventors in patents granted in a given year (e.g., 2000) to STEM Bachelors and PhDs granted that year and in the previous five years (1995-2000).[5] The *% Female STEM Bachelors* changed little during the period (35% to 37%) and the gap between the *% Female STEM Bachelors* and *% Female New Inventors* remained large: 37% versus 14% by 2015. In contrast, the presence of women in the pool of STEM PhDs increased significantly, from 25% to 35%.[6] The gap between the *% Female STEM PhDs* and *% Female New Inventors* remained large and increased over our period: the *% Female STEM PhDs* was more than two times higher than the *% Female New Inventors* by 2015 (35% versus 14%). Our results show that female new inventor inclusion is not rising as fast as women in STEM: at current annual rates of change, parity in female PhDs will be achieved in 21 years versus 139 years for female new inventors.

These aggregate STEM and inventor statistics may hide field-specific differences: The presence of female inventors in the U.S. varies significantly by patent technology class (Table 2). Let's consider the two largest classes by the count of women new inventors: Computers & Communications and Drugs & Medical patents granted in 2000-2015. Computers & Communications represents 36% of patents in the economy and 33% of all female new inventors and yet it has a low inclusivity score of 12.1% Female New Inventors (of all new inventors). In contrast, Drugs & Medical accounts for only 13% of U.S. patents but is the second largest class for female new inventors (24%) and it has the highest inclusivity score of 25.5%.

Is the women STEM pipeline limiting female new inventors because of field-level mismatches? While STEM fields cannot be mapped precisely into patenting classes, we can approximate the relationship between the pipeline in specific STEM fields and the patents in related technological fields. Focusing on the most inclusive field, we map the Biological & Biomedical Bachelors and PhDs to the Drugs & Medical inventor data and still find a significant gap. Drugs & Medical

[5] This lag takes into account that there is a delay between the patent filing and issued year and between graduation year and when graduates are at risk of patenting.
[6] The count of female STEM PhDs now represents 8% of all female STEM Bachelors graduates (2010–2015).

patents have the highest inventor inclusivity score: *% Female New Inventors* is 25.5%. Yet, this score is about 24 percentage points lower than expected since women's participation in Biological & Biomedical PhDs is 49% (1995-2015 graduates) and in Bachelors is 59% (Table 3). Similarly, in Computers & Communications women represent 12.1% of new inventors versus 20% of PhDs and 23% of Bachelors.

Our findings strongly suggest that the inventor gender gap is not just about STEM education choices. So, *where is female STEM talent best utilized across the economy?*

4. Potential Catalysts: Patenting is Concentrated in Few Regions, Organizations, and Individuals.

We want to examine whether there are parts of the innovation economy where patenting and inclusion are high so that we can identify catalysts for change: that is, contexts where best practices seem to lead to high levels of inclusion, and settings with high patent intensity where the use of these practices might have a significant positive impact. To do this, we measure the skewness of patenting activity in each of our three different contexts. Then we determine the degree to which, among the top patent producers, some of the regions, organizations and individuals are more inclusive than others. Our results could inform best practices for change.

4.1. Top Patenting Regions.

The economic geography literature shows that patents are highly concentrated geographically by field (Feldman and Audretsch, 1999; Delgado, Porter, Stern, 2014; Delgado, 2020). We therefore use Economic Areas (defined by the U.S. Bureau of Economic Analysis) as the geographic unit to identify the top patenting regions; they better capture a relevant market and the economic specialization of regions. There are 179 mutually exclusive economic areas (EAs) covering the entire continental United States (Johnson and Kort, 2004).

We find that the top ten patenting EAs account for 55% of patents and 51% of new inventors in the 2000-2015 patents (Table 4 and Figure 3) versus 34% of all U.S. jobs in 2015. Perhaps not surprisingly, the top patenting EA is San Jose-San Francisco-Oakland, CA (with 17% of all patents and 13% of all new inventors), followed by the New York EA and then the Greater Boston EA. In many of these regions, and especially the top EA, performance is driven by significant patenting in information technology as well as in other sectors, including life sciences in the Boston EA (Forman, Goldfarb, and Greenstein, 2016; Delgado, 2020). This patenting performance is fueled by, among others, immigrant innovators (Saxenian, 2002; Kerr, 2008; Kerr et al., 2017). Yet, we know very little about the presence of female inventors in top patenting regions (Delgado et al., 2018). It is therefore important to understand how large patenting organizations in and across these regions shape inclusive outcomes.

4.2. Top Patenting Organizations.

We examine the role of universities and firms in bringing new inventors into the innovation economy. Table 4 shows that the top 30 firms by patenting account for 25% of all patents and 19% of new inventors in the economy. Firms will shape overall levels of inclusion because the vast majority of STEM talent (Bachelors, Masters and PhDs) will work at firms. In contrast, universities generate only 4% of all patents. Nonetheless, they are important organizations as they play a key role in shaping the skills and attitudes toward innovation of young PhD students (Pezzoni et al., 2016; Azoulay et al., 2017; Delgado and Murray, 2020), and early access to resources may lead to cumulative advantage (Merton, 1968; Allison and Stewart, 1974; Allison et al., 1982). We find that the top 25 universities shape the behavior of over 50% of patenting activity by universities; accounting for 2% of U.S. patents and contributing 4% of (highly trained) new inventors.

4.3. Top Inventors within Organizations.

Within organizations there are 'superstars' in science and innovation who shape outputs and define the micro-climate for research (Azoulay, Fons-Rosen, and Zivin, 2019; Delgado and Murray, 2020), and superstar inventor-CEOs can drive firm patenting outcomes (Islam and Zein, 2020). Building on Delgado and Murray (2020), we define Top Inventors (TIs) as those with seven or more patents granted within an organization during 2000-2015 (the 90^{th} percentile value across U.S. inventors). Given their prolific activity and the team-based nature of patenting, these inventors likely play an outsized role in bringing new inventors into the innovation economy as part of their teams. We find that many patents (and many new inventors) in our sample of top patenting organizations are produced by few top inventors (Table 5): TIs within the top 30 firms represent 19% of their pool of inventors, generate 84% of their patents, and account for the inclusion of 65% of their new inventors. Academic TIs at the top 25 universities represent only 6% of inventors, generate 59% of patents, and account for 45% of their new inventors.

The outsized role of top inventors in inclusion suggests that it is important to examine whether there is variation in inclusivity among prolific inventors within their organizations and to highlight the practices that lead to high rates of inclusion (or to call out prolific inventors who have unusually low levels of inclusion).

5. Variation in Female Inventor Inclusivity across the top patenting regions, organizations and individuals.

The high skewness of patenting suggests that in order to catalyze changes in inclusion we must understand the variation in patenting behaviors among the top 10 regions, 30 firms and 25 universities (and among their top inventors). We examine this variation through our *% Female New Inventors* metric across the most recent set of patents in our data (2011-2015).

5.1. Female Inventor Inclusivity Variation across Top Patenting Regions.

Figure 2 shows the *% Female New Inventors* score across EAs compared to the U.S. economy (14.5% in 2011-2015 patents). The map illustrates the 90 EAs that together account for about 98% of the patents. There is large variation across regions, even across the top ten patenting EAs: scores range from 11.2% for Dallas and Detroit EAs (below the U.S. average) to 18.9% in New York EA (Figure 3).

Regional differences in inclusivity could be driven by regional specialization in different technology classes. Thus, we compare the two classes with the largest count of female new inventors: Computers & Communications and Drugs & Medical (Figures 4 and 5, respectively). We find important variation conditioning on particular technology classes, and relevant differences across the two classes. These differences come against a backdrop in which Computers & Communications patenting is more geographically concentrated than Drugs & Medical (consistent with studies showing the high clustering of Information Technology activities, in particular in San Jose-San Francisco-Oakland, CA (Delgado, 2020)). In terms of inclusion, some top patenting regions have high inclusivity (above the U.S. score) in both technologies (New York, Chicago and

San Jose EAs), while others have low inclusivity in both (Dallas and Los Angeles EAs). Importantly, there is variation in inclusion across technologies *within* a region: e.g., Seattle and San Diego have scores above the U.S. average for Drugs & Medical but below for Computers & Communications. This variation within region could be driven by large patenting organizations that concentrate their inventive activities there (e.g., Amazon in Seattle) and by specialized regional clusters that could vary in their inclusion practices.

The different patent composition of regions and the variation in inclusion across technology classes within regions justify the need to compute the inclusivity index to compare the overall performance of the top regions (Figure 3). Five of the EAs perform better than the U.S. economy in both the score and index. New York has the highest score (18.9%) and index (3.1%) out of the ten EAs. Other EAs underperform relative to the U.S. economy (negative index): Dallas, Los Angeles, Minneapolis, and Detroit.

While the rate of female new inventors is high in some regions, it remains much lower than the supply of women STEM talent trained within each region. To quantify this gap, we compute for each region the STEM bachelor and PhD graduates (2006-2015), by gender, trained by the universities located in each region (See Appendix). The *% Female STEM Bachelors* score ranges from 35% (Detroit) to 41% (San Jose), much higher than the new inventor inclusivity scores (Figure 3). The ratio of *% Female New Inventors* to *% Female STEM Bachelors* is highest at New York, yet it is only 0.5 (with lowest is being Dallas with a ratio of 0.3).[7] Likewise, the ratio of *% Female New Inventors* to *% Female STEM PhDs* is also highest in New York at only 0.5. Overall these findings suggest that the supply of locally trained female STEM graduates is not the central issue in explaining the high inventor gender gap across top patenting regions.

The ability to retain talent and to engage women in innovation may vary across regions with different innovation ecosystems and sets of organizations. Thus, we ask next: *what organizations (universities and firms) drive these regional differences?*

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[7] The correlation coefficient between the rate of female new inventors and STEM graduates is positive but small (0.2 for Bachelors and 0.3 for PhDs).

5.2. Female Inventor Inclusivity Variation across Top Universities.

With their increasing numbers of female STEM students, can leading research universities be catalysts for change and influence overall regional inclusivity? We know that women's inclusion in innovation tends to be higher at universities than at firms (e.g., Whittington and Smith-Doer, 2008; Delgado and Murray, 2020). We are interested in assessing the variation among universities (which ones are more inclusive than others) so as to identify and inform best practices for change across regions and across the U.S. innovation economy.

As noted earlier, the top 25 U.S. universities generate 2% of all patents but 4% of all the new inventors in the economy. The presence of female new inventors in their patents is higher than in the U.S. economy overall: 22.6% versus 14.5% in 2011-2015 patents (8 pp gap).[8] Each of the top universities have an inclusivity score higher than the U.S. average (Figure 6), but there is large variation across them, from 17.6% (Purdue) to 29.5% (University of Pennsylvania).

The higher inclusivity of universities could be driven by their technology composition. The patent composition of the U.S. economy is very different from that of universities (Delgado and Murray, 2020): Drugs & Medical is the largest technology class in the 25-universities, with about 40% of 2011-2015 patents (versus only 15% of U.S. patents). Furthermore, individual universities vary in their patent composition. We compute the inclusivity index for the pool of 25-university patents and for each university to control for technology class composition (See Equations 1 and 2 in the Appendix). Some universities move up in the ranking based on the index: MIT has a higher percentage of patents in Mechanical (a field with fewer women) and moves up in the ranking from 20th (score) to 9th (index). All universities (except one) have positive inclusivity indices, which confirms the greater inclusion of universities than the U.S. economy. Importantly, there is large variation in the index, ranging from 8.3% at Northwestern University to -5.2% at Case Western Reserve University.[9] This suggests that other factors (beyond the technology field) influence university inclusivity.

[8] The top 25 universities have similar rates of inclusion of female new inventors as all universities (Table 6).
[9] Case Western Reserve's negative index is driven by its low inclusion (below the U.S. scores) in multiple technology classes, and especially in Drugs & Medical patents. Many of these patents are assigned to the Cleveland Clinic Foundation.

Next we compare universities to their regions (Figure 7). We find that top universities are more inclusive than their regions: each has a *% Female New Inventors* greater than their region. This gap ranges from 13 pp for Northwestern University (28% versus 15.3% in Chicago EA) to 1 pp for University of Florida. On average, the university-versus-region gap is 7.3 pp in the *% Female New Inventors* score (and 3.6% in the index). All universities (except Case Western Reserve) also have an index value greater than their regions.

This higher inclusivity of universities suggests that they have the potential to be regional catalysts for change. However, universities still have far to go to reach parity in engaging female inventors in their patents. So, we assess whether the limiting factor is the supply of women STEM PhDs trained by each of these universities. We find that universities under-utilize their female STEM PhD pipeline (Figure 8). In fact, there is a large female STEM PhD to female New Inventor gap across universities. In the pool of 25-universities the *% Female STEM PhDs* is 10 p.p. higher than *% Female New Inventors* (33% versus 23%). There is a large STEM PhD-Inventor gap for each university. This strongly suggests that the rate at which female PhDs engage in university patenting is much lower than that of men (Delgado and Murray, 2020).

5.3. Female Inventor Inclusivity Varies across Top Firms

Firms account for about 96% of U.S. patents and thus strongly shape overall levels of inclusion. The top 30 firms account for 25% of patents and 19% of all new inventors in the economy (Table 4). The presence of female new inventors in firms' patents is very similar to that in the U.S. economy: 14.9% versus 14.5% in 2011-2015 patents, with 13 of the top firms having inclusion scores above the U.S. average. As with regions and universities, we find large variations in the *% Female New Inventors* across top patenting firms (Figure 9): from 27.5% in Johnson & Johnson (with Drugs & Medical as the main tech class) to 8.1% in Broadcom (with Computers & Communications as the main class).

Inclusivity scores do not allow us to properly compare inclusion across firms because firm patents tend to be highly concentrated in one (main) technology class (e.g., 74% of IBM patents are in Computers & Communications). Thus, the inclusivity index is essential to account for firm-level variation in technology specialization. For example, IBM moves up from 7th to 3rd in the ranking, while Medtronic moves down from 5^{th} to 20^{th}. The *% Female New Inventors* index for the pooled 30-firms patents is 1.3%. Half of the firms do better than the U.S. economy (positive index), ranging from AT&T with a 9.4% index to 0% in Hewlett-Packard. More troubling, given the magnitude of their patenting activity, the other half of firms are doing worse than the U.S. economy (negative index), ranging from -0.2% in Boeing to -5.6% in Boston Scientific.

Finally, a firm's main technology class shapes the type of STEM skills that are likely to be relevant to the firm and thus the role of female STEM levels as a potential constraint to inclusion. We find that most of our firms have inclusivity scores lower than the U.S. % female STEM graduates in their main technology: the % Female STEM Bachelors is 19% in Computers & Communications and 59% in Biological & Biomed fields, but the average inclusivity score is 14% and 23% across top firms whose main class are Computers & Communications and Drugs & Medical, respectively.

There are a few exceptions: AT&T, IBM (the largest patent producer) and Xerox have scores close to the STEM supply in Computers & Communications. This could be related to their practices to incentivize patenting across their employees (Bhaskarabhatla and Hegde, 2014) or to other critical and effective organizational practices that can serve as catalysts of change for low performing firms. More broadly, our findings suggest the urgent need for insights into the drivers of firm inclusivity, including the role of key individuals (top inventors) inside organizations.

5.4. Female Inventor Inclusivity Varies across Top Inventors within Organizations.

To what extent might key individuals – Top Inventors – serve as catalysts for female inventor inclusion? Although patenting takes place within regions and organizations, the process of invention is driven by small teams of individuals. As noted earlier, in most organizational settings a few Top Inventors produce many patents (Table 5). Their autonomy, reputation, and patenting intensity likely give them a key role in shaping the organizational culture for patenting and thus more specifically for female inventor inclusion. At universities, as faculty and PIs of labs, they have a role in training and mentoring new inventors among their graduate students (Pezzoni et al. 2016; Gaule and Piacentini, 2018; Delgado and Murray, 2020). This can have long-lasting effects on students' careers. At firms, Top Inventors (whom we might consider to be invention ‘superstars’) may have less discretion in building their teams (although this is very poorly understood in the literature) but still have some autonomy in how they pursue their projects.

To examine the role of TIs within top patenting organizations, we divide the pooled 25-university and pooled 30-firm patents into four groups based on the absence or presence of a top inventor: Non-TI, TI, Female TI, and Male TI patents (Table 7). Then we compare the inclusivity score across these four types of patents. Overall, Top Inventor patents have a higher inclusivity score than Non-TI patents in the university and firm settings. In the 25 universities, female TIs represent only 9% of all TIs, but their patents have much higher inclusivity scores than those of male TIs (7 pp gap). Similarly, in the 30 firms, female TIs are 8% of all TIs and their patents have higher inclusivity than male TIs patents (also by 7 pp gap). We obtain similar findings using the inclusivity index.

These results suggest that Top Inventors indeed exert a strong influence over the inclusivity of their organizations (both within universities and firms). Further, there is significant variation across TIs in their inclusivity practices – among all TIs but also specifically female versus male TIs. This calls for the need to understand the role of these key individuals in driving the inclusivity of their organizations. In other words, it is not sufficient to study organization-level drivers of inclusion; we also need to pay attention to the potential role of catalytic individuals whose inclusion of new inventors, and especially female new inventors, in their work has a strong impact on the U.S. economy.

6. Accelerating Change in Gender Inclusion in Innovation: Lessons and Next Steps.

Accelerating change in gender inclusion in the innovation economy – in patenting and in the subsequent commercialization of inventions – is important for economic and social performance. Changes in the regional, organizational and individual practices around patenting have the potential to advance the inclusion of inventors from a wide range of different backgrounds and experiences and therefore to increase the productivity of our economy. Nonetheless, increases in gender inclusion in patenting have been slow to materialize over the past 20 years, with only a 0.15 pp annual increase in female inventor inclusion and a 0.26 pp annual increase for female new inventor inclusion. At this rate of change it would take over a century to reach parity. Given the more rapid increase in women moving into STEM education (especially PhDs), our work moves beyond the traditional focus on the STEM education pipeline to explore whether, when and where inventors (especially new inventors) are included in patenting.

We have shown that the participation of women in STEM Bachelors (*% Female STEM Bachelors*) and in STEM PhDs *(% Female STEM PhDs*) have remained much larger than the participation of female new inventors into patents (*% Female New Inventors*). Furthermore, the *% Female STEM PhDs* has been increasing much faster than the *% Female New Inventors* during our study period. The national-level gap of over 20 percentage points between the % female new STEM graduates and female new inventors by 2015 warrants further investigation at the regional level and across organizations and individuals. This paper has examined this variation in the most recent set of patents in our data (2011-2015).

At the regional level, the top ten patenting Economic Areas are responsible for over 50% of patents. They vary widely in their female new inventors inclusion scores (11% to 19%), with each of these rates being much lower than the rate of female STEM Bachelors and PhDs trained by universities within each region. The inclusion ranking shifts once we control for the composition of patents within a region using our inclusivity index – e.g. accounting for whether a region is specialized in the life sciences or computers and communications. However, New York remains significantly more inclusive at the top of the ranking (3% index) than Dallas, which remains ranked 10th and underperforming relative to the economy (-2% index). The ratio of *% Female New Inventors* to *% Female STEM Bachelors* is also highest in New York, but is only 0.5. We find that if each top EA were to have its *% Female New Inventors* score equal to the *% Female STEM Bachelors* in the given region, we would make significant inroads into inclusion in the innovation economy: the number of female new inventors in the U.S. economy would have grown by 26% annually. That is, there would be almost 40,000 additional women new inventors during 2011-2015, and the inclusivity score in the economy would increase from 14.5% to 28.3%.[10]

[10] The change in female NIs in each EA is computed under the assumption that the number of male NIs remained constant. A similar finding (21% annual growth in the number of female NIs in the economy) holds if the EAs inclusivity scores were to be equal to the *% Female STEM PhDs* (versus Bachelors).

Our analysis recognizes that much of the regional-level variation in inclusivity is related to the behavior of firms and universities located within the regions. We find that across organizations, the top 25 U.S. universities have significantly higher rates of inclusion of female new inventors than either the U.S. economy as a whole or the top 30 firms (both by score and index). Among universities, and accounting for patent composition, all but one are more inclusive than the U.S. economy and their region. This indicates their importance in seeding the inclusion of female new inventors. That said, universities also display significant variation in their rates of inclusivity, ranging from 18% to 30% in our score and from -5% to 8% in our index. While universities can serve as catalysts for inclusion, each university has inclusivity scores lower than their *% Female STEM PhDs*. We find that if each top university were to have the % *Female New Inventors* score equal to the *% Female STEM PhDs*, the number of female new inventors in the economy would have grown by 1% annually (i.e., 1,526 additional new inventors during 2011-2015).[11]

Shifting our attention to firms, we examine female new inventors among the top 30 firms, responsible for over 25% of U.S. patents. Importantly, these firms vary widely in their inclusivity scores (8% to 28%). Firms are specialized in particular technology fields, so it is especially important to use our inclusivity index to compare firms. According to our index there is significant variation between inclusion at the top five firms (7 to 9 pp above U.S. average) versus the bottom five (3 to 6 pp below U.S. average).

In the absence of firm-level data on own-supply of STEM female employees, we use the U.S. % female STEM Bachelors by field as an imperfect proxy. Nonetheless, firms with the higher indices seem to better utilize the female STEM pipeline. In particular, AT&T and IBM have inclusivity scores similar to the % female STEM Bachelors in fields related to their main technology (Computers & Communications). Once again, we find that if each top firm were to have the *% Female New Inventors* score equal to the *% Female STEM Bachelors* (in fields related to their main technology class), the number of female new inventors in the U.S. economy would have grown by 4% annually (i.e., 5,759 additional new inventors during 2011-2015).[12]

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[11] The change in female NIs in each university is computed under the assumption that the number of male NIs remained constant.

[12] The estimated change in female NIs in each firm is computed keeping the number of male NIs in the firm fixed. Figure 9 shows that 24 firms have as their main technology class Computers & Communications or Drugs & Medical,

By understanding the variation in the rate of participation of female new inventors across these organizations, we can identify specific settings with organizational (and individual) practices that seemingly lead to greater inclusion, thus laying the foundations for deeper analysis. Such analysis will allow us to pinpoint specific practices that then can be more widely adopted across the economy. These organizations and their inclusive individuals also will serve as role models and catalysts for change. Moreover, by focusing on those contexts – regions, firms, universities and even individuals – producing the vast majority of the inventions that are filed every year, we can identify potential leverage points for inclusion. If we can upgrade the behavior of the laggards among these prolific people and places, then we can make a significant difference in our economy.

Our work also underscores the importance of calculating the types of metrics and rankings for a range of regions, organizations and individuals on an annual basis. For policymakers, this approach makes it possible to track improvements in inclusion in a granular way that may be of interest to the states and their sub-regions. It further holds the promise of capturing the causal impact of specific policy interventions and how they might differentially shape the inclusive nature of different types of organizations: new versus old, large versus small, those close to universities compared to those in more peripheral regions. For organizational leaders, our rankings, in particular our inclusion index, make it possible to perform annual benchmarking against peer organizations and against prior performance. Managers also might consider variations in inclusion rates from one business unit to another (and from one region to another). They could use the inclusion index to capture the effectiveness of specific organizational interventions at the business unit or division level. The same is true for universities where it is possible to rank and celebrate the most inclusive of faculty and to understand their practices more clearly. When combined with organization-specific data on the potential pool of innovators (i.e., those at risk of becoming inventors), our approach becomes particularly powerful as a way to examine pockets of best

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and we approximate their STEM pipeline using the U.S. % female STEM Bachelors in Computers & Communications and Biological & Biomedical sciences, respectively. Two firms have Chemicals as main technology and we approximate their STEM supply with the % female STEM Bachelors in Biological & Biomedical; and 4 firms have Electrical & Elec. or Mechanical as main technology, and we use % female Bachelors in Engineering as relevant STEM supply (Table 3). The same finding (4% annual growth in the number of female NIs in the economy) holds if firm inclusivity scores were to be equal to the *% Female STEM PhDs* (vs. Bachelors).

practice – as demonstrated by the link we make between STEM students within particular universities and their participation in invention and patenting.

Much work remains for innovation scholars who seek to understand the causes and consequences of inclusion in patenting within and across organizations, particularly when it comes to new inventors entering the innovation economy at different stages in their careers. At the organizational level, we should explore the role of culture and other organizational drivers of inclusion, motivated in part by the potential benefits from change and by the high rates of variation in inclusion among top patent producers elucidated in our work. Scholars should continue to seek out useful interventions and natural experiments that can shed light on inclusion. One obvious study would examine the ways in which the Covid-19 shock (and subsequent move to more remote working practices) differentially impacted male versus female (new and existing) inventors. This could be a window into the wider issues of how geography and work practices shape diversity and inclusion. Another challenge is to understand the relationship between leadership composition and inclusion. Using our methods, it would be possible, for example, to examine the degree to which changes in senior leadership (e.g., the appointment of more diverse and inclusive leadership at the level of the Chief Technological Officer, Head of R&D, or even CEO) changes inclusion. Other more targeted policy or program interventions within large innovation-oriented organizations also could be the subject of significant analysis and evaluation.

Our finding that new female inventors enter into the innovation economy from universities at higher rates than from other organizations suggests another line of research. It would be fruitful to study the pathways of inventors from their early PhD training in university laboratories through their inventive career across different organizations. It would be useful to understand whether male versus female new inventors graduating from PhD programs with experience as inventors make differential contributions to the innovation economy compared to one another and compared to other PhD students who do not patent while in graduate training. And, even before such new inventors leave the training grounds of their universities, we might seek to understand the drivers of variation in inclusion among top faculty inventors who often serve as PhD advisors and key role models (e.g., Delgado and Murray, 2020).

Finally, turning to the regional level, our approach provides insights into understanding variation in inclusion across regions. It has been suggested that some regions are inherently more tolerant and creative (e.g., Florida, 2002). Yet these characteristics have not been fully linked to diversity and inclusion in innovation. Relatedly, prior work shows that economies of agglomeration improve innovation and entrepreneurship, but we know very little about the female innovators' participation in industry clusters (e.g., Rosenthal and Strange, 2012; Delgado et al. 2018). Our approach provides a platform for connecting lines of scholarly research emphasizing regional variation in culture, rules, norms, and socioeconomic networks to research that emphasizes innovation outcomes. The inclusive nature of innovation provides an important window into both the culture and practice of innovation, not only for female inventors but also for the diverse range of individuals whose talents are essential to our long term economic future.

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Table 1. Female Inventor Inclusivity in the U.S. Economy

Year	U.S. Patents Granted	Female Inventors (FIs)	Male Inventors (MIs)	Female New Inventors (FNIs)	Male New Inventors (MNIs)	% FIs	% FNIs	% Female Patents	% Patents +1 FI
2015	127,300	18,740	168,134	6,300	37,688	10.0%	14.3%	7.8%	18.9%
2011-15	584506	55958	467370	30245	177670	10.7%	14.5%	7.8%	18.7%
2000-15	1394632	106243	939836	73511	486129	10.2%	13.1%	7.2%	17.1%
$PPA_{00\text{-}15}$						$0.15\%^{**}$	$0.26\%^{**}$	$0.11\%^{**}$	$0.34\%^{**}$

Notes: The analysis includes utility patents of U.S. origin granted to organizations. For this set of patents we use the inventors located in the US (USPTO). The definition of inventor is organization specific (i.e., an individual with patents in two organizations counts as two inventors). In the U.S. sample the organization refers to the first assignee listed in the patent. PPA is the estimated Percentage Point Annual Change (** $p<0.01$) – the slope in the 2000-2015 annual trends. See Figure 1.

Table 2. Presence of Female New Inventors in the U.S. Economy by Technology Class

	% Patents		% All Female New Inventors ($FNI_{Tech}/FNIs$)		% Female New Inventors Inclusivity Score	
	2000-15	2011-15	2000-15	2011-15	2000-15	2011-15
U.S. Total	**100%**	**100%**	**100%**	**100%**	**13.1%**	**14.5%**
Chemical	11%	9%	14%	13%	17.7%	18.9%
Computers & Comm.	36%	42%	33%	36%	12.1%	13.4%
Drugs & Medical	13%	15%	24%	25%	25.5%	26.4%
Electrical & Elec.	18%	16%	10%	9%	8.7%	9.6%
Mechanical	11%	9%	7%	6%	7.0%	7.9%
Other	11%	10%	11%	11%	11.3%	12.6%

Notes: Technology class definitions are based on Hall, Jaffe, and Trajtenberg (2001).

Table 3. Presence of Female STEM Graduates in the U.S. Economy by Field

	% Female STEM Bachelors			**% Female STEM PhDs**		
	1995-2015	2006-2015	2010-15	1995-2015	2006-15	2010-15
U.S. STEM Degrees Flow	**36.7%**	**37.0%**	**37.0%**	**31.1%**	**34.2%**	**35.0%**
Agriculture [a]	47.1%	50.6%	51.8%	36.8%	44.3%	46.6%
Biological & Biomedical [b]	58.7%	59.2%	58.8%	48.8%	52.2%	53.1%
Computer & Comm. [c]	22.7%	19.1%	19.0%	20.4%	21.3%	21.0%
Engineering Tech. [d]	18.1%	18.0%	18.2%	19.1%	22.1%	22.7%
Math & Statistics [e]	44.7%	43.5%	43.1%	27.8%	29.3%	28.8%
Natural Resources [f]	45.0%	47.4%	48.2%	39.4%	44.8%	46.3%
Physical [g]	40.1%	40.2%	39.6%	29.2%	32.4%	33.2%

Notes: Authors' calculations (IPEDS) based on all U.S. institutions granting STEM degrees. Our definition of STEM includes these National Center for Education Statistics fields: [a] 01-02; [b] 26; [c] 10-11; [d] 14-15 and 41; [e] 27; [f] 03; and [g] 40. This is the definition of STEM Graduates used throughout this paper. See Appendix.

Table 4. Patenting and New Inventors Generated by Top Regions, Firms, and Universities

	Patents, 2000-2015	%	New Inventors	%
U.S. Economy	1,394,632	100%	607,732	100%
10-Economic Areas (of 179)	763,992	55%	311,381	51%
30-Firms	346,033	25%	115,952	19%
All Universities (201)	59,105	4%	45,823	8%
25-Universities	32,032	2%	23,940	4%

Notes: Top 10 EAs, top 30 Firms and top 25 Universities by granted patent count in 2011-2015. See Appendix.

Table 5. Patents and New Inventors Generated by Top Inventors

	Inventors	%	Patents	%	Team-Size	New Inventors	%
U.S. Patents, 2000-15	1,130,834	100%	1,394,632	100%	2.7	607,732	100%
Top Inventors (7+ patents)	114,071	**10%**	873,878	**63%**	2.9	241,317	**40%**
30-Firms Patents, 2000-15	183,933	100%	346,033	100%	2.8	115,952	100%
Top Inventors	34,167	**19%**	289,038	**84%**	3.0	75,948	**65%**
25-Univ Patents, 2000-15	37,314	100%	32,032	100%	2.8	23,940	100%
Top Inventors	2,243	**6%**	18,956	**59%**	3.0	10,664	**45%**

Notes: We define Top Inventors as those with 7+ patents granted within an organization during 2000-2015 (90th percentile value in the U.S. Economy). In the U.S. sample the organization refers to the first assignee code in the patent. Team Size is the average number of inventors across patents.

Table 6. % Female New Inventors in the U.S. Economy, Top 25 Universities, and Top 30 Firms

	Patents Granted Year	% Female New Inventors Score	% Female New Inventors Index
U.S.	2000-2015	13.1%	0%
	2011-2015	14.5%	0%
25-Universities	2000-2015	21.2%	3.8%
	2011-2015	22.6%	4.0%
All-Universities	2000-2015	21.2%	3.4%
	2011-2015	22.8%	3.7%
30-Firms	2000-2015	13.8%	1.6%
	2011-2015	14.9%	1.3%

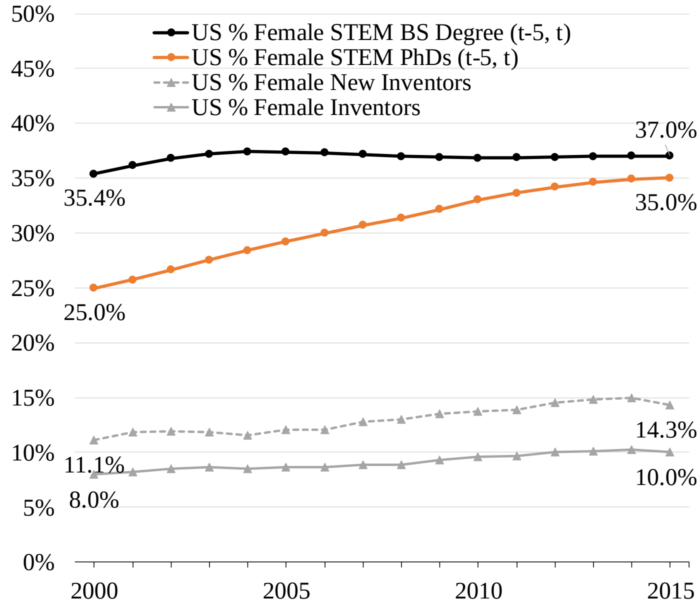
Notes: See Equation 1 in the Appendix for the Index definition (weighted average across tech sub-scores).

Table 7. % Female New Inventors in Top Inventors Patents

	# TIs	**% Female New Inventors Score**
25-Universities 2000-2015		
No-Top Inventor Patents		20.9%
Top Inventors Patents:		22.4%
Female Top Inventors (FTIs)	208	29.2%
Male Top Inventors (MTIs)	2,035	22.0%
30-Firms 2000-2015		
No-Top Inventor Patents		12.3%
Top Inventors Patents:		15.7%
Female Top Inventors (FTIs)	2,538	22.9%
Male Top Inventors (MTIs)	28,717	15.5%

Notes: The indicators are based on the pooled patents by type: No-TI, at least one TI (FTI or MTI) patents. New Inventors excludes those who become Top Inventors in 2000-2015. Similar findings using the % FNIs Index.

Figure 1. Trends in % Female STEM Degrees and Female New Inventors in the U.S. Economy

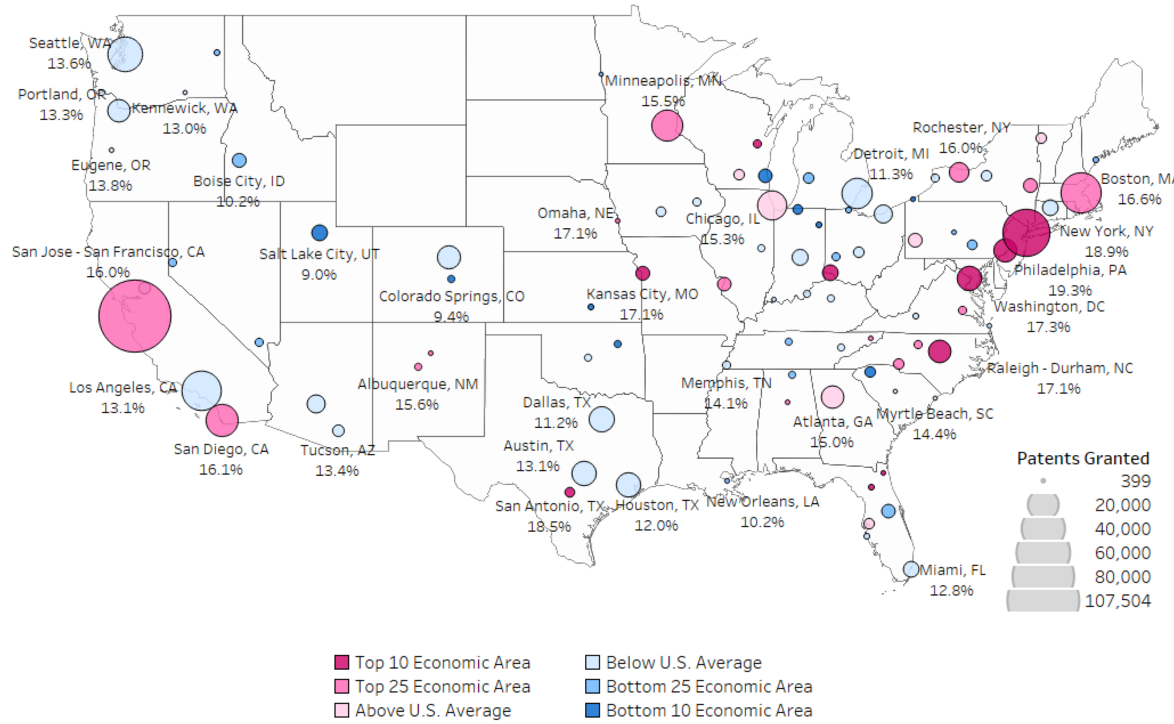


U.S. Economy

	Annual Change	Years to Parity
% FBS	0.04%	(117, **317**, +1,000)
% FPhDs	0.71%**	(19, **21**, 23)
% FNIs	0.26%**	(117, **139**, 171)
% FIs	0.15%**	(235, **266**, 307)

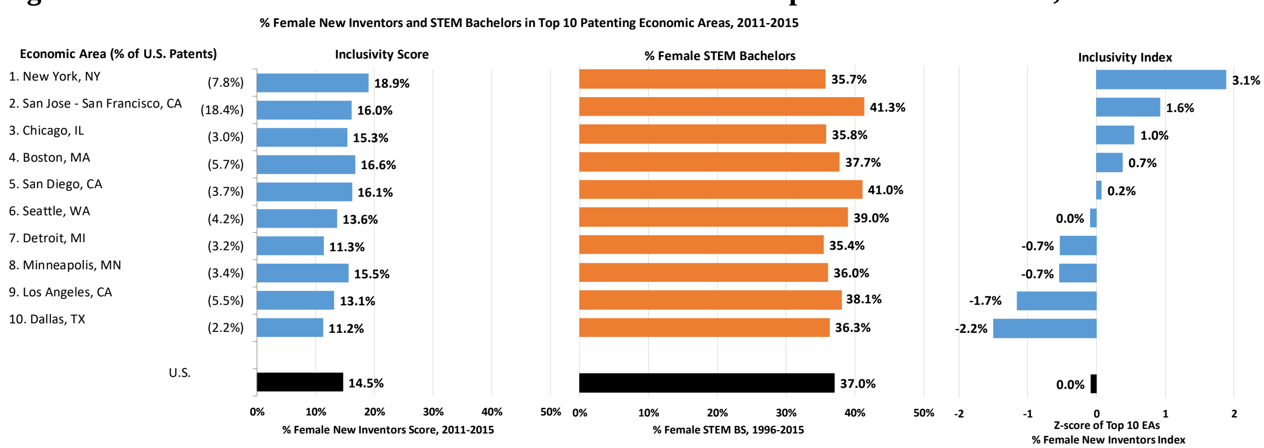
Notes: Authors' calculations. Adapted from Delgado and Murray (2020). Inventors in patents granted in yeart *t* are compared to STEM PhDs and Bachelor of Science (BS) degrees granted in year *t* and the previous five years (IPEDS data). This time window takes into account that there is a delay between the patent filing and issued year and delay between graduation date and when graduates are at risk of patenting in an organization. The estimated Annual Change is the slope in the 2000-15 annual trends (** p <0.01). Parity means that the score is 50%. Years to parity (and 95% CI estimates) are based on slope estimates.

Figure 2. % Female New Inventors across Economic Areas, 2011-2015



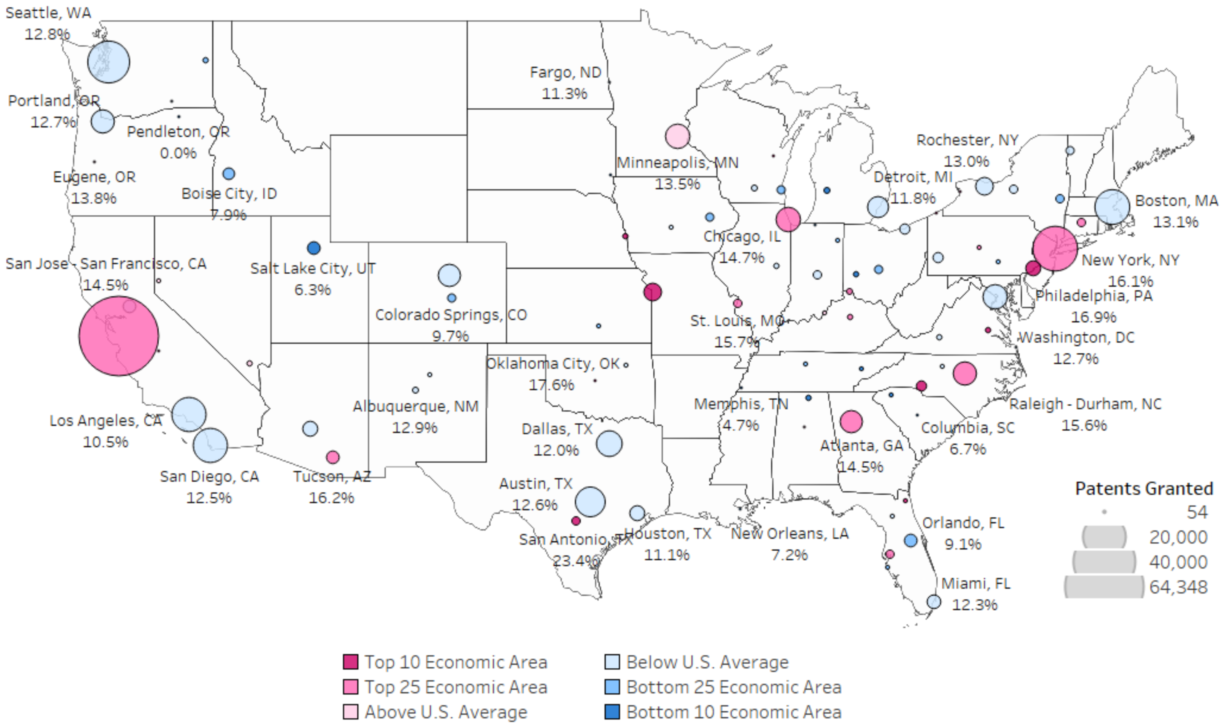
Notes: The *% Female New Inventors* score refers to all (organization) patents by inventors located in the region (i.e., the number of women new inventors divided by the number of gender-matched new inventors in each EA). Circle size on map is proportional to total patents granted in 2011-15. Circles in pink have inclusivity above the U.S. average (14.5%). The map shows the top 90 EAs (out of 179) by patent count. They account for about 98% of patents issued.

Figure 3. % Female New Inventors and STEM Bachelors in Top 10 Economic Areas, 2011-2015



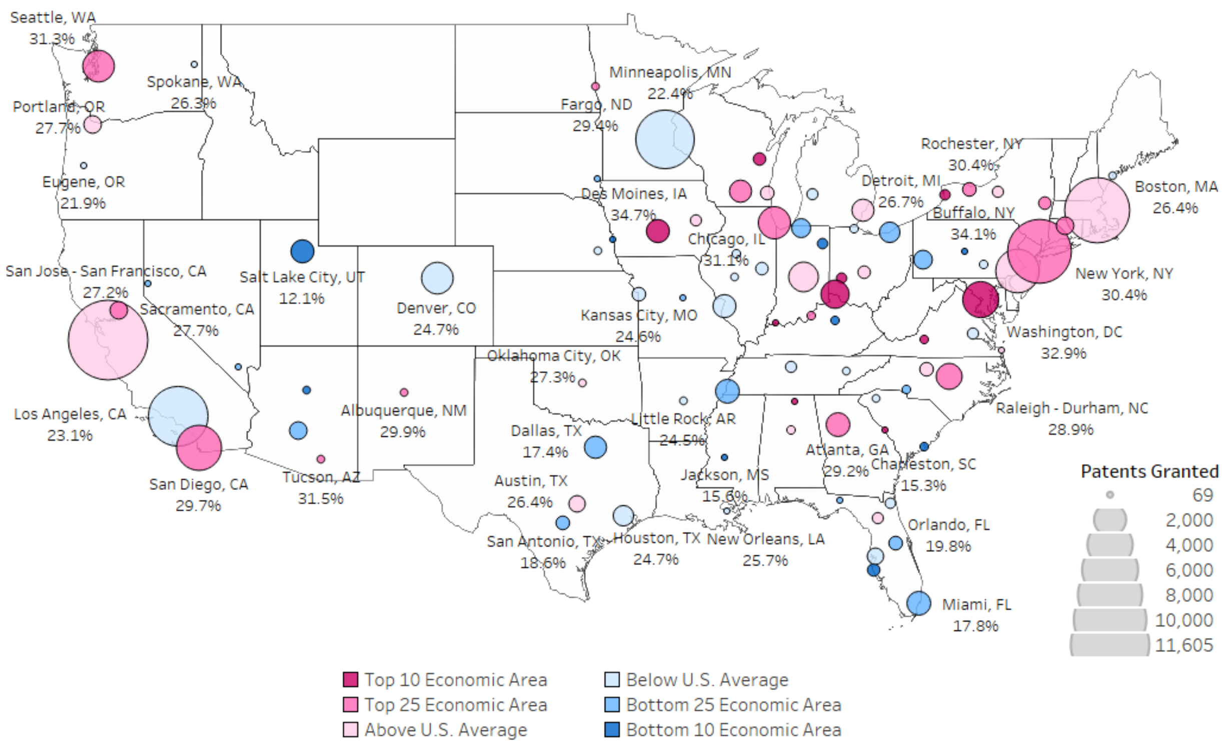
Notes: The top 10 EAs ranked by 2000-2015 patenting are: San Jose-San Francisco-Oakland, CA; New York-Newark-Bridgeport, NY-NJ-CT-PA; Boston-Worcester-Manchester, MA-NH; Los Angeles-Long Beach-Riverside, CA; Seattle-Tacoma-Olympia, WA; Minneapolis-St. Paul-St. Cloud, MN-WI; Detroit-Warren-Flint, MI; Chicago-Naperville-Michigan City, IL-IN-WI; San Diego-Carlsbad-San Marcos, CA; and Dallas-Fort Worth, TX. New York EA has the highest score of 18.9% and the highest index (3.1%) across the top 10 patenting EAs. STEM Bachelors computed by gender based on the graduates trained by universities located in the region (2006-2015).

Figure 4. % Female New Inventors across Economic Areas, Computers & Com., 2011-2015



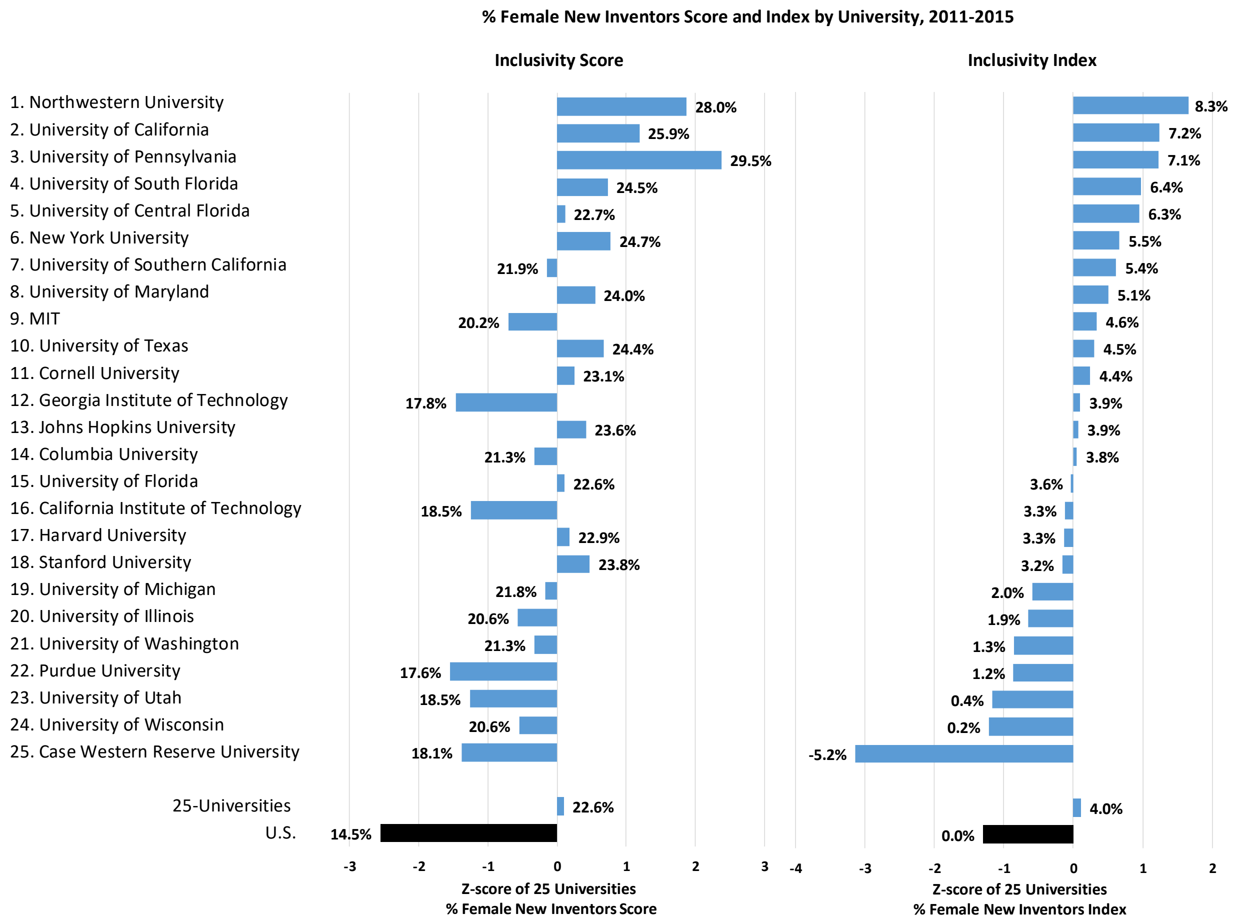
Notes: *% Female New Inventors* scores for Computers & Com. patents in each EA. Circle size on map proportional to the patents granted in the technology in 2011-15. Circles in pink have inclusivity above the U.S. average (13.4%).

Figure 5. % Female New Inventors across Economic Areas, Drugs & Medical, 2011-2015



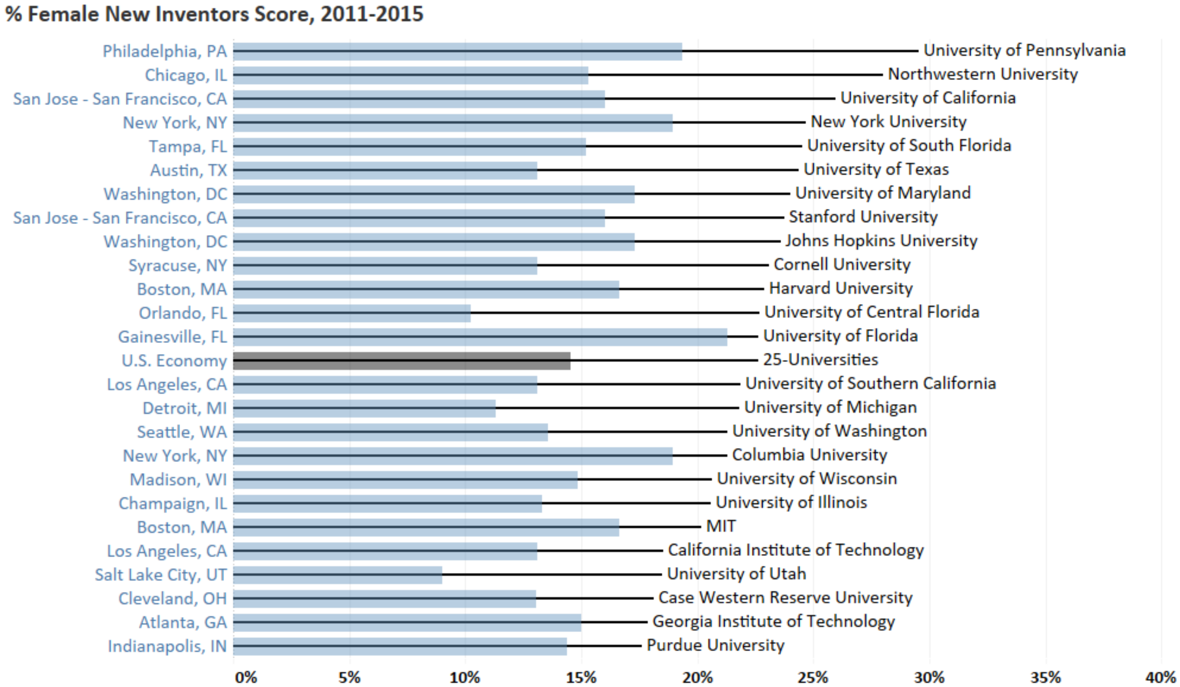
Notes: *% Female New Inventors* scores for Drugs & Medical patents in each EA. Circle size on map proportional to the patents granted in the technology in 2011-15. Circles in pink have inclusivity above the U.S. average (26.4%).

Figure 6. The % Female New Inventors across 25-Universities: Score and Index, 2011-2015



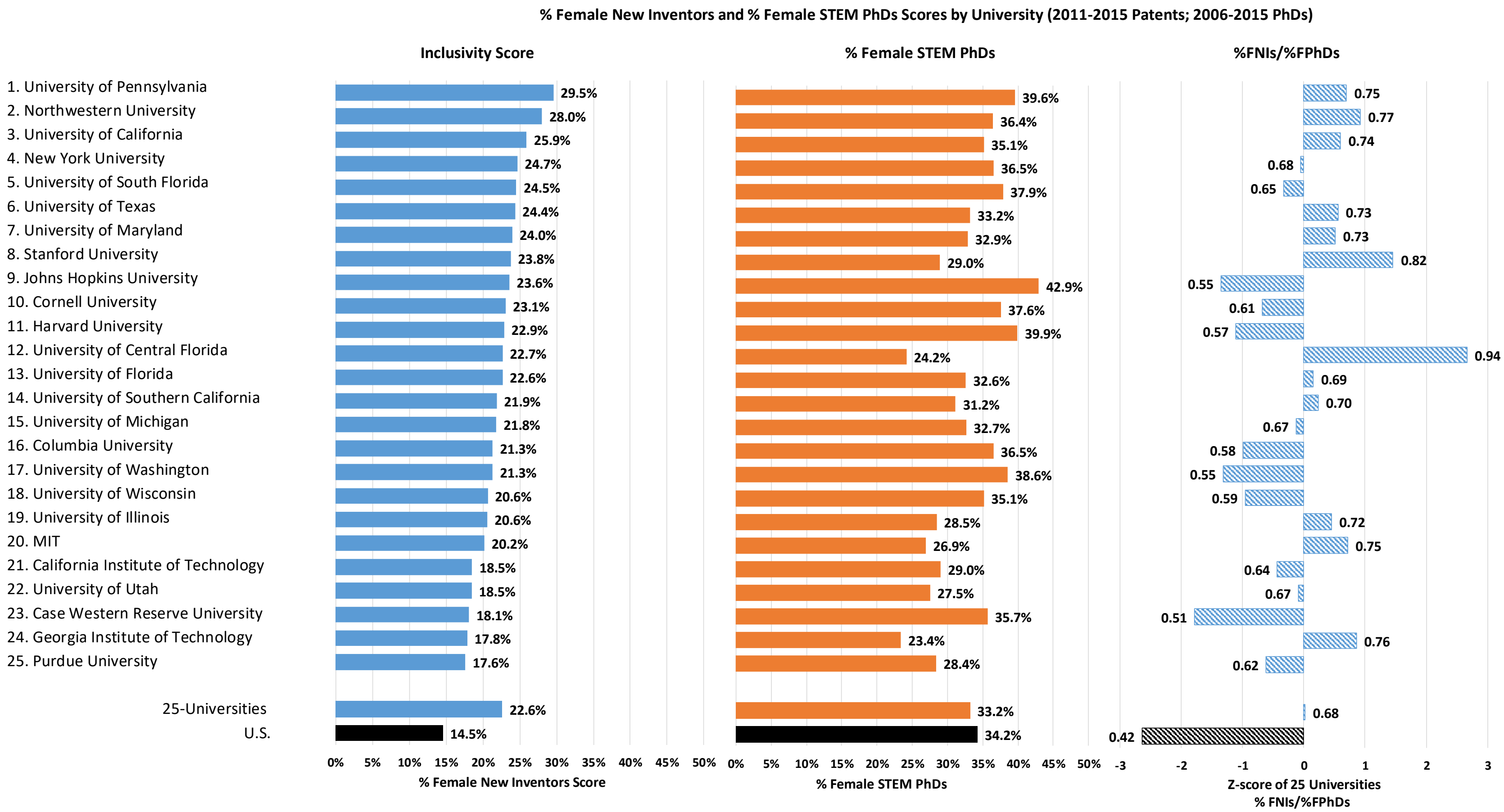
Notes: The inclusivity index is a weighted average of the university's tech-class scores (see Equation 2 in the Appendix). We also report the indicators for the pooled patents of the 25-Universities and the U.S. Economy.

Figure 7. Inclusivity of University vs. Region: % Female New Inventors, 2011-2015



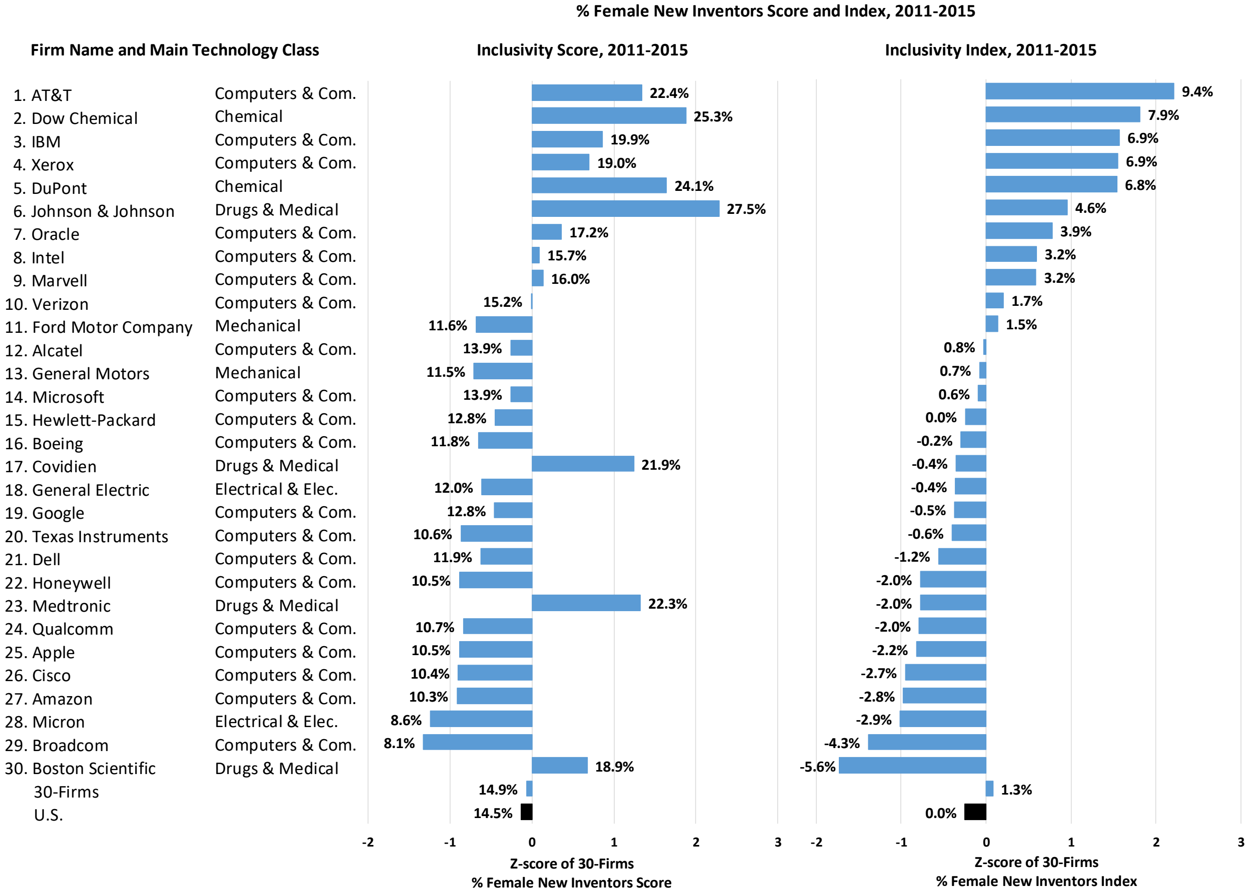
Notes: Each university % FNI score is compared to that of its region (Economic Area).

Figure 8. % Female New Inventors and STEM PhDs by University (2011-15 patents, 2006-15 PhDs)



Notes: Flow of STEM PhD holders by gender (IPEDS, 2006-2015 graduates).

Figure 9. The % Female New Inventors across 30-Firms: Score & Index, 2011-2015



Notes: Inclusivity indicators computed based on all the patents of the firm 2011-2015 (all technologies). The figure shows the main technology of firm patents. Firms patent in multiple tech classes, but on average a single (main) tech concentrates 73% of firm patents.

Appendix: Materials and Methods for

Mapping the Regions, Organizations and Individuals that Drive Inclusion in the Innovation Economy

Mercedes Delgado and Fiona Murray

STEM Degrees by Gender in the US Economy and by University

The Integrated Postsecondary Educational Data System (IPEDS) offers annual data on STEM Bachelor's Degrees and PhD completions by field and gender for U.S. institutions of higher education. We use institution names to associate IPEDS institutions with our list of universities (Delgado and Murray 2020).

Our definition of STEM includes the following National Center for Education Statistics (NCES) fields that are more likely to patent: 01, 02, 03, 10, 11, 14, 15, 26, 27, 40, and 41. In the year-2000 classification these are named, respectively: *Agriculture, agriculture operations, and related sciences* (01); *Agricultural sciences* (02); *Natural resources and conservation* (03); *Communications Technologies/Technicians and Support Services* (10) *Computer and information sciences and support services* (11); *Engineering* (14); *Engineering technologies/technicians* (15); *Biological and biomedical sciences* (26); *Mathematics and statistics* (27); *Physical sciences* (40); and *Science technologies* (41).

Method: Female Inventor Inclusivity Scores and Indices

To analyze women's inclusion in the U.S. economy, we define metrics that characterize the presence of female versus male inventors (located in the U.S.) in utility patents. Our first task is to assign the probable gender of each of the inventors on a patent using our name-gender match algorithm (Delgado and Murray, 2020). We then compute three main Female Inventor Inclusivity (FII) scores for the organizations in our sample. The *% Female Inventors* (FIs) of total inventors (i.e., the number of FIs divided by all gender-matched inventors). Second, the *% Female New Inventors* (FNIs) of total new inventors (i.e., the number of new (first patent granted) FIs divided by all gender-matched new inventors). Third, the *% Female Patents* (FPs) of total patents (i.e., the number of patents by women divided by the number of gender-matched patents).

We compute the FII scores at multiple levels of analysis: for the entire pool of U.S. patents, across regions (economic areas) and fields, the top patenting universities (25-universities), the top patenting firms (30-firms) and their top inventors.

Note that our definition of inventor in the paper is organization specific (i.e., an individual with patents in two organizations (e.g., two universities) during the particular time period counts as two distinct inventors. The inventor id is sourced from the USPTO PatentsView's rawinventor data accessed in June 2017.

In the region-level analysis, we focus on economic areas as the regional unit (Johnson and Kort, 2004), and the definition of inventor is an inventor-organization-region in the particular set of patents (e.g., if an IBM inventor is located in two different economic areas (EAs) during the given period it will be allocated to each of the two EAs).[13]

Female Inventor Inclusivity Scores by Technology Class and Indices

The inclusivity scores and the supply of STEM women vary across patent technology classes (Delgado and Murray, 2020). Thus, we develop inclusivity **indices** (for each of the three inclusivity scores) to account for variation in patent composition across technology classes in different sets of patents (e.g., universities versus firms). Thus, we compute the inclusivity scores by technology class using the six classes identified by Hall, Jaffe, and Trajtenberg (2001). Then we build an "inclusivity index": a weighted average of the six technology-class inclusivity sub-scores. We compute the indices at multiple levels of analysis: the pool of the top universities (*u25*) and top firms (*f30*) in Equations 1a and 1b, each organization (firm or university *o*) in Equation 2, and each region *r* in Equation 3:

$$Inclusivity\ Index_{u25} = \sum_{tech} Share\ Patents_{u25}^{tech} * (Inclusivity\ Score_{u25}^{tech} - Inclusivity\ Score_{US}^{tech}) \tag{1a}$$

$$Inclusivity\ Index_{f30} = \sum_{tech} Share\ Patents_{f30}^{tech} * (Inclusivity\ Score_{f30}^{tech} - Inclusivity\ Score_{US}^{tech}) \tag{1b}$$

$$Inclusivity\ Index_{o} = \sum_{tech} Share\ Patents_{o}^{tech} * (Inclusivity\ Score_{o}^{tech} - Inclusivity\ Score_{US}^{tech}) \tag{2}$$

$$Inclusivity\ Index_{r} = \sum_{tech} Share\ Patents_{r}^{tech} * (Inclusivity\ Score_{r}^{tech} - Inclusivity\ Score_{US}^{tech}) \tag{3}$$

The index first normalizes each score relative to the U.S. by technology class (e.g., difference between the 25-universities and the U.S. score for patents granted in the same time period); and then weighs each normalized score based on the share of patents in the technology class ($Share\ Patents^{tech}$).

Equation 1 allows us to compare the inclusivity of types of organizations that may have different technology composition of their patents like the top 25 universities versus the top 30 firms and the U.S. economy. For example, in 2011-2015, the % *Female New Inventors index* shows a 4 percentage point greater presence of women new inventors in top-25 university patents than the U.S. economy. Equation 2 allows us to compare across individual organizations that can vary in the technology class composition of their patents (e.g., MIT has many patents in Mechanical which is a field with fewer women). Finally, Equation 3 allows us to compare across regions which might specialize in different technology classes.

[13] Inventors may have multiple addresses within the same patent, and so, we use a weighting function: patent-inventor-location is the unique observation; location can be any administrative unit (e.g., EAs). Note that even if an inventor has multiple addresses within a patent they often correspond to the same region (EA) in our analysis.

University Sample: University-Patent Assignee Bridge

To create our university sample, we build a bridge to map USPTO patent assignee codes into individual universities. We identify the set of 201 universities with at least five patents in the 2011-2015 period, and separate out the top-25 universities by patent count in the same period (25-Universities sample). The definition of the patents of a particular university is based on the first assignee listed in the patent. In our sample of top 25 universities, more than 90% of the patents granted (2000-2015) have only one assignee. See Delgado and Murray (2020) for the detailed university-patent bridge.

Firm Sample: Firm-Patent Assignee Bridge

To create our top patenting firms sample, we identify the set of top 30 firms by granted patent count in the 2011-2015 time period. Next, we build a bridge to map USPTO patent assignee codes into individual firms. The definition of patents attributed to a specific firm is based on the first assignee listed in the patent. In the USPTO data, some firms assign their patents to a single assignee entity (e.g., IBM), and thus are allocated a single assignee code, while others have multiple codes. Thus, we created a bridge to map patent assignee codes to firms. On average each firm is associated with 13 distinct assignee codes.

To build the firm-assignee bridge, we employed name-matching techniques to match patent assignee names to a list of parent and subsidiary names obtained from SEC sources. For each firm, we generate candidate matches by searching for patent assignee names that share words with the list of names or common abbreviations. These potential matches are then evaluated manually to determine whether they represent patent activity of the focal firm.

We further corroborate the preciseness of the bridge by crosschecking and integrating the list of assignee names and patents with Arora, Belenzon, and Sheer (2017). The latter dataset has data on 25 out of our top 30 firms. Among these entities, the overlap is substantial: in the 2010-2015 period the two datasets agree on over 90% of patents.