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## STUDY OF THE ESTABLISHED PROGRAM TO STIMULATE COMPETITIVE RESEARCH (EPSCoR)

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A report from the Evaluation and Assessment Capability  
Section of the National Science Foundation.

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# Study of the Established Program to Stimulate Competitive Research (EPSCoR)

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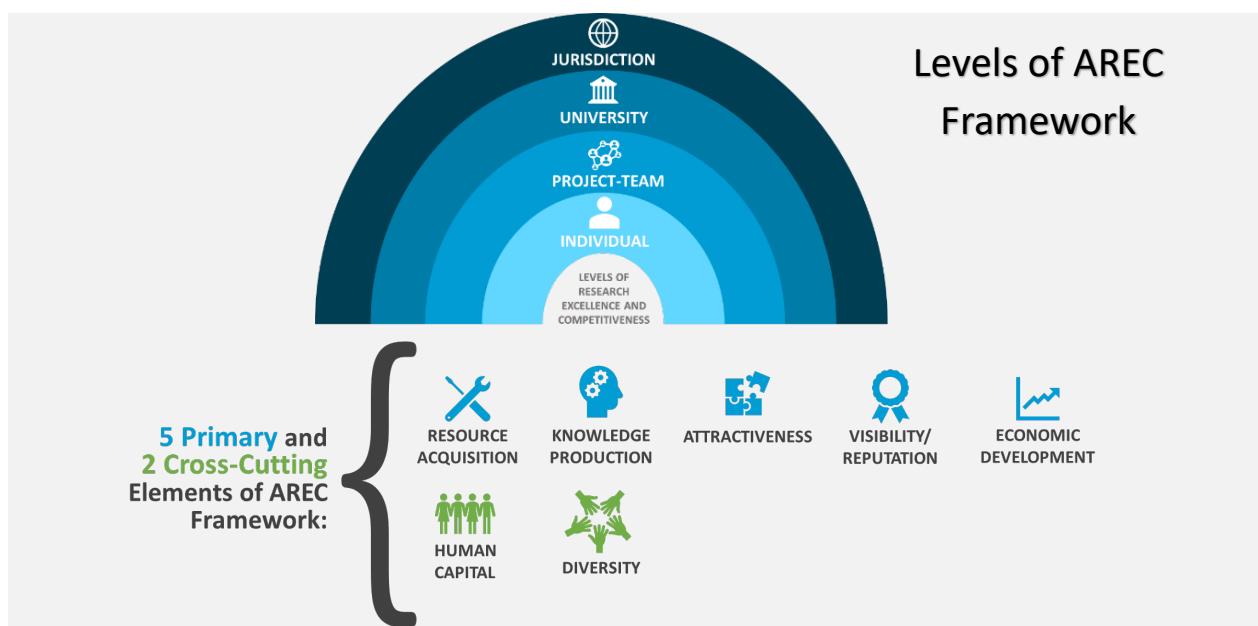
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## EXECUTIVE SUMMARY

The National Science Foundation (NSF) Established Program to Stimulate Competitive Research (EPSCoR) is the largest jurisdiction-specific, federally funded research program in the United States. The program is designed to enrich jurisdictional research capacity and ultimately improve the research competitiveness of jurisdictions that have historically received little federal research and development (R&D) funding. EPSCoR operates within the context of the U.S. academic research system, the success of which depends on both federal investment in research and the fundamental capacity of jurisdictions and universities to compete for and carry out research. Because the development and sustainability of research excellence and competitiveness occurs within such a complex institutional and environmental context, it is critical to recognize the different dimensions of research achievement and the structural characteristics of the research system that advances or constrains it. Traditionally, a jurisdiction's ability to obtain grant funding is the primary indicator of research competitiveness, as it demonstrates the ability to acquire resources in a competitive environment. However, this narrow definition results in insufficient attention to the constellation of resources and conditions (i.e., human, financial, institutional, and social) that are required to conduct scientific research. Additionally, this definition limits evaluators' and policymakers' understanding of how improvements in existing capacity can result in research excellence. The focus on funding amounts at a jurisdiction level also ignores the interplay of research capacity and excellence across all levels of the jurisdictional ecosystem.

This study develops a new and flexible theoretical framework called **Academic Research Excellence and Competitiveness (AREC)**, which builds on information gathered from existing literature to incorporate factors related to academic research competitiveness that NSF can apply in the context of EPSCoR. The newly developed AREC framework is a multilayered, embedded system that incorporates the context, complexity, and temporal nature of academic research activities, as depicted below:



The study also examines the

1. variation in context based on a broad range of jurisdiction-level factors,
2. variation in the strategies employed to improve research competitiveness across the range of EPSCoR awards, and
3. relevant research competitiveness outcomes comparable across jurisdictions with similar characteristics.

It is important to note that this study is not an evaluation. Rather, the study's purpose is to develop comprehensive knowledge of the key factors that contribute to jurisdictional AREC, as well as the jurisdictional variability within these key factors. The study aims to use this knowledge to answer six primary research questions (RQs) related to *contextual variability*, *strategic variability*, *outcome variability*, *effectiveness*, *institutionalization*, and *improvement*. Addressing these questions will ultimately allow NSF to better understand how to use EPSCoR as a mechanism to increase AREC throughout the United States.

The study team relied primarily on publicly available administrative data and descriptive quantitative analysis to answer the six primary RQs. The study team identified, collected, and compiled variables to serve as measures for key AREC constructs. These compiled data provide NSF with jurisdiction-level measures that can be used to develop a consistent set of indicators that exemplify research competitiveness and allow NSF to monitor progress over time.

Using the compiled variables, the study team conducted analyses to examine variability in jurisdictional contextual factors, strategies, and outcomes. These analyses demonstrate the intertwining nature of jurisdictions' contextual characteristics, strategic activities, and research competitiveness outcomes. A jurisdiction's unique context affects the strategies available for increasing AREC, which ultimately influences the AREC outcomes reached by the jurisdiction.<sup>1</sup> This study provides a better understanding of the complex variability, across jurisdictions, of factors involved in AREC, which will help guide EPSCoR's future investments, programmatic decisions, and portfolio management. A caveat to the analyses is that large portions of the logic models were challenging to construct using measures from publicly available extant data sources and, as a result, the study team's analyses provide only a partial picture of the AREC framework. Nonetheless, that partial picture is an important one for improving our understanding of AREC.

## Overall Findings

It is helpful to recognize that the EPSCoR track-level awards are nested within the contexts of EPSCoR programs,<sup>2</sup> universities, and ultimately jurisdictions. The contextual characteristics of the jurisdictions help determine the range of strategies available to EPSCoR programs for

<sup>1</sup> Though the AREC framework includes jurisdiction, university, project/team, and individual levels, the study team chose to focus primarily on analysis of jurisdiction-level data to address the primary RQs.

<sup>2</sup> The "EPSCoR Program" represents the jurisdiction-level EPSCoR institutions (EPSCoR jurisdictional office and other committees or units) that propose and implement awards to enhance jurisdiction research competitiveness. Jurisdiction context concerns the characteristics of the state or territory that contains the EPSCoR Program.

development and implementation, which can in turn impact AREC outcomes in these jurisdictions. To effectively capture the diversity of EPSCoR jurisdictions, as well as provide an aggregate picture of jurisdictions' contextual factors, programmatic strategies, and progress toward outcomes, the study examines EPSCoR using measures from both the jurisdiction and the university levels, although all the analyses are conducted at the jurisdiction level.

## RESEARCH QUESTIONS

### Contextual Variability



- a. What factors best describe the common characteristics that typify this contextual variability?
- b. To what extent and in what ways does the research competitiveness context currently vary across EPSCoR jurisdictions?
- c. Are there any clusters/groups of jurisdictions with common contextual features that can be identified across the program?

### Strategic Variability



- a. What common characteristics typify the range of implementation variability?
- b. To what extent and in what ways do the S&E research base and mechanisms currently deployed for improvement vary across jurisdictions?
- c. Are there any clusters/groups of jurisdictions with common implementation strategies that can be identified across the program?

### Outcome Variability



- a. What jurisdictional, institutional, and other characteristics typify the range of variability observed in research competitiveness definitions and performance?
- b. To what extent and in what ways does the variability in context and strategy across EPSCoR jurisdictions influence the identification of relevant indicators of research competitiveness?
- c. Are there any clusters/groups of jurisdictions with common context and/or strategy characteristics that can be used to understand variability in research competitiveness?

### Effectiveness



- a. What differences and similarities exist with respect to implementation strategies and levels of research competitiveness, as defined for this study, for EPSCoR jurisdictions?
- b. Are there specific strategies or combinations of strategies with evidence of stronger influence or contribution toward research competitiveness than others? For example, how do EPSCoR and non-EPSCoR institutions in similar Carnegie Classification of Institutions of Higher Education (Carnegie Classification) institutional classification categories currently compare with respect to research competitiveness as defined for the study?
- c. What career pathways have been developed? To what extent are these career pathways diverse and inclusive, especially for early career researchers?

### Institutionalization



- a. What ongoing evaluation processes, practices, and structures—in particular those related to stakeholder engagement, data collection, and analysis—are feasible to support and sustain the current and future implementation of a longitudinal program-level evaluation with common measures and a consistent yet flexible analytic approach?

### Improvement



- a. What insights can be drawn from the evidence compiled to address RQs 1 through 5 that can be used to inform programmatic strategic directions?

### Supplementary Research Questions



1. What is AREC, and how can it be conceptualized into a framework?
2. How can the AREC framework be incorporated in a logic model with different levels/units of analysis (jurisdiction and institutional levels)?
3. How can the AREC framework be translated for identifying research competitiveness measures that can be used in tracking progress for accountability purposes?

## FINDINGS RELATED TO CONTEXTUAL VARIABILITY

Jurisdictions vary along several contextual dimensions that can influence the extent and nature of the jurisdiction's contribution to the overall national research competitiveness. The study team conducted an exploratory factor analysis to categorize the 20 contextual variables into 3 underlying latent indicators from the AREC logic models. The findings are highlighted below.

### EPSCoR jurisdictions vary along several measures in three contextual domains.

#### Environment and Institutional Capacity



**Compared to non-EPSCoR jurisdictions, a majority of EPSCoR jurisdictions**

- are less populous,
- have populations that tend to live in nonmetropolitan areas,
- have varying levels of racial diversity, and
- have similar numbers of research-intensive doctoral universities and associate colleges.

#### Research Capacity



**Compared to non-EPSCoR jurisdictions, most EPSCoR jurisdictions**

- have a smaller economic base,
- confer lower percentage of S&E degrees,
- have a low percentage of S&E workers (except for the jurisdictions in the Northeast United States), and
- receive low federal funding, possibly due to the low number of research-intensive doctoral universities.

**Some EPSCoR jurisdictions rely more heavily on federal funding due to the presence of federally funded labs or initiatives in those jurisdiction.**

#### Jurisdiction-Level Financial Resource Capacity



**EPSCoR jurisdictions' governments seem to support R&D activities to complement federal funding for research at academic institutions, albeit to a much lower extent than some non-EPSCoR jurisdictions.**

### Jurisdictions cluster around similar contextual measures.

Cluster 1	Cluster 2	Cluster 3	Cluster 4
Alabama Kentucky Louisiana South Carolina Missouri Tennessee Arizona Colorado Indiana	Maryland Massachusetts Minnesota Washington Wisconsin Arkansas Iowa Kansas Mississippi Nevada Oklahoma Utah Connecticut Oregon	Alaska Delaware Hawaii Idaho Maine Montana Nebraska New Hampshire New Mexico North Dakota Rhode Island South Dakota Vermont West Virginia Wyoming	All other non-EPSCoR jurisdictions

**Note:** Current EPSCoR Jurisdictions, Past EPSCoR Jurisdictions, Non-EPSCoR Jurisdictions

## FINDINGS RELATED TO STRATEGIC VARIABILITY

The study team coded and analyzed a sample of 61 most recent EPSCoR award reports across the 31 EPSCoR jurisdictions for Tracks-1, -2, and -3. These reports provide a view of the strategic variability in EPSCoR jurisdictions, but that view is limited to what was reported by awardees. Some jurisdictions have multiple EPSCoR awards, which may result in strategic activities that evolve due to a combination of factors but mostly due to the variability in the jurisdictional context. The findings are highlighted below:

### EPSCoR jurisdictions vary among reported strategic activities.

#### Strategic Activities



##### EPSCoR funding mostly supported the following strategic activities:

- Building cyberinfrastructure
- Holding workshops, camps, or seminars
- Funding undergraduate students, graduate students, or existing faculty
- Supporting collaborative relationships within a jurisdiction
- Building state or local programs
- Creating instructional or curricular material

#### Research Purpose



##### Activities were conducted primarily for the purpose of

- research,
- education, and
- community outreach and engagement.

#### Infrequently Reported Activities



No awards reported activities focused on supporting lesbian, gay, bisexual, or transgender individuals.

##### There were relatively few reported activities related to

- hiring new researchers or administrative staff,
- supporting researchers to attend courses,
- funding individuals with disabilities, and
- building collaborative relationships between different departments within the same university .

The variability in strategies used may be attributed to differing needs or objectives but could potentially be due to program changes or inconsistencies in reporting.

Analyzed reports spanned across three tracks:

#### Track-1

Alaska	Nebraska
Alabama	New Hampshire
Arkansas	New Mexico
Delaware	Nevada
Guam	Oklahoma
Hawaii	Puerto Rico
Iowa	Rhode Island
Idaho	South Carolina
Kansas	South Dakota
Kentucky	Tennessee
Louisiana	Utah
Maine	U.S. Virgin Islands
Missouri	Vermont
Mississippi	West Virginia
Montana	Wyoming
North Dakota	

#### Track-2

Alaska	Nebraska
Alabama	New Hampshire
Arkansas	Nevada
Delaware	Oklahoma
Hawaii	Puerto Rico
Idaho	Rhode Island
Kansas	South Carolina
Kentucky	South Dakota
Louisiana	Tennessee
Maine	Utah
Missouri	Vermont
Mississippi	West Virginia
Montana	Wyoming
North Dakota	

#### Track-3

Alaska
Alabama
Arkansas
Delaware
Idaho
Kentucky
Louisiana
Maine
Montana
Nebraska
New Hampshire
Nevada
South Dakota
Vermont

Note: Current EPSCoR Jurisdictions and Past EPSCoR Jurisdictions

## FINDINGS RELATED TO OUTCOME VARIABILITY

Though EPSCoR primarily aims to increase research competitiveness through federal investments in human capital and research infrastructure in the jurisdictions' postsecondary institutions, the program may also create other positive externalities such as high-skills job creation and broad economic growth. All EPSCoR activities, including state committees and their science and technology plans, can combine to increase support for science and engineering (S&E) activities in the jurisdiction. The study team conducted an exploratory analysis to identify underlying latent factors, and the results are outlined below:

### EPSCoR jurisdictions vary along several measures in four outcome domains.

#### Human Capital Production



Compared to non-EPSCoR jurisdictions, a majority of EPSCoR jurisdictions

- produce low numbers of graduate students in S&E (relative to their population) except for jurisdictions with at least one highly reputed research-intensive doctoral university, and
- have a low percentage of their workforce with postsecondary education relative to their populations.

#### Reputation in Knowledge Production



The highest ranking institution in most EPSCoR jurisdictions tends to have lower national ranking in research capability and reputational measures compared to non-EPSCoR jurisdictions.

Jurisdictional Indicators of high reputation in knowledge production, such as NAI Fellows, SBIR program awards, and issued patents, are less prevalent in EPSCoR jurisdictions compared to non-EPSCoR jurisdictions.

Past EPSCoR jurisdictions tend to perform better on reputation in knowledge production measures than current EPSCoR jurisdictions.

#### Economic Development



Compared to non-EPSCoR jurisdictions, nearly all EPSCoR jurisdictions' economies present relatively limited opportunities for S&E graduates because the jurisdictions generally lag in the development of high-tech industries, with the exception of Utah.

#### Diversity in Labor Force



EPSCoR jurisdictions tend to have numbers of women participating in S&E graduate education and workforce that are similar to the numbers in non-EPSCoR jurisdictions, but they also tend to have lower participation by minorities in S&E graduate education and workforce.

Jurisdictions of similar EPSCoR status tend to cluster together around outcome measures.

#### Cluster 1

Alabama	Maine	Oklahoma
Alaska	Mississippi	Rhode Island
Arkansas	Montana	South Dakota
Delaware	Nebraska	Vermont
Hawaii	New Mexico	West Virginia
Louisiana	North Dakota	Wyoming

#### Cluster 2

Iowa	South Carolina
Idaho	Missouri
Kansas	Tennessee
Kentucky	Utah
Nevada	
New Hampshire	

#### Cluster 3

All non-EPSCoR jurisdictions

Note: Current EPSCoR Jurisdictions, Past EPSCoR Jurisdictions, Non-EPSCoR Jurisdictions



## Limitations

Though the study provides substantial contributions to understanding of AREC in the context of EPSCoR, it does have some conceptual and data-related limitations. To implement the AREC framework at the jurisdiction and university levels, this study relied entirely on publicly available extant datasets. This results in incomplete data coverage of the AREC framework and its related logic models. In addition, although award reports were the most reliable data source to capture the strategies used by the jurisdictions to improve research competitiveness, there were still many reporting differences that made it challenging to ensure jurisdictions were providing the same level of coverage. Given data availability (or lack thereof), the study team suggests exercising caution while using the findings of the study, especially for making significant programmatic decisions. Rather, the study team believes that the AREC framework will be most helpful in the areas of refining program planning and communication, while taking into account other sources of information related to EPSCoR. The data inventory presented in this study can inform EPSCoR management on the progress made by each of the jurisdictions over the years, even though it cannot be used to draw causal conclusions about how to increase research competitiveness. Given the combination of somewhat limited availability of data for fully testing the framework and the varied political and institutional cultures within the jurisdictions, the application of the AREC framework and the accompanying logic models to a specific project, institutional, or jurisdictional context should be done in a tailored way.

*The AREC framework and the corresponding data inventory provide theoretical underpinnings and data assessment that demonstrate the potential for application and substantial use by NSF in the future.*

## Recommendations

The study's findings lend themselves to two groups of recommendations. First, the study team presents recommendations on how the AREC framework and resulting observations can inform program conceptualization and design. Second, the study team presents actionable recommendations specific to EPSCoR implementation and operation.

### 1. RECOMMENDATIONS FOR COMMUNICATING, REFINING, AND IMPLEMENTING AREC FOR EPSCoR

**Recommendation 1.1 – Solicit EPSCoR Community Input to Communicate and Refine the AREC Framework.** *We recommend that the NSF EPSCoR office organize EPSCoR project investigators' community meetings where the framework can be addressed and refined if needed.* This is important to the framework's future use in communication and project evaluation or other activities.

**Recommendation 1.2 – Implement AREC Elements in EPSCoR.** *We recommend that the vetted AREC framework be refined and consciously structured for implementation as a guide for evaluation of EPSCoR projects.* For example, NSF EPSCoR could develop concise guidance and explanation of the AREC framework. This structured approach would produce a common

language and shared conceptualization that would enable standardizing of elements while allowing for tailoring of evaluation components to specific projects/jurisdictions.

## **2. RECOMMENDATIONS FOR CHANGES IN EPSCOR PROGRAMMATIC ELEMENTS AND FUTURE EVALUATIONS**

*Recommendation 2.1 – Create a Common Data Repository.* **We recommend the development of a more robust data repository based on AREC-relevant elements to provide a more complete understanding of the research capacities and complexities within jurisdictions.** The standardized reporting form and the longitudinal data can increase understanding across the jurisdictions' contexts and strategies used, and the outcome measures. The reporting form and the longitudinal data can also provide EPSCoR staff with the ability to track whether projects successfully meet the objectives of the EPSCoR award.

*Recommendation 2.2 – Conduct Future EPSCoR Evaluations.* **We recommend small, focused implementation studies be conducted, focusing on similar clusters of jurisdictions to thoroughly examine the jurisdictions' efforts to improve research competitiveness.** We suggest including current EPSCoR-eligible jurisdictions that are just below the eligibility cutoff, and previously EPSCoR-eligible jurisdictions that are just above the eligibility cutoff, to be included in one of these possible studies. The differences in implementation strategies across these two types of jurisdictions and their contributions to research competitiveness will provide some exploratory evidence regarding which strategies/activities seem to be influential in improving research competitiveness and can be incorporated across other EPSCoR jurisdictions.

*Recommendation 2.3 – Standardize the Measures Used for Evaluation.* A minor but consequential finding of the study is that significant variation exists in jurisdiction size, which makes it difficult to meaningfully compare measures across jurisdictions. **We recommend that NSF standardize the evaluation measures.**

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# 1. INTRODUCTION

## Overview of EPSCoR

Created by the National Science Board in 1978, the National Science Foundation (NSF) Established Program to Stimulate Competitive Research (EPSCoR)<sup>3</sup> is the largest jurisdiction-specific,<sup>4</sup> federally funded research program in the United States. The program is designed to enrich jurisdictional research capacity and ultimately improve the research competitiveness of jurisdictions that have historically received little federal research and development (R&D) funding. Specifically, EPSCoR aims to increase research competitiveness through federal program investments in human capital and other research infrastructure in the jurisdiction's postsecondary institutions. Importantly, EPSCoR is not a traditional research program, as exemplified by its stated objectives, which address not only research capacity but also the building blocks of research competitiveness such as infrastructure; human capital, including diverse participation; social capital in the form of collaboration; and broader impacts.

EPSCoR's objectives are

- to catalyze the development of research capabilities and the creation of new knowledge that expands jurisdictions' contributions to scientific discovery, innovation, learning, and knowledge-based prosperity;
- to establish sustainable science, technology, engineering, and mathematics (STEM) education, training, and professional development pathways that advance jurisdiction-identified research areas and workforce development;
- to broaden direct participation of diverse individuals, institutions, and organizations in the project's science and engineering research and education initiatives;
- to effect sustainable engagement of project participants and partners, the jurisdiction, the national research community, and the general public through data sharing, communication, outreach, and dissemination; and
- to impact research, education, and economic development beyond the project at academic, government, and private sector levels.

Over time, EPSCoR has evolved in focus and developed different funding mechanisms to address various factors relevant to research competitiveness in its jurisdictions. This study primarily focuses on the Research Infrastructure Improvement (RII) and Co-Funding program.

- The RII program uses several different investment strategies to support lasting improvements in a jurisdiction's academic research infrastructure to increase research competitiveness, organized along four tracks:

<sup>3</sup> Note: The remainder of this study uses the term "EPSCoR" to refer to NSF EPSCoR. The American Innovation and Competitiveness Act (AICA, P.L. 114-329), enacted on January 6, 2017, renamed EPSCoR from the original name—Experimental Program to Stimulate Competitive Research.

<sup>4</sup> NSF defines jurisdictions as U.S. states, territories, and commonwealths.

- *RII Track-1 Awards* (up to \$20 million for 5 years). Intended to improve the research competitiveness of jurisdictions by improving their STEM academic research infrastructure critical to the particular jurisdiction's science and technology (S&T) initiative or plan.
- *RII Track-2 Focused EPSCoR Collaborations* (up to \$4 million for 4 years). Collaborative awards between two to three EPSCoR jurisdictions to build interjurisdictional collaborative teams of EPSCoR investigators in scientific focus areas consistent with NSF priorities.
- *RII Track-3 Awards* (up to \$3.75 million for 5 years). Intended to broaden participation of underrepresented groups in STEM fields supported by NSF—underrepresented minorities (URMs), women, people with disabilities, and people residing in underserved rural regions of the United States.
- *RII Track-4 EPSCoR Research Fellows Awards*. Provides opportunities for nontenured investigators to further develop their individual research potential through extended collaborative visits to the nation's premier private, governmental, or academic research centers.
- The Co-Funding program leverages EPSCoR investment with that from other NSF Directorates and Offices to facilitate participation of EPSCoR scientists and engineers in NSF programs and initiatives.

## Overview of EPSCoR Jurisdictions

The number of EPSCoR jurisdictions has grown from the initial set of 8 to the current 28, with a total of 31 current and past jurisdictions.<sup>5</sup> These 31 jurisdictions, as well as academic research institutions and faculty within these jurisdictions, play a key role in U.S. research competitiveness. S&T-based innovation depends on a well-trained, high-tech workforce at all levels, and EPSCoR jurisdictions contribute substantially to developing and sustaining this workforce. EPSCoR jurisdictions<sup>6</sup> encompass 21 percent of U.S. businesses that account for 19 percent of U.S. Gross State Product (GSP). EPSCoR jurisdictions account for 22 percent of the employed U.S. workforce in professional, scientific, and technical services. In addition, research institutions in EPSCoR jurisdictions include a large share of U.S. academic research scientists and engineers, conferring 18 percent of science and engineering (S&E) PhDs and enrolling 12 percent of S&E postgraduate students. Academic research institutions in EPSCoR jurisdictions represent S&T centers around which high-tech companies can locate to create opportunities and wealth and improve quality of life. Furthermore, there is capacity to expand enrollment in many EPSCoR academic institutions and further develop the workforce in EPSCoR jurisdictions.

<sup>5</sup> As of fiscal year (FY) 2019, NSF determined that Missouri, Tennessee, and Utah had exceeded the eligibility thresholds and are not eligible for RII awards. South Carolina has exceeded the eligibility threshold but is currently still eligible for RII awards. National Science Foundation. (n.d.). *FY 2020 eligibility table*. Retrieved from: [https://www.nsf.gov/od/oia/programs/epscor/Eligibility\\_Tables/FY-2019-Eligibility.pdf](https://www.nsf.gov/od/oia/programs/epscor/Eligibility_Tables/FY-2019-Eligibility.pdf)

<sup>6</sup> This includes both current and past eligible EPSCoR jurisdictions. Data are not available for Puerto Rico, Guam, and the U.S. Virgin Islands for some of the measures.

Consequently, EPSCoR jurisdictions and their respective academic institutions represent a significant underutilized resource as the United States competes globally.

## EXHIBIT 1.1 MAP OF CURRENT AND PAST ELIGIBLE EPSCoR JURISDICTIONS

## Research Competitiveness

environment.<sup>7,8</sup> However, this narrow definition results in insufficient attention directed toward the constellation of resources and conditions (i.e., human, financial, institutional, and social) that are required to conduct scientific research, and it limits evaluators' and policymakers' understanding of how improvements in existing capacity can result in research excellence. The focus on grant dollars at a jurisdiction level also ignores the interplay of capacity and excellence across all levels of the jurisdictional ecosystem. Therefore, it is necessary to develop a new theoretical framework to adequately incorporate other factors related to academic research competitiveness that NSF can apply in the context of EPSCoR.

## Study Rationale

Since its creation, EPSCoR has always used the percentage of NSF funding levels as a primary determinant of eligibility to participate. The current eligibility for EPSCoR participation is restricted to jurisdictions that receive 0.75 percent or less of total NSF research funds over a 3-year period.<sup>9</sup> The Science and Technology Policy Institute (STPI) report<sup>10</sup> from 2011–2013 provides a detailed history of the eligibility for participation in EPSCoR.

EPSCoR eligibility and progress of jurisdictions in increasing research competitiveness have been subject to scrutiny. There is a limited definition of what constitutes competitiveness (or lack of competitiveness), as well as a lack of generally agreed-upon and applicable measures to track progress toward competitiveness.

Although federal funding is important to consider in decision making related to eligibility, NSF is interested in developing more comprehensive knowledge of jurisdictional variability to better understand which factors are most important for increasing jurisdictional research competitiveness. The complex variability in the context and composition of EPSCoR jurisdictions and strategies, combined with different investment tracks, awards, and scientific foci, requires a considerably more tailored set of measures to accurately and reliably demonstrate research competitiveness. This study provides a better understanding of the contextual complexities and variabilities of the jurisdictions to help EPSCoR's future investments and the management of its portfolio moving forward.

The **purpose** of this study is two-fold:

1. Develop a flexible framework to explore, define, and measure research competitiveness

<sup>7</sup> Wu, Y. (2010). Tackling undue concentration of federal research funding: An empirical assessment on NSF's Experimental Program to Stimulate Competitive Research (EPSCoR). *Research Policy*, 39(6), 835–841.

<sup>8</sup> Wu, Y. (2012). The cross-state distribution of federal funding in the USA: The case of financing academic research and development. *Science and Public Policy*, 40(3), 316–326.

<sup>9</sup> Any current EPSCoR jurisdiction that no longer meets the eligibility criterion for the RII awards is still eligible to participate in the EPSCoR co-funding and outreach opportunities for a period of 3 years.

<sup>10</sup> Zuckerman, B. L., Parker, R. A., Jones, T. W., Rieksts, B. Q., Simon, I. D., Watson III, G. J. . . . Rambow, P. B. (2014, December). *Evaluation of the National Science Foundation's Experimental Program to Stimulate Competitive Research (EPSCoR): Final report*. IDA Paper P-5221. Alexandria, VA: Institute for Defense Analyses Science & Technology Policy Institute.

2. Collect and use measures that assess jurisdictions' research competitiveness in relation to the unique jurisdictional contexts of the EPSCoR awardees for strategic program improvements

To address the first purpose, the study proposes an **Academic Research Excellence and Competitiveness (AREC)** framework built on existing knowledge that examines the framework's ability to inform and support academic research competitiveness. NSF requested that the study team construct, operationalize, and demonstrate a multidimensional AREC framework that can be directly applied to EPSCoR, as well as broader contexts.

To address the second purpose, the study team primarily relied on publicly available administrative data and rigorous quantitative analyses to provide NSF an understanding of how the unique contextual and strategic qualities of EPSCoR jurisdictions relate to research competitiveness outcomes. The findings will help refine existing, and tailor future, EPSCoR program-level activities and funding. Our study builds on two recent EPSCoR evaluations. The first, conducted by STPI from 2011–2013, focused on NSF EPSCoR, as well as other EPSCoR programs (the U.S. Department of Defense, U.S. Department of Energy, National Aeronautics and Space Administration [NASA], and U.S. Department of Agriculture). The second, conducted by the National Academy of Science (NAS) in 2013,<sup>11</sup> specifically addressed NSF EPSCoR. From these assessments, the following overarching recommendations were offered relevant to the evaluation:

- **STPI Report.** Evaluation of the National Science Foundation's Experimental Program to Stimulate Competitive Research: Final Report, 2014
  - The EPSCoR Section should focus future program-level evaluation efforts on the research competitiveness goal and not on improvements in the S&E research base within EPSCoR jurisdictions (p. 37).
  - Small, focused studies analyzing differences between EPSCoR and non-EPSCoR jurisdictions; in particular, aspects of research competitiveness or S&E research base quality may be appropriate to guide future EPSCoR efforts (p. 38).
- **NAS Report.** The Experimental Program to Stimulate Competitive Research, 2013
  - The evaluation process conducted during and after an EPSCoR project's implementation should be made more rigorous by developing and implementing an effective, reliable, and valid third-party evaluation design that is consistent with other federal evaluation approaches such as those developed by the Office of Management and Budget (OMB) (p. 53).

Our study adds to the aforementioned reports by

- examining and integrating the existing body of interdisciplinary knowledge on academic research capacity, competitiveness, and excellence to develop a flexible, multidimensional framework and corresponding logic model that effectively translate

<sup>11</sup> National Academy of Sciences, National Academy of Engineering, and Institute of Medicine. (2013). *The Experimental Program to Stimulate Competitive Research*. Washington, DC: The National Academies Press. doi:<https://doi.org/10.17226/18384>



AREC for the development of policy options/formulation and to support evaluative activities going forward;

- ascertaining the extent to which the logic model can be tested using existing data and empirically testing components of the model within existing data constraints; and
- investigating a set of jurisdiction-level measures to develop consistent indicators that exemplify research competitiveness and allow NSF to monitor progress over time.

It is important to note that this study is not an evaluation. Rather, it intends to develop a comprehensive knowledge of the key factors that contribute to jurisdictional AREC, as well as jurisdictional variability in these key factors. The study also aims to operationalize this knowledge to ultimately allow NSF to better understand how to use EPSCoR as a mechanism to increase AREC throughout the nation.

## Primary Research Questions

To fulfill the study's aim of operationalizing AREC to inform NSF decision making, the study team has been tasked with answering the following six categories of primary research questions (RQs):

1. **Contextual Variability**
  - a. What factors best describe the common characteristics that typify this contextual variability?
  - b. To what extent and in what ways does the research competitiveness context currently vary across EPSCoR jurisdictions?
  - c. Are there any clusters/groups of jurisdictions with common contextual features that can be identified across the program?
2. **Strategic Variability**
  - a. What common characteristics typify the range of implementation variability?
  - b. To what extent and in what ways do the S&E research base and mechanisms currently deployed for improvement vary across jurisdictions?
  - c. Are there any clusters/groups of jurisdictions with common implementation strategies that can be identified across the program?
3. **Outcome Variability**
  - a. What jurisdictional, institutional, and other characteristics typify the range of variability observed in research competitiveness definitions and performance?
  - b. To what extent and in what ways does the variability in context and strategy across EPSCoR jurisdictions influence the identification of relevant indicators of research competitiveness?
  - c. Are there any clusters/groups of jurisdictions with common context and/or strategy characteristics that can be used to understand variability in research competitiveness?
4. **Effectiveness.**
  - a. What differences and similarities exist with respect to implementation strategies and levels of research competitiveness, as defined for this study, for EPSCoR jurisdictions?



- b. Are there specific strategies or combinations of strategies with evidence of stronger influence or contribution to research competitiveness than others? For example, how do EPSCoR and non-EPSCoR institutions in similar Carnegie Classification of Institutions of Higher Education (Carnegie Classification) institutional classification categories currently compare with respect to research competitiveness as defined for the study?
  - c. What career pathways have been developed? To what extent are these career pathways diverse and inclusive, especially for early career researchers?
- 5. **Institutionalization.**
  - a. What ongoing evaluation processes, practices, and structures—in particular those related to stakeholder engagement, data collection, and analysis—are feasible to support and sustain the current and future implementation of a longitudinal program-level evaluation with common measures and a consistent yet flexible analytic approach?
- 6. **Improvement.**
  - a. What insights can be drawn from the evidence compiled to address RQs 1 through 5, and how can they be used to inform programmatic strategic directions?

## Supplementary RQs

The primary RQs served as the foundation for all study activities including theory development, data collection, and data analysis. However, answering the primary RQs required further exploration of AREC in order to translate a loosely established concept into clearly defined, empirically testable measures. Consequently, the study team also addressed three supplementary RQs:

- 1. What is AREC, and how can it be conceptualized into a framework?
- 2. How can the AREC framework be incorporated in a logic model with different levels/units of analysis (jurisdiction and institution levels)?
- 3. How can the AREC framework be translated for identifying research competitiveness measures that can be used in tracking progress for accountability purposes?

## Study Approach

To establish a theoretical foundation for AREC, the study team first expanded on findings and recommendations from the previous STPI and NAS reports. In addition, the study team conducted a comprehensive literature review of a variety of relevant sources. These activities informed the development of an AREC framework, as well as several associated logic models for the jurisdiction and institution levels (Chapter 2).

To develop a robust understanding of the existing data available for use in examining AREC across jurisdictions, the study team drew from the theoretical foundations to identify extant, publicly available data sources and relevant variables that could be used to operationalize the AREC framework and corresponding logic models. The study team then identified key measures for AREC, compiled a dataset for analysis, and discussed data limitations (Chapter 3).

Although the AREC framework includes jurisdiction, university, project/team, and individual levels, the study team chose to focus primarily on analysis of jurisdiction-level data to approach addressing the primary RQs. This decision was based on data availability and applicability. There are few extant administrative data sources that contain AREC measures at the project/team or individual levels. In addition, EPSCoR most directly targets jurisdictions as the primary unit of change in its efforts to increase AREC. Specifically, to examine variation in jurisdictions' contextual characteristics, strategies, and outcomes related to AREC, the study team empirically tested the identified key measures in a series of rigorous quantitative and qualitative analyses that included descriptive, factor, cluster, and document analyses as outlined in Exhibit 1.2. Further discussion of the extent to which each RQ is answered, along with explanations for RQs that were not answered, is provided in Chapter 4.

## EXHIBIT 1.2 PRIMARY RQS, DATA SOURCES, AND ANALYTICAL APPROACH

	Data Sources						
Research Question	NSF/NCSES Survey Data	NSF Administrative Data and State EPSCoR Websites	IPEDS/Carnegie Classification Data	State Census and Budget Data	Patent, Start-Up, and Commercialization Data	Other Administrative Data	Analysis
Contextual Variability							
To what extent and in what ways does the research competitiveness context currently vary across EPSCoR jurisdictions?	✓		✓	✓	✓	✓	Descriptive analysis
What factors best describe the common characteristics that typify this contextual variability?							Factor analysis
Are there any clusters/groups of jurisdictions with common contextual features that can be identified across the program?							Cluster analysis
Strategic Variability							
To what extent and in what ways do the S&E research base and mechanisms currently deployed for improvement vary across jurisdictions?		✓					Document analysis
What common characteristics typify the range of implementation variability?							Document analysis
Are there any clusters/groups of jurisdictions with common implementation strategies that can be identified across the program?							Not addressed
Outcome Variability							

[illegible]

	Data Sources						
Research Question	NSF/NCSES Survey Data	NSF Administrative Data and State EPSCoR Websites	IPEDS/Carnegie Classification Data	State Census and Budget Data	Patent, Start-Up, and Commercialization Data	Other Administrative Data	Analysis
measures and a consistent yet flexible analytic approach?							
Improvement							
What insights can be drawn from the evidence compiled to address RQs 1 through 5 that can be used to inform programmatic strategic directions?	Synthesize results from the above RQs for actionable recommendations for NSF, including suggestions from academic experts						

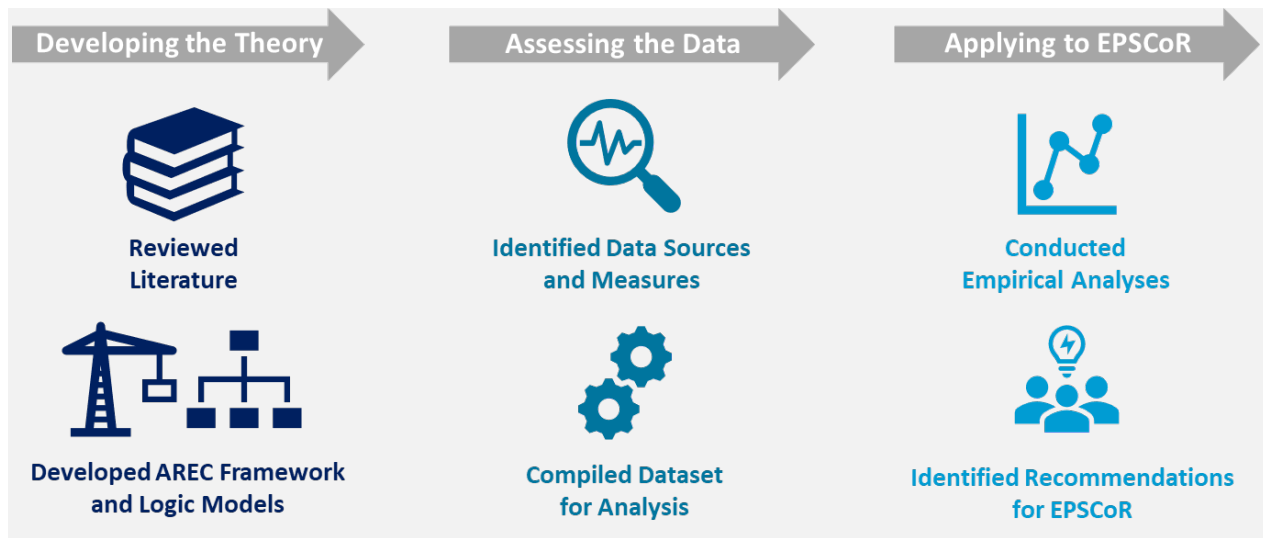
Note: NCSES – National Center for Science and Engineering Statistics. IPEDS – Integrated Postsecondary Education Data System. Other Administrative Data include National Institutes of Health (NIH) Research Portfolio Online Reporting Tools, Academic Ranking of World Universities (ARWU), and Quacquarelli Symonds (QS) World University Rankings.

Regarding the data sources listed above, the study team largely drew on survey data from NSF and NCSES for university- and jurisdiction-level information related to AREC. NSF administrative data and state EPSCoR websites refers to the EPSCoR award reports analyzed to understand program activities. The study team also looked at IPEDS and Carnegie Classification data for university characteristics, as well as state census and budget data for jurisdictional demographic and economic characteristics. Patent, start-up, and commercialization data provided additional insight into jurisdictional economy. Other administrative data included university ranking surveys and data related to Guam, Puerto Rico, and the U.S. Virgin Islands.

Descriptive analysis presents counts of contextual and outcome measures in bar charts, differentiating jurisdictions currently eligible for EPSCoR, eligible for EPSCoR in the past, and never eligible for EPSCoR. Factor analysis reveals underlying constructs that characterize these measures. Cluster analysis groups states that are similar in terms of these variables into clusters. Document analysis was used to extract information on EPSCoR awards' strategies and activities from award reports in each jurisdiction.

Finally, the study team summarized key findings and provided recommendations to guide NSF in making funding decisions that increase jurisdictional AREC (Chapter 9). The study components are shown in Exhibit 1.3.

## EXHIBIT 1.3 STUDY COMPONENTS



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## 2. DEVELOPING THE THEORY

The complexity of the U.S. academic research system necessitates clear definition and understanding of the many different institutional, economic, and social characteristics that contribute to research excellence and competitiveness. Ability to obtain grant funding serves as the traditional indicator of competitiveness, but this definition fails to account for the interwoven landscape of additional characteristics that help or hinder AREC. As such, identifying and examining contextual factors, strategies, and outcomes related to AREC is the main purpose of this study. The study team developed a new theoretical framework for AREC, as well as corresponding logic models, to expand this traditional definition of AREC to include the multitude of other factors involved.

Scholars have theorized that academic research excellence can be increased through program investments in human capital and other research infrastructure.<sup>12</sup> However, there is no single accepted definition of AREC or its components. Based on a strong foundation in interdisciplinary theory and existing empirical work, this study aims to contribute theoretically and conceptually to develop a more comprehensive definition of AREC. The approach is based on the identification, selection, and operationalization of various AREC dimensions on established and accepted definitions and measures of research competitiveness, when possible.

This chapter addresses the first purpose of the study:

1. To develop a flexible framework to explore, define, and measure research competitiveness in relation to the unique jurisdictional contexts of each EPSCoR awardee

This chapter also answers the following supplementary RQs, which aim to define the theoretical foundations necessary to answer the primary RQs.

1. What is AREC and how can it be conceptualized?
2. How can AREC be incorporated in logic models at different levels/units of analysis (jurisdiction and institution levels)?

These questions were addressed iteratively and continually through the learning process and activities of this study, resulting in an ongoing refinement of the preliminary AREC framework. The study conceptualized and operationalized the AREC framework through an iterative process of scholarly review and collaborative thinking between the study team and NSF.

<sup>12</sup> Bozeman, B., & Boardman, C. (2014). *Research collaboration and team science: A state-of-the-art review and agenda*. SpringerBriefs.

## Literature Review

Under the direction of NSF, the study team conducted a literature review to understand how different disciplines and approaches define and characterize AREC. The review covered a broad range of disciplines, subdisciplines, and research areas including innovation, entrepreneurship, STEM education, gender and diversity, the sociology of science, economic development, science policy, team science, research competitiveness, and higher education. Given the applied nature of this study, the study team also reviewed reports from U.S. national policy organizations and state agencies, as well as university institution reports on research competitiveness. The scan drew on academic and grey literature from the United States, international sources from the European context, and the Organisation for Economic Cooperation and Development. Following this review, the study team developed a keyword-based tagging schema to code each article. Coding was reviewed and agreed upon by the study team. The resulting bibliography provides a theoretical and policy literature foundation for the study and is stored on a bibliographic management system, the *Mendeley.com* website (shareable upon request).

## AREC Framework

Drawing from this multidisciplinary theoretical and empirical foundation, the study team presents a multilayered AREC framework that incorporates the context, complexity, and temporal nature of academic research activities. From the review, the study team identified four levels of focus in the competitiveness literature (jurisdiction, university, project/team, and individual) and five primary dimensions of AREC (resource acquisition, knowledge production, attractiveness, visibility/reputation, and economic development). Definitions for each of these levels and elements are presented in Exhibits 2.1 and 2.2, respectively. In addition, the AREC framework recognizes two important cross-cutting dimensions of competitiveness: human capital and diversity.

## EXHIBIT 2.1 LEVELS OF ANALYSIS FOR THE AREC FRAMEWORK



### Jurisdiction Research Excellence and Competitiveness (JREC)

Captures the macro-dimension of the AREC framework, which corresponds to the level associated with political jurisdictions, such as states or territories. All other levels of the framework are embedded within the jurisdiction level. Jurisdiction-level actors include the range of academic, nonprofit, and private sector organizations that contribute to jurisdiction-level competitive advantage in science. Relationships among research institutions, state- or jurisdiction-level policies and incentives, R&D programs and strategies, political and constituency support, infrastructure quality and maintenance, and investment strategies all contribute to JREC. An analysis at the jurisdiction level could include a comparison across jurisdictions.



### University Research Excellence and Competitiveness (UREC)

Recognizes that the unit of analysis is often a specific type of institution, such as a university, center, department, or major laboratory. Universities are key producers of knowledge and have significant potential to produce human capital. University efforts to translate and commercialize knowledge can also contribute to economic advantages and new business development. Whether universities can convert resources into competitive advantage depends on university policies, decisions, investments, and capacity, as well as on influences from other levels of AREC.



### Project-Team Research Excellence and Competitiveness (PREC)

Relates to the collaborative or team level of analysis. R&D programs invest in projects and collaborative teams that undertake scientific research. A substantial amount of literature on team science demonstrates that effective management of projects and teams is an important determinant of their success in terms of knowledge produced, innovation, and sustainability over time. PREC depends upon the individual scientists involved, as well as the nature and quality of the collaborations among individuals. Because many projects and teams are associated with multiple jurisdictions or universities, the analytical referent may be difficult to establish, making analysis of PREC complex.



### Individual Research Excellence and Competitiveness (IREC)

Addresses the researcher as a unit of analysis. Researchers seek resources, produce knowledge and technology, and gain a reputation in their fields. IREC considers the ability of researchers to convert training, support, networks, and opportunities into advances that bring further gains and increase their relative advantage within the relevant community of researchers.



## EXHIBIT 2.2 ELEMENTS OF THE AREC FRAMEWORK

 <p><b>Resource Acquisition</b></p>	<p>Captures the ability to obtain funding and other resources at any level of analysis. Although this element includes financial resources, such as grant awards, it also includes other resources such as human capital, equipment, and other infrastructure, and administrative or political support. Competitiveness often requires successful leveraging of and building upon existing capacities at multiple AREC levels.</p>
 <p><b>Knowledge Production</b></p>	<p>Represents the ability to leverage existing capacities and new investments to produce new knowledge and innovation. Research competitiveness is gained when entities at any AREC level demonstrate advantages and related visibility compared to other relevant units. Both excellence and competitiveness can be attained in a nonlinear fashion by production and the process of production. The Knowledge Production element is where the construct of excellence is most relevant and is demonstrated in a variety of knowledge career outcomes and related products.</p>
 <p><b>Attractiveness</b></p>	<p>Recognizes the ability of actors at different levels of the AREC framework to compete in enticing others to join them. This dimension, which is often fostered indirectly through various R&amp;D-favoring policies, quality of life measures, and approaches and policy mechanisms to improve diversity and infrastructure, highlights the importance of developing a good place to work, invest, learn, and live.</p>
 <p><b>Visibility/Reputation</b></p>	<p>Involves the relative prominence of an entity at any of the different AREC levels. Reputation is a key currency in academia and is a critical factor for signaling capacity and potential contribution to science and innovation. It also has an indirect effect on the perceived capacity and potential contribution of other associated entities at different AREC levels.</p>
 <p><b>Economic Development</b></p>	<p>Considers competence and capacity for commercialization and potential contribution of research to industry. It includes the production of new inventions, successful innovation of new products and processes, and successful commercialization of research outputs. Entities at different levels advance competitiveness through partnerships, management of technology transfer, commercialization policies, and researcher ability and motivation.</p>
 <p><b>Human Capital</b></p>	<p>Considers the technical, managerial, and scientific ability in the research system, and is a critical component at all levels of the AREC framework and across all AREC elements. For example, human capital is a dimension of the resource acquisition level through hiring, but the attractiveness of a university also determines recruitment and retention of faculty, as well as student interest.</p>
 <p><b>Diversity</b></p>	<p>Recognizes that race, ethnicity, gender, income, and family background are important dimensions of academic competitiveness. Diversity increases intellectual contribution at the team/project level. Lack of diversity creates significant scientific and technical capacity divides that can negatively affect competitive advance at the jurisdiction and institution levels.</p>

AREC is a nested framework, such that elements at one level can be influenced by elements at other levels. This systems-oriented approach recognizes that academic institutions and other organizations or groups interact to produce key knowledge, innovation, and social outcomes.<sup>13,14</sup> Furthermore, the relationships among these institutions within the system are nonlinear and include multiple feedback and feedforward pathways. In the education field, Bronfenbrenner's work<sup>15,16</sup> on ecological systems theory posits four subsystems—microsystem, mesosystem, exosystem, and macrosystem—that operate dynamically such that changes in any one subsystem affect the others over time. Microsystem refers to individual-level experiences, mesosystem captures organizational dimensions, exosystem can be broadly understood to address the institutions that operate to connect and influence microsystem and mesosystem structures, and macrosystem comprises the broader social context within which the other systems are nested.

Similar to other systems approaches, these subsystems interact over time to shape a complex learning environment.<sup>17</sup> Edquist and others used an innovation systems approach to explain how institutional and organizational factors interact to produce critical innovation outcomes.<sup>18</sup> This systems approach recognizes that institutions set resilient and enduring innovation pathways that result in jurisdiction-level innovation cultures. This approach also confirms that contextual factors matter in the outcomes of program investments. For example, AREC at an individual level will likely be affected by the jurisdiction, university, and project levels. The quality and excellence of institutions may also provide distinguishing resources that differentiate the research quality and outcomes of individual faculty and research teams.

Therefore, AREC is situated within a science, technology, and innovation system that includes multiple interconnected stakeholders and influences. Although the AREC elements are distinctly defined, any element may be influenced by the others. All AREC elements (Exhibit 2.2) have relevance across the AREC levels (Exhibit 2.1). For each element, the context of competition may be at the regional, national, or international levels. Exhibit 2.3 brings both aspects together.<sup>19</sup>

<sup>13</sup> Bronfenbrenner, U. (1994). Ecological models of human development. In *International encyclopedia of education*, Vol. 3 (2nd ed.). Oxford: Elsevier. Reprinted in: M. Gauvain & M. Cole (Eds.), *Readings on the development of children* (2nd ed.) (pp. 37–43). NY: Freeman

<sup>14</sup> Kok, M. O., & Schuit, A. J. (2012). Contribution mapping: A method for mapping the contribution of research to enhance its impact. *Health Research Policy and Systems*, 10(1), 21. <https://doi.org/10.1186/1478-4505-10-21>

<sup>15</sup> Bronfenbrenner, U. (1979). *The ecology of human development: Experiments in nature and design*. Cambridge, MA: Harvard University Press.

<sup>16</sup> Bronfenbrenner, U. (2005). *Making human beings human: Bioecological perspectives on human development*. Thousand Oaks, CA: Sage Publications.

<sup>17</sup> Pickett, S. T. A., & Cadenasso, M. L. (2002). The ecosystem as a multidimensional concept: Meaning, model, and metaphor. *Ecosystems*, 5(1), 1–10. <https://doi.org/10.1007/s10021-001-0051-y>

<sup>18</sup> Edquist, C. (2009). Systems of innovation: Perspectives and challenges. In J. Fagerberg & D. C. Mowery (Eds.), *The Oxford handbook of innovation*. Retrieved from <https://doi.org/10.1093/oxfordhb/9780199286805.003.0007>

<sup>19</sup> A full representation of the AREC framework is presented as Exhibit A.1 in Appendix A.

## EXHIBIT 2.3 AREC FRAMEWORK

ELEMENTS						
AREC FRAMEWORK		Resource Acquisition	Knowledge Production	Attractiveness	Visibility/ Reputation	Economic Development
LEVELS	JREC	Jurisdiction's capacity and/or ability to obtain federal R&D funding and other resources or capital	Jurisdiction's capacity for knowledge and innovation generation, stemming from its knowledge base	Jurisdiction's capacity to compete with other states or countries for talents (both "make" and "buy") and industries	Relative prominence of a jurisdiction among its peers, both domestic and international	State-level competence to apply and commercialize new knowledge and ideas
	UREC	A higher education institution's strategic interest in and ability to obtain research resources and sponsor research	Knowledge base of a university, including its human capital, and the growth of that base	Capacity to compete with other institutions, both domestic and international, for talents and funding	Institution's prominence among its domestic and international peers and counterparts, both in rankings and in perceptions of their capacity for research leadership	Institutional relationships with industry and tech transfer procedures, recruitment, and development
	PREC	A team's ability to obtain and leverage resources for research	A team's capacity to generate knowledge primarily visible through intellectual diversity and scientific and technical human capital	A team's ability to recruit talented team members and attract external attention and investment	All forms of broader recognition emerging from a team's past or current research activity	A team's contribution to regional and national economy through commercialization of research and industry partnerships
	IREC	An individual researcher's capacity and motivation to compete for government and other external funding	An individual researcher's knowledge production as an output and a process	An individual researcher's ability to draw inputs to successful research ventures	An individual researcher's prominence within and outside their field of subfield	An individual researcher's ability and openness to converting knowledge into innovations relevant to the regional and national economy
Cross-Cutting Elements: Human Capital and Diversity						

## AREC Framework and Associated Logic Models

As a next step, the study team organized the AREC framework into a temporal logic model, which would in turn enable us to begin operationalizing the AREC framework to address the study's primary RQs. The theoretical framework provides a literature-based characterization of AREC, but further work was needed to translate the framework for use in practice. We addressed this challenge using an iterative approach: (a) using existing logic models as a guide, (b) designing an initial AREC general logic model, (c) verifying assumptions through references to the literature and review of the project's Technical Working Group (TWG),<sup>20</sup> and (d) revising the logic model based on feedback from the TWG. These models came from two sources: (1) logic models used by U.S. federal agencies and related large science programs, projects, and centers, including those developed by EPSCoR; and (2) those used by research programs developed in other countries.

A review of existing logic models was useful because they reflect policy and implementation understanding, as well as expectations for research investments and activities. The study team collected and organized these models and identified the flow of inputs, activities, outputs, and outcomes most relevant to research programs, while also superimposing the key elements of the AREC framework as relevant. Using these existing logic models enabled the iterative checking process against the literature, thereby blending academic and policy perspectives for development of the AREC logic model.

While the AREC framework is applied across levels of analysis, the initial generalized logic model presented in Exhibit 2.4 does not distinguish AREC levels. The study team presents this model to demonstrate how the AREC framework can be adapted for a temporal model where short- and long-term outcomes are organized by AREC element. It is important to recognize the endogenous nature of excellence, competitiveness, and capacity development inherent in logic models applicable to AREC. For example, the capacity to produce competitive and excellent outputs and outcomes often depends on the capacity of the system at the input stage. These causal linkages and mechanisms across the model are often complex and multifaceted. For example, multiple different activities may affect a single output. As a result, the logic models provide an important but flexible guide for evaluative purposes, both for EPSCoR and other programs focused on fostering research excellence and competitiveness. The AREC framework aims to provide a useful basis for developing R&D evaluation methodology in which AREC constructs are considered intermediate- or long-term outcomes that can be used for R&D program or project evaluation.

<sup>20</sup> TWG members are JoAnn Canales, Senior Dean-in-Residence at Council of Graduate Schools; Ann Doucette, Research Professor, Claremont Graduate University; Maryann Feldman, Heninger Distinguished Professor, University of North Carolina; Steven Kubisen, Managing Director, Technology Commercialization Office, George Washington University; and Charles Wessner, Research Professor, Georgetown University.

## EXHIBIT 2.4 GENERALIZED LOGIC MODEL

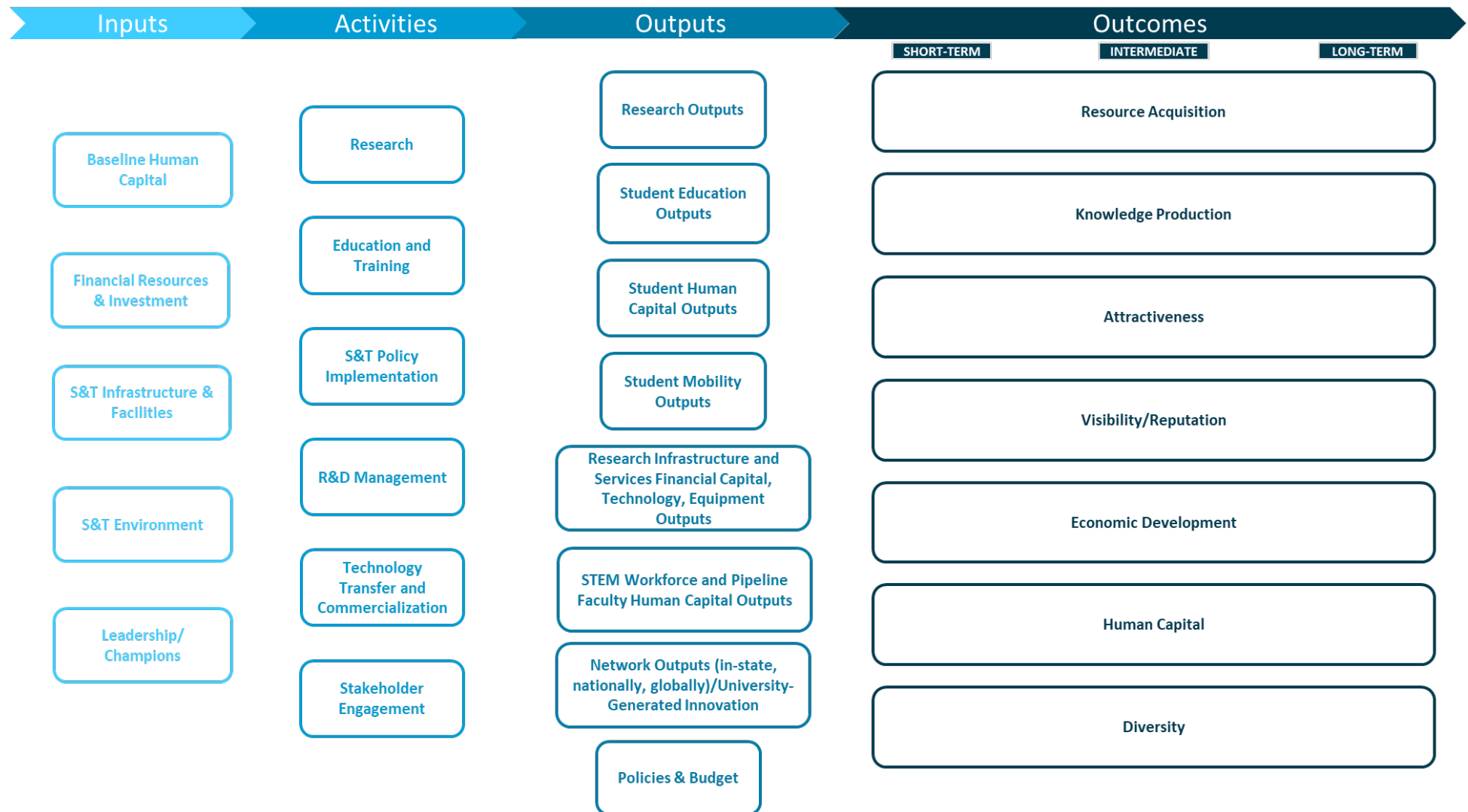


Exhibit 2.5 presents the logic model for the jurisdiction-level, as this level is particularly applicable in the EPSCoR context.

## EXHIBIT 2.5 JURISDICTION-LEVEL LOGIC MODEL

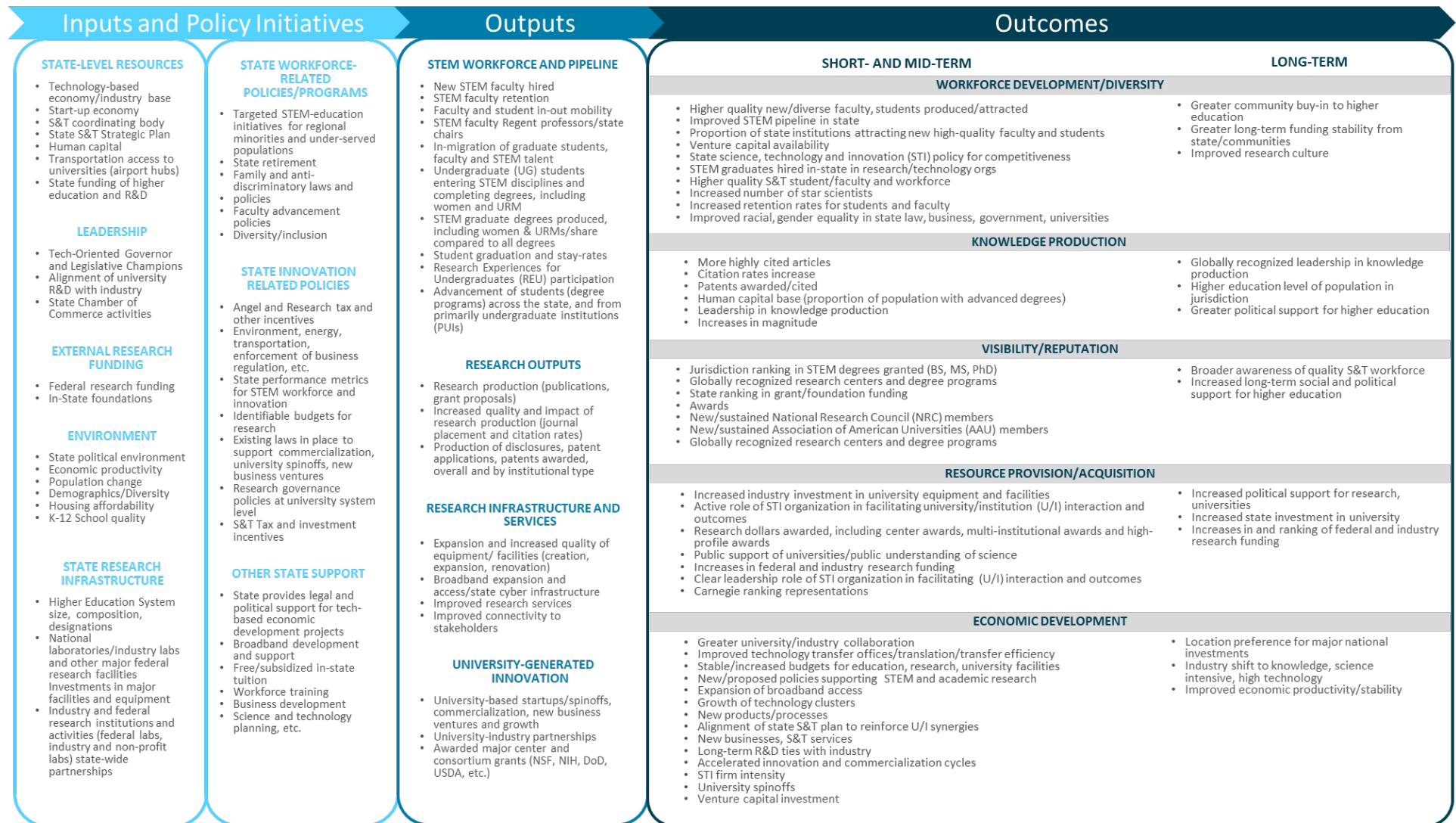
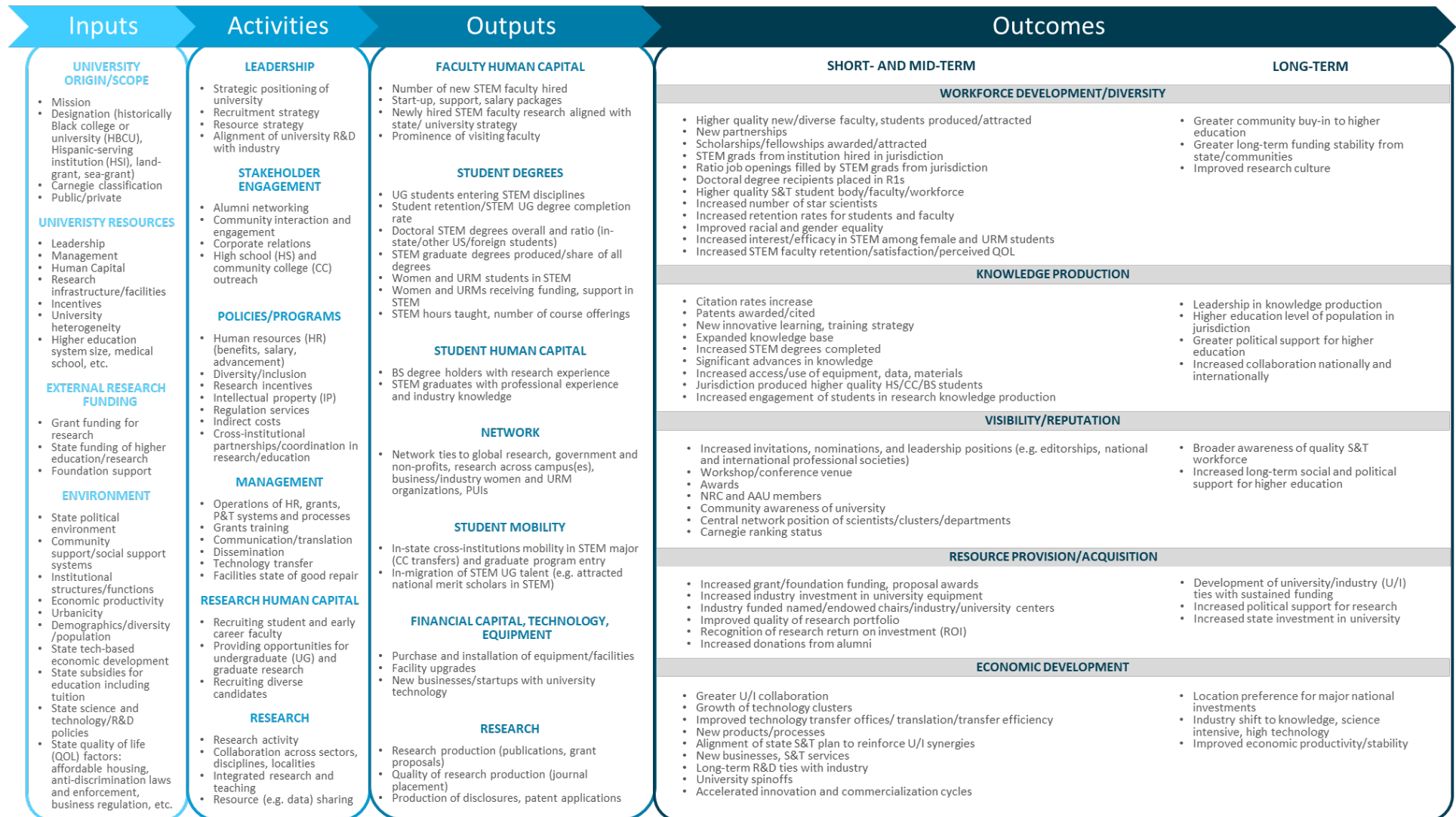




Exhibit 2.6 presents the university-level logic model for doctoral institutions, whereas the university-level logic model for teaching institutions can be found in Appendix A.

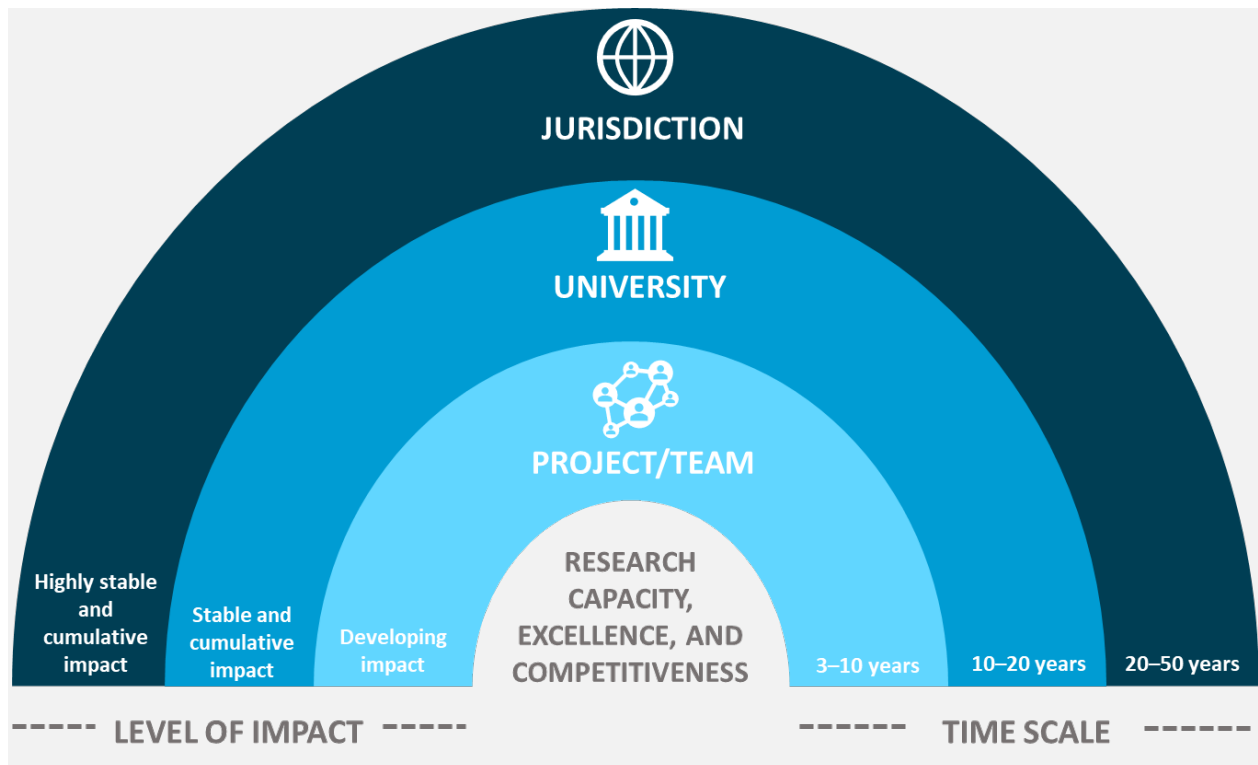
## EXHIBIT 2.6 UNIVERSITY-LEVEL (DOCTORATE) LOGIC MODEL



## APPLYING THE AREC LOGIC MODEL AT DIFFERENT LEVELS

Given the study team's systems-based approach, the logic models at the ecosystem, university, and project levels are embedded in layers as shown in Exhibit 2.7. Importantly, the rate of outcome-driven change occurring in each subsystem differs significantly, such that capacity development, excellence, and competitiveness are more rapidly achieved at the project/team level than at the university level, and so on.

### EXHIBIT 2.7 EMBEDDED SYSTEMS FOR U.S. ACADEMIC RESEARCH



#### *Applying the AREC Logic Model to Project/Team Level*

To demonstrate the embedded nature of scientific investments in projects and teams, the study team illustrates and discusses how elements at the project/team level interrelate with AREC elements at the university and jurisdiction levels.

We selected EPSCoR RII Track-1 projects as an example because these projects are a complex program addressing broad research-capacity development goals. For context, Track-1 projects are eligible for 5 years of funding at a total of \$20 million. These are diverse projects with the expectation of not only producing excellent scientific outcomes but also working across institutions in the state, and demonstrating STEM workforce developments, including increased diversity. EPSCoR is also similar to large center proposals that typically include specific attention to project S&E research, interuniversity project management, coordination and communication, student and early career workforce development, inclusion and diversity, and outreach and engagement, all of which are key for achievement of project objectives and the production of



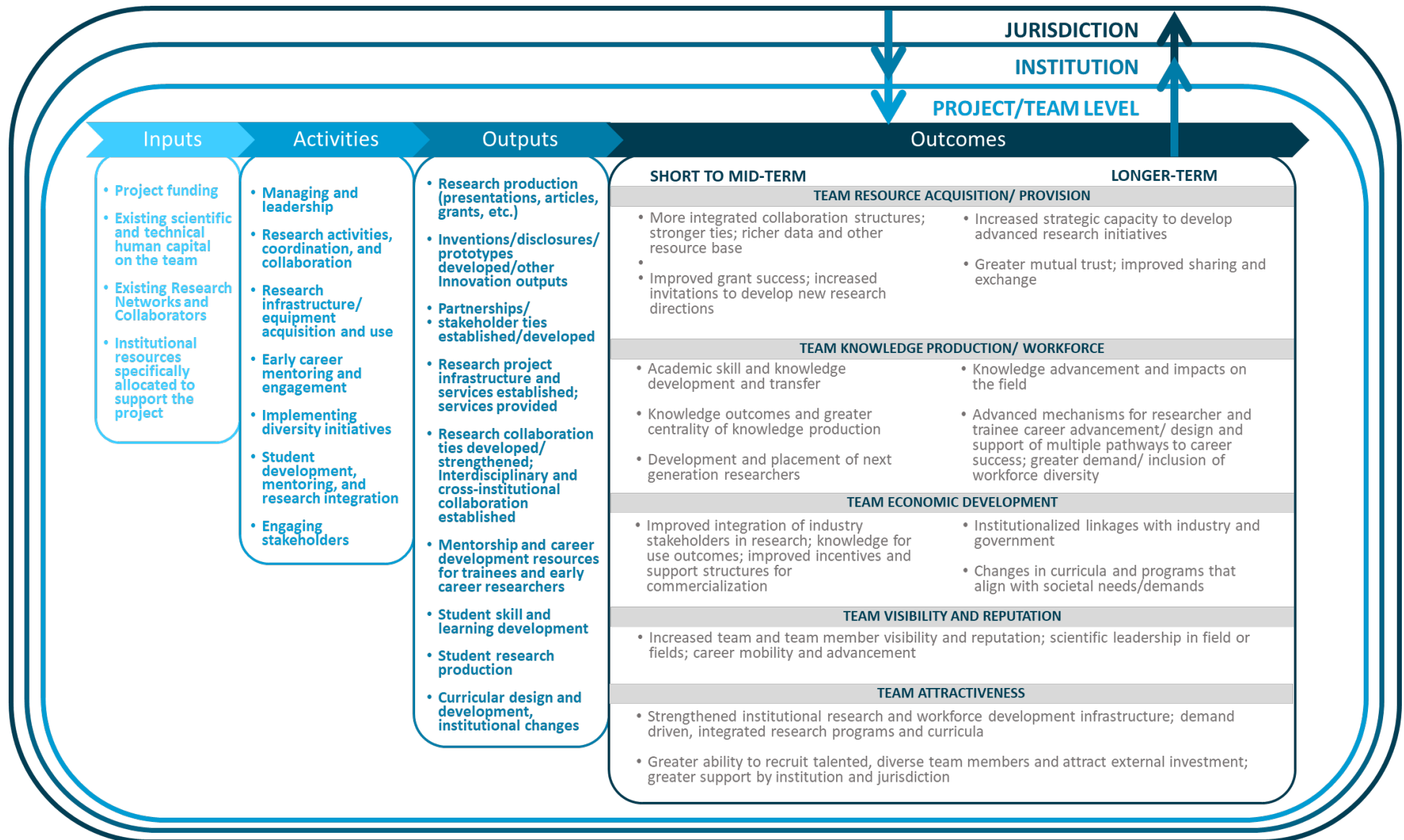
varied outcomes. Considering these broader project components expands the view of project activities to include research-specific work and infrastructure development and planning as well as other work central to the development and diffusion of this knowledge through, for example, the development of external stakeholder ties. To illustrate this, the most recent EPSCoR Track-1 solicitation notes the following:

*Track-1 proposals are unique in their jurisdiction-wide scope and complexity; in their **integration of individual researchers, institutions, and organizations**; and in their role in developing the diverse, well-prepared, **STEM-enabled workforce** necessary to sustain research competitiveness and catalyze economic development in the jurisdiction. . . . All elements of the project design are expected to advance the proposal's overarching vision and serve to improve the **jurisdiction's overall R&D competitiveness** in the chosen topical area(s). Development of **meaningful partnerships** as part of the RII Track-1 project is encouraged as a means of enhancing the jurisdiction's R&D competitiveness. Proposals should include strong intellectual engagement of diverse participants from institutions of higher education across the submitting EPSCoR jurisdiction, as well as **productive partnerships between the jurisdiction's academic institutions and organizations** in its governmental, nonprofit, and commercial sectors.<sup>21</sup>*

As an example, Exhibit 2.8 shows the application of the AREC logic model at the project or center level for a Track-1 EPSCoR project in a logic model framework. The study team has nested the project subsystem within the institutional and jurisdictional subsystems to illustrate how this conceptualization can inform a project- or center-level evaluation.

<sup>21</sup> National Science Foundation. (2019). *EPSCoR research infrastructure improvement program track-1: (RII Track-1)* (NSF 9580). Retrieved from <https://www.nsf.gov/pubs/2019/nsf19580/nsf19580.htm>

## EXHIBIT 2.8 PROJECT-/CENTER-LEVEL LOGIC MODEL (NESTED IN AREC FRAMEWORK)



The left side of the diagram shows that inputs to the study team are driven both by the research funding investment and the context that determines policies (e.g., hiring and faculty buy-out policies); institutional resources (which are also affected by state-level funding and policies); and visibility and partnerships that already exist for the institution.

Within academic institutions, large team science initiatives or centers can serve as visible leaders of interdisciplinary research and stakeholder engagement, thereby helping to shift research cultures in those institutions. By including a large number of students and other early career researchers, these initiatives and centers help shape the careers of individuals who may not have had these opportunities otherwise. These accomplishments are enabled or constrained by administrative and buy-out policies in their institutions, their ability to attract high-quality researchers and students to their projects, and other factors. These examples and others highlight the fact that large team science initiatives operate in an embedded system and have the potential to impact research capacity in several ways. Through the structure and processes of research engagement, these teams also build the research skills, capacity, and interest of trainees and the emerging STEM workforce engaged with the project; build external partnerships and visibility; and produce and disseminate knowledge to the academic and external stakeholder communities.

NSF recognizes that increased competitiveness requires a broad approach to capacity development in the jurisdiction. Aligned with the overall purpose of this study, assessing the progress of EPSCoR jurisdictions toward competitiveness and excellence would necessitate considering the complex context within which investments are made. This type of nested, multidimensional competitiveness structure is highly relevant for EPSCoR, which aims to increase jurisdiction-wide research capacity by improving the competitiveness of institutions through greater research capacity of teams and individuals within them.

The study expects that

- most AREC elements will be relevant for all AREC levels,
- different assessment approaches likely will be needed and will be relevant for each element and level,
- not all elements will be relevant across all EPSCoR projects,
- cross-cutting elements will be relevant across multiple elements and levels, and
- elements across levels will interact.

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## 3. ASSESSING THE DATA

After developing the AREC framework and logic models, the study team assessed how these theoretical constructs can be translated to identify research competitiveness measures to track jurisdictions' progress across the logic model's research competitive dimensions. To answer the study's primary RQs, it was necessary to first measure the logic model's inputs, activities, outputs, and outcomes for each EPSCoR and non-EPSCoR jurisdiction. The study team investigated relevant data sources, identified variables to measure the logic model constructs, and compiled these variables to create a dataset that could be used to explore the study's primary RQs. The last section in this chapter discusses the extent to which data are available to measure the logic model constructs and acknowledges the data limitations of this study.

### Data Sources

An extensive search for data sources to operationalize the AREC framework and logic model was conducted, primarily focusing on publicly available administrative datasets and EPSCoR awardees' annual reports.

As a first step, the study team identified administrative datasets with themes related to AREC (e.g., higher education, S&E, R&D, and jurisdictional economy) that could potentially contain relevant variables. As the aim was to track research competitive progress for accountability purposes, the study team decided to include only extant, publicly available data in the search. In addition, only a few extant administrative datasets contain variables that relate to the *project/team* or *individual* levels of the AREC framework. As a result, this search focused more on extant administrative datasets that were likely to contribute at the *jurisdiction* and *university* levels of the AREC framework.

The datasets identified in the initial search were maintained by NSF and other federal agencies, as well as private and nongovernmental organizations (see the final list of datasets used in Exhibit 3.1). The study team refined the initial list of potential datasets through feedback from the TWG and NSF program staff before conducting additional investigations into each dataset to determine which sources were most closely aligned with the AREC framework and associated logic model.<sup>22</sup> Datasets were excluded if they did not pertain to the study context, did not align with a level of analysis in the AREC framework (jurisdiction or institution level), or duplicated measures available in other datasets that were more consistently captured.

The administrative datasets provided quantitative data on contextual and outcome variability at the jurisdiction and university levels. To gain a more in-depth understanding of the strategic variability of projects across jurisdictions, the study team also examined EPSCoR annual reports for insight on project activities.

<sup>22</sup> The restricted-use data sources reviewed by the study team had limited coverage, did not include needed identifiers, or replicated information that was also publicly available.

A total of 61 previous and current EPSCoR awardee reports were analyzed for strategic variability across EPSCoR jurisdictions.<sup>23</sup> Any awards that were co-funded or were EPSCoR Workshops were not included for the purposes of this study. The study team identified 318 total awards across 5 tracks (i.e., Track-1, Track-2,<sup>24</sup> Track-3, Track-4, and Track-C2<sup>25</sup>). Track-4 awards were not included due to their purpose of increasing individual research capacity and varying number of awardees per jurisdiction at any given time. To capture the most comprehensive and recent information about strategic activities for each award type in each jurisdiction, the study team focused their analysis on final reports. In many cases, these final reports linked a supplemental report to their submission instead of including their findings in the standard template. In final reports that stated that their data could be found in this attachment, the study team coded the supplemental file instead. In cases for which grantees were in no-cost-extension (NCE) years, final reports discussed the award aggregate activities to date. The study team coded these activities, which included NCE activities and activities from previous years.

The data sources in Exhibit 3.1 were identified as having the potential to provide data to operationalize the AREC framework and associated logic models, as well as answer the primary RQs.

### EXHIBIT 3.1 DATA SOURCES EXAMINED TO IDENTIFY RELEVANT MEASURES

Data Source	Description
<i>NSF/NCSES</i>	
Survey of Federal Science and Engineering Support to Universities, Colleges, and Nonprofit Institutions (FSESUCNI)	Collects comprehensive data on federal S&E funding to individual academic and nonprofit institutions
Higher Education Research and Development Survey (HERD)	Collects information on R&D expenditures by field of research and source of funds, on types of research and expenses, and on headcounts of R&D personnel
Survey of Science and Engineering Research Facilities (SERF)	Collects data on the amount, construction, repair, renovation, and funding of research facilities, as well as the computing and networking capacities at U.S. colleges and universities
Survey of Earned Doctorates	Collects information on the doctoral recipient's educational history, demographic characteristics, and postgraduation

<sup>23</sup> Previous and current EPSCoR awards under the Office of the Director were explored on the NSF award search website: <https://www.nsf.gov/awardsearch/>

<sup>24</sup> Earlier Track-2 awards assigned individual award numbers to each jurisdiction within an interstate collaboration. It was determined the reports across the same interstate collaboration were exact duplicates of each other, so those awards were linked and only one of the full reports was analyzed for this study. For later Track-2 awards that assigned one award number for multiple jurisdictions participating in a collaborative infrastructure, strategic activities were associated with each jurisdiction included in the award.

<sup>25</sup> Track-C2 appeared to be a defunct award from EPSCoR that had a focus on building cyberinfrastructure, and therefore was not analyzed for strategic variability.

Data Source	Description
	plans; results are used to assess characteristics of the doctoral population and trends in doctoral education and degrees
Survey of Graduate Students and Postdoctorates in Science and Engineering (SGSPSE)	Collects data on graduate enrollment and postdoctorate appointments, demographics, and sources of financial support
Science and Engineering State Profiles (SESP)	Presents selected data (including by major S&E fields) from NCSES surveys on employed science, engineering, or health (SEH) doctorate holders; S&E doctorates awarded; SEH graduate students and postdoctorates; federal R&D obligations by agency and performer; total and business R&D expenditures; and higher education R&D performance
NSF State Indicators	Provides 60 principal S&T indicators for the United States, individual states, the District of Columbia (DC), and Puerto Rico
EPSCoR Annual Reports	Provides information on strategic activities
<b>Other Federal Agencies</b>	
Integrated Postsecondary Education Data System (IPEDS); NCES	Provides core postsecondary education data in fundamental areas such as enrollment, program completion and graduation rates, institutional costs, student financial aid, and human resources
Bureau of Economic Analysis (BEA)	Provides GSP <sup>26</sup>
Data Retrieval Tools; U.S. Department of Labor Bureau of Labor Statistics (BLS)	Collects essential economic information such as labor market activity, working conditions, and price changes in the economy
American FactFinder; U.S. Department of Commerce Bureau of the Census (Census)	Provides data from several censuses and surveys (e.g., the American Community Survey <sup>27</sup> )
State Census and Budget Data; U.S. Department of Commerce, Census	Provides data on state and local governments' fiscal relationships.
North American Industry Classification System (NAICS)	Provides total number of business establishments in a jurisdiction
Minority Business Development Agency (MBDA)	Provides data on the growth of minority-owned businesses

<sup>26</sup> The World Bank data were used to provide gross state product (GSP) for Puerto Rico, Guam, and the U.S. Virgin Islands.

<sup>27</sup> For more information, please see: [https://factfinder.census.gov/faces/nav/jsf/pages/what\\_we\\_provide.xhtml](https://factfinder.census.gov/faces/nav/jsf/pages/what_we_provide.xhtml)

Data Source	Description
Centers for Disease Control and Prevention National Center for Health Statistics (NCHS)	Provides data on county metropolitan categorization based on population level and density (Urban-Rural Classification Scheme for Counties)
<i>Private and Non-Governmental Organizations</i>	
The Carnegie Classification of Institutions of Higher Education	Derives from empirical data on colleges and universities, the Carnegie Classification has been widely used in the study of higher education, both to represent and control for institutional differences, and in the design of research studies to ensure adequate representation of sampled institutions, students, or faculty
Quacquarelli Symonds (QS) World University Rankings	Ranks the world's top universities by region and subject
Academic Ranking of World Universities (ARWU), Shanghai Ranking Consultancy	Uses six objective indicators to rank world universities, including the number of alumni and staff winning Nobel Prizes and Fields Medals, number of highly cited researchers selected by Thomson Reuters, number of articles published in <i>Nature</i> or <i>Science</i> , number of articles indexed in the Science Citation Index-Expanded and Social Sciences Citation Index, and per capita performance of an institution
National Academy of Inventors (NAI)	Lists the names and institutional affiliations of NAI Fellows.
National Venture Capital Association Yearbook (NVCA)	Provides quarterly reports on venture capital (VC) activity by state
Small Business Innovation Research (SBIR) and Small Business Technology Transfer Research (STTR)	Provides data on the numbers and amounts of SBIR and STTR awards by state
State Technology and Science Index (STSI)	Reports on S&T capabilities and broader commercialization ecosystems that contribute to company growth, high value-added job creation, and overall economic growth
World Bank	Provides GSP for Puerto Rico, Guam, and the U.S. Virgin Islands

## Data Measures

After compiling the relevant set of data sources, the study team identified how each variable within these data sources can be used to represent the logic model constructs.

### ADMINISTRATIVE DATASETS

The study team examined each specific variable within the final list of administrative datasets (identified in Exhibit 3.1) that could be used to measure jurisdiction- and university-level research competitiveness constructs in the AREC framework or the associated logic models. The study team engaged in an iterative process of matching variables to constructs, compiling a comprehensive list of covered constructs and their potential measures. This process often resulted in multiple variables that provided duplicative measures for a construct. As a result, the study team established criteria to choose the most appropriate variable to measure a particular construct in the logic model. When available, the study team specifically selected STEM-related variables. When choosing between duplicative STEM-related variables, the variable that had the most data coverage of jurisdictions or universities was selected. This process led to a refined list of nonduplicative measures connected to the jurisdiction and institution levels of the AREC logic model as listed in Exhibits 3.2 and 3.3, respectively.

### EXHIBIT 3.2 KEY MEASURES AT THE JURISDICTION LEVEL: REPRESENTING AREC LOGIC MODEL CONSTRUCTS

Logic Model Constructs	Key Measures at the Jurisdiction Level (Data Source)
	<i>Inputs</i>
Start-up economy	Capital invested by VC companies in each state (NVCA)
	State R&D expenditures in 2015 (SESP)
State funding of higher education and R&D	State expenditure on higher education in 2015 (thousands of dollars) (Census)
	Total R&D expenditures by state with funding from the Federal Government in 2015
Human capital	Total population in a state for each year 2012–2017 (Census)
Investments in major facilities and equipment	Academic research space in 2015 (thousands of square feet) (SESP)
	Federal S&E R&D obligations in 2014 (SESP)
	Total federal obligations for S&E R&D to state universities and colleges in 2014 (SESP)
Federal research funding	Whether or not a state was eligible for EPSCoR in FY 2018 (NSF)
	Total dollar amount in awards given to each state for Phases I and II combined in 2017 (SBIR-STTR)
	Total NSF research funding per \$100,000 of state's GSP in 2015 (STSI)
	Total NIH funding received by state in 2017 (NIH)
Economic productivity	Real GSP for 2017 in millions of chained 2009 dollars (BEA)



Logic Model Constructs	Key Measures at the Jurisdiction Level (Data Source)
Demographics/diversity	Total number of businesses in a state as classified by an NAICS code in 2017 (NAICS)
	Total number of Inc. 500 companies (that have had total net revenue/income more than triple over most recent 5 years) in a state, per 10,000 business establishments in 2015 (STSI)
	Percentage of state metropolitan population vs. total state population size in 2013 (NCHS)
	Percentage minority of state population in 2015 (Census)
Population change	Percentage female of state population in 2015 (Census)
	Jurisdiction population in 2017 (Census)
State political environment	Political culture
Higher Education System size, composition, designations	Carnegie Classification in 2010 (Carnegie)
<b>Outputs</b>	
In-migration of graduate students, faculty, and STEM talent	Number of SEH graduate students in 2016 (SESP)
	Number of SEH postdoctorates in 2017 (SESP)
Undergraduate students entering STEM disciplines and completing degrees	Percentage of bachelor's degrees in each state that are in S&E disciplines (STSI)
	Proportion of workers who earned bachelor's degrees, master's degrees, or PhDs in S&E out of total civilian workers in 2014 (STSI)
STEM graduate degrees produced	Number of S&E doctorates awarded in 2016 (SESP)
<b>Short- and Mid-Term Outcomes</b>	
Patents awarded/cited	Utility patents issued to state residents in 2015 (SESP)
	Number of NAI Fellows in each state in 2015 (NAI)
Human capital base (proportion of population with advanced degrees)	Number of employed SEH doctorate holders in 2017 (SESP)
	Percentage of population in state age 25 and older with bachelor's degree in 2014 (STSI)
	Percentage of population in state age 25 and older with master's degree or higher in 2014 (STSI)
	Percentage of population in state age 25 and older with doctorate in 2014 (STSI)
	Total employment in professional, scientific, and technical services in 2016 (Census)
Improved racial and gender equality in state	Percentage distribution of Black workers in professional and business services in state in 2016 (BLS)

Logic Model Constructs	Key Measures at the Jurisdiction Level (Data Source)
law, business, government, and universities	Percentage distribution of Asian workers in professional and business services in state in 2016 (BLS)
	Percentage distribution of Hispanic/Latino workers in professional and business services in state in 2016 (BLS)
	Percentage distribution of female workers in professional and business services in state in 2016 (BLS)
	Percentage of women in professional, scientific, and technical services employment in 2016 (Census)
	Percentage of disabled persons with full-time employment in 2013 (Census)
	Parity ratio of number of minority-owned S&E businesses in 2012 (MBDA)
<i>Long-Term Outcomes</i>	
Increases in federal and industry research funding	Rate at which state's research proposals were given NSF funding in 2015 (STSI)
	Average yearly growth of high-tech industries from 2010–2015 (STSI)
Industry shift to knowledge, science intensive, high technology	Percentage of workforce composed of S&E occupations in 2017 (NSF State Indicators)
	Concentration of high-tech industries in state in 2015 (STSI)
	Number of high-technology industries whose employment grew faster than the national average for the overall economy from 2010–2015 (STSI)
	Percentage of businesses in a state defined as high-tech in 2014 (STSI)
	Percentage of employment in a state that is within one of the high-tech industries in 2015 (STSI)
	Number of Technology Fast 500 companies per 10,000 businesses in 2015 (STSI)

### EXHIBIT 3.3 KEY MEASURES AT THE UNIVERSITY LEVEL: REPRESENTING LOGIC MODEL CONSTRUCTS

Logic Model Constructs	Key Measures at the University Level (Data Source) <sup>28</sup>
<i>Inputs</i>	
Research infrastructure/facilities	Value of R&D expenditures in S&E fields in 2015 (HERD)
Grant funding for research	Value of all agency federal obligations for S&E R&D in 2015 (FSESUCNI)
	Value of NSF federal obligations for S&E R&D in 2015 (FSESUCNI)
<i>Activities</i>	
Human resources (salary)	Average weighted monthly salary for professors in 2015 (IPEDS)
Facilities state of good repair	Costs for repair and renovation of S&E research space started between FY 2012 and FY 2015 (SERF)
<i>Outputs</i>	
Purchase and installation of equipment/facilities	Costs for new construction of S&E research space started between FY 2012 and FY 2015 (SERF)
Student retention	Number of STEM bachelor's degrees completed in 2015 (IPEDS)
STEM graduate degrees produced	Number of S&E graduate students in 2015 (SGSPSE)
Doctoral STEM degrees overall	Number of earned S&E doctorates in 2015 (SGSPSE)
Women and URM students in STEM	Percentage of minority full-time S&E graduate students in 2015 (SGSPSE)
	Percentage of female full-time S&E graduate students in 2015 (SGSPSE)
Research production (publication, grant proposals)	Score on papers published in <i>Nature</i> or <i>Science</i> from 2017 (ARWU)
Quality of research production (journal placement)	Score on papers indexed in science and social science fields from 2017 (ARWU)
<i>Short- and Mid-Term Outcomes</i>	
Expanded knowledge base	Score on per capita academic performance from 2017 (ARWU)
Citation rates increase	Score on highly cited researchers from 2017 (ARWU)
Awards	Score of staff of an institution winning Nobel Prizes and Fields Medals from 2017 (ARWU)
Community awareness of university	Score on academic reputation based on expert opinion from 2017 (QS)

<sup>28</sup> Select university-level variables from Exhibit 3.3 are included in analysis, aggregated to the jurisdiction level.

Mapping publicly available administrative dataset variables to the AREC logic model can provide a way for monitoring jurisdiction- and university-level progress on key components of research competitiveness as defined by the AREC framework. In addition, this demonstrates the range of data available for operationalizing the AREC framework that are publicly available and regularly updated. This extensive inventory of AREC-related datasets is a major contribution of this study.

## **EPSCoR ANNUAL REPORTS**

In addition to the contextual input and outcome data collected in the administrative datasets, EPSCoR awardee project reports provide valuable insight into the strategic variability across collaborative teams to improve the research infrastructure. The study team originally investigated the feasibility of capturing strategic variability through different modes of reporting including award proposal abstracts, award reports, and EPSCoR jurisdiction websites. However, it was determined that the award proposal abstracts were too brief and EPSCoR websites had too much variability in content and structure to efficiently extract information. Jurisdictions also often had general websites that shared information about work from multiple streams of federal funding to build research capacity and competitiveness. This made it difficult to isolate strategic activities that were specifically related to NSF EPSCoR funding, and the websites often disseminated findings or outcomes that were the result of various activities.

The final reports contained information about project objectives and activities that can enhance NSF's understanding of how jurisdictions allocate EPSCoR funds. A caveat is that these data are available only for EPSCoR jurisdictions and that the information in these reports is limited to what was reported by the awardees. The report narratives do not provide detailed budget analyses of jurisdiction expenses on EPSCoR projects but can provide a glimpse of the variability in spending to build research competitiveness and capacity.

From the total 318 awards ever awarded since the inception of EPSCoR, the study team coded a sample of 61 EPSCoR reports across the 31 EPSCoR jurisdictions. The reports were carefully chosen to represent each EPSCoR jurisdiction and award tracks with reports available for analysis. The reports were pulled from the NSF eJacket system in January 2020. Reports were screened and vetted for feasibility of use for coding and analyses. During this process and with existing knowledge about the program, the study team developed a coding framework that captured various activities that jurisdictions might conduct using EPSCoR funding. During the coding process, new subcategories were discovered and discussed by the coding team for inclusion, but no additional categories were added. The study team developed nine activity categories:

- **Leadership Support** – Supporting committees, task forces, or advisory groups that provide oversight or guidance
- **Policies** – Supporting development or implementation of federal, state, or local policies
- **Programs** – Supporting development or implementation of federal, state, or local programs
- **Diversity** – Supporting URM groups including but not limited to women; racial/ethnic minorities; lesbian, gay, bisexual, or transgender (LGBT) individuals; individuals with

disabilities; tribal/native groups; individuals from rural areas; and unspecified URM groups

- **Infrastructure** – Supporting building cyberinfrastructure, purchasing equipment or expendable materials, or securing physical space
- **Funding Personnel** – Supporting existing personnel or students
- **Hiring Personnel** – Supporting the recruitment of new personnel or students
- **Building Collaborative Relationships** – Supporting relationships between jurisdictions (i.e., Track-2 awards); partnerships between different organizations and entities within a jurisdiction; and relationships between different operational units at a single university
- **Training Activities** – Supporting attendance at or holding of conferences, workshops, courses, etc., to train individuals

During the development of the coding framework, the study team determined that the aforementioned activities could be done for varying motivations or purposes. The following reasons were coded with an activity to indicate the motivation behind the activity:

- **Broadening Participation** – Any effort to increase URM participation in STEM
- **Building Database** – Developing cyberinfrastructure or data collection procedures to create a systematic mechanism to store data
- **Dissemination** – Reporting or exchanging findings or announcements of EPSCoR activities
- **Education** – Funding instructional or learning activities for individuals
- **Innovation** – Funding the capacity to generate new ideas or processes to validate or patent innovative ideas
- **Management** – Systems or processes funded to improve operations or performance management
- **Professional Development** – Training activities designed to support advancement of career pathways
- **Outreach and Engagement** – Efforts to engage stakeholders or provide services to the community or partners
- **Research** – Conducting laboratory or field research activities
- **Strategy** – Strategic activities designed to plan, develop, and reevaluate the mission and vision of increasing research capacity or competitiveness in a jurisdiction(s)

Relationships between these activities and their underlying motivations are discussed in more depth in Chapter 6.

## Preparation of Data for Analysis

### ADMINISTRATIVE DATASETS

After finalizing the list of variables to serve as AREC measures, the study team extracted and cleaned the variables from the administrative datasets to prepare for analysis. The study team used state or institution names to match observations across the various datasets, allowing for all variables to be merged into two master datasets: jurisdiction level and university level.

Using these two master datasets as a foundation for the analysis, the study team manipulated and built on the variables when appropriate. The study team recognized the importance of university-level variation in understanding AREC, although in consultation with NSF ultimately decided that university-level data could be most actionable for EPSCoR jurisdictions if presented in the context of jurisdictions. As a result, the combined master dataset used for quantitative analyses included jurisdiction-level variables and select university-level variables aggregated to the jurisdictional level.

To best address the primary RQs, which largely focus on variability across jurisdictions in contextual, strategic, and outcome measures, the analyses frame university-level measures as they relate to the jurisdiction level. For example, analyses examine how jurisdictions compare on aggregated university-level measures or how universities differ in EPSCoR and non-EPSCoR jurisdictions.

The significant variation in jurisdictions makes it difficult to meaningfully compare measures across jurisdictions. As a result, when appropriate, the study team standardized variables using population size, GSP, or number of S&E workers. This standardization allows for examination of variation among jurisdictions of similar size and capacity.

#### EXHIBIT 3.4 KEY MEASURES USED IN ANALYSIS

Factor	Contextual Measures
Environment and Institutional Capacity	Total population
	Percentage of URMs
	Metro categorization
	Political culture
	Number of doctoral universities, by type (R1, R2, R3)
	Number of nondoctoral universities, by type (associate, baccalaureate, master's)
	Number of minority-serving institutions (MSIs), by type (historically black colleges and universities [HBCUs], Hispanic-serving institutions [HSIs], tribal colleges and universities [TCUs])
Research Capacity	GSP per capita
	Total number of businesses per capita
	Percentage of population age 25 and older with a baccalaureate degree in S&E
	Percentage of residents employed in professional, scientific, and technical services
	Capital invested by VC firms per S&E worker
	Federal obligations for S&E R&D per S&E worker
	Federal obligations for S&E R&D to universities per S&E worker
	Total NSF funding per S&E worker
	Total NIH funding per S&E worker
	Total STTR-SBIR award funding per S&E worker

Jurisdiction	R&D expenditure per S&E worker
Level Financial	R&D expenditure with federal funding per S&E worker
Resource	Expenditure on higher education per S&E worker
Capacity	Academic research space per doctoral university
Factor	Outcome Measures
Human Capital Production	Number of SEH graduate students per 100,000 residents
	Number of S&E doctorates awarded per resident
	Number of SEH postdocs per resident
	Number of employed PhDs in SEH per resident
	Percentage of population age 25 and older with bachelor's degree
	Percentage of population age 25 and older with at least a master's degree
	Percentage of population age 25 and older with doctorate
	Proportion of workers who earned a bachelor's, master's, or PhD in S&E
Reputation in Knowledge Production	Maximum score in jurisdiction from R1 (or R2 if no data for R1) for papers published in <i>Nature</i> or <i>Science</i>
	Maximum score in jurisdiction from R1 (or R2 if no data for R1) for papers indexed in science or social science fields
	Maximum score in jurisdiction from R1 (or R2 if no data for R1) for per capita academic performance
	Maximum score in jurisdiction from R1 (or R2 if no data for R1) for highly cited researchers
	Number of NAI Fellows
	Number of SBIR program awards
	Number of utility patents
Economic Development	Percentage of workforce composed of S&E occupations
	Percentage of businesses that are defined as high-tech
	Percentage of employment within one of the high-tech industries
	Concentration of high-tech industries
	Jurisdiction's relative performance in generating fast-growing high-tech enterprises
	Number of high-tech industries with employment growing faster than average
	Total number of Inc. 500 companies per 10,000 business establishments
Gender and Racial Diversity in Labor Force	Percentage of female full-time S&E graduate students
	Percentage women in professional, scientific, and technical services employment
	Percentage of minority full-time S&E graduate students
	Percentage of Black workers in professional and business services
	Percentage of Hispanic/Latino workers in professional and business services

## **EPSCOR ANNUAL REPORTS**

Two coders developed the coding framework and debriefed daily to discuss unique observations or discrepancies. Other members of the study team were consulted and served as peer debriefers to ensure the rigor of the coding process. All coding was done in NVivo 12. Codes were exported to and collated in Excel spreadsheets where they were then cross-tabulated for analyses. The lead coder analyzed the codes and conducted an extensive review of the findings with the second coder.

## **Data Limitations**

### **DATA LIMITATIONS FOR ADMINISTRATIVE DATA**

In compiling the data to address the primary RQs, the study team gained an understanding of the limited extent to which data related to AREC framework and associated logic models are available and accessible. Identifying the areas of the AREC logic models that have available data also highlighted areas that do not seem to have any. Large portions of the logic models were difficult to operationalize using measures from extant data sources. Full logic models demonstrating data availability and limitations at the jurisdiction level can be found in Appendix A. These logic models also distinguish constructs for which there may be data available that could not be used for this study due to data restrictions and applicability issues.

When considering the available data compiled for this study, variables covered all 50 U.S. states. However, there was varied coverage for nonstate U.S. jurisdictions, such as districts and territories. Some data sources did not have data available for DC, American Samoa, Guam, Northern Mariana Islands, Puerto Rico, and the U.S. Virgin Islands.

### **DATA LIMITATIONS FOR EPSCOR ANNUAL REPORTS**

There was also a great variability in formats across annual reports over time. Earlier awardees tended to provide reports of activities in a standardized form, whereas the later awardees provided detailed reports attached to a submission form. This means the density and possibly comprehensiveness also varied across reports over time. In some cases, even though the system registered an award as being completed in 2019, the final reports may not have reflected NCEs that were granted and ongoing at the time the reports were downloaded from eJacket. In other cases, for which the coded report was submitted at the end of the NCE, it is unclear whether the activities reported were representative of the entire duration of the award or only reported further activities conducted during the NCE period. The study team examined both the final report and the NCE reports to determine which one had more information and coded that report.

Although the data gaps represent limitations for the current study, assessing the extent to which data are available helps establish areas that could benefit from further data collection and ensures due diligence by confirming that the study team identified all usable data for the purposes of this study.



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## 4. ANALYSIS APPROACH

This chapter outlines the study team’s approach to addressing the primary RQs highlighted in Chapter 1. Specifically, this chapter aims to connect the primary RQs to the analysis conducted and to clearly indicate which questions were answered and to what extent. The sections in this chapter detail the various methods used to operationalize the data collected to answer the RQs that were addressed fully. For primary RQs that were not addressed or only partially addressed, this chapter discusses the limitations involved that prevented the study team from fully addressing the question(s).

Understanding the nature of variation in characteristics of jurisdictional AREC is important in the context of EPSCoR, as the program is designed to improve the capacity, capability, and competitiveness of researchers and institutions in eligible EPSCoR jurisdictions. Improving research competitiveness in low-competitive jurisdictions calls for a multifaceted effort that requires NSF investment in physical and human scientific infrastructure and involves other factors, including integration of key stakeholders (e.g., private sector, government, community groups); jurisdictions’ efforts to develop a trained and diverse workforce; programs for S&E education and outreach; and design of an effective and sustained institutional system that creates a highly skilled S&E workforce and provides them with opportunities to stay in the jurisdiction. The rich and complex programmatic effort of EPSCoR blends scientific research and discovery with additional focus on the STEM workforce, translational impacts on local economies and communities, and institutional enhancement and change; this approach necessitates further understanding of variations in other factors related to jurisdictional AREC.

It is helpful to recognize that track-level awards are nested within the contexts of EPSCoR,<sup>29</sup> universities, and ultimately jurisdictions. The contextual characteristics of the jurisdictions help determine the range of strategies available to EPSCoR for development and implementation across all four RII Tracks. Jurisdictions’ use of available strategies can impact their AREC outcomes. To effectively capture the diversity of EPSCoR jurisdictions and provide an aggregate picture of jurisdictions’ contextual factors, programmatic strategies, and progress toward outcomes, the study examines EPSCoR using measures from two levels of analysis: jurisdiction and university.<sup>30</sup>

### Technical Approach Background

This section provides the technical details for the methods used to address the primary RQs for questions that were fully or partially answered.

<sup>29</sup> The term “EPSCoR” represents the jurisdiction-level EPSCoR institutions (e.g., EPSCoR jurisdictional office and other committees or units) that propose and implement projects/awards to enhance jurisdiction-wide research competitiveness. Jurisdiction context concerns the characteristics of the state or territory that contains EPSCoR.

<sup>30</sup> The institutional measures within a jurisdiction are aggregated to the jurisdiction level, as explained in Chapter 3.

### ADDRESSING RQS 1, 2, AND 3

In order to address the first three RQs regarding contextual, strategic, and outcome variability, the study team conducted quantitative and qualitative analysis to explore the variations in key characteristics of AREC across EPSCoR and non-EPSCoR jurisdictions, as well as the underlying factors describing these variations and the grouping of jurisdictions around these characteristics. Specifically, the study team used factor analysis, descriptive analysis, cluster analysis, and document analysis, as described below.

#### *Factor Analysis*

Factor analysis was employed in this study to answer RQs 1a and 3a, which related to contextual and outcome variability, respectively. Factor analysis is a statistical method used to describe variability among a large number of observed, correlated variables that reflect a smaller number of unobserved/underlying latent variables called factors. Essentially, a factor is a construct that is a condensed statement of the relationships between similar variables. Factor analysis allows for examination of the relationships between these measures and the location of the underlying latent variable that these measures represent. For the purposes of this study, revealing the underlying factors also facilitates conceptual organization of the variables and guides the presentation of descriptive analyses in the report.

The study team first assessed whether the factor analysis was reasonable using several different criteria/tests highlighted in the literature: correlation across the measures, Kaiser-Meyer-Olkin measures of sampling adequacy, and Bartlett's test of sphericity. In addition, the commonalities of each measure were calculated to confirm that each measure shared common variance with other measures. Once the factor analysis was deemed suitable, the study team used the principal factor method to analyze the correlation matrix.<sup>31</sup> Initial eigenvalues were used to select the number of underlying factors using the factor loadings due to (a) theoretical support, (b) the "leveling off" of eigenvalues on the scree plot, and (c) the insufficient number of primary loadings ( $> 0.5$ ) and difficulty of interpreting the subsequent factors. Sensitivity tests were conducted to estimate the difference between the number of underlying factors, as well as the rotation technique used for the final solution.

After finalizing the factor analysis, the factor labels were selected as the measures in each factor aligned with the appropriate logic model domains and/or AREC framework. Internal consistency for each of the scales was examined using Cronbach's alpha. Composite scores were created for each of the underlying factors using a regression scoring method. Higher scores indicated greater resources available for each factor. These factor scores can be used for preliminary grouping of jurisdictions; however, we rely on the more sophisticated clustering approach described below.

The specific decisions employed for contextual and outcome factor analyses are described in detail in Appendix D.

<sup>31</sup> The principal component factor model was found inappropriate because the model assumes that the uniquenesses across the variables are 0. However, considerable uniqueness was found after the four factors.

## Descriptive Analysis

In order to address RQs 1b and 3b, which aimed to characterize the way that context and outcomes related to AREC vary across EPSCoR and non-EPSCoR jurisdictions, respectively, the study team presented descriptive analyses. These analyses present contextual and outcome measures in bar charts, differentiating jurisdictions currently eligible for EPSCoR, eligible for EPSCoR in the past, and never eligible for EPSCoR. The factor analysis served as a basis for the descriptive analyses, as the factors identified conceptual domains by which to present the analyses for each contextual and outcome measure. The descriptive analyses specifically showed how EPSCoR jurisdictions compare with non-EPSCoR jurisdictions in terms of various contextual and outcome measures.

## Cluster Analysis

The study team used exploratory cluster analysis to answer RQs 1c and 3c, which related to understanding how jurisdictions grouped around contextual and outcome variables, respectively. Cluster analysis is a more sophisticated machine learning method used to group observations into a number of clusters based on the values of several measured variables, so that similar observations are grouped in the same cluster. Cluster analysis allowed the study team to identify groups of jurisdictions with common contextual features and outcomes and assess the extent to which EPSCoR jurisdictions and non-EPSCoR jurisdictions tend to group together. Although many different methods of cluster analysis have been developed, the literature focuses almost exclusively on two types: hierarchical agglomerative methods<sup>32</sup> and iterative partitioning methods.<sup>33</sup> The study team selected hierarchical clustering as it is most commonly used in the literature. We discuss any differences that occur using partitioning methods. There are four decisions involved in conducting this procedure, and the method employed is presented in the following manner:

- *Measuring* distance between observations – using Euclidean distance method<sup>34</sup> to measure similarity
- *Measuring* distance between groups – using the average linkage because it is reasonably robust
- *Selecting* the observable variables –the variables in the factor analysis are included

<sup>32</sup> Hierarchical agglomerative cluster analysis involves a series of steps, whereby individual cases (people) begin as individual clusters, and step-by-step, the most similar clusters are joined, eventually resulting in one cluster containing all cases. Each step is irreversible, so clusters joined at one step cannot be separated later in the clustering process. Hierarchical clustering procedures result in the same number of cluster solutions as there are entities to cluster.

<sup>33</sup> Iterative partitioning methods (e.g., K-means cluster analysis) begin by dividing the entities into the required number of clusters, calculating the cluster centroids, and relocating the entities to their nearest cluster centroid. The process of calculating the new cluster centroids and relocating entities continues until all the entities are closer to their own cluster centroid than any other and the solution is, therefore, stable. Iterative partitioning techniques differ from hierarchical methods in two key ways. First, the number of clusters is specified by the researcher before the analysis takes place and, therefore, only one cluster solution is given. Second, cases can be moved from one cluster to another during the clustering process to optimize the cluster solution.

<sup>34</sup> Squared Euclidean distance was used as the value of the measures and is more important than the pattern of the measures across time.

- *Selecting* the optimal number of groups – using the two stopping rules:<sup>35</sup> the Caliński and Harabasz pseudo-F index and the Duda-Hart  $Je(2)/Je(1)$  index with the associated pseudo- $T^2$

The specific decisions employed for the contextual and outcome cluster analyses are described in detail in Appendix D.

### *Document Analysis*

Document analysis was used to answer RQs 2a and 2b, which address commonalities and variation in implementation activities of EPSCoR jurisdictions. Document analysis is a cost-effective, unobtrusive method that systematically extracts relevant information from existing documents. Since there is a lack of administrative data on S&E capacity-building strategies employed by jurisdictions, the study team used EPSCoR award reports to glean a better understanding of activities conducted related to increasing AREC. The study team coded a sample of the most recent EPSCoR reports across the 31 EPSCoR jurisdictions, ensuring representation of each EPSCoR jurisdiction and award tracks available for analysis. The study team developed a coding framework that captured various activities that jurisdictions might conduct using EPSCoR funding (see details in Chapter 3). This coding framework was used to extract this information from the reports and summarize reported implementation activities.

### **ADDRESSING RQ 4**

The study team was able to partially address RQ 4b, as it related to comparing the research competitiveness of institutions of similar Carnegie Classifications in EPSCoR and non-EPSCoR jurisdictions. The study team compared measures related to reputation in knowledge production, one of the domains of research competitiveness, for the highest-ranking doctoral institution in the jurisdiction.

### **ADDRESSING RQ 5**

The RQ 5 focused on identifying an ongoing, sustainable evaluation structure that would allow NSF to continue to monitor and evaluate the program. The study team was able to partially address this RQ by creating a data inventory and associated dashboard tool. NSF can use the dashboard to longitudinally track outcomes to observe progress across the elements of the AREC framework. The dashboard displays tile maps and bar charts for the contextual and outcome measures, which can be chosen by the user. If it continues to be updated, this dashboard will provide a sustainable method to track common measures that can be used for eligibility, as well as for evaluation of the program's progress in increasing jurisdictional AREC.

The compilation of publicly available data relevant to AREC, as shown in Chapter 3, also facilitates ongoing monitoring of the program by identifying variables to track. However, this data inventory reveals critical gaps in data coverage of the AREC framework that limits its use for program planning, design, operation, and evaluation. As such, the study team was able to

<sup>35</sup> Distinct clustering is signaled by a high Caliński and Harabasz pseudo-F index, as well as by a large  $Je(2)/Je(1)$  index associated with a low pseudo- $T^2$  surrounded by much larger pseudo- $T^2$  values.

partially answer RQ 5 but maintains that more consistent data collection of measures in the AREC logic model would enhance evaluation processes, practices, and structures.

## ADDRESSING RQ 6

The study team was able to partially answer primary RQ 6, which asks about insights that could be drawn from the evidence collected throughout the study. The study team worked with academic experts to synthesize the results found from the quantitative and qualitative analyses conducted to answer RQs 1–3. This resulted in actionable recommendations that can inform NSF’s programmatic decision making related to operationalizing the theoretical framework and improving program implementation.

## Limitations of the Analysis Approach

This section details limitations of the analysis approach, as well as how these limitations hindered the ability to fully answer the RQs that were not addressed.

Given that this study was motivated by EPSCoR’s interest in measuring AREC, the analyses highlight notable differences in AREC measures between EPSCoR-eligible and non-EPSCoR-eligible jurisdictions. The analyses presented in the following chapters are subject to *substantial* caveats. As noted in the previous chapter, large portions of the AREC logic models are not adequately covered by existing publicly accessible measures, so the study team’s analyses provide only a partial picture of AREC. Additionally, many accessible measures are coarse metrics that may not be sensitive to small changes in AREC induced by particular programs or policies. Finally, the relatively small number of U.S. jurisdictions (55) makes it difficult to conduct complex analyses at the jurisdiction level.<sup>36</sup>

Although award reports were the most reliable data source that could be used to capture strategic variability, there were still many reporting differences that made it challenging to ensure jurisdictions were providing the same level of coverage. While the study team was able to capture and analyze the activities reported in awardee final reports, the extent to which each awardee presented a comprehensive picture of their project varied. Because of this, it was not possible to answer RQ 2c: “Are there any clusters/groups of jurisdictions with common implementation strategies that can be identified across the program?” Additionally, since many awardees were in different years of their award periods, the nature of awardee activities inherently varied. The inconsistencies present within awardee reports made it difficult for the study team to consistently measure or analyze strategic activities across all jurisdictions.

The factors that impeded the study team’s ability to answer RQ 2c also prevented the study team from being able to answer RQ 4a. This RQ inquired about the similarities and differences between strategies and progress in increasing research competitiveness. The variation in the comprehensiveness, level of detail, award focus, and context of awardee reports, as well as the frequent internal inconsistencies in awardee reports, made it difficult to accurately connect specific implementation strategies to outcomes in jurisdictional research competitiveness. In













<sup>36</sup> See Appendix E for an exploratory analysis to explore pathways between measures of AREC logic model contexts, inputs, outputs, and outcomes.









addition, understanding how implementation strategies relate to levels of research competitiveness requires measurement of change from before to after the implementation of the strategy. However, this study solely captured levels of research competitiveness at one point in time rather than longitudinally.

Study efforts were also often limited by the lack of publicly available data needed to address certain questions. For example, there are not consistently captured data on career pathways developed by a jurisdiction's institutions, particularly for early career researchers. The study team was unable to address RQ 4c as a result, as this question asked about the nature of career pathways being developed in EPSCoR jurisdictions.

Given the limitations described in Chapter 3 and this chapter, Exhibit 4.1 provides an overview of the extent to which and the method with which each RQ was answered.

#### EXHIBIT 4.1 EXTENT TO WHICH EACH RQ WAS ANSWERED

RQ Area	RQ	Answered?	Method
<b>(1) Contextual Variability</b> 	(1a) What factors best describe the common characteristics that typify this contextual variability?		Factor analysis
	(1b) To what extent and in what ways does the research competitiveness context currently vary across EPSCoR jurisdictions?		Descriptive analysis
	(1c) Are there any clusters/groups of jurisdictions with common contextual features that can be identified across the program?		Cluster analysis
<b>(2) Strategic Variability</b> 	(2a) What common characteristics typify the range of implementation variability?		Document analysis
	(2b) To what extent and in what ways do the S&E research base and mechanisms currently deployed for improvement vary across jurisdictions?		Document analysis
	(2c) Are there any clusters/groups of jurisdictions with common implementation strategies that can be identified across the program?		
<b>(3) Outcome Variability</b> 	(3a) What jurisdictional, institutional, and other characteristics typify the range of variability observed in research competitiveness definitions and performance?		Factor analysis
	(3b) To what extent and in what ways does the variability in context and strategy across EPSCoR jurisdictions influence the identification of relevant indicators of research competitiveness?		Descriptive analysis
	(3c) Are there any clusters/groups of jurisdictions with common context and/or strategy characteristics that can be used to		Cluster analysis

RQ Area	RQ	Answered?	Method
	understand variability in research competitiveness?		
<b>(4) Effectiveness</b> 	(4a) What differences and similarities exist with respect to implementation strategies and levels of research competitiveness, as defined for this study, for EPSCoR jurisdictions?		
	(4b) Are there specific strategies or combinations of strategies with evidence of stronger influence or contribution toward research competitiveness than others? For example, how do EPSCoR and non-EPSCoR institutions in similar Carnegie Classification institutional classification categories currently compare with respect to research competitiveness as defined for the study?		Analysis of reputation in knowledge production measures
	(4c) What career pathways have been developed? To what extent are these career pathways diverse and inclusive, especially for early career researchers?		
<b>(5) Institutionalization</b> 	(5a) What ongoing evaluation processes, practices, and structures—in particular those related to stakeholder engagement, data collection, and analysis—are feasible to support and sustain the current and future implementation of a longitudinal program-level evaluation with common measures and a consistent yet flexible analytic approach?		Dashboard
<b>(6) Improvement</b> 	(6a) What insights can be drawn from the evidence compiled to address RQs 1 through 5 that can be used to inform programmatic strategic directions?		Conclusion and recommendations



## 5. FINDINGS RELATED TO CONTEXTUAL VARIABILITY

Although all EPSCoR jurisdictions contribute to the nation's research competitiveness, jurisdictions vary along several contextual dimensions that can influence the extent and nature of their contributions. This chapter addresses primary RQ 1, which focuses on this contextual variability. Exhibit 5.1 describes the study team's approach to answering the three sub-questions related to contextual variability.

### EXHIBIT 5.1 APPROACH TO ADDRESSING RQS RELATED TO CONTEXTUAL VARIABILITY

This chapter addresses the three research questions related to **Contextual Variability**.

**(1a) What factors best describe the common characteristics that typify this contextual variability?**



The study team conducted **factor analysis** on 20 measures to identify **3 underlying factors** that typify contextual variability.

**(1b) To what extent and in what ways does the research competitiveness context currently vary across EPSCoR jurisdictions?**



The study team conducted **descriptive analysis** to understand **jurisdictional variation** in the contextual measures that compose the three contextual factors, displayed in **bar charts**.

**(1c) Are there any clusters/groups of jurisdictions with common contextual features that can be identified across the program?**



The study team conducted **cluster analysis** to demonstrate how **jurisdictions cluster** around the contextual measures.



Using the contextual measures collected based on logic model constructs as described in Chapter 3, the study team conducted factor analysis to understand the factors underlying contextual variability. Guided by these factors, the study team next examined the extent to which and the ways that these measures vary across EPSCoR and non-EPSCoR jurisdictions using descriptive analysis. This descriptive analysis provides further insights into how research competitiveness context varies across the EPSCoR jurisdictions and in comparison, to non-EPSCoR jurisdictions. Finally, the study team performed cluster analysis to understand how jurisdictions group in terms of the key contextual measures. The details of the factor and cluster analysis are explained in Chapter 4.

The findings presented in this section are intended to help NSF better understand the landscape of EPSCoR jurisdictions in contextual measures identified as relevant to AREC, as well as to operationalize the study's theoretical foundations and data search. In this chapter, all the analyses for the contextual measures examine patterns in a single measure in a particular year.

## Underlying Factors that Best Describe Contextual Variability

**This section addresses RQ 1a: What factors best describe the common characteristics that typify this contextual variability?**

Many of the contextual measures listed in Exhibit 3.4 in Chapter 3 are strongly correlated with other measures in the same domain, as well as across domains from the logic model (see Exhibit D.1 in Appendix D). This correlation highlights that several of the contextual measures are trying to underscore the same latent factor. Theoretically, jurisdictions with a sizeable number of very high research-focused universities are also jurisdictions with large economic bases that are able to attract more state and federal R&D funding.

The study team conducted exploratory factor analysis to discover which factors best describe the common characteristics that typify jurisdictional variability in contextual measures of AREC. As each of the 20 contextual measures implicitly reflect underlying latent indicators in the logic model, this analysis also tests the categorizations and examines the correlations between these latent factors. The exploratory factor analysis indicates that the following 3 latent factors underlie the 20 contextual measures that are available:



**Environment and Institutional Capacity**



**Research Capacity**



**Jurisdiction-Level Financial Resource Capacity**

Promax rotation provided the best-defined factor structure, for which all measures in the analysis had primary loading greater than 0.35, and only two measures had a cross-loading of greater than 0.35. The factor loading matrix for this final solution is presented in Exhibit D.3 in Appendix D. The three factor labels—environment and institutional capacity, research capacity, and jurisdiction-level financial resource capacity—were selected as the measures in each factor aligned with the appropriate logic model domains and/or AREC framework. Exhibit 5.2 shows the results of the factor analysis on the contextual measures.

For the **environment and institutional capacity factor**, there are two main underlying sub-factor constructs:

1. Jurisdiction Environment
  - a. This sub-factor includes the total population and the percentage of URM population. Other factors such as percentage of women in the jurisdiction, urbanicity, and political culture of the jurisdiction further influences the jurisdiction's contextual research capacity.
2. Institutions in the Jurisdiction
  - a. Local academic institutions and universities play an important role in determining the research competitiveness of the regions in which they operate. This sub-factor includes the diversity of the postsecondary academic institutions in the jurisdiction. The main loading factors for this construct are the number of R1 and R3 institutions, as well as associate colleges, in the jurisdiction.

For the **research capacity factor**, there are two main underlying sub-factor constructs:

1. Jurisdiction's Economic Base
  - a. This sub-factor helps determine the strength of a jurisdiction's economic base as it is closely aligned to the strength of its research base and it adds to the jurisdiction's contextual knowledge. The main loadings for this sub-factor includes measures of productivity (GSP per capita), the number of S&E workers, and the percentage of the population in the jurisdiction with a bachelor's degree in S&E.
2. R&D Funding Received by the Jurisdiction from the Federal Government
  - a. In addition to helping build the jurisdiction's economic base, building a strong research base requires considerable financial resources and infrastructure. This sub-factor includes the funding provided by various federal sources to entities in the jurisdiction. The main loading factors for this sub-factor construct are the federal obligations for S&E R&D to universities and colleges, the amount in SBIR-STTR awards, and the funding received from NIH and NSF.

Finally, for the **jurisdiction-level financial resource capacity**, the two main loading factors are the jurisdiction's R&D expenditures from its own budget as well as from the federal funding sources.

Internal consistency for each factor was verified using Cronbach's alpha. The alphas for the first two factors were high: 0.89 for environment and institutional capacity (7 items) and 0.80 for research capacity (10 items); and moderate for jurisdiction-level financial resource capacity

(0.67; 5 items).<sup>37</sup> Additional details of the factor analysis on the contextual measures are presented in Appendix D.

Overall, the exploratory analysis indicated that three distinct factors were underlying the jurisdictional research competitiveness contextual measures, and these factors were moderately internally consistent.

## EXHIBIT 5.2 EXPLORATORY FACTOR ANALYSIS FOR CONTEXTUAL MEASURES AT THE JURISDICTION LEVEL

	Environment and Institutional Capacity	Research Capacity	Jurisdiction- Level Financial Resource Capacity
<b>Total Population</b>	<b>0.99</b>		
<b>Number of R1 Institutions</b>	<b>0.89</b>		
<b>Number of R2 Institutions</b>	<b>0.48</b>		
<b>Number of R3 Institutions</b>	<b>0.93</b>		
<b>Number of Associate Institutions</b>	<b>0.91</b>		
<b>VC Capital Invested Per S&amp;E Worker<sup>†</sup></b>	<b>0.61</b>	<i>0.40</i>	
<b>Percentage of URMs</b>	<b>0.47</b>		
<b>Total Federal Obligations for S&amp;E R&amp;D to Universities and Colleges Per S&amp;E Worker</b>		<b>0.70</b>	
<b>Percentage of Bachelor's Degrees in S&amp;E</b>		<b>0.67</b>	
<b>Total Amount in SBIR-STTR Awards Per S&amp;E Worker</b>		<b>0.65</b>	
<b>Real GSP Per Capita</b>		<b>0.64</b>	
<b>Total NIH Funding Per S&amp;E Worker</b>		<b>0.62</b>	
<b>Total Number of S&amp;E Workers</b>		<b>0.62</b>	<i>-0.36</i>
<b>Total NSF Research Funding Per S&amp;E Worker</b>		<b>0.57</b>	
<b>Total Number of Businesses Per Capita</b>		<b>0.40</b>	
<b>Total Federal Obligations for S&amp;E R&amp;D Per S&amp;E Worker</b>		<b>0.36</b>	
<b>State R&amp;D Expenditures Per S&amp;E Worker</b>			<b>0.77</b>
<b>Total R&amp;D Expenditures Per S&amp;E Worker by State with Funding from the Federal Government</b>			<b>0.58</b>
<b>Academic Research Space Per S&amp;E Worker</b>			<b>0.49</b>
<b>State Expenditure on Higher Education Per Capita</b>			<b>0.42</b>

Notes: Extraction Method: Principal Axis Factoring. Rotation Method: Promax with Kaiser Normalization.

Factor loading < 0.35 are suppressed. Variables with secondary loadings of much lower value than the primary loadings are italicized. See Appendix D for detailed analysis.

<sup>†</sup> VC invested per S&E worker is discussed in jurisdiction's Research Capacity.

<sup>37</sup> No substantial increases in alpha for any of the scales could have been achieved by eliminating more items.

## Key Contextual Factors that Vary Across EPSCoR Jurisdictions

**This section addresses RQ 1b: To what extent and in what ways does the research competitiveness context currently vary across EPSCoR jurisdictions?**

Understanding how jurisdictions vary along these key contextual dimensions is important, as contextual differences in jurisdictions where EPSCoR operates affect the strategies available and used by these jurisdictions. In particular, context can affect strategies intended to broaden participation of URMs, women, and groups underserved in rural areas, especially in STEM fields (RII Track-3 awards).

To understand the extent to which and how the contextual measures vary across EPSCoR jurisdictions, the study team conducted descriptive analysis for each measure. The contextual measures are grouped according to three key factors: environment and institutional capacity, research capacity, and jurisdiction-level financial resource capacity.

### Environment and Institutional Capacity

#### Summary

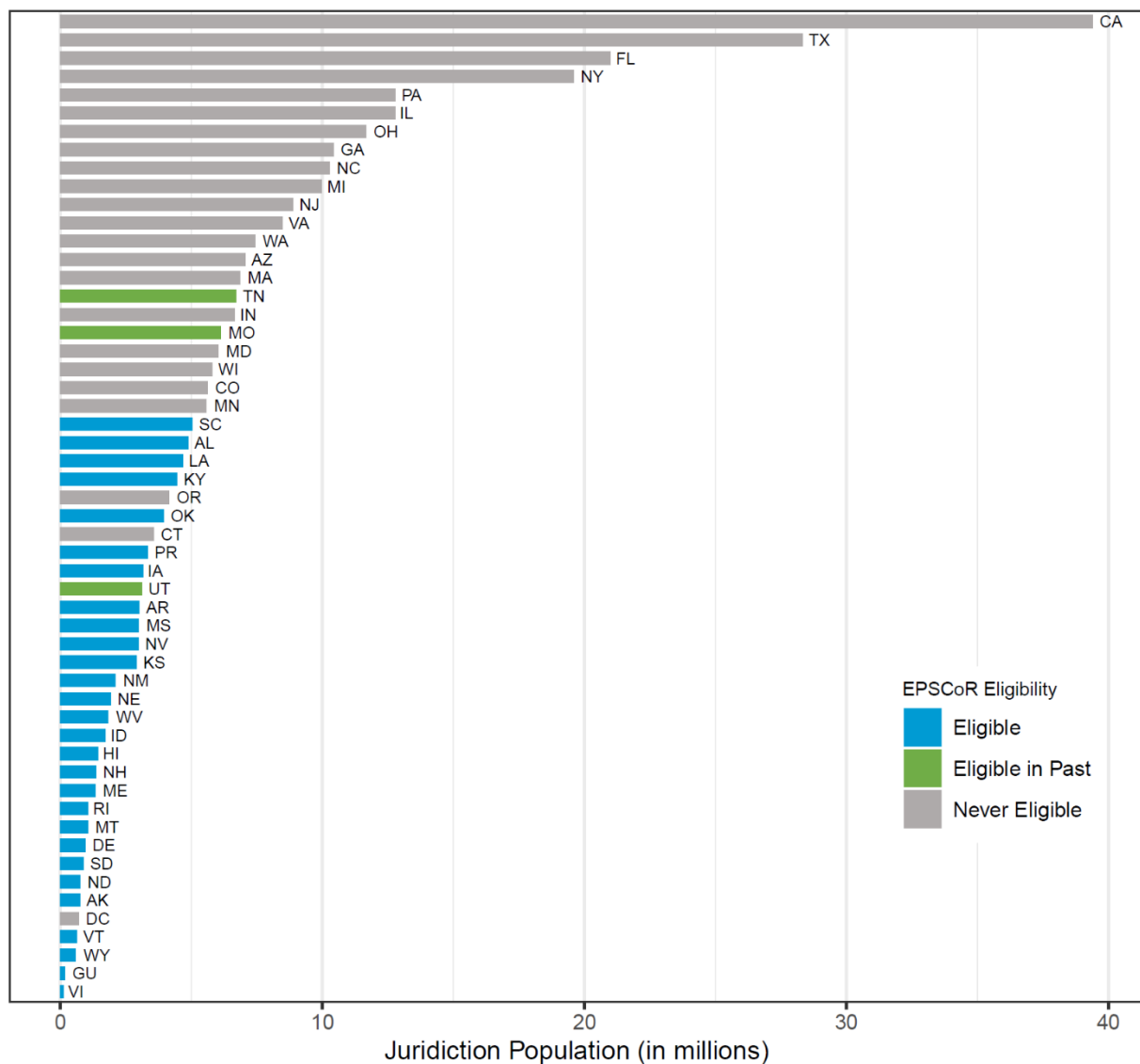


- Compared to non-EPSCoR jurisdictions, a majority of EPSCoR jurisdictions are less populous, have populations that tend to live in nonmetropolitan areas, have varying racial diversity, and have small numbers of research-intensive doctoral universities and associate colleges.

## Jurisdictional Environment

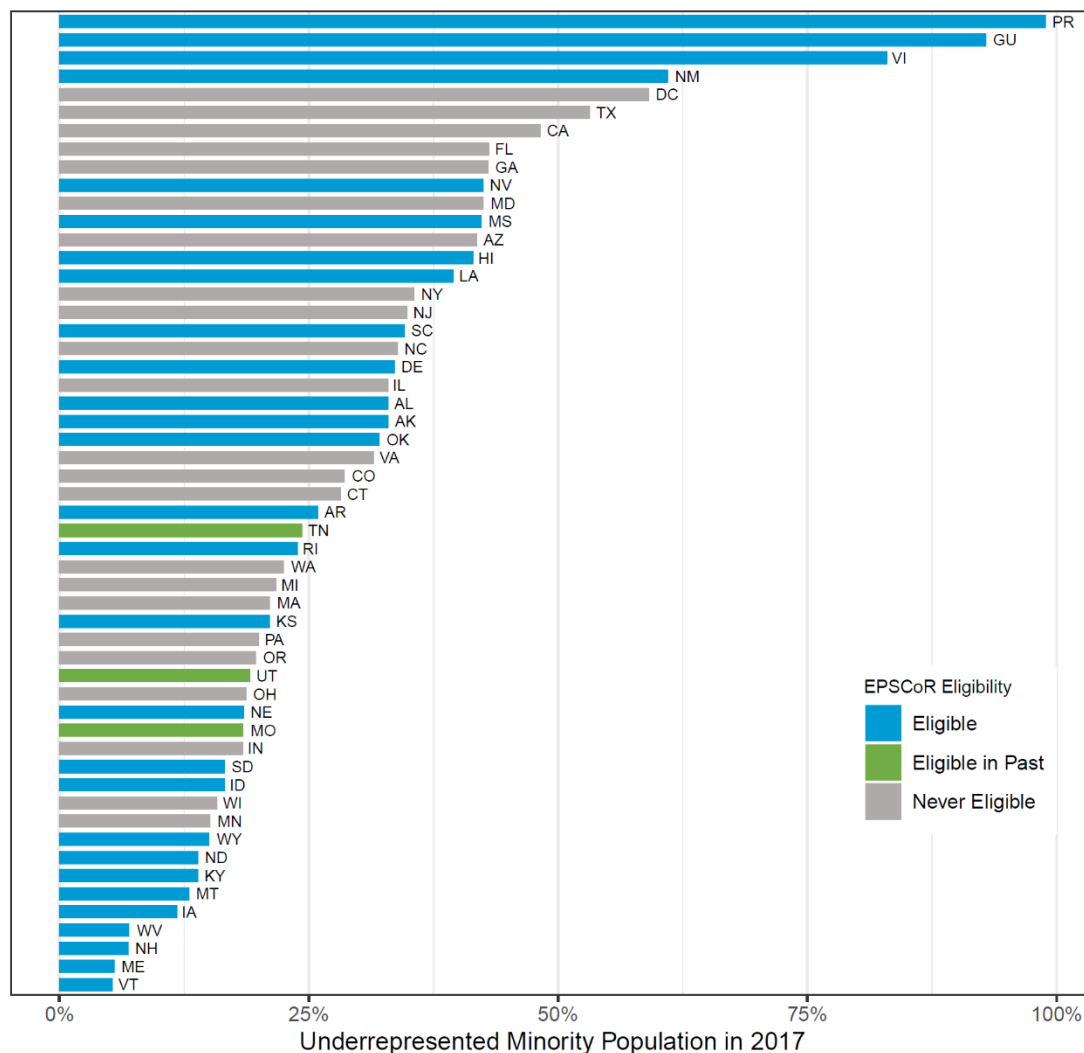
Most EPSCoR-eligible jurisdictions tend to be less populous, especially in the Mountain West and Northeast and in Guam and the U.S. Virgin Islands. The jurisdictions in the Mountain West have a population of approximately 1 million or fewer, and large swaths of the states in these jurisdictions are sparsely populated (see Exhibit 5.3). The current eligible EPSCoR jurisdictions account for 18.2 percent of the U.S. population in 2017, whereas the jurisdictions eligible in the past (Tennessee, Missouri, and Utah) accounted for an additional 4.8 percent of the U.S. population in 2017. More than three of every four U.S. residents live in jurisdictions that have never been eligible for EPSCoR (76.9 percent).

EXHIBIT 5.3 JURISDICTION POPULATION SIZE IN 2017



Nationally, women comprise 51 percent of the population and were a majority in nearly four out of five states in 2017. However, their percentage varies slightly across jurisdictions, with DC and Alaska having the highest and lowest percentages of women at nearly 53 percent and 48 percent, respectively (see Exhibit B.1 in Appendix B). The size of the URM<sup>38</sup> population also varies across EPSCoR jurisdictions, with a majority of the states in the South and the U.S. territories (Puerto Rico, Guam, and the U.S. Virgin Islands) having a URM population greater than 30 percent in 2017 (see Exhibit 5.4). Around 5 percent of the population in EPSCoR jurisdictions in New England is composed of URMs, and one in six people in the Mountain West states represented URMs in 2017.

#### EXHIBIT 5.4 JURISDICTIONS' URM POPULATION IN 2017



<sup>38</sup> Percentage of URM is calculated as the percentage of population who are not non-Hispanic white or Asian in the jurisdiction as estimated in the Census.

In addition to the two measures described in Exhibits 5.3 and 5.4, jurisdictions' urbanicity and political culture provide some insight into EPSCoR's environmental context. Nearly four-fifths of the U.S. population live in urban counties.<sup>39</sup> Based on the definition of urban county, population in each county, and overall state population, the study team developed four urbanicity categories. Each jurisdiction was assigned to an urbanicity category: large metro, large nonmetro, small metro, or small nonmetro.<sup>40</sup> Most EPSCoR jurisdictions are small nonmetro areas, with a few exceptions listed below (see Exhibit 5.5):

- EPSCoR-eligible Louisiana and South Carolina are large metro jurisdictions.
- EPSCoR-eligible Alabama and previously EPSCoR-eligible Tennessee and Missouri are large nonmetro jurisdictions.
- EPSCoR-eligible Delaware, Nevada, and Rhode Island and previously EPSCoR-eligible Utah are small metro jurisdictions.

States' political cultures shape their populations' perceptions and actions related to the functions or expectations of the state government. State political system characteristics influenced by the political culture greatly contribute to variation in states' investment in R&D and higher education. Each jurisdiction can be categorized as follows:<sup>41</sup>

- Moralistic – Most states in upper New England, Midwest, Mountain West, and West coast states belong to this categorization.
- Traditionalistic – Most Southern states belong to this categorization.
- Individualistic – Most Mid-Atlantic states and states spanning directly west from Ohio to Wyoming belong to this categorization, including Alaska, Hawaii, and DC.

<sup>39</sup> U.S. Census Bureau, 2010 decennial census, Table P2. <https://data.census.gov/cedsci/>

<sup>40</sup> Counties are classified as metro or nonmetro using the OMB definition based on the population density and labor market, for which densely settled centers of greater than 50,000 people are designated as metro counties, and other counties are designated as nonmetro counties. This county-level designation is aggregated to the jurisdiction level with percentage of population in the metro counties to form the following four categories:

- Large metro – Population of state above the median U.S. population and with 80 percent of the state population living in metro counties
- Large nonmetro – Population of state above the median U.S. population and with fewer than 80 percent of the state population living in metro counties
- Small metro – Population of state below the median U.S. population and with 80 percent of the state population living in metro counties
- Small nonmetro – Population of state below the median U.S. population and with fewer than 80 percent of the state population living in metro counties

<sup>41</sup> Daniel Elazar first put forth this theory in the book *American Federalism: A View from the States* in 1966. U.S. states can be divided into three dominant political subcultures:

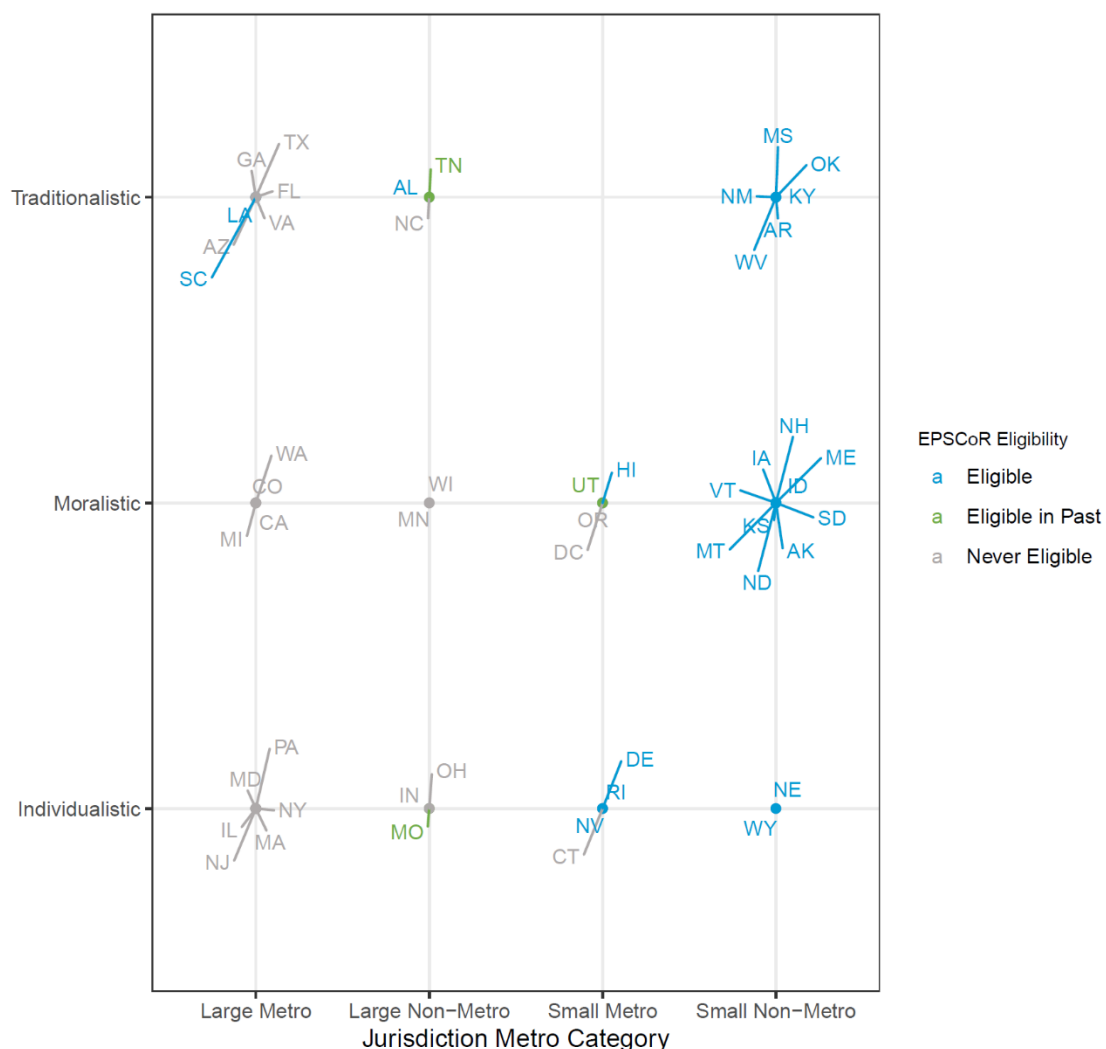
- Traditionalistic – Government viewed as a hierarchical institution charged with protecting and maintaining the existing social order, an elite-centered status quo.
- Moralistic – Government viewed as egalitarian institution charged with pursuing the common good to better the society and promote general welfare.
- Individualistic – Government viewed as minimalist institution charged with protecting the functionality of the marketplace but is otherwise not active.

See Elazar, D. (1966). *American federalism: A view from the states*. New York: Crowell. Retrieved from <https://www.worldcat.org/title/american-federalism-a-view-from-the-states/oclc/498687>

These definitions help categorize the jurisdictions and make it possible to identify groups or clusters of jurisdictions that are similar on these two dimensions. As shown in Exhibit 5.5, there are only a few overlaps between EPSCoR and non-EPSCoR jurisdictions along the two measures:

- Past EPSCoR jurisdictions (Missouri, Tennessee, and Utah) do not fall in the same group as most of the current EPSCoR jurisdictions.
- Current EPSCoR jurisdictions (Alabama and Hawaii) fall in the same group as past EPSCoR jurisdictions (Tennessee and Utah, respectively).
- Current EPSCoR jurisdictions (Delaware, Nevada, and Rhode Island) fall in the same group as Connecticut.

## EXHIBIT 5.5 JURISDICTION METRO CATEGORIZATION AND POLITICAL CULTURE



Note: Data are not available for Guam, Puerto Rico, and the U.S. Virgin Islands.



### *Postsecondary Academic Institutions in the Jurisdiction*

University R&D represents a vital component of overall research competitiveness in the United States. Academic institutions are responsible for performing about 10 to 15 percent of total U.S. R&D and account for a substantial portion of their state's economic development.<sup>42</sup> The U.S. higher education system consists of diverse academic institutions that train students in S&E across degree levels and fields. These institutions include research and doctorate-granting universities, primarily undergraduate institutions (PUIs), MSIs, community colleges, and others, and some institutions span multiple categories. Local universities play an important role in determining the research competitiveness of the region in which they operate, as universities directly contribute to the jurisdiction's research competitiveness by educating the local workforce, creating human capital, and producing intellectual property. Universities also contribute indirectly to research competitiveness through their basic research activities, which can help create and advance industries in their region in unpredictable ways. In addition, universities enable tacit knowledge sharing through informal networks and the transition of students from academia to the workforce.<sup>43</sup> Given the variety of ways that universities contribute to jurisdictions' research competitiveness, it is useful to understand how different types of academic institutions are distributed across EPSCoR jurisdictions.

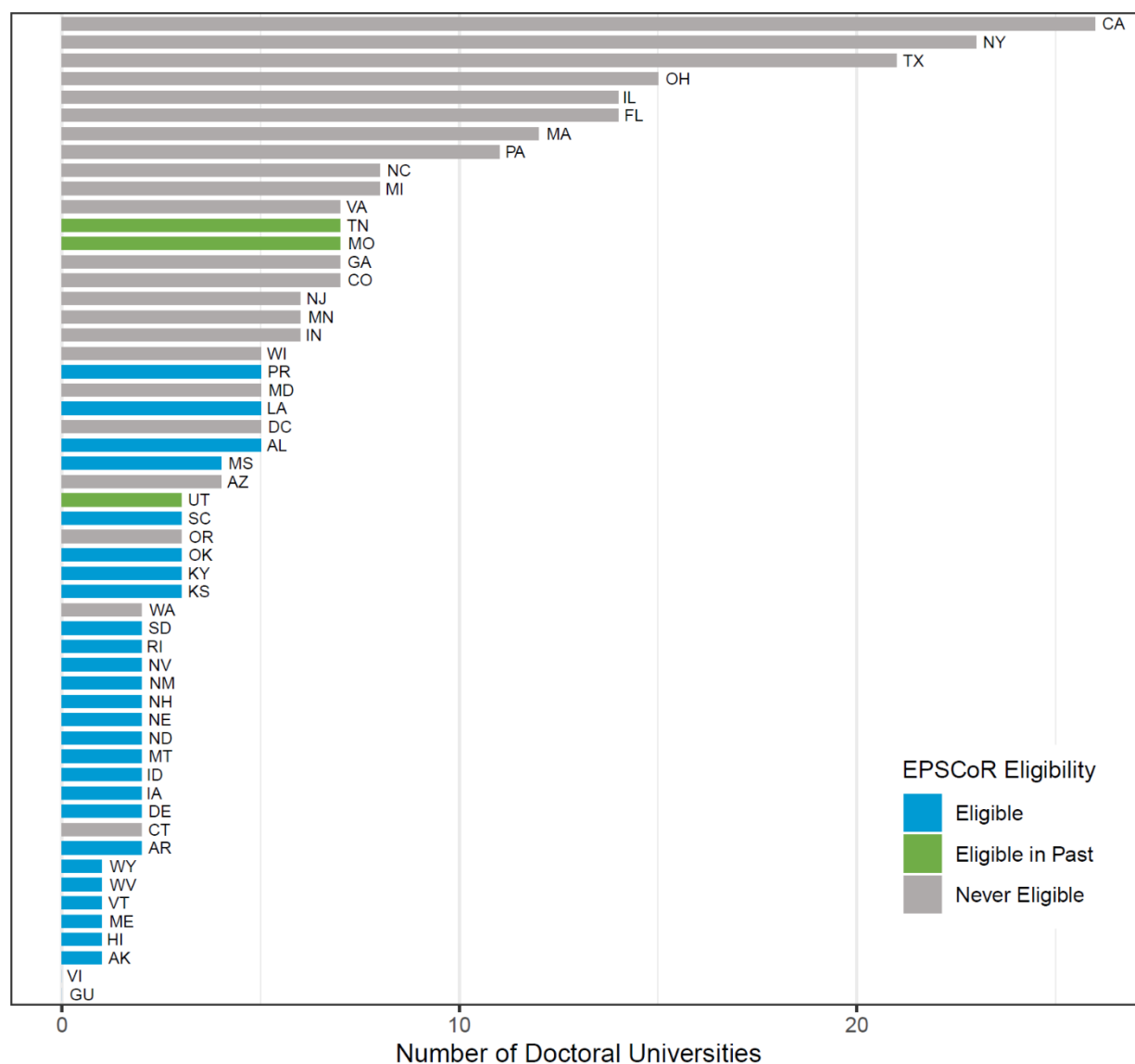
Significant differences in the numbers and types of postsecondary educational institutions exist among EPSCoR jurisdictions. The Carnegie Classification distinguishes between institutions on the basis of the prevalence of degrees they grant. Using this classification, there are 295 doctoral universities in the 50 states, DC, Guam, Puerto Rico, and the U.S. Virgin Islands.<sup>44</sup> However, only 21 percent of these doctoral institutions reside in the 28 current EPSCoR jurisdictions, with a further 6 percent in previously eligible EPSCoR jurisdictions (see Exhibit 5.6). Some non-EPSCoR jurisdictions have multiple public higher education systems. For example, California has 3: the 10-campus University of California, the 23-campus California State University, and the 112-campus California Community Colleges System. In contrast, Wyoming, which is an EPSCoR jurisdiction, supports a single state doctoral university. Guam and the U.S. Virgin Islands—both EPSCoR jurisdictions—currently do not have a doctoral university. Several other EPSCoR jurisdictions are dominated by one or two main doctoral-granting universities, and only a few EPSCoR jurisdictions have more than four large research institutions (e.g., Alabama, Louisiana, Mississippi, and Puerto Rico). In previously eligible jurisdictions, Tennessee and Missouri have seven doctoral universities, and Utah has three.

<sup>42</sup> National Science Board, National Science Foundation. (2020). *Academic research and development. Science and engineering indicators 2020* (NSB-2020-2). Alexandria, VA. Retrieved from <https://nces.nsf.gov/pubs/nsb20202>

<sup>43</sup> Studies of regional economic clusters suggest that this knowledge sharing facilitates the recognition of the economic value of basic research findings, as well as the conversion of these findings into private sector solutions or new commercial opportunities.

<sup>44</sup> This information is using the 2010 Carnegie Classification. The 2015 classification added 43 additional doctoral universities. Further details on the classifications and their categories can be found in the definitions section of the classification website: <http://carnegieclassifications.iu.edu/definitions.php>.

## EXHIBIT 5.6 NUMBER OF DOCTORAL UNIVERSITIES IN EACH JURISDICTION

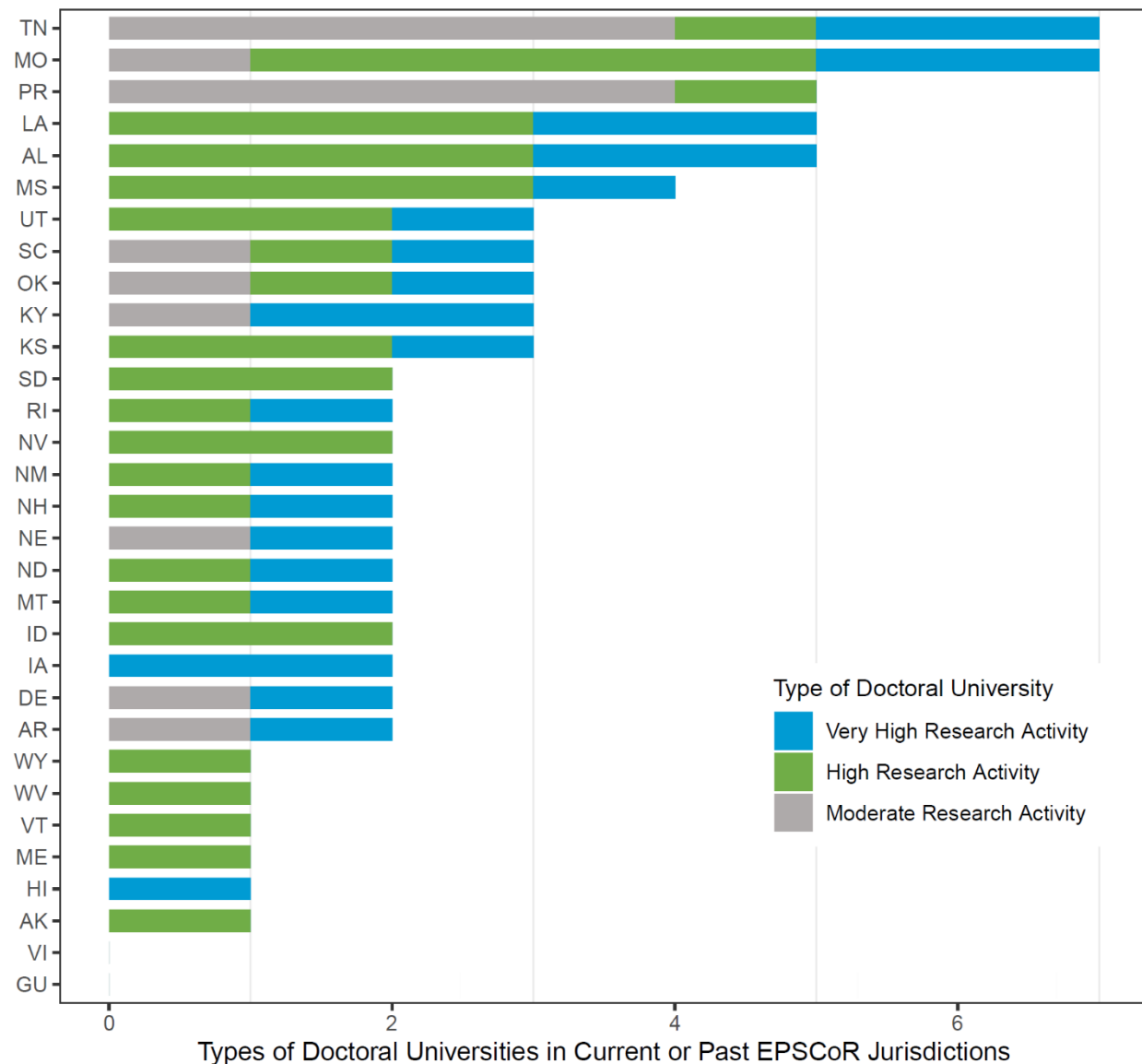


Note: As defined by Carnegie Classification.

It should be noted that doctoral universities in EPSCoR jurisdictions have varying levels of research activities (see Exhibits 5.6 and 5.7 for EPSCoR and non-EPSCoR jurisdictions, respectively). Carnegie Classification distinguishes three categories of doctoral institutions: R1 (very high research activity), R2 (high research activity), and R3 (moderate research activity). Most EPSCoR jurisdictions have at least one R1 doctoral university, with the exception of nine that only have R2 universities, and Guam and the U.S. Virgin Islands have no doctoral university. EPSCoR jurisdictions tend to have fewer R2 doctoral universities compared to non-EPSCoR jurisdictions (notice the change in scale across Exhibits 5.7 and 5.8). All non-EPSCoR jurisdictions have at least two R1 doctoral universities (see Exhibit 5.8) except for Minnesota and Wisconsin. Washington and Connecticut have two R1 doctoral universities and none in the other

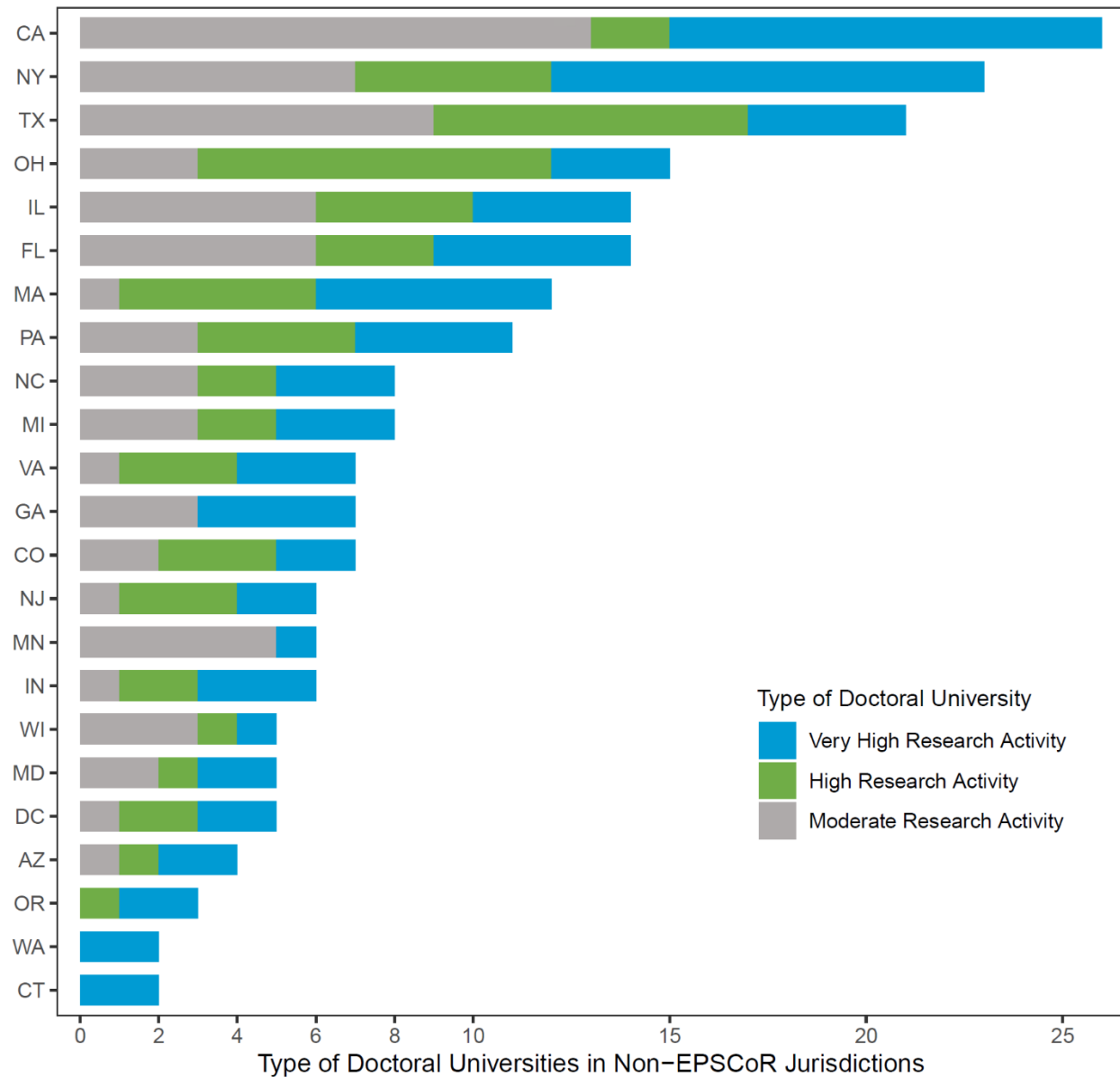
classifications. Generally, R1 doctoral universities have high research activity per capita and can provide numerous research resources and opportunities to students and faculty.

### EXHIBIT 5.7 TYPES OF DOCTORAL UNIVERSITIES IN CURRENT OR PAST EPSCoR JURISDICTIONS



Note: As defined by Carnegie Classification.

## EXHIBIT 5.8 TYPES OF DOCTORAL UNIVERSITIES IN NON-EPSCOR JURISDICTIONS



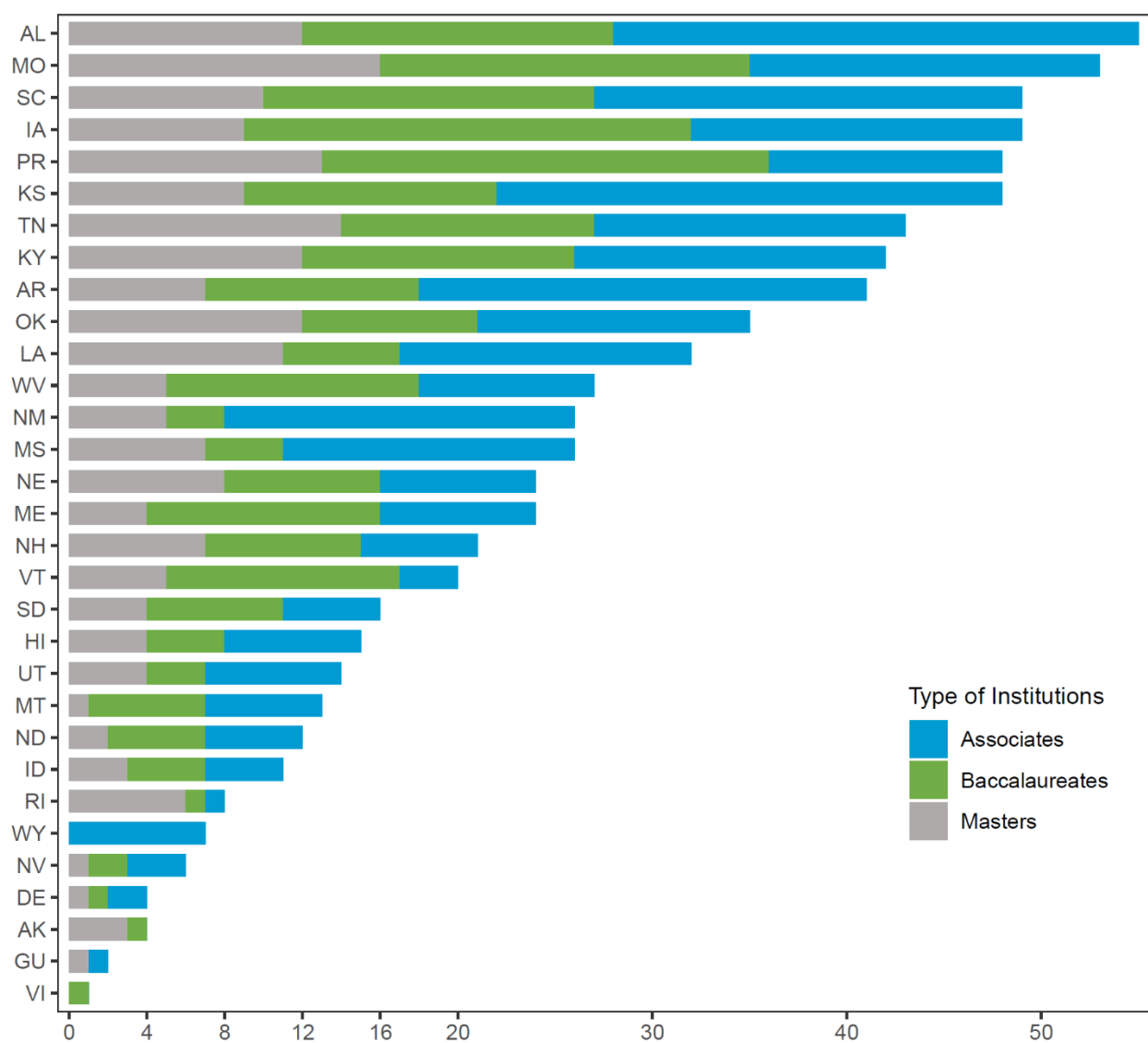
Note: As defined by Carnegie Classification.

Nondoctoral academic institutions such as community colleges play an important role in preparing students to enter the workforce quickly or transition to 4-year academic institutions. Community colleges account for approximately one-quarter (24 percent) of higher education institutions and awarded 226,000 associate degrees in S&E and technology fields in 2017. Among those students who earned a bachelor's degree in S&E between 2010 and 2017, about half (47 percent) had attended community college, and nearly a fifth (18 percent) had earned an associate degree.<sup>45</sup> Similarly, master's (16 percent) and bachelor's institutions (14 percent) account for 30 percent of higher education institutions and enroll one-third (32 percent) of postsecondary students, playing a significant role in S&E workforce training.

The number of master's-granting, bachelor's-granting, and associate institutions in a jurisdiction also varies across EPSCoR and non-EPSCoR jurisdictions (see Exhibits 5.9 and 5.10 for EPSCoR and non-EPSCoR jurisdictions, respectively). For example, Wyoming has seven associate institutions and no other universities with the exception of one doctoral institution. Conversely, Alaska and the U.S. Virgin Islands have no associate institutions. Guam has one associate institution and one master's-granting institution. EPSCoR jurisdictions tend to have fewer institutions, primarily due to the size of some jurisdictions compared to non-EPSCoR jurisdictions. This institutional variability underlies the complexity of cross-institutional interactions that are typically built into EPSCoR projects, as well as the inherent administrative complexity. The variability affects the requisite distribution of funding, team development, and leadership strategies.

<sup>45</sup> National Science Board, National Science Foundation. (2020). *Science and engineering indicators 2020: The state of U.S. science and engineering*. NSB-2020-1. Alexandria, VA. Retrieved from <https://nces.nsf.gov/pubs/nsb20201/>

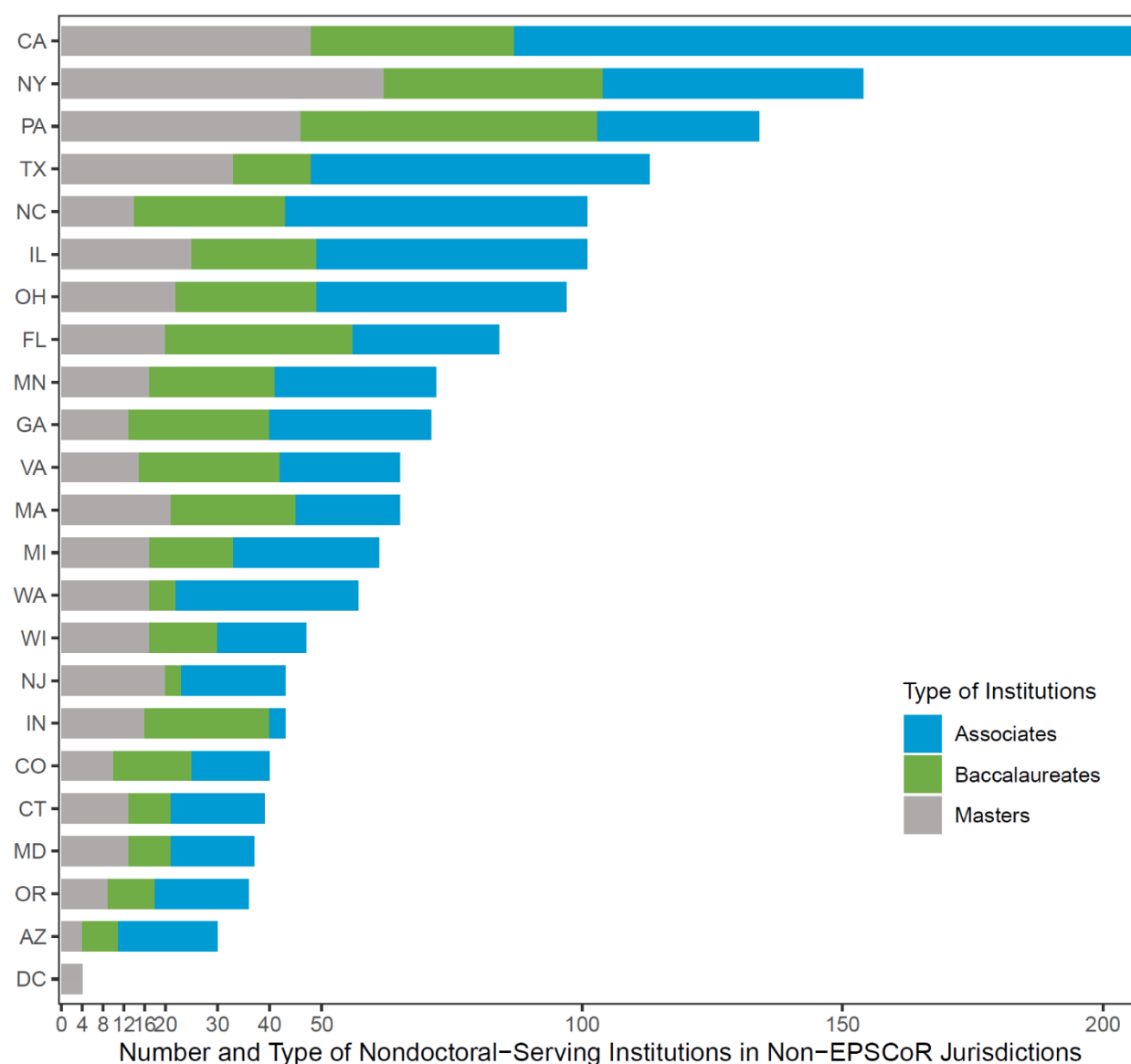
## EXHIBIT 5.9 NUMBER AND TYPE OF NONDOCTORAL-SERVING INSTITUTIONS IN CURRENT AND PAST EPSCoR JURISDICTIONS



Number and Type of Nondoctoral-Serving Institutions in Current or Past EPSCoR Jurisdictions

Note: As defined by Carnegie Classification.

## EXHIBIT 5.10 NUMBER AND TYPE OF NONDOCTORAL-SERVING INSTITUTIONS IN NON-EPSCOR JURISDICTIONS



Note: As defined by Carnegie Classification.

Jurisdictions also vary in terms of the number and type of MSIs catering to the minority population in their jurisdictions (see Exhibit 5.11). These institutions include HBCUs,<sup>46</sup> HSIs,<sup>47</sup>

<sup>46</sup> National Center for Education Statistics. (n.d.). *Digest of education statistics: 2018 – Table 313.10. Fall enrollment, degrees conferred, and expenditures in degree-granting historically Black colleges and universities, by institution: 2016, 2017, and 2016-17*. Data accessed from:

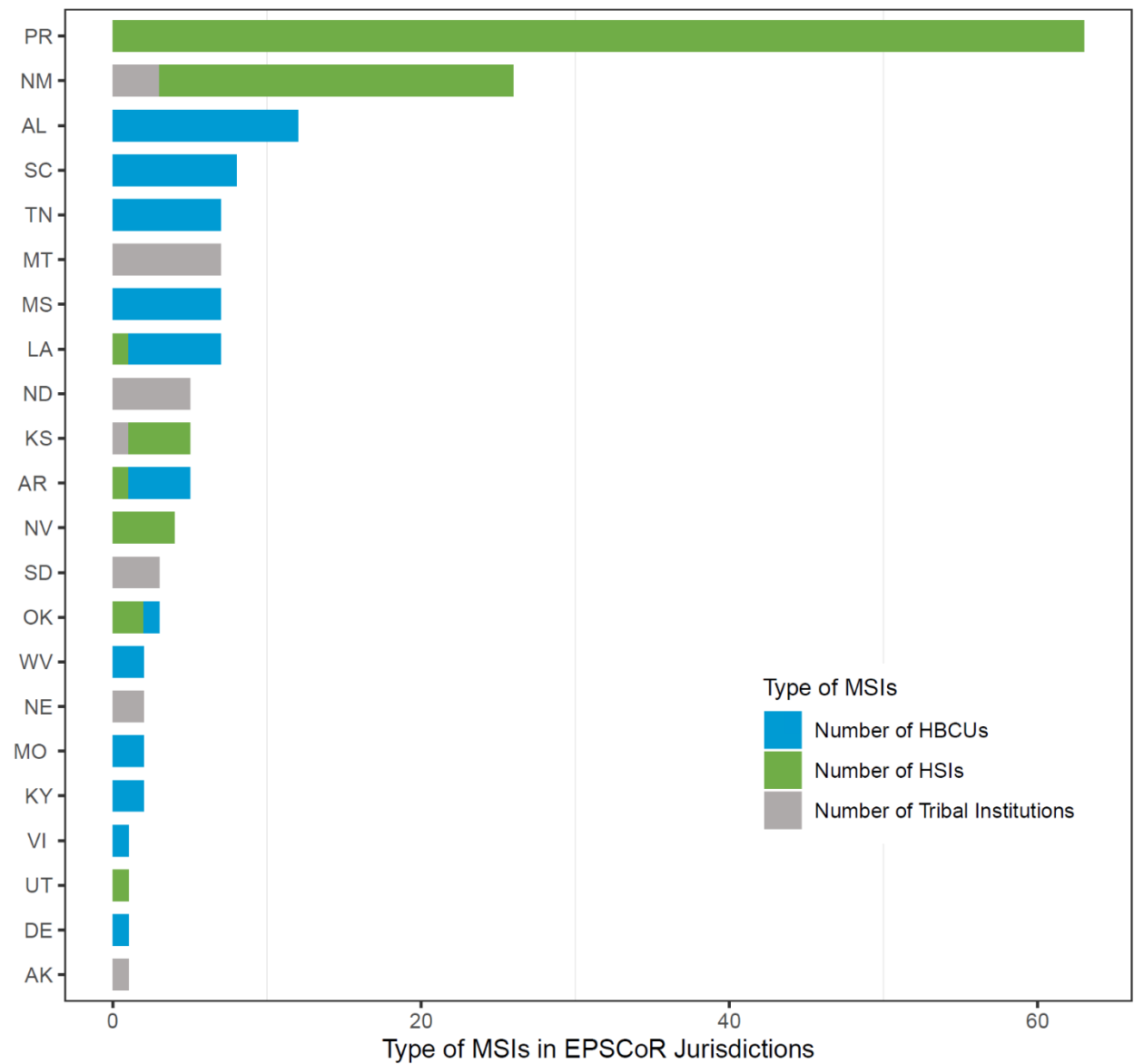
[https://nces.ed.gov/programs/digest/d18/tables/dt18\\_313.10.asp?current=yes](https://nces.ed.gov/programs/digest/d18/tables/dt18_313.10.asp?current=yes)

<sup>47</sup> Hispanic Association of Colleges and Universities. (n.d.). *HACU member Hispanic-serving institutions (HSIs)*. Data accessed from:

[https://www.hacu.net/assnfe/CompanyDirectory.asp?STYLE=2&COMPANY\\_TYPE=1,5&SEARCH\\_TYPE=0](https://www.hacu.net/assnfe/CompanyDirectory.asp?STYLE=2&COMPANY_TYPE=1,5&SEARCH_TYPE=0)

and TCUs. The distribution of MSIs impacts the number of minority students enrolling in higher education and completing degrees and also influences the availability of URM students in their jurisdiction's STEM workforce.

#### EXHIBIT 5.11 NUMBER AND TYPES OF MSIS IN EPSCOR JURISDICTIONS



Note: Hawaii, Guam, Idaho, Iowa, Maine, New Hampshire, Rhode Island, Vermont, and Wyoming have no HBCUs, HSIs, or Tribal Institutions.



## RESEARCH CAPACITY

### Summary



- Compared to non-EPSCoR jurisdictions, most EPSCoR jurisdictions have a smaller economic base, confer a lower percentage of S&E degrees, and have a low percentage of S&E workers—except for the jurisdictions in the Northeast United States.
- Compared to non-EPSCoR jurisdictions, nearly all EPSCoR jurisdictions and the universities in these jurisdictions receive low federal funding, possibly due to the low number of research-intensive doctoral universities. Some EPSCoR jurisdictions rely more heavily on funding from the Federal Government due to the federally funded labs or initiatives in their jurisdictions.

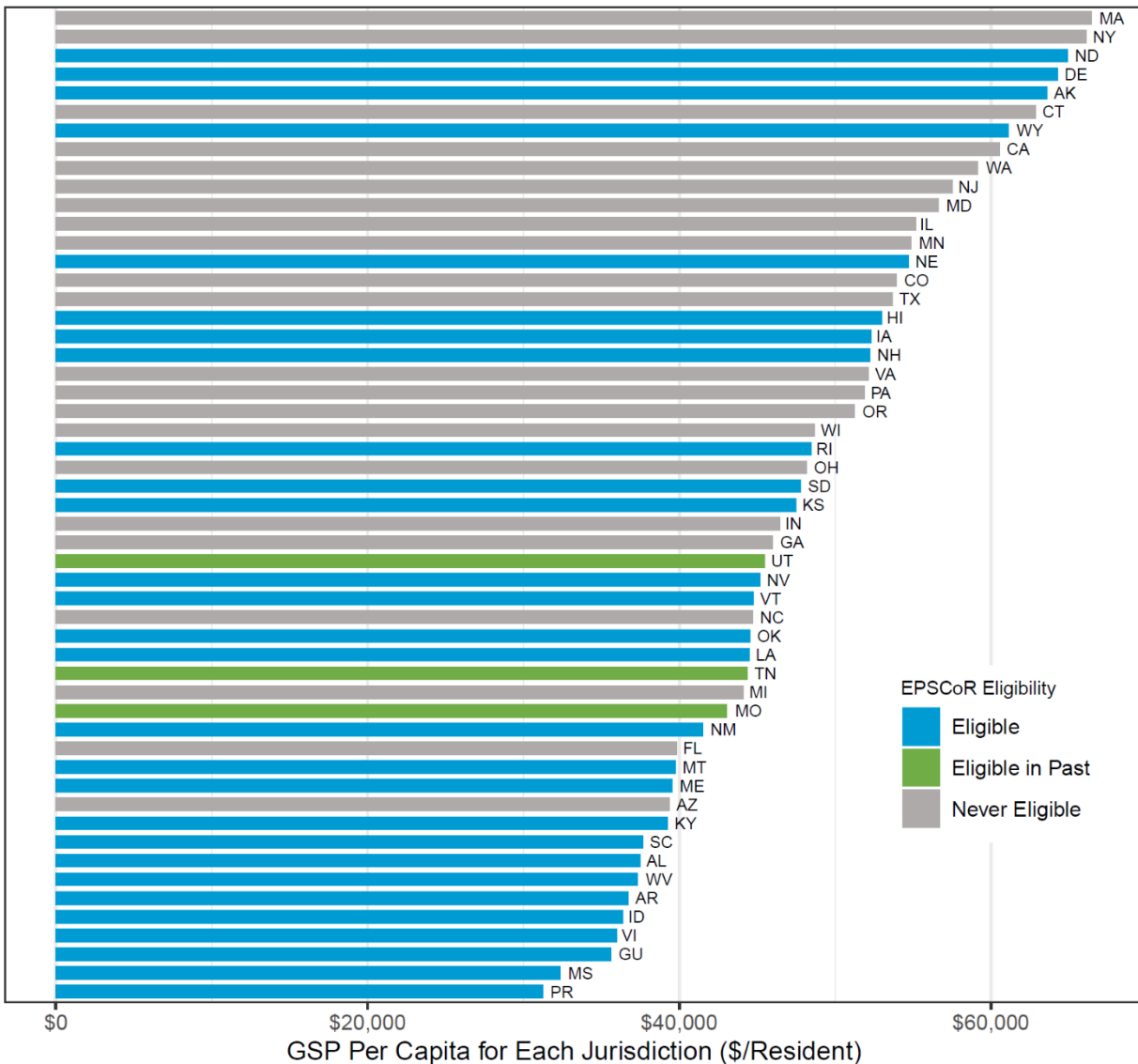
As a main objective, EPSCoR aims to increase jurisdiction-level support for S&E by strengthening the jurisdiction's research base. The strength of a jurisdiction's research base is closely related to the strength of its economic base, as building a strong research base requires considerable financial resources and infrastructure. Jurisdictions differ in terms of the strength of their economic base, as some have more developed industrial and entrepreneurial business environments than others. This section provides context on jurisdictions' S&E capabilities and broader ecosystems within which jurisdictions operate that may contribute to expansion of certain firms in the industry, high-skills job creation, and broader economic growth. Similarly, a jurisdiction's economic base provides a foundation to assess how future growth may occur or how to help jurisdictions adapt to economic changes.

### *Jurisdiction's Economic Base*

GSP per capita provides a measure of wellbeing and helps contextualize a jurisdiction's economic base in terms of productivity. Productivity can drive economic growth and improve the economic wellbeing of residents in the jurisdiction. Out of all the jurisdictions, DC, Massachusetts, and New York have the highest per capita GSP. DC had a GSP per capita of more than \$150,000 in 2017, more than twice that of the next jurisdiction, primarily due to the large Federal Government presence and small population size. Most EPSCoR-eligible jurisdictions were at the lower end of the scale for GSP per capita in 2017,<sup>48</sup> with Puerto Rico and Mississippi having the lowest (less than \$32,000) (see Exhibit 5.12).

<sup>48</sup> Current EPSCoR jurisdictions are at the lower end of GSP in 2017. Past EPSCoR-eligible jurisdictions are in the middle (above EPSCoR jurisdictions but below non-EPSCoR jurisdictions). See Exhibit B.3 in Appendix B.

## EXHIBIT 5.12 GSP PER CAPITA FOR EACH JURISDICTION IN 2017



Note: DC (not displayed) – gross state product per capita of \$159,266 in 2017

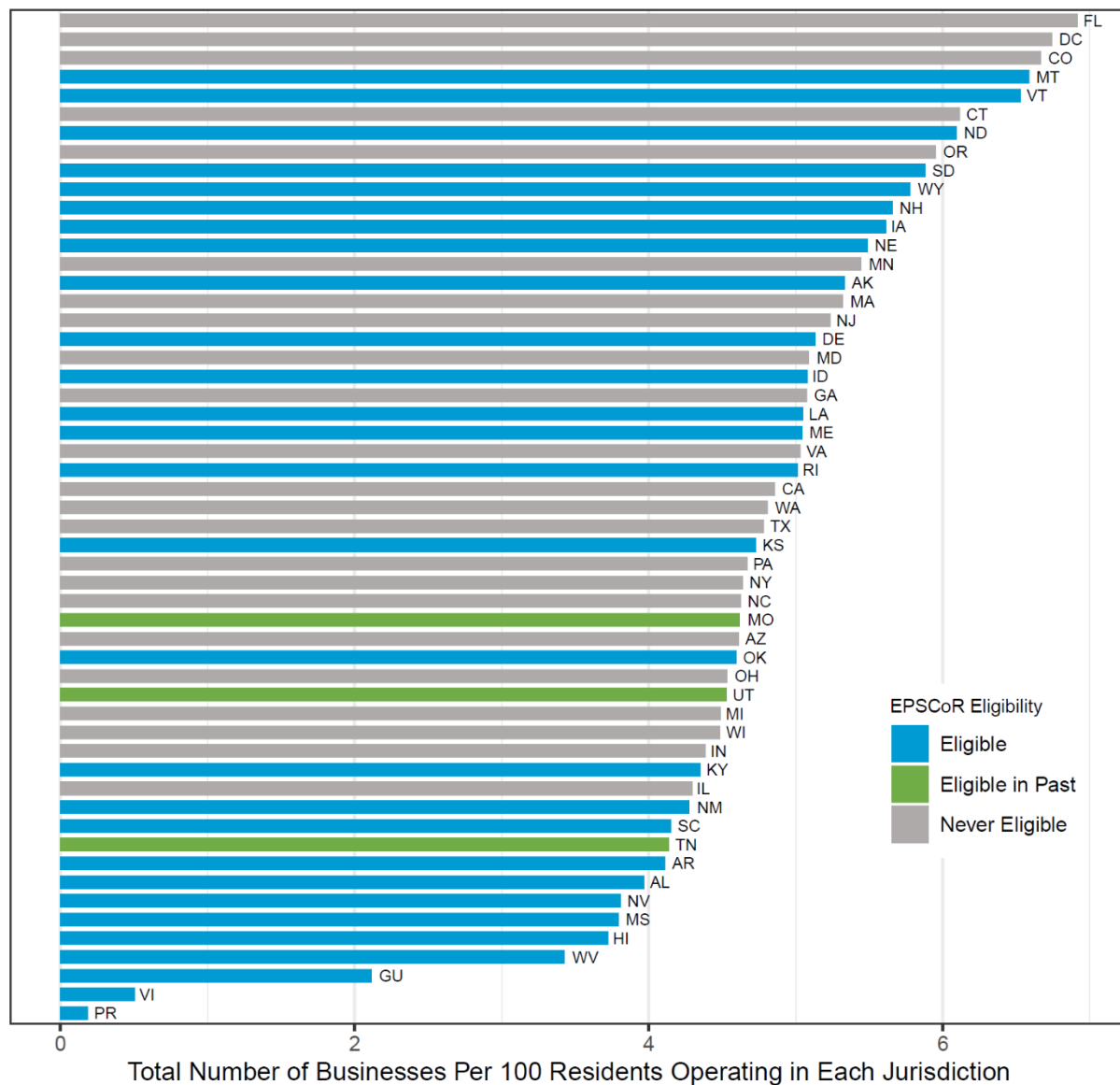
Possibly fueled by a recent oil boom due to new technology able to access previously inaccessible pockets of oil, North Dakota,<sup>49</sup> Alaska, and Wyoming have high GSP per capita. These jurisdictions' economic boom could spur further growth by creating new jobs and businesses, as these states also have a high number of businesses per 100 residents<sup>50</sup> (see

<sup>49</sup> North Dakota Compass. (2020). *Data highlight*. Retrieved from <https://www.ndcompass.org/trends/Data-Highlight/Data-Highlight.php>

<sup>50</sup> Ellis, B. (2014, July 14). *How North Dakota's economy doubled in 11 years*. Retrieved from <https://money.cnn.com/2014/06/11/news/economy/north-dakota-economy/>

Exhibit 5.13).<sup>51</sup> However, the rural and sparse nature of these oil boom states may also require more businesses per capita, so more in-depth and careful investigation is needed for these Mountain states. Similarly, the U.S. territories (Guam, Puerto Rico, and the U.S. Virgin Islands) have the lowest number of businesses per 100 residents.

#### EXHIBIT 5.13 TOTAL NUMBER OF BUSINESSES PER 100 RESIDENTS OPERATING IN EACH JURISDICTION IN 2017



<sup>51</sup> Current EPSCoR jurisdictions are at the lower end of total number of businesses in 2017. Past EPSCoR-eligible jurisdictions are in the middle (above EPSCoR jurisdictions but below non-EPSCoR jurisdictions). See Exhibit B.4 in Appendix B.

The S&E workforce makes significant contributions to the jurisdiction's economic growth and research competitiveness. S&E workers fuel the jurisdiction's innovative capacity through their research, development, and other technologically advanced work activities. As a result, there has been an emphasis on developing S&E expertise and associated workforce at various levels, from associate degrees to PhDs. In addition, skilled technical workers provide critical support to scientific R&D. The share of employment in the S&E workforce indicates the extent to which jurisdictions have sufficient depth of high-caliber technical talent. The percentage of the workforce with an S&E bachelor's degree is a useful measure of human capital production, but it is not a reliable measure of human capital stock due to high interstate mobility.<sup>52</sup> For example, more than half of doctorate recipients complete their doctorate in one state and then are subsequently employed in a different state. Exhibits 5.14 and 5.15 show the percentages of jurisdictions' populations with a bachelor's degree in S&E and the percentages of the populations working in professional, scientific, or technical sectors,<sup>53</sup> respectively. The EPSCoR jurisdictions in the upper Northeast have higher percentages of their labor force with a bachelor's degree in S&E, as well as relatively higher percentages of S&E workforce (especially New Hampshire and Vermont). In contrast, most EPSCoR jurisdictions in the South are at the lower end on both of these indicators.

#### JURISDICTION SPOTLIGHT

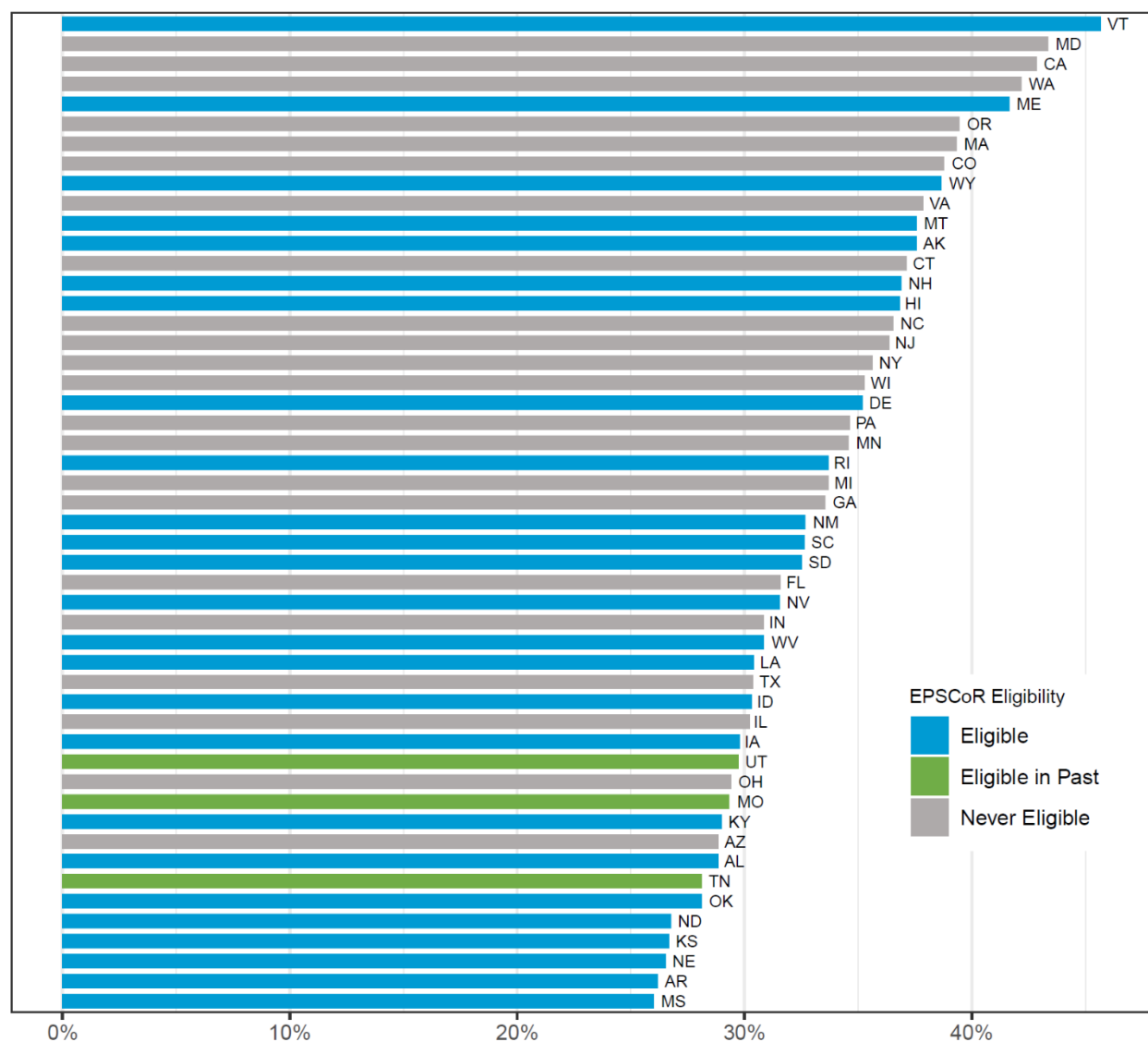
Maryland's success in its S&E workforce development may be attributed to the **Employment Advancement Right Now (EARN Maryland) program**, a public-private partnership to engage high-tech firms while providing credentials to get workers back into the workforce. In addition, the University of Maryland system provides the need-based **Promise Scholarship** to target high-tech fields such as neuroscience, cybersecurity, and engineering. Drawing from a \$219 million donation, the scholarship provides up to \$5,000 to cover 2 years of community college, aiming to reduce college cost and increase the state's high-tech workforce.

Both these indicators show the strength (or weakness) of EPSCoR jurisdictions' workforce skill levels, as well as the jurisdictions' ability to produce S&E degree recipients needed to maintain and replenish that workforce. For example, Utah's Pathways program supports a collaborative effort between the private and public sectors to address industry workforce needs as the state continues to build its S&E workforce.

<sup>52</sup> National Science Foundation, National Center for Science and Engineering Statistics. (2018). *Doctorate recipients from U.S. universities: 2017* (Special Report NSF 19-301). Alexandria, VA: National Science Foundation. Retrieved from <https://nces.nsf.gov/pubs/nsf19301/>

<sup>53</sup> Current EPSCoR jurisdictions are at the lower end of the number of S&E workers in 2017 and past EPSCoR eligible jurisdictions are in the middle. See Exhibit B.5 in Appendix B.

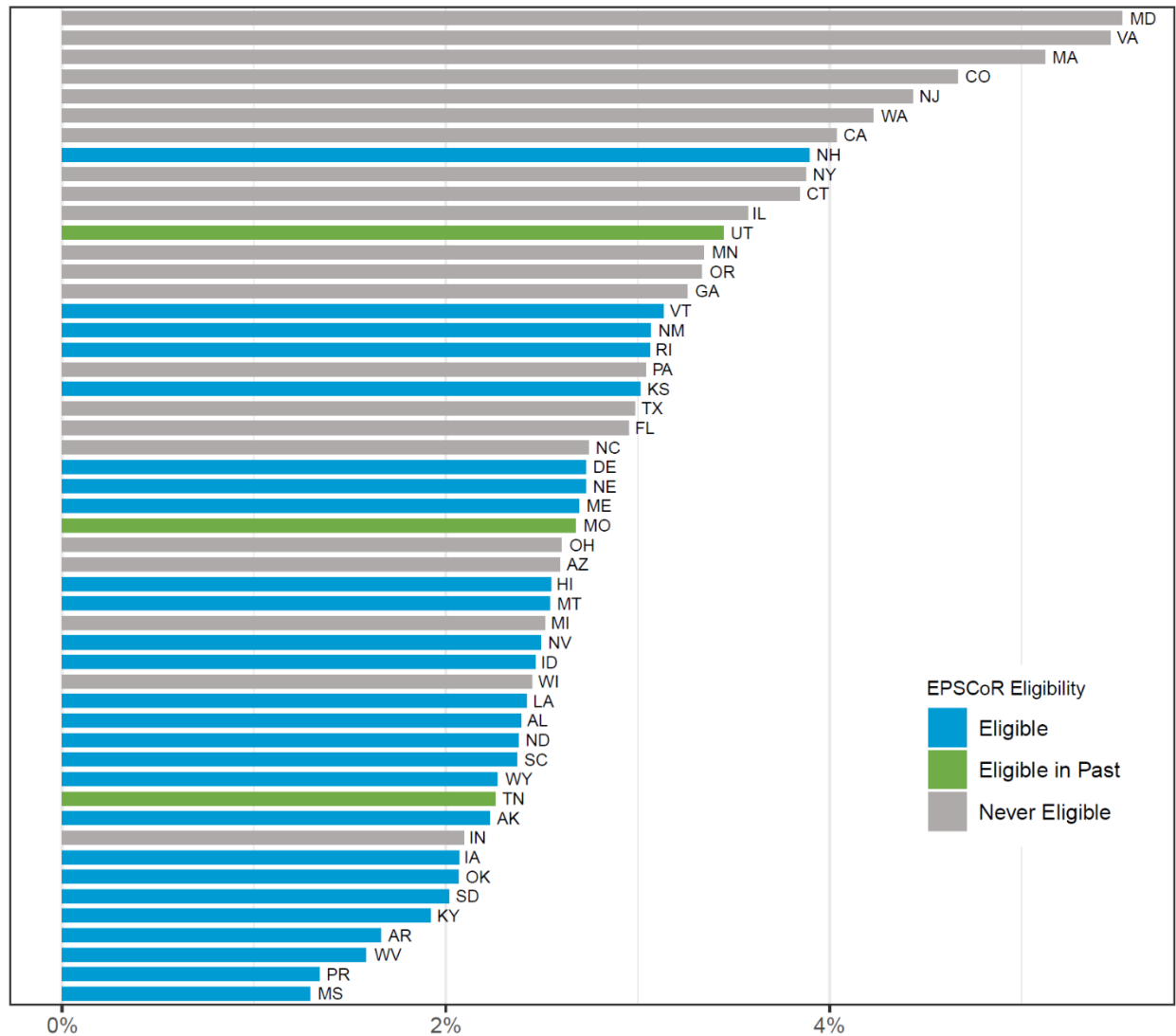
# EXHIBIT 5.14 PERCENTAGES OF JURISDICTION POPULATIONS 25 YEARS OR OLDER WITH A BACHELOR'S DEGREE IN S&E IN 2014



Percentage of Population 25 Years or Older with a Bachelor's Degree in S&E

Note: Data are not available for Guam, Puerto Rico and the U.S. Virgin Islands.

**EXHIBIT 5.15 PERCENTAGE OF RESIDENTS EMPLOYED IN PROFESSIONAL, SCIENTIFIC, AND TECHNICAL SERVICES IN EACH JURISDICTION IN 2016**

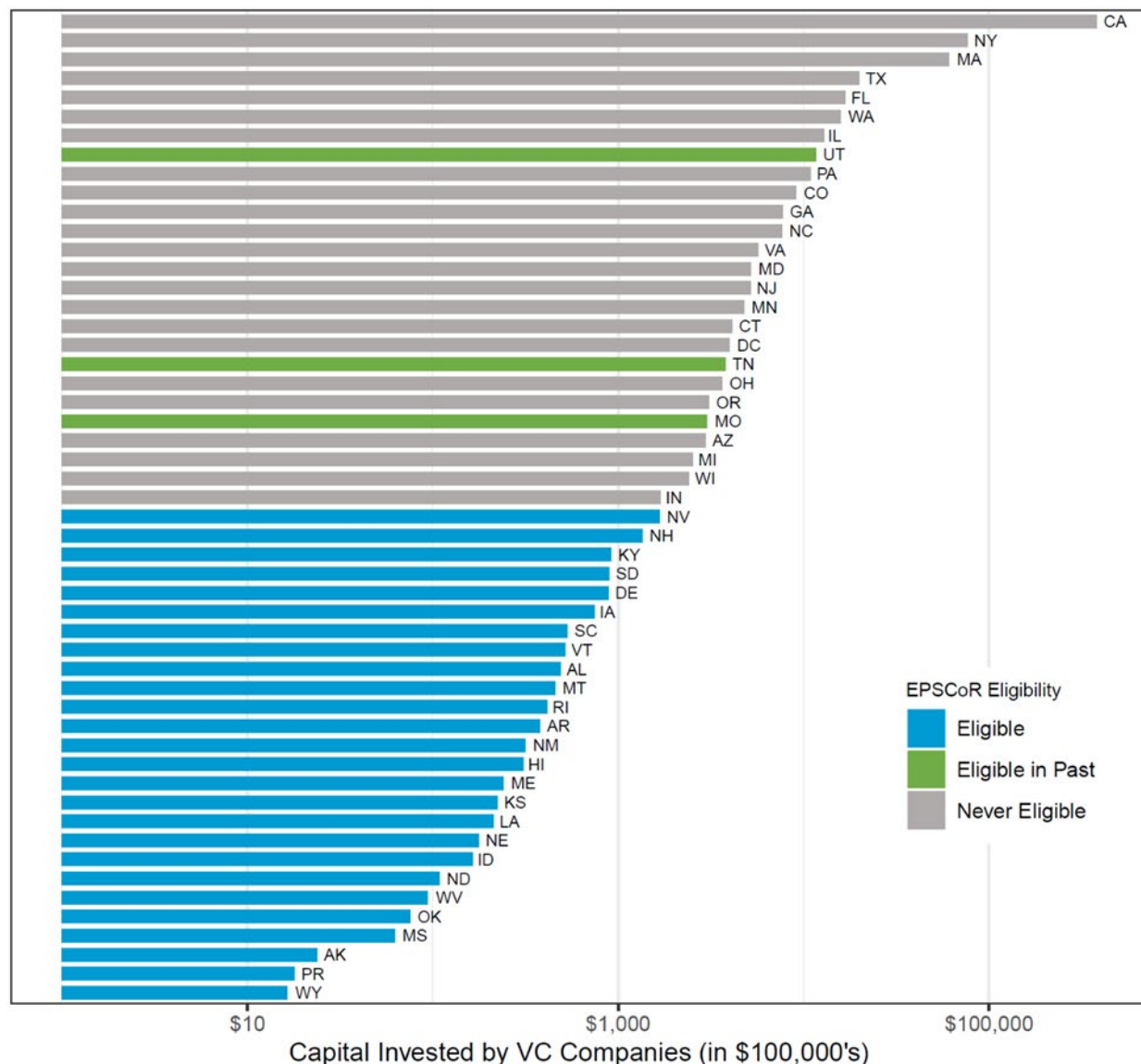


Percentage of Residents Employed in Professional, Scientific, and Technical Services

Note: Data are not available for Guam and the U.S. Virgin Islands. DC (not displayed) = 9.4 percent employed in professional, scientific, and technical services in 2016.

Entrepreneurial capacity and infrastructure can also help jurisdictions create new S&E jobs and attract companies and further investment. VC funding can be crucial to the jurisdiction's ability to maintain economic growth and create opportunity, especially from early stage funding. In 2016, VC firms invested nearly \$70 billion across more than 8,000 deals in 7,700 companies across all U.S. states and territories. As shown in Exhibit 5.16, in 2016 most EPSCoR-eligible jurisdictions were receiving relatively small amounts of capital from VC firms. The three past EPSCoR-eligible jurisdictions—Utah, Tennessee, and Missouri—successfully secured high levels of VC in 2016.

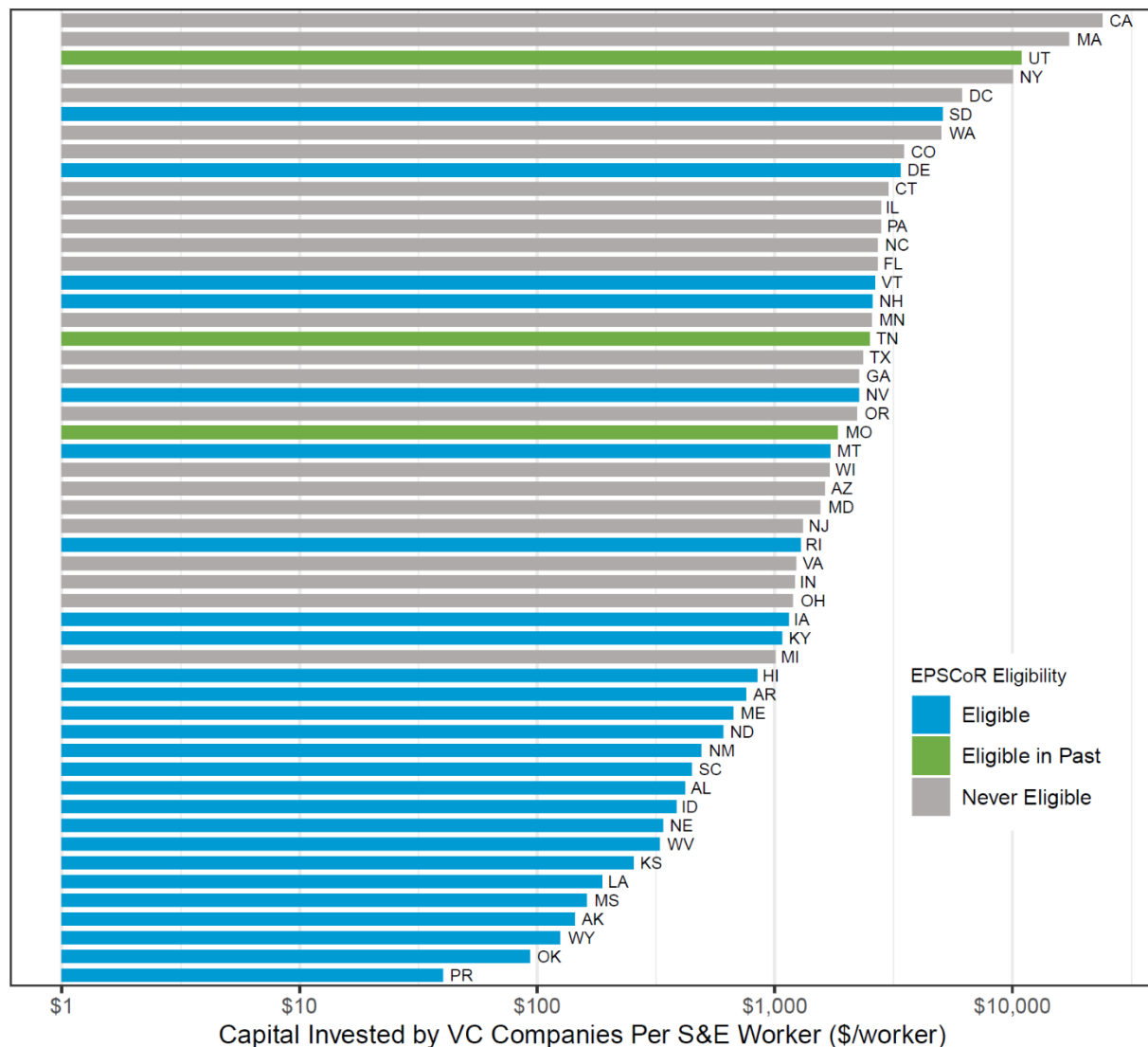
**EXHIBIT 5.16 CAPITAL INVESTED BY VC FIRMS IN EACH JURISDICTION IN 2016**



Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands.

However, concentrating on the total dollar amount may be misleading as the numbers of businesses and percentages of people employed in the professional, scientific, and technical sector in EPSCoR jurisdictions tend to be smaller than in non-EPSCoR jurisdictions (see Exhibits 5.13 and 5.15, respectively), predominantly due to the smaller populations. Exhibit 5.17 shows the capital invested by VC firms per S&E worker in each jurisdiction in 2016. Some EPSCoR jurisdictions like Delaware, New Hampshire, and Vermont have higher rankings, possibly due to their proximity to jurisdictions with high VC funding like Massachusetts and New York. Previously eligible EPSCoR jurisdictions like Utah have relied on state universities to acquire capital from VC firms. For example, the University of Utah is the top knowledge producer for the state and leads the country in commercializing university R&D.

## EXHIBIT 5.2 CAPITAL INVESTED BY VC FIRMS PER S&E WORKER IN EACH JURISDICTION IN 2016



Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands. Number of S&E workers is defined as the employment in professional, scientific, and technical services from the Census data in 2016.



Most EPSCoR jurisdictions lag in raising capital for existing firms and new company formations, which are crucial resources needed for these firms to succeed. In the absence of VC companies, entrepreneurs may rely on either federal or state funding.

### ***R&D Funding Received by the Jurisdiction from the Federal Government***

R&D funding increases jurisdictions' research capacities and abilities to develop research infrastructure, which can create opportunities for innovation and economic development. R&D conducted by higher education institutions is a key component of overall R&D research but has mostly concentrated on performing basic research. On the other hand, high-tech firms have primarily undertaken exploratory applied work. Both types of research efforts lead to improved and innovative products, support creation of high-tech industries, and help fulfill worker needs. Infrastructure and capability to attract research funding, as well as cultural value placed on innovative research activities in the jurisdiction, are key components necessary for research success in both settings.

U.S. R&D expenditure increased from \$406.6 billion in 2010 to \$493.7 billion in 2015 and is estimated to increase to more than \$580 billion in 2018.<sup>54</sup> The U.S. R&D system consists of various actors who perform R&D through different funding sources. Most R&D funding is provided by the Federal Government, especially funding for academic institutions.<sup>55</sup> This subsection reviews each jurisdiction on the following R&D indicators for funding from the Federal Government:

- Total federal obligations for S&E R&D
- Total federal obligations for S&E R&D to universities
- Total NSF funding received
- Total NIH funding received
- Total STTR awards<sup>56</sup> and SBIR program<sup>57</sup>

Exhibit 5.18 shows the federal obligations for S&E R&D per S&E worker in each jurisdiction in 2014. Standardized measures illuminate diversity among jurisdictions of similar size. For example, large jurisdictions have more federal obligations for S&E R&D (see Exhibit B.16 in Appendix B), but the same measure per S&E worker shows substantial variation unrelated to the jurisdiction size. In 2014, EPSCoR jurisdictions New Mexico and Alabama both had relatively high federal obligations for S&E R&D per S&E worker. However, other EPSCoR jurisdictions such as Puerto Rico, Kansas, Louisiana, Kentucky, Wyoming, and Maine were relatively low in federal obligations for S&E R&D per S&E worker.

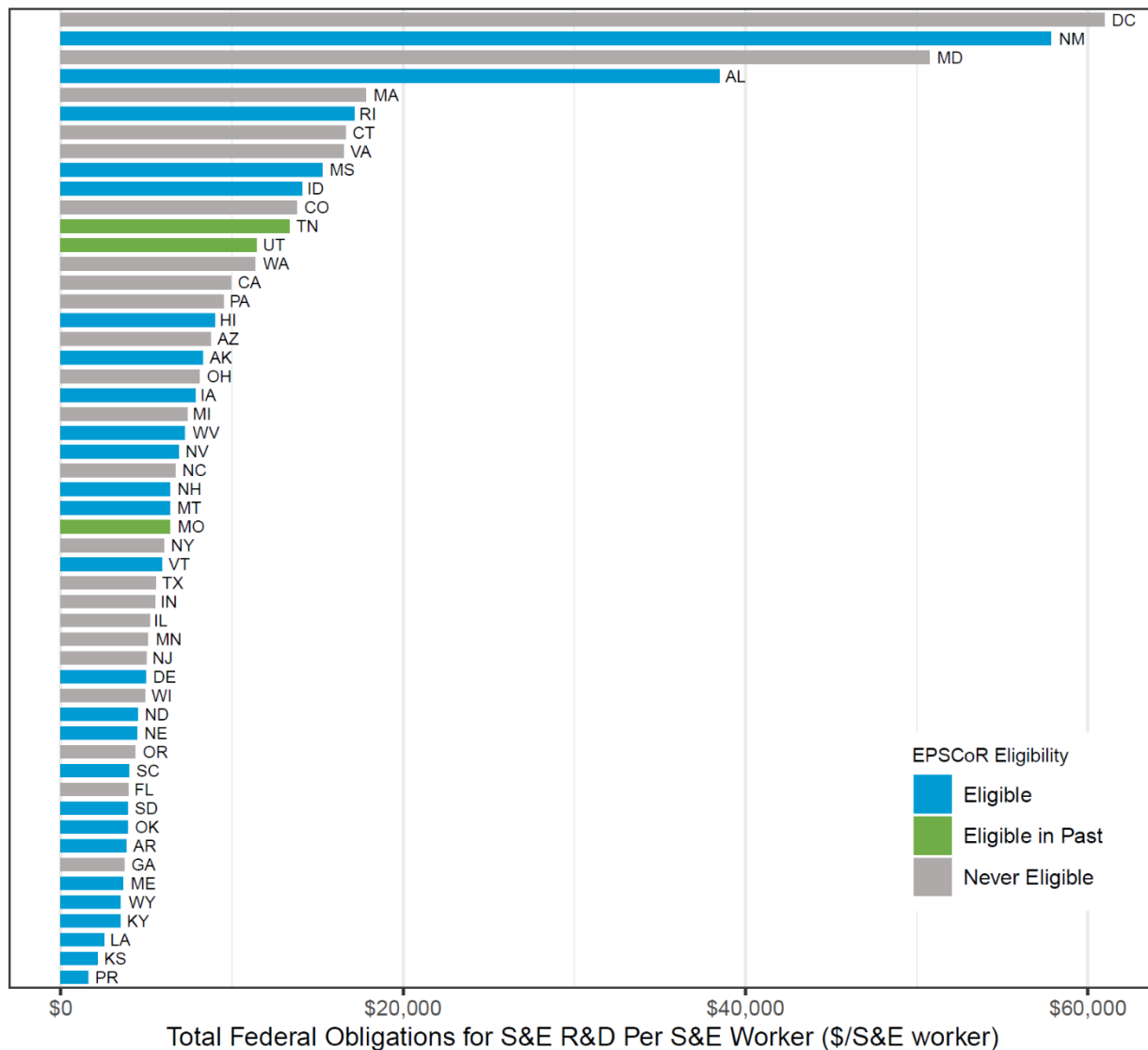
<sup>54</sup> Boroush, M. (2020). *U.S. R&D increased by \$32 billion in 2017, to \$548 billion; estimate for 2018 indicates a further rise to \$580 billion*. NCSSES InfoBrief (NSF 23-09). Retrieved from <https://www.nsf.gov/statistics/2020/nsf20309/nsf20309.pdf>

<sup>55</sup> *ibid.* See Table 3 – U.S. R&D expenditures by performing sector and source of funding in 2017.

<sup>56</sup> The NASA SBIR and STTR programs fund the R&D of innovative technologies that align with NASA needs. STTR awards are federally funded research grants to innovative small businesses and nonprofit research institutes to support technology commercialization efforts.

<sup>57</sup> The SBIR program funds costly startup and development stages and encourages commercialization of research findings to for-profit small businesses.

## EXHIBIT 5.18 FEDERAL OBLIGATIONS FOR S&E R&D PER S&E WORKER FOR EACH JURISDICTION IN 2014



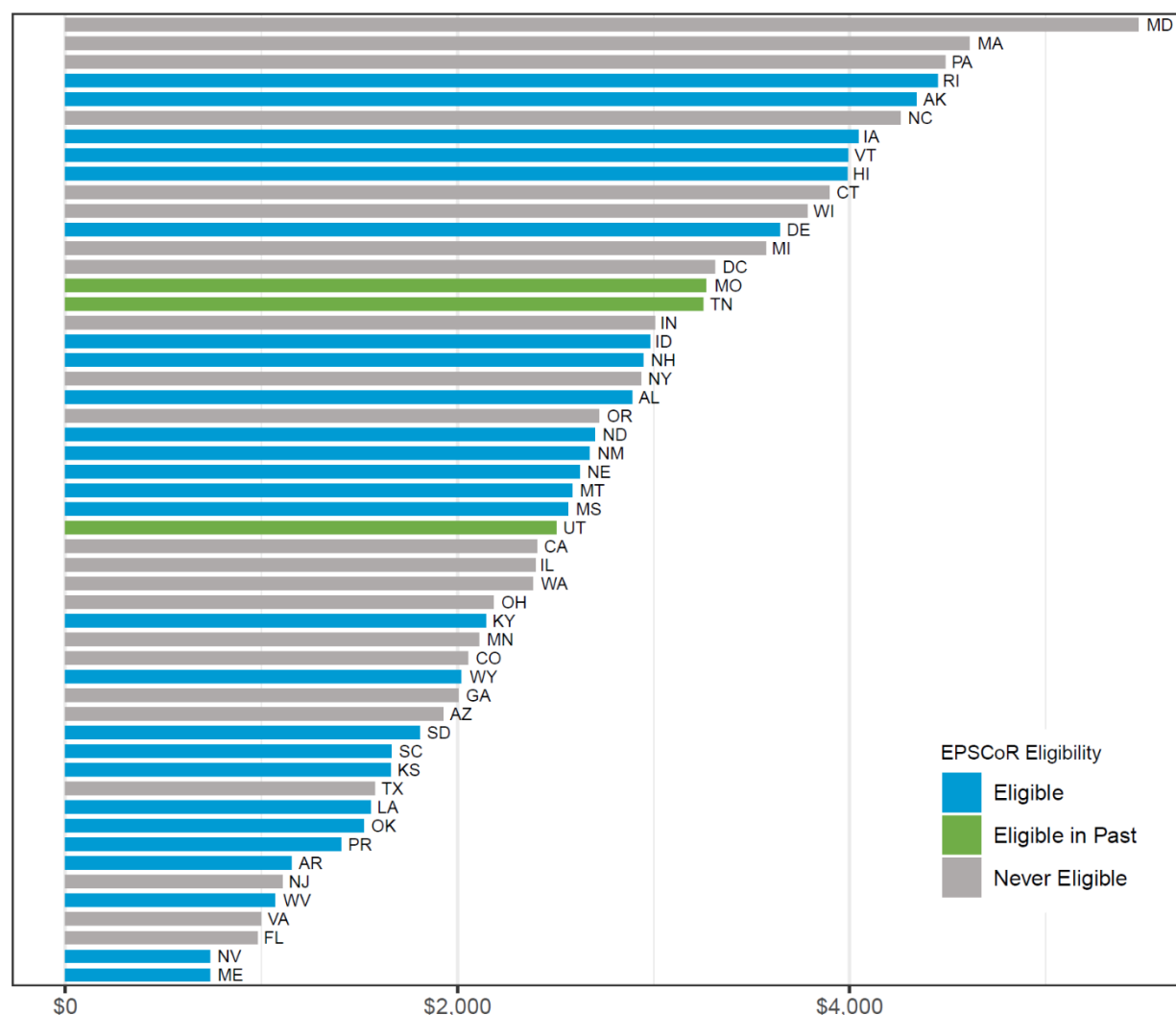
Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands. Number of S&E workers is defined as the employment in professional, scientific, and technical services from the Census data in 2016.

In FY 2014, federal agencies obligated \$31.2 billion to universities to support S&E, an increase of 6 percent from FY 2013.<sup>58</sup> During the same time period, funding for R&D to universities and colleges also increased by 6 percent to \$27.7 billion. The top 100 universities received the largest amounts of federal R&D S&E support,<sup>59</sup> accounting for 81 percent of all S&E obligations for R&D in FY 2017. The top 100 includes 18 institutions of higher education located in current and past EPSCoR jurisdictions, including 4 private universities—Washington University in St. Louis (Missouri, ranked 15); Vanderbilt University (Tennessee, ranked 23); Brown University (Rhode Island, ranked 71); and Dartmouth College (New Hampshire, ranked 79). Only 14 public universities in current and past EPSCoR jurisdictions were ranked in the top 100, with University of Alabama (ranked 40) and University of Utah (ranked 44) as the only state universities ranked in the top 50. Of the 28 current EPSCoR jurisdictions, 16 jurisdictions have no institution listed in the top 100. Accounting for the S&E workers in each EPSCoR jurisdiction in 2014, smaller states like Rhode Island, Alaska, Vermont, and Delaware have relatively high per-S&E-worker federal obligations for S&E R&D funding to universities; whereas Maine, Nevada, West Virginia, and Arkansas have relatively low federal obligations for S&E R&D funding per S&E worker in 2014 (see Exhibit 5.19).

<sup>58</sup> Pece, C. (2018, July). *Federal science and engineering obligations to academic institutions reach \$31.6 billion in FY 2016; support from HCBUs declines for the second year in a row*. NCSES InfoBrief (NSF 18-310). Retrieved from <https://www.nsf.gov/statistics/2018/nsf18310/nsf18310.pdf>

<sup>59</sup> National Science Foundation, National Center for Science and Engineering Statistics. (2017). *Survey of federal science and engineering support to universities, colleges, and nonprofit institutions fiscal year 2017: Table 4*. Retrieved from <https://ncesdata.nsf.gov/fedsupport/2017/index.html>

## EXHIBIT 5.19 FEDERAL OBLIGATIONS FOR S&E R&D FUNDING TO UNIVERSITIES PER S&E WORKER IN 2014



Total Federal Obligations for S&E R&D Funding to Universities Per S&E Worker (\$/S&E worker)

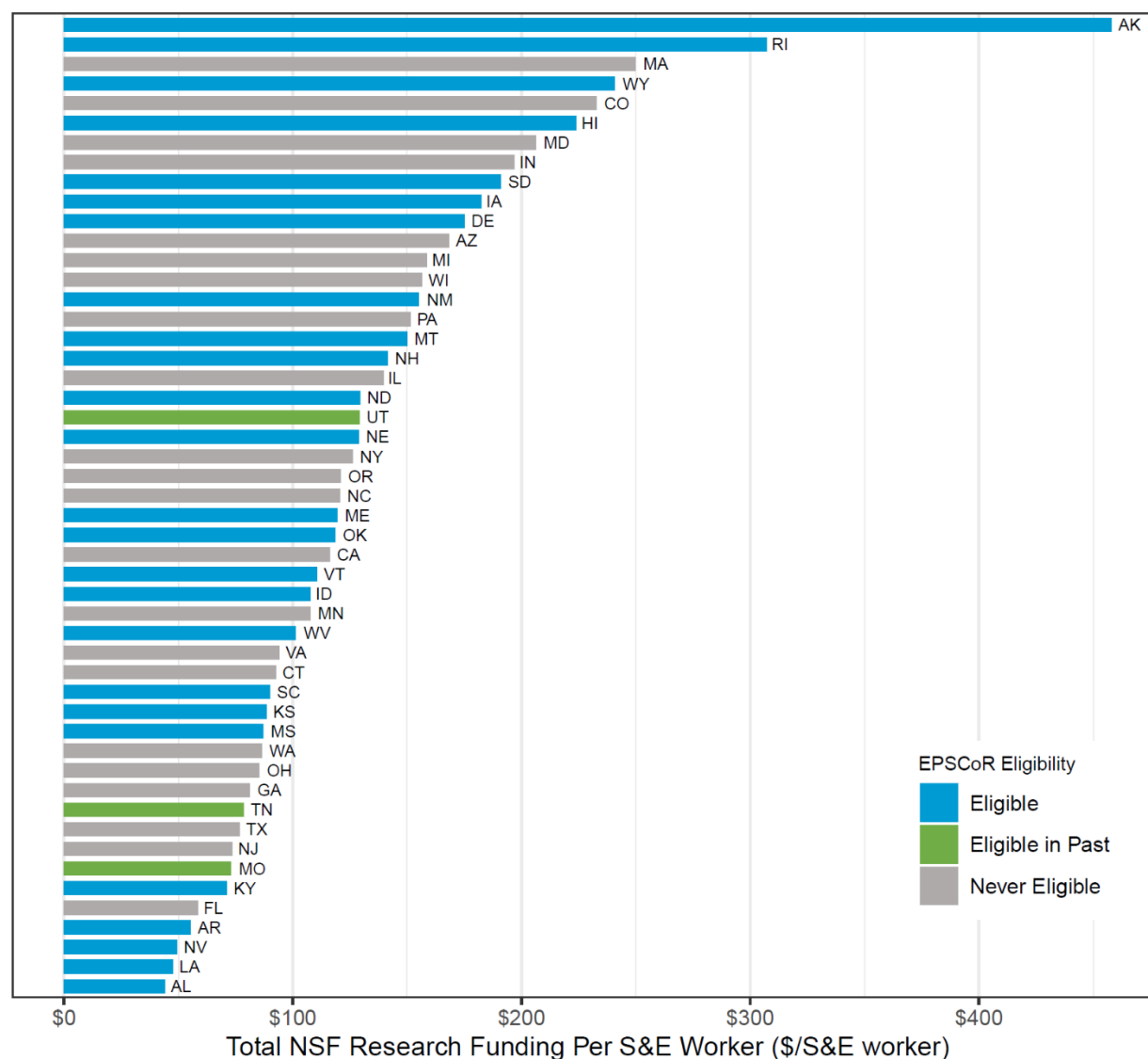
Note: Data are not available for Guam and the U.S. Virgin Islands. Number of S&E workers is defined as the total employment in professional, scientific, and technical services from the Census data in 2016.

Similarly, Alaska, Rhode Island, and Wyoming were in the top five and Alabama, Louisiana, Nevada, and Arkansas were in the bottom five of all EPSCoR jurisdictions for NSF funding per S&E worker in the jurisdiction in 2015. The top 100 universities that received the largest amount of NSF-financed higher education R&D support<sup>60</sup> accounted for 80 percent of all NSF funding for higher education R&D in FY 2018. Among the top 100 institutions of higher education, 1 in 4 are located in 31 current and past EPSCoR jurisdictions, including 4 private universities—Brown University (Rhode Island, ranked 65); Vanderbilt University (Tennessee, ranked 74); Washington

<sup>60</sup> National Science Foundation, National Center for Science and Engineering Statistics. (2020). *Higher education research and development survey fiscal year 2018: Table 25*. Retrieved from <https://ncesdata.nsf.gov/herd/2018/html/herd18-dt-tab025.html>

University in St. Louis (Missouri, ranked 76); and Dartmouth College (New Hampshire, ranked 78). Only 21 public universities in current and past EPSCoR jurisdictions were ranked in the top 100, with University of Utah (ranked 40) and Iowa State University (ranked 49) as the only 2 state universities in the top 50. Only 1 out of the 37 R2 institutions (Utah State University, ranked 79) is in the top 100. Of the current 28 EPSCoR jurisdictions, 14 jurisdictions have at least 1 institution in the top 100.

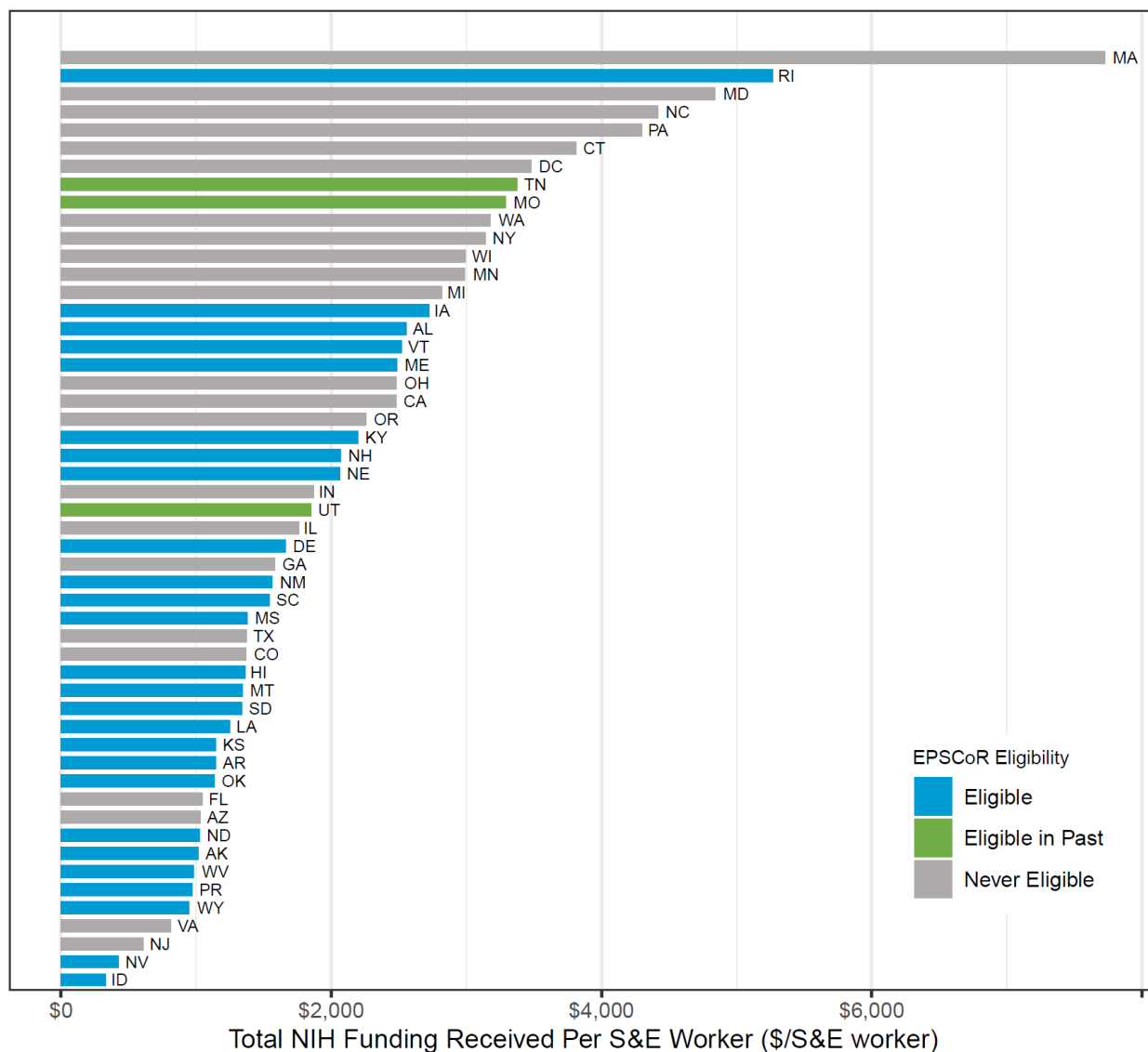
#### EXHIBIT 5.20 TOTAL NSF FUNDING PER S&E WORKER FOR EACH JURISDICTION IN 2015



Note: Data are not available for Guam, Puerto Rico and the U.S. Virgin Islands. Number of S&E workers is defined as the total employment in professional, scientific, and technical services from the Census data in 2016.

Rhode Island was the only current EPSCoR jurisdiction in the top 10 for NIH funding per S&E worker in 2017. Tennessee and Missouri, eligible for EPSCoR in the past, were also in the top 10. In 2017, Idaho and Nevada received the lowest NIH funding per S&E worker in their jurisdictions (see Exhibit 5.21).

#### EXHIBIT 5.21 TOTAL NIH FUNDING PER S&E WORKER FOR EACH JURISDICTION IN 2017



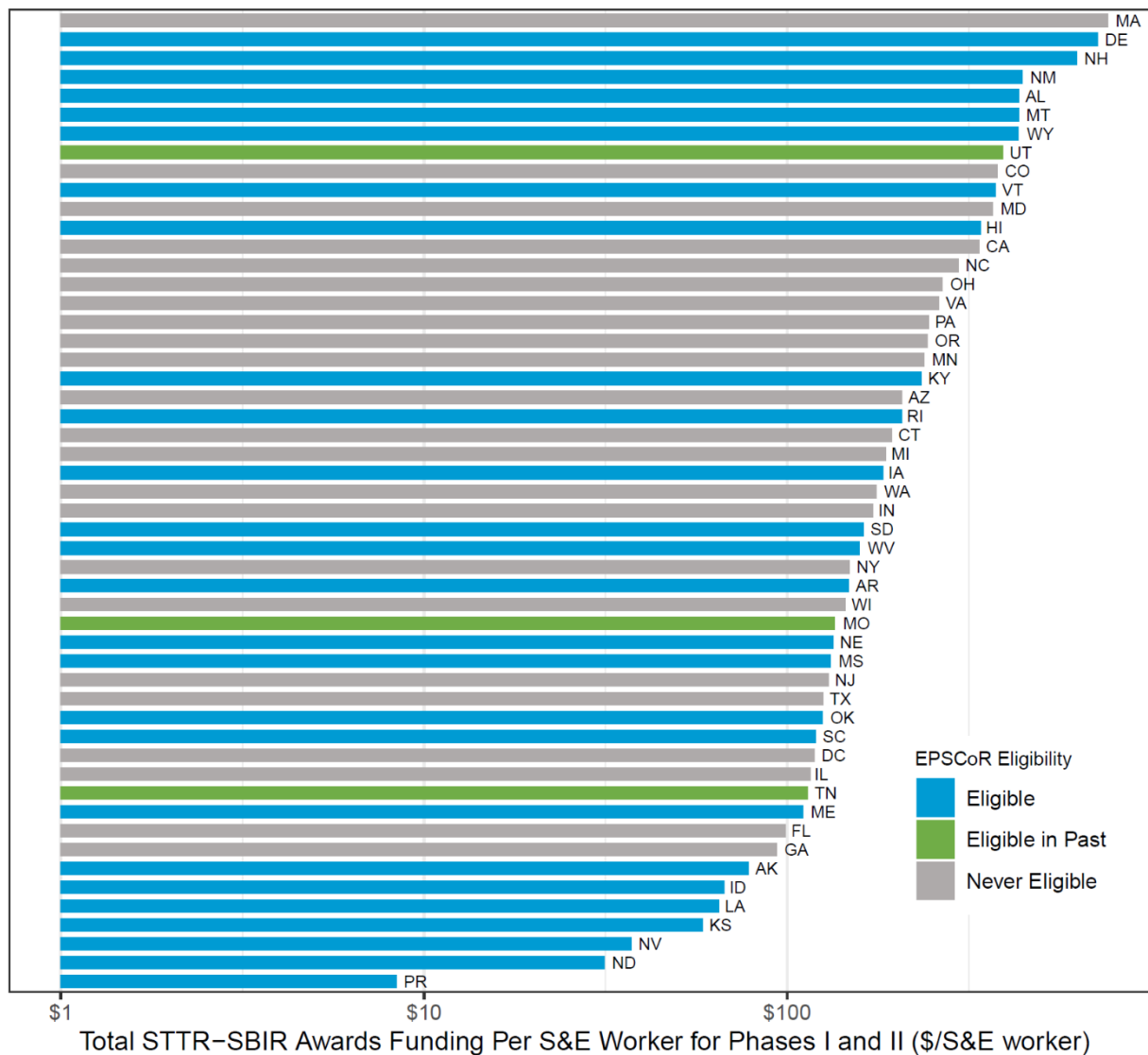
Note: Data are not available for Guam and the U.S. Virgin Islands. Number of S&E workers is defined as the total employment in professional, scientific, and technical services from the Census data in 2016.

Jurisdictions can also get funding through the SBIR and STTR programs. The SBIR and STTR programs have three phases:

- Phase I provides the opportunity to establish the scientific, technical, and commercial merit of the project; the feasibility of the proposed innovation; and the quality of the small business's performance. Successful completion of Phase I objectives is a prerequisite to consideration for a Phase II award. The SBIR and STTR Phase I contracts last for 6 and 13 months, respectively, both with maximum funding amounts of \$125,000.
- Phase II is focused on the development, demonstration, and delivery of the innovation. Only small businesses awarded a Phase I contract are eligible to submit a proposal. Phase II projects are chosen as a result of competitive evaluations and based on selection criteria provided in the solicitation. Phase II contracts last for 24 months with a maximum funding of \$750,000.
- Phase III is the commercialization of innovative technologies, products, and services resulting from either a Phase I or II contract. Phase III contracts are funded from sources other than the SBIR and STTR programs.

EPSCoR-eligible jurisdictions Delaware, New Hampshire, New Mexico, Alabama, Montana, and Wyoming, along with previously eligible jurisdiction Utah, had relatively high per-S&E-worker STTR and SBIR funding in 2017. EPSCoR-eligible jurisdictions such as Puerto Rico, North Dakota, Nevada, Kansas, Louisiana, Idaho, and Alaska had comparatively low per-S&E-worker STTR and SBIR funding (see Exhibit 5.22).

## EXHIBIT 5.22 TOTAL STTR-SBIR AWARD FUNDING PER S&E WORKER FOR EACH JURISDICTION IN 2017



Note: Data are not available for Guam and the U.S. Virgin Islands. Number of S&E workers is defined as the total employment in professional, scientific, and technical services from the Census data in 2016.

As seen through these four indicators, jurisdictions vary in terms of the federal R&D funding levels per S&E worker. Each jurisdiction has some reliance on federal funding, as some states have federally funded labs or initiatives located in their state institutions. In addition, some jurisdictions have well-established research universities that are able to compete successfully for federal funding against other institutions in non-EPSCoR jurisdictions in select fields or disciplines (as seen in NIH and NSF funding). However, some EPSCoR jurisdictions do have very low research capacity.





## Jurisdiction-Level Financial Resource Capacity

### Summary

- EPSCoR jurisdictions' state governments seem to support R&D activities to complement federal funding for research at academic institutions, albeit to a much lower extent than the Federal Government.

In addition to variations among jurisdictions in terms of federal R&D funding levels, jurisdictions also vary in amounts of state R&D funding received. State governments can support R&D activities to complement (or add in the absence of) federal funding and often fund research at academic institutions, albeit to a much lower extent (\$4.6 billion in 2017).<sup>61</sup> Some jurisdictions' governments invest more in R&D and higher education than others; some jurisdictions have stronger policy incentives for firms to undertake R&D. This subsection reviews each jurisdiction on the following R&D indicators for funding from the state government:

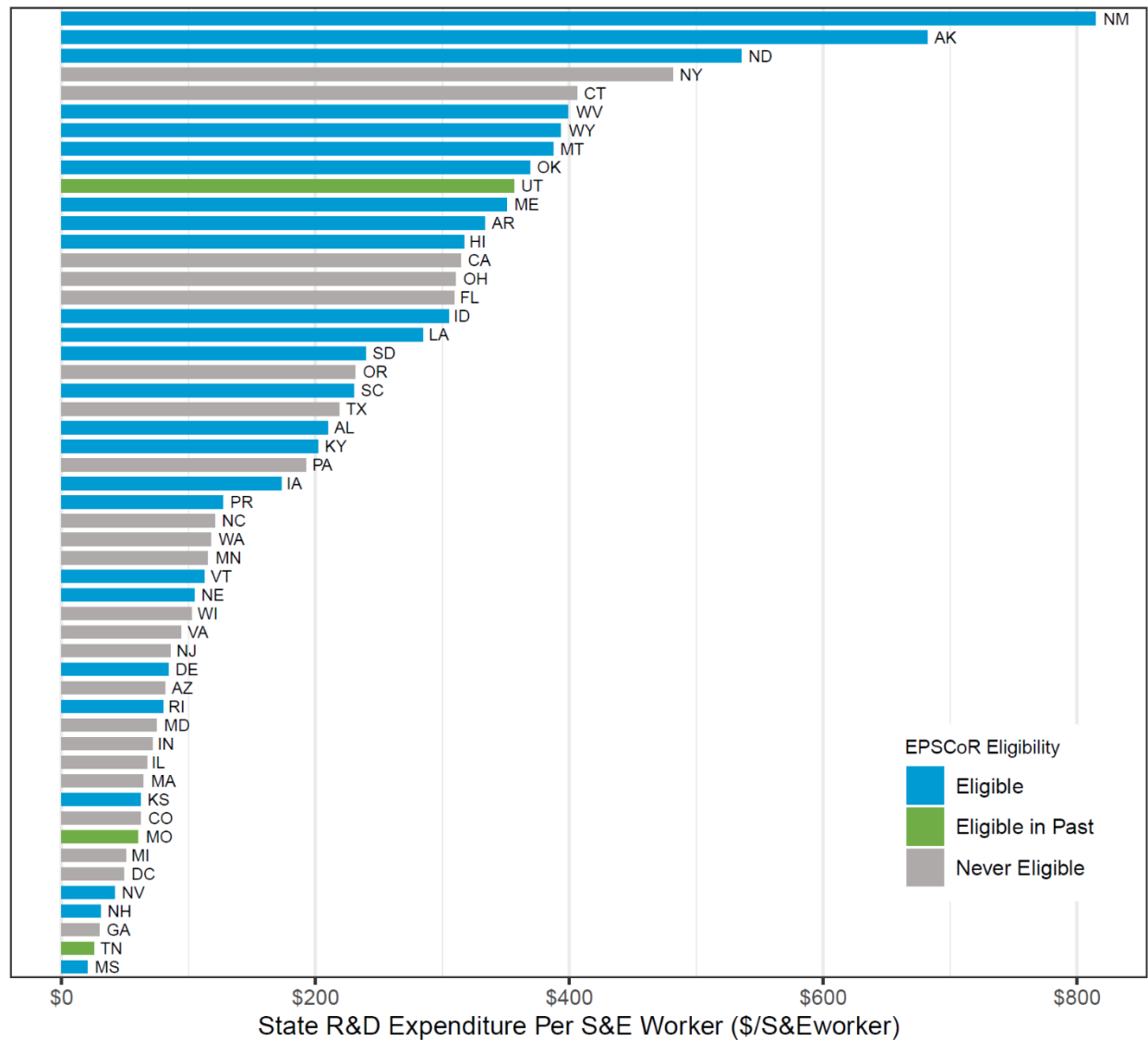
- State R&D expenditure
- State R&D expenditure with federal funding
- State expenditure on higher education
- State academic research space

Exhibit 5.23 examines R&D expenditure per S&E worker in the jurisdiction in 2015.<sup>62</sup> New Mexico, Alaska, and North Dakota have relatively high R&D expenditure per S&E worker from their respective state governments, whereas Mississippi, Tennessee, New Hampshire, and Nevada have relatively low state R&D expenditure per S&E worker.

<sup>61</sup> Table 1 – U.S. R&D expenditures by performing sector and source of funding in 2017. See Boroush, M. (2020). *U.S. R&D increased by \$32 billion in 2017, to \$548 billion; estimate for 2018 indicates a further rise to \$580 billion*. NCSES InfoBrief (NSF 23-09). Retrieved from <https://www.nsf.gov/statistics/2020/nsf20309/nsf20309.pdf>

<sup>62</sup> Exhibits B.6 and B.7 in Appendix B provide total state R&D expenditures in 2015 and in 2017, respectively. Most EPSCoR jurisdictions are at the bottom of the exhibit with slight variation across the 2 years.

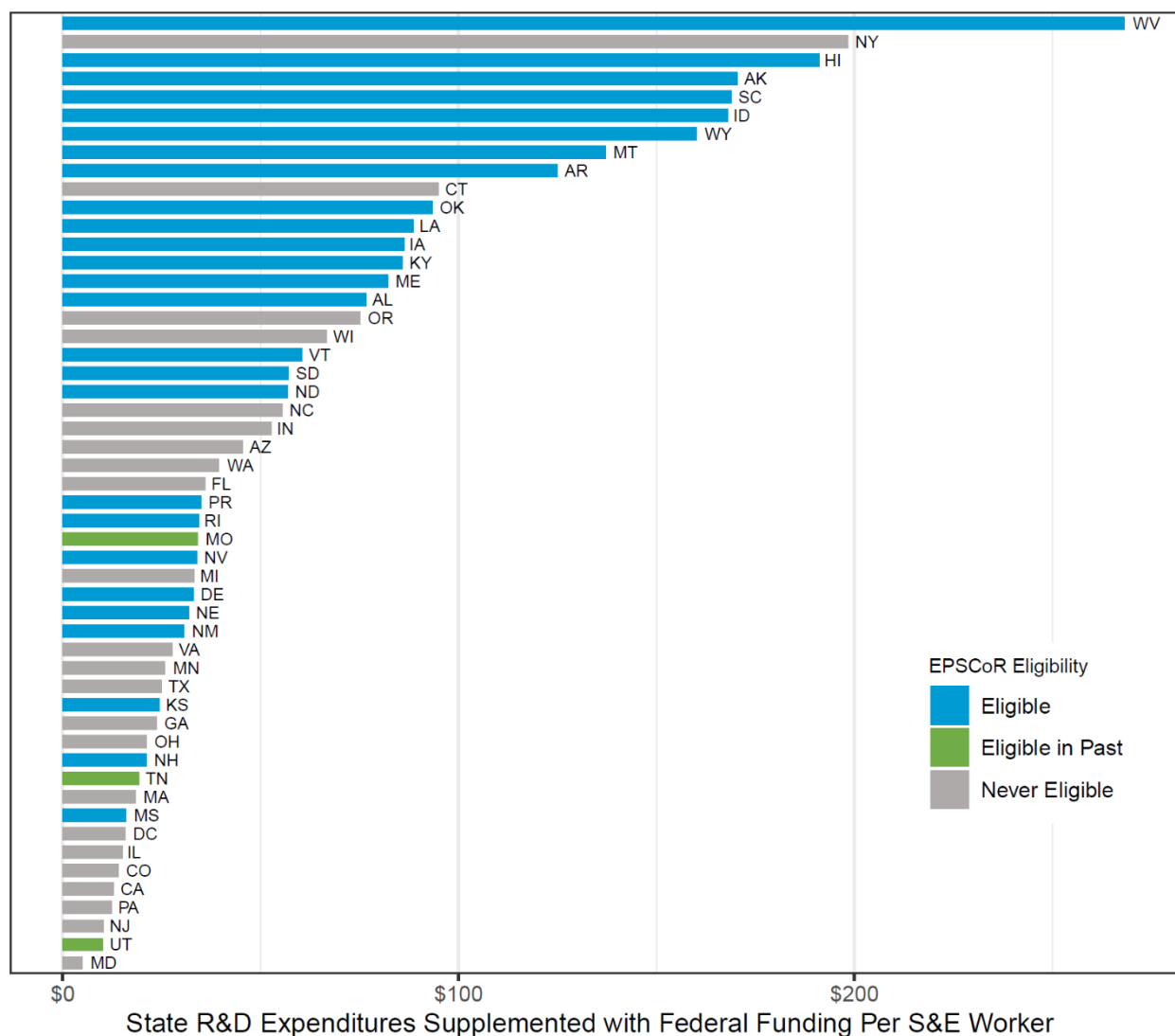
## EXHIBIT 5.23 STATE R&D EXPENDITURE PER S&E WORKER IN 2015



Note: Data are not available for Guam and the U.S. Virgin Islands. Number of S&E workers is defined as the total employment in professional, scientific, and technical services from the Census data in 2016.

Federal funding often serves to supplement states' funding for R&D and, as a result, represents a portion of states' R&D expenditures. Most EPSCoR jurisdictions had a relatively high R&D expenditure supplemented by federal funding per S&E worker in 2015 compared to non-EPSCoR jurisdictions. Utah, Mississippi, Tennessee, and New Hampshire had relatively low state R&D expenditures supplemented by federal funding per S&E worker in 2015 (see Exhibit 5.24). However, Mississippi, Utah, and Tennessee had high levels of federal obligations for S&E R&D per S&E worker in 2015 (see Exhibit 5.18). In addition, Utah had a high level of state R&D expenditure per S&E worker (see Exhibit 5.23) and New Hampshire had a high level of STTR-SBIR award funding per S&E worker (see Exhibit 5.22).

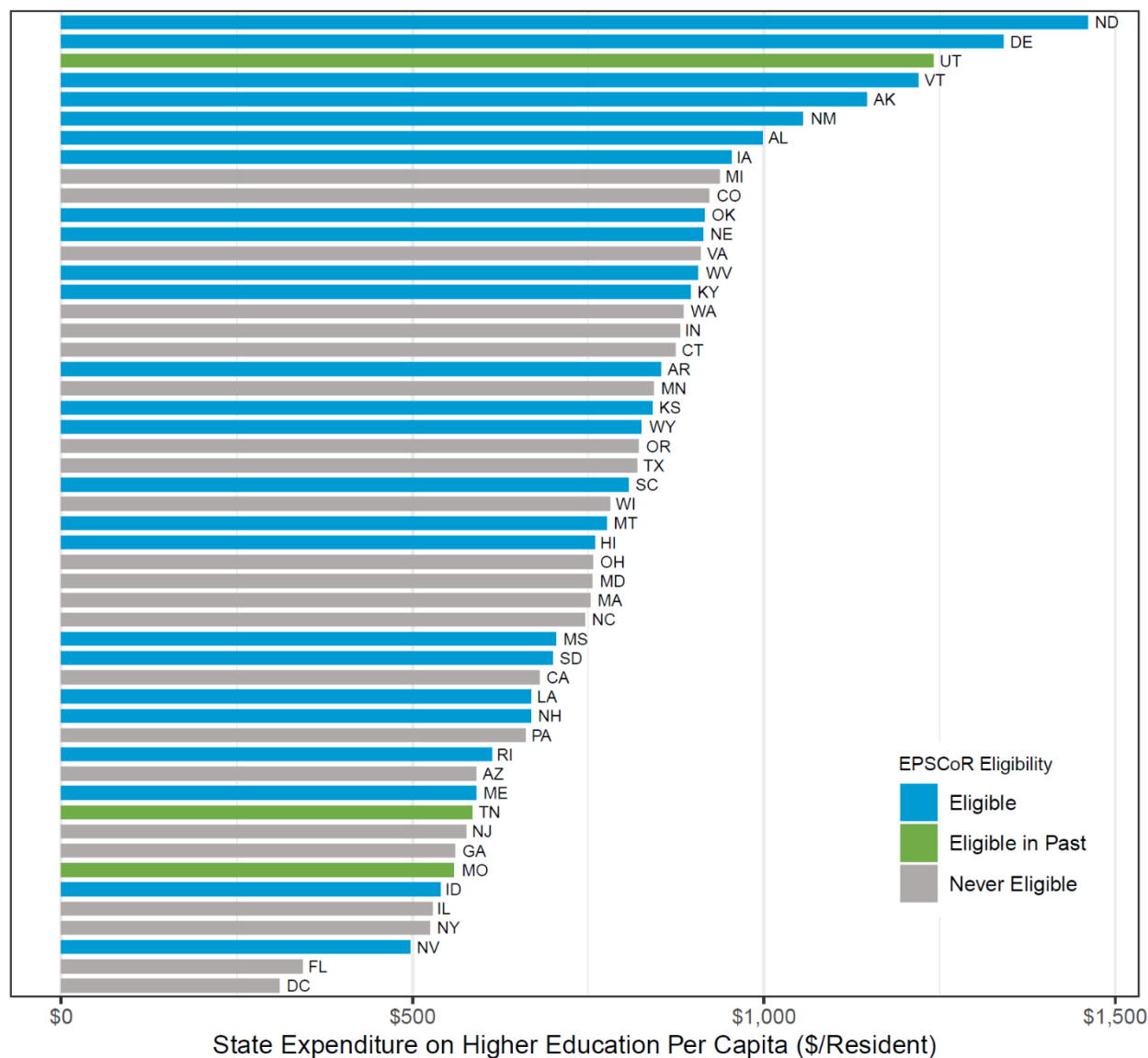
#### EXHIBIT 5.24 STATE R&D EXPENDITURE SUPPLEMENTED BY FEDERAL FUNDING PER S&E WORKER IN 2015



Note: Data are not available for Guam and the U.S. Virgin Islands. Number of S&E workers is defined as the total employment in professional, scientific, and technical services from the Census data in 2016.

Most EPSCoR jurisdictions had relatively high state expenditure on higher education per capita in 2015, with Nevada and Idaho having relatively low state expenditure on higher education per capita in those jurisdictions (see Exhibit 5.25).<sup>63</sup> Each EPSCoR jurisdiction has developed an S&T Plan that articulates a unique combination of jurisdiction-level R&D priorities and serves as a reference point for jurisdiction-level EPSCoR projects. In addition, these S&T plans may provide insights into the state's priorities and the funding the respective jurisdiction provides for R&D.

#### EXHIBIT 5.25 STATE EXPENDITURE ON HIGHER EDUCATION PER CAPITA IN 2015

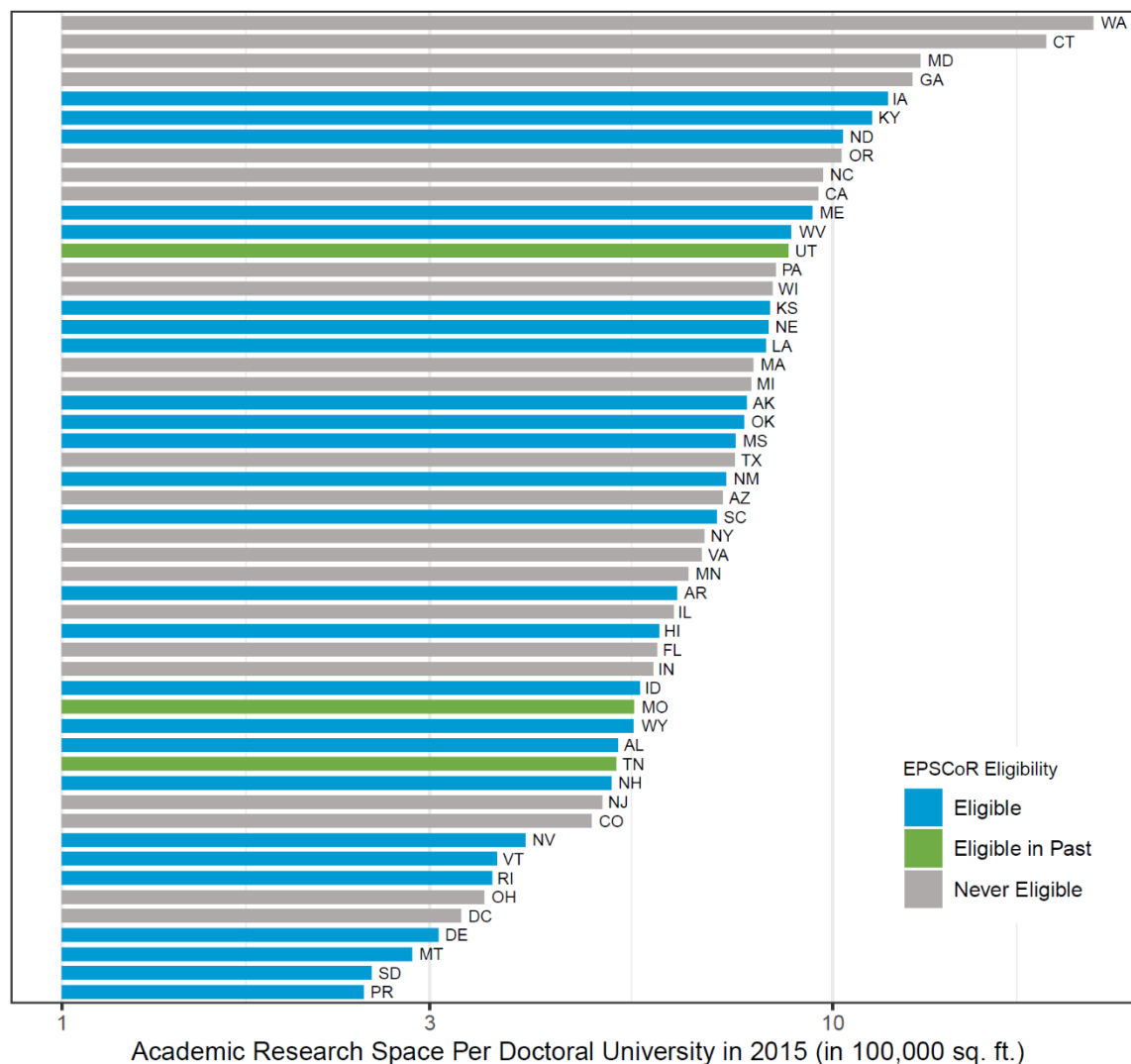


Note: Data are not available for Guam, Puerto Rico and the U.S. Virgin Islands.

<sup>63</sup> Exhibit B.8 in Appendix B provides the total state expenditure on higher education in 2015. Alabama, Kentucky, and Oklahoma are jurisdictions with high expenditure on higher education along with the past EPSCoR jurisdictions.

In addition to financial resources, physical infrastructure is also an essential resource for conducting R&D, especially at an academic institution (e.g., laboratories). Overall, U.S. colleges and universities had 213.4 million square feet of research space available in 2015, which is slightly higher than the 211.8 million square feet available in 2013, continuing more than two decades of expansion.<sup>64</sup> However, accounting for the number of doctoral universities in each jurisdiction, some EPSCoR jurisdictions such as Iowa, Kentucky, and North Dakota have considerably more space allotted for research than other EPSCoR jurisdictions like Puerto Rico, South Dakota, Montana, and Delaware (see Exhibit 5.26).

#### EXHIBIT 5.26 ACADEMIC RESEARCH SPACE PER DOCTORAL UNIVERSITY IN EACH JURISDICTION IN 2015



Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands.

<sup>64</sup> National Science Board, National Science Foundation. (2016). *Science & engineering indicators 2016. Chapter 5: Academic research and development*. Retrieved from <https://www.nsf.gov/statistics/2016/nsb20161/uploads/1/8/chapter-5.pdf>

## Cluster of Jurisdictions with Common Contextual Factors

**This section addresses RQ 1c: Are there any clusters/groups of jurisdictions with common contextual features that can be identified across the program?**

Next, using the 20 contextual measures described in the previous section across the 3 latent factors, the study team conducted an exploratory cluster analysis, a more sophisticated machine learning method to identify jurisdictions with similar contextual features (see details in Appendix D). Identifying these groups enables comparison of the strategies used and, to some extent, the comparison of outcomes that might be best suited to each group. As the emphasis is on grouping EPSCoR jurisdictions, the additional five groups of non-EPSCoR jurisdictions were combined into one cluster (Cluster 4). Jurisdictions with similar contextual measures were identified and clustered as follows:

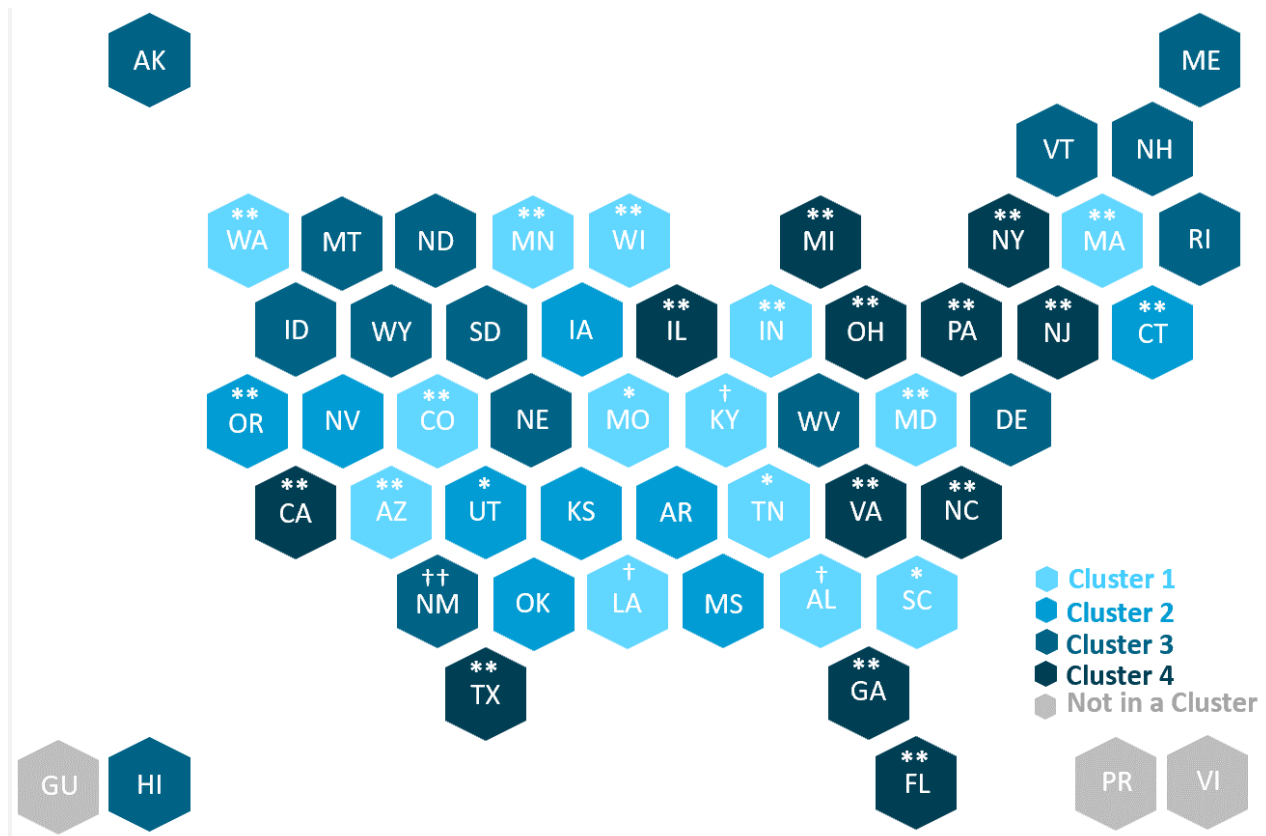
- Cluster 1 – Alabama, Kentucky, Louisiana, Missouri\*, South Carolina, Tennessee\*, Arizona\*\*, Colorado\*\*, Indiana\*\*, Maryland\*\*, Massachusetts\*\*, Minnesota\*\*, Washington\*\*, Wisconsin\*\*
- Cluster 2 – Arkansas, Iowa, Kansas, Mississippi, Nevada, Oklahoma, Utah\*, Connecticut\*\*, Oregon\*\*
- Cluster 3 – Alaska, Delaware, Hawaii, Idaho, Maine, Montana, Nebraska, New Hampshire, New Mexico, North Dakota, Rhode Island, South Dakota, Vermont, West Virginia, Wyoming
- Cluster 4 – All other non-EPSCoR jurisdictions (not listed above).

(see Exhibit 5.27; \*- indicates past EPSCoR jurisdictions, \*\*- indicates jurisdictions never eligible for EPSCoR)

Examining these cluster groupings shows that the jurisdictions that closely form relatively homogenous groups are most similar to each other in their population sizes.<sup>65</sup> This fact further highlights that the contextual measures are highly correlated with each other and the jurisdiction size plays a significant role across the three contextual factor domains: environment and institutional capacity, research capacity, and jurisdiction-level financial resource capacity. Nevertheless, the exploratory cluster analysis still helps identify and organize jurisdictions into smaller subgroups to directly compare their strategies and associated outcomes.

<sup>65</sup> The result is consistent without population size included in the cluster analysis.

## EXHIBIT 5.27 GROUPING OF JURISDICTIONS BY CONTEXTUAL MEASURES



Notes: \* indicates eligible for EPSCoR in the past; \*\* indicates never eligible for EPSCoR. Data are not available for Guam, Puerto Rico, and the U.S. Virgin Islands and as a result they are not in a cluster.

† Alabama, Kentucky, and Louisiana were in Cluster 2 in some of the sensitivity tests.

†† New Mexico was in Cluster 2 in one of the sensitivity tests.

Cluster 1 can be further broken down into two groups with Tennessee, Arizona, Indiana, Massachusetts, and Washington forming the new group. However, this was not the optimal number of groups as determined by the preset criteria.

## Summary of Contextual Variability Findings

### EPSCoR jurisdictions vary along several measures in three contextual domains.

#### Environment and Institutional Capacity



Compared to non-EPSCoR jurisdictions, a majority of EPSCoR jurisdictions

- are less populous,
- have populations that tend to live in nonmetropolitan areas,
- have varying levels of racial diversity, and
- have similar numbers of research-intensive doctoral universities and associate colleges.

#### Research Capacity



Compared to non-EPSCoR jurisdictions, most EPSCoR jurisdictions

- have a smaller economic base,
- confer lower percentage of S&E degrees,
- have a low percentage of S&E workers (except for the jurisdictions in the Northeast United States), and
- receive low federal funding, possibly due to the low number of research-intensive doctoral universities.

Some EPSCoR jurisdictions rely more heavily on federal funding due to the presence of federally funded labs or initiatives in those jurisdiction.

#### Jurisdiction-Level Financial Resource Capacity



EPSCoR jurisdictions' governments seem to support R&D activities to complement federal funding for research at academic institutions, albeit to a much lower extent than some non-EPSCoR jurisdictions.

### Jurisdictions cluster around similar contextual measures.

Cluster 1		Cluster 2	Cluster 3		Cluster 4
Alabama	Maryland	Arkansas	Alaska	North Dakota	All other non-EPSCoR jurisdictions
Kentucky	Massachusetts	Iowa	Delaware	Rhode Island	
Louisiana	Minnesota	Kansas	Hawaii	South Dakota	
South Carolina	Washington	Mississippi	Idaho	Vermont	
Missouri	Wisconsin	Nevada	Maine	West Virginia	
Tennessee		Oklahoma	Montana	Wyoming	
Arizona		Utah	Nebraska		
Colorado		Connecticut	New Hampshire		
Indiana		Oregon	New Mexico		

Note: Current EPSCoR Jurisdictions, Past EPSCoR Jurisdictions, Non-EPSCoR Jurisdictions



## 6. FINDINGS RELATED TO STRATEGIC VARIABILITY

The strategies EPSCoR jurisdictions employ to enact change in their research competitiveness can vary across projects and tracks and depends on the jurisdictional context. This chapter addresses primary RQ 2, which focuses on this strategic variability. Exhibit 6.1 describes the study team's approach to answering the three subquestions related to strategic variability.

### EXHIBIT 6.1 APPROACH TO ADDRESSING RQS RELATED TO STRATEGIC VARIABILITY

This chapter addresses the three research questions related to **Strategic Variability**.

**(2a) What common characteristics typify the range of implementation variability?**



Using the **logic model** developed in Chapter 2 and the **literature review**, the study team identified **nine common activities** that typify the strategies used by the EPSCoR jurisdictions.

**(2b) To what extent and in what ways do the S&E research base and mechanisms currently deployed for improvement vary across jurisdictions?**



The study team conducted **qualitative analysis** by coding 61 awardee reports to understand how these **9 activities varied across jurisdictions**.

**(2c) Are there any clusters/groups of jurisdictions with common implementation strategies that can be identified across the program?**



As the awardee reports varied in detail across tracks, were awardee-reported, and were not verified by the study team, the study team was not able to go beyond describing the strategic variability to identify clusters of jurisdictions with common implementation strategies.

Of the 318 awards granted in EPSCoR (see Exhibit 6.2), a sample of 61 (19 percent) most recent EPSCoR award reports across the 31 EPSCoR jurisdictions for Track-1, Track-2, and Track-3 were coded. These reports provide a glimpse of the strategies used in EPSCoR jurisdictions but are limited to what is reported by awardees. Some

jurisdictions have multiple EPSCoR awards, which may cause strategic activities to evolve due to a combination of various factors. Some of these factors have been described earlier in Chapter 4 as data reporting limitations, but some relate to jurisdictional contextual variability.

*EPSCoR funding mostly supported activities related to research, education, and community outreach or engagement. Strategic variability across jurisdictions appears to be due to inconsistencies in the level of detail in annual reports.*

## EXHIBIT 6.2 TOTAL EPSCoR AWARDS PER JURISDICTION

Jurisdiction	Track-1	Track-2	Track-3	Track-4	Track-C2	Total
Alaska	4	2	1	8	1	16
Alabama	3	2	1	12	1	19
Arkansas	4	3	1	3	0	11
Delaware	3	4	1	5	1	14
Guam	1	0	0	0	0	1
Hawaii	2	1	0	3	3	9
Iowa	2	0	0	0	0	2
Idaho	4	4	1	5	1	15
Kansas	4	6	0	7	1	18
Kentucky	3	3	2	3	0	11
Louisiana	3	5	1	6	1	16
Maine	5	5	1	2	1	14
Missouri	1	1	0	0	0	2
Mississippi	2	5	0	5	2	14
Montana	4	3	1	3	1	12
North Dakota	2	2	0	1	1	6
Nebraska	3	4	1	2	1	11
New Hampshire	3	6	1	5	0	15
New Mexico	4	3	0	2	1	10
Nevada	3	2	1	2	1	9
Oklahoma	3	2	0	5	1	11
Puerto Rico	3	3	1	0	0	7
Rhode Island	3	5	0	4	1	13
South Carolina	4	5	0	5	1	15
South Dakota	3	3	1	7	1	15
Tennessee	1	1	0	0	0	2
Utah	1	1	0	0	1	3
U.S. Virgin Islands	1	0	0	1	1	3
Vermont	3	3	1	3	1	11
West Virginia	3	2	0	2	1	8
Wyoming	3	1	0	1	0	5
<b>Total</b>	<b>88</b>	<b>87</b>	<b>16</b>	<b>102</b>	<b>25</b>	<b>318</b>

## This section addresses RQ 2a: What common characteristics typify the range of implementation variability?

The study team employed a rigorous methodology in analyzing award reports for strategic activities. A sample of 61 EPSCoR final reports were coded across the 31 EPSCoR jurisdictions. The reports were carefully chosen to represent each EPSCoR jurisdiction and award tracks with reports available for analysis. The reports were pulled from the NSF eJacket system in January 2020 and screened and vetted for feasibility of use for coding and analyses. During this process and with existing knowledge about the EPSCoR from the logic model, the study team developed a coding framework that captured various activities that jurisdictions might conduct using EPSCoR funding.<sup>66</sup> There were nine activity categories: **leadership support, policies, programs, diversity, infrastructure, funding personnel, hiring personnel, building collaborative relationships, and training activities**. A more in-depth overview of these activities can be found in Chapter 3.

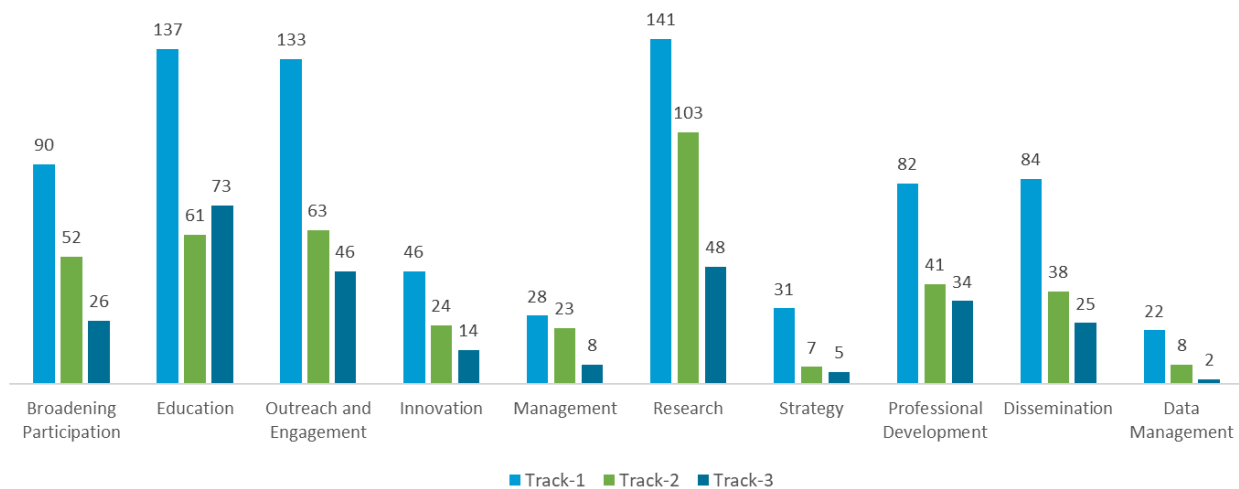
During the development of the coding framework, the study team determined that these nine activities could be conducted for varying motivations or purposes. For example, purchasing equipment might have other direct motivations that would improve research capacity or competitiveness. Because of the potential variation in purpose behind these activities, the study team coded the aforementioned activities along 10 different motivations: **broadening participation, building a database, dissemination, education, innovation, management, professional development, outreach and engagement, research, and strategy**.

As shown in Exhibit 6.3, the most common activities undertaken across the tracks were related to conducting research, education, and outreach and engagement. For Track-1 and Track-2 awards, the greatest number of activities was related to conducting research. Track-3 awards most often supported education. The fewest activities conducted for each award type were related to management, strategic planning, and building databases. These activities in any jurisdiction were not required to be frequent, as many were annual regulatory activities.

Despite the intended focus of Track-3 awards on increasing diversity and inclusion to promote research competitiveness in jurisdictions, a relatively low number of activities focused on broadening participation of URM groups. Six Track-3 awards had no reported activities geared toward broadening participation. Compared to other award reports with low activity, three of these Track-3 reports were for final reports during the NCE period, and three were brief, bulleted lists provided for the standard reporting form with no attachments. However, it is unclear whether the award track shifted in focus over time, broadening participation activities were concentrated in earlier phases of the award and not heavily emphasized in later reports, these jurisdictions misinterpreted the award solicitation, or other diversity and inclusion activities were conducted that were not captured by the coders.

<sup>66</sup> During the coding process, new subcategories were discovered and discussed by the coding team for inclusion, but no additional categories were added.

## EXHIBIT 6.3 VARIABILITY IN PURPOSES FOR STRATEGIC ACTIVITIES, BY AWARD TRACK



EPSCoR jurisdictions more frequently reported activities in the following areas (from highest to lowest):

- Supporting or building cyberinfrastructure
- Holding workshops for training or engagement
- Funding education and research experiences for undergraduate students
- Supporting collaborative partnerships within a jurisdiction
- Funding local or jurisdictional programs for training or engagement
- Creating materials for curriculum development, training, or engagement
- Funding education and research experience for graduate students
- Funding research capacity for existing faculty

Across all EPSCoR jurisdictions, award reports least frequently mentioned activities in the following areas (from lowest to highest):

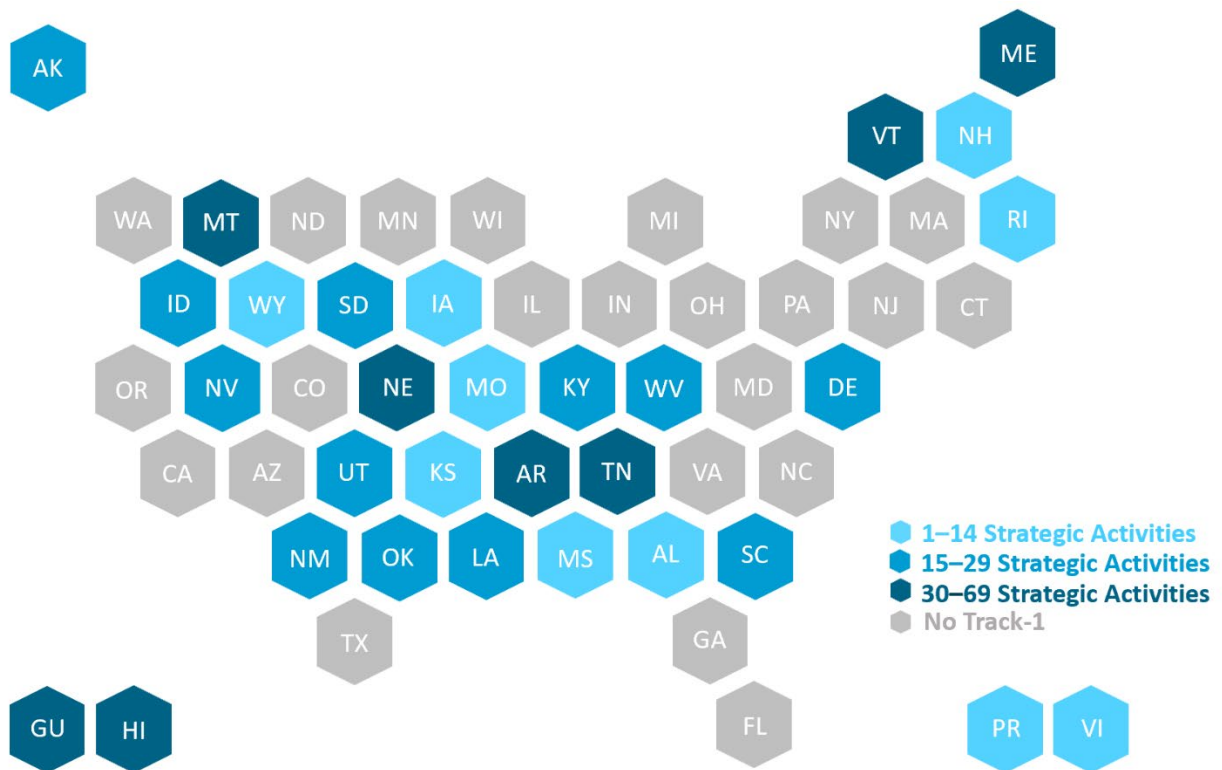
- Supporting LGBT individuals
- Hiring student researchers
- Funding the attendance of training courses
- Hiring postdoctoral fellows
- Supporting individuals with disabilities
- Hiring nonfaculty research staff
- Purchasing expendable materials
- Hiring administrative staff
- Supporting collaborative relationships between units within a university
- Hiring new faculty

## This section addresses RQ 2b: To what extent and in what ways do the S&E research base and mechanisms currently deployed for improvement vary across jurisdictions?

### TRACK-1 AWARDS

The study team found considerable strategic variability in Track-1 awards by jurisdiction. Although Exhibit 6.4 does not show evidence that the number of activities is related to geographic region or size, other contextual factors may drive strategic variability. Of the 7 Track-1 awards with fewer than 10 types of activities extracted from the award final or supplemental reports, 5 of the reports submitted only included activities in the NCE period, and 2 were brief with little detail. Though some jurisdictions may have conducted more activities than conveyed in their final reports, this remains a limitation of the analysis of award reports. As shown in Exhibit 6.3, the most common purposes for Track-1 awards across all jurisdictions continue to be for research, education, and engagement or outreach, which is consistent with findings across all award tracks.

### EXHIBIT 6.4 STRATEGIC VARIABILITY OF TRACK-1 AWARDS BY JURISDICTION



## TRACK-2 AWARDS

The strategic variability and collaborations of Track-2 awards had many interesting patterns. Exhibit 6.5 lists the interjurisdictional partnerships and the titles of their respective Track-2 awards, which show a clear purpose in the collaboration. For example, Alaska and Hawaii had an interest in studying the impact of dynamic climate changes on Pacific water resources. Researchers formed a strategic partnership between these two jurisdictions based on the unique, extreme climate changes in this region. Similarly, shared interests related to region-specific issues in the Gulf Coast (Mississippi, Louisiana, and Alabama); Northeast (New Hampshire, Maine, and Vermont); and Northwest (Montana, Wyoming, and South Dakota) facilitated collaborative relationships for three other Track-2 awards. Proposals rationalized these collaborations by intentionally including jurisdictional partners with similar socioeconomic, climate, and ecological features.

### EXHIBIT 6.5 INTERJURISDICTIONAL COLLABORATIONS FOR TRACK-2 AWARDS WITH EXPLICIT CONNECTIONS

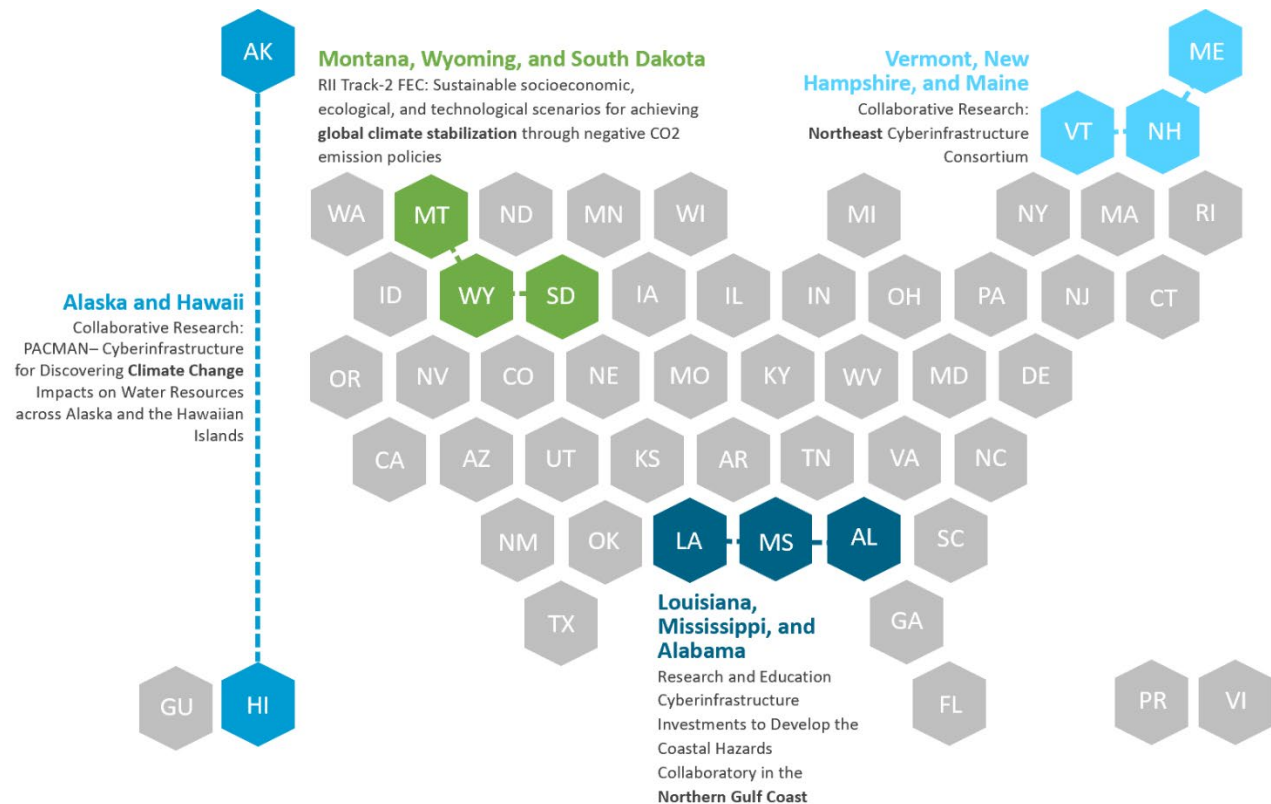
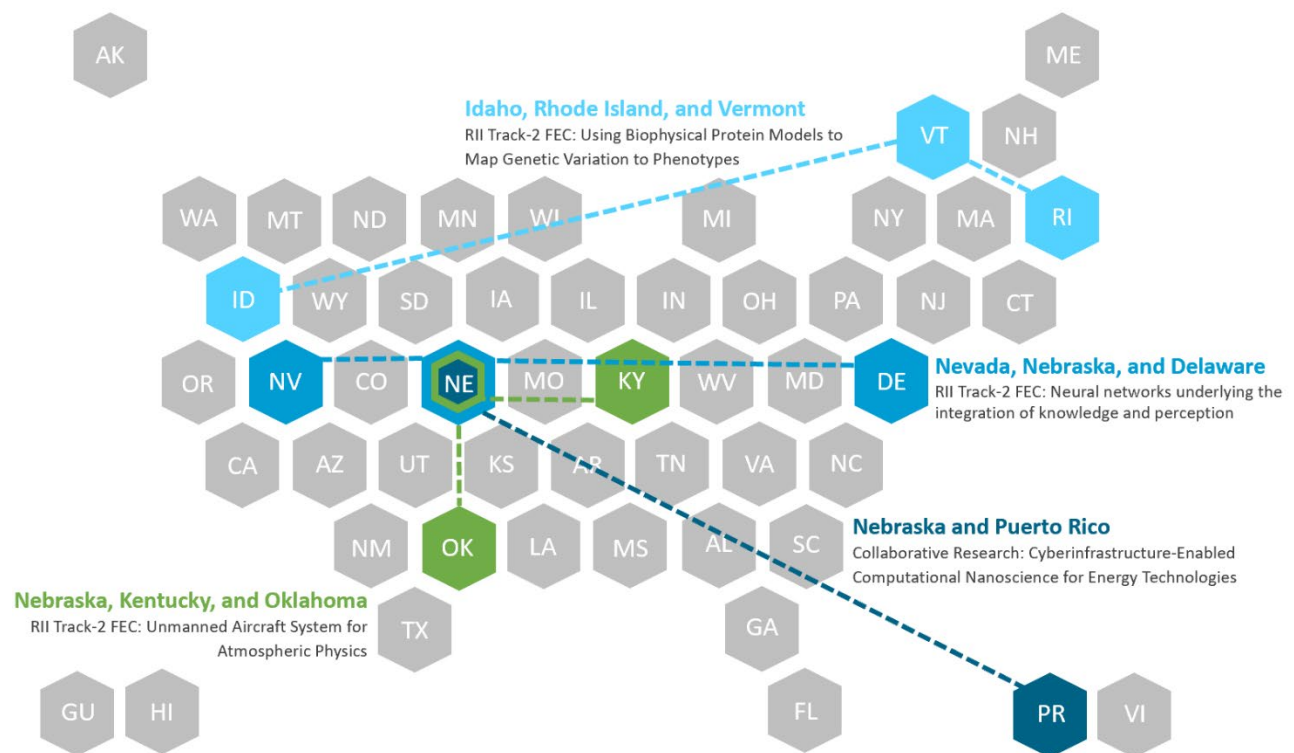


Exhibit 6.6 provides examples in which collaborative relationships between Track-2 partners may be less explicit. In these cases (i.e., based on award titles, proposal abstracts, and award reports), the topics do not appear to be regionally dependent. Partnerships may have been formed or inspired by other factors such as collegial relationships. Interestingly, three awards included Nebraska as a collaborative partner. In either explicit or implicit collaborations, the strategic activities in those jurisdictions varied by the focus of their award. For example, most Track-2 activities focused on building interjurisdictional research collaboration and a cyberinfrastructure to support that endeavor. In order for jurisdictions to effectively share data, communicate, and coordinate their activities across jurisdictions, cloud-based servers, reliable telecommunications, and management systems or processes became essential components of jurisdictions' complex cyberinfrastructures.

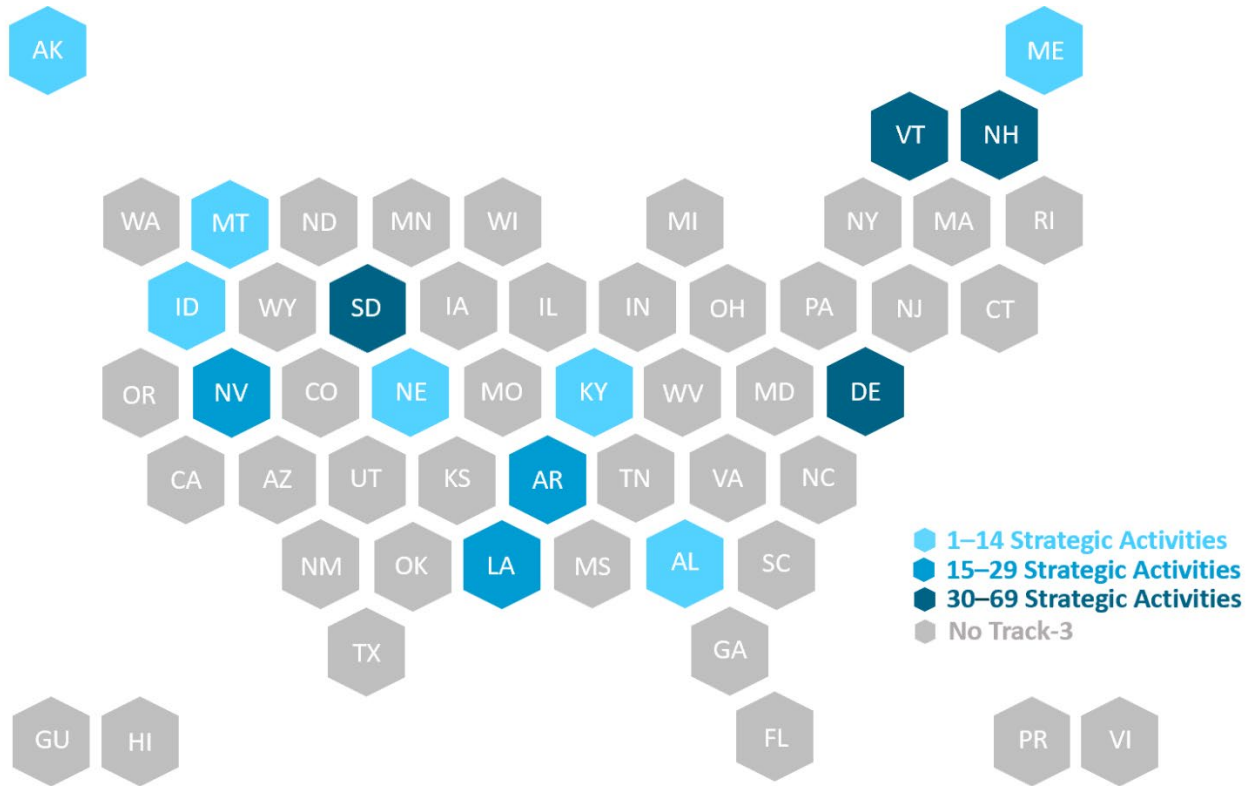
## EXHIBIT 6.6 INTERJURISDICTIONAL COLLABORATIONS FOR TRACK-2 AWARDS WITH IMPLICIT CONNECTIONS



### TRACK-3 AWARDS

There does not appear to be a relationship between the variability of strategic activities in jurisdictions for Track-3 awards based on geographic regions (see Exhibit 6.7). Most variability observed between these jurisdictions is related to the density of the award reports. This further demonstrates the limitations of using award reports to capture strategic variability across EPSCoR jurisdictions.

#### EXHIBIT 6.7 STRATEGIC VARIABILITY OF TRACK-3 AWARDS, BY JURISDICTION





**This section addresses RQ 2c: Are there any clusters/groups of jurisdictions with common implementation strategies that can be identified across the program?**

Jurisdictions have different needs and objectives for research competitiveness, between jurisdictions and for awards in the same jurisdiction. For example, a second Track-1 award for a jurisdiction begins at a different baseline or has a different focus than the first Track-1 award for the same jurisdiction. This means that activities may vary even within the same jurisdiction between the first and second awards. The study team reviewed the most recent award report submitted since the NAS report and, as a result, the earlier activities are not captured in this report. Further, each jurisdiction has varying baseline capacity. For example, Rhode Island and North Dakota would not be expected to have similar strategic activities due to their contextual differences for academic research space available per doctoral university in their respective jurisdictions (see Exhibit 5.26). Therefore, the effectiveness of the activities cannot be judged by a jurisdiction's successful change in EPSCoR eligibility status upon EPSCoR award completion. This reality may complicate efforts to link variability in a jurisdiction's strategies to the jurisdiction's outcomes, as well as complicating attempts to discover trends or commonalities among groups of jurisdictions, make judgments about activity effectiveness, or imply any causality.

In addition, while the study team was able to capture and analyze the activities reported in awardee final reports, the extent to which each awardee presented a comprehensive picture of their project varied greatly. Due to inconsistencies in detail level within awardee reports, as well as the different focus for each subsequent award and the context for the award, it was not practical or feasible for the study team to accurately account for jurisdictions with common implementation strategies. Furthermore, the reporting inconsistencies present within awardee final reports impeded the study team's efforts to consistently measure or analyze strategic activities across all jurisdictions. Additionally, since many awardees were in different years of their award period, the nature of awardee activities inherently varied. Without doing a deep dive into each jurisdiction specifically, it would be difficult to judge the purpose of awardees' strategies to improve research competitiveness.

## Summary of Strategic Variability Findings

### EPSCoR jurisdictions vary among reported strategic activities.

#### Strategic Activities



EPSCoR funding mostly supported the following strategic activities:

- Building cyberinfrastructure
- Holding workshops, camps, or seminars
- Funding undergraduate students, graduate students, or existing faculty
- Supporting collaborative relationships within a jurisdiction
- Building state or local programs
- Creating instructional or curricular material

#### Research Purpose



Activities were conducted primarily for the purpose of

- research,
- education, and
- community outreach and engagement.

#### Infrequently Reported Activities



No awards reported activities focused on supporting lesbian, gay, bisexual, or transgender individuals.

There were relatively few reported activities related to

- hiring new researchers or administrative staff,
- supporting researchers to attend courses,
- funding individuals with disabilities, and
- building collaborative relationships between different departments within the same university .

The variability in strategies used may be attributed to differing needs or objectives but could potentially be due to program changes or inconsistencies in reporting.

Analyzed reports spanned across three tracks:

#### Track-1

Alaska	Nebraska
Alabama	New Hampshire
Arkansas	New Mexico
Delaware	Nevada
Guam	Oklahoma
Hawaii	Puerto Rico
Iowa	Rhode Island
Idaho	South Carolina
Kansas	South Dakota
Kentucky	Tennessee
Louisiana	Utah
Maine	U.S. Virgin Islands
Missouri	Vermont
Mississippi	West Virginia
Montana	Wyoming
North Dakota	

#### Track-2

Alaska	Nebraska
Alabama	New Hampshire
Arkansas	Nevada
Delaware	Oklahoma
Hawaii	Puerto Rico
Idaho	Rhode Island
Kansas	South Carolina
Kentucky	South Dakota
Louisiana	Tennessee
Maine	Utah
Missouri	Vermont
Mississippi	West Virginia
Montana	Wyoming
North Dakota	

#### Track-3

Alaska
Alabama
Arkansas
Delaware
Idaho
Kentucky
Louisiana
Maine
Montana
Nebraska
New Hampshire
Nevada
South Dakota
Vermont

Note: Current EPSCoR Jurisdictions and Past EPSCoR Jurisdictions

## 7. FINDINGS RELATED TO OUTCOME VARIABILITY

Variation in outcome characteristics related to AREC across EPSCoR jurisdictions builds on variation in contextual characteristics and strategies used. Jurisdictional context plays a role in determining available strategies to increase AREC, and these contextual and strategic factors intertwine to influence the jurisdiction's AREC outcomes. This chapter addresses primary RQ 3, which focuses on this outcome variability. Exhibit 7.1 describes the study team's approach to answering the three sub-questions related to outcome variability.

### EXHIBIT 7.1 APPROACH TO ADDRESSING RQS RELATED TO OUTCOME VARIABILITY

This chapter addresses the three research questions related to **Outcome Variability**.

**(3a) What jurisdictional, institutional, and other characteristics typify the range of variability observed in research competitiveness definitions and performance?**



The study team conducted **factor analysis** on 26 measures to identify 4 **underlying factors** that typify outcome variability.

**(3b) To what extent and in what ways does the variability in context and strategy across EPSCoR jurisdictions influence the identification of relevant indicators of research competitiveness?**



The study team conducted **descriptive analysis** to understand **jurisdictional variation** in the outcome measures that compose the three contextual factors, displayed in **bar charts**.

**3c) Are there any clusters/groups of jurisdictions with common context and/or strategy characteristics that can be used to understand variability in research competitiveness?**



The study team conducted **cluster analysis** to demonstrate how **jurisdictions cluster** around the outcome measures.

Using the available outcome measures collected based on logic model constructs as described in Chapter 3, the study team conducted factor analysis to understand the factors underlying outcome variability. Guided by these factors, the study team next examined the extent to which and the ways these measures vary across EPSCoR and non-EPSCoR jurisdictions, using descriptive analysis. This descriptive analysis provides further insights into how research competitiveness outcomes vary across the EPSCoR jurisdictions and in comparison to non-EPSCoR jurisdictions. Finally, the study team performed cluster analysis to understand how jurisdictions group in terms of the key outcome measures. The details of the factor and cluster analysis are explained in Chapter 4. This chapter also provides insights into the foundation on which future economic growth can build as EPSCoR helps jurisdictions increase their R&D capabilities.

## Underlying Factors that Best Describe Outcome Variability

**This section addresses RQ 3a: What jurisdictional, institutional, and other characteristics typify the range of variability observed in research competitiveness definitions and performance?**

Given the diversity of EPSCoR jurisdictional contexts, as well as their programs' strategies and components, the study team also analyzed key outcomes relevant to jurisdictional research competitiveness.<sup>67</sup> Though EPSCoR primarily aims to increase research competitiveness through federal investments in human capital and research infrastructure in the jurisdiction's postsecondary institutions, EPSCoR may foster other positive externalities such as high-skills job creation and broad economic growth. All EPSCoR activities, including state committees and their S&T plans, can synergistically increase support for S&E activities in the jurisdiction. However, many of these outcome measures are strongly correlated with other measures in the same domain, as well as across domains in the logic models (see Exhibit D.7 in Appendix D). Theoretically, jurisdictions with high concentrations of high-tech industries will also have greater proportions of workers in S&E occupations.

The study team conducted an exploratory factor analysis to identify underlying latent factors, which allowed for examination of any correlation between the factors. The factor analysis also served to categorize the measures related to indicators in the logic models, as these measures implicitly reflect the indicators.

<sup>67</sup> The unit of analysis is a jurisdiction, and the institution-level information presented has been aggregated to the jurisdiction-level. All descriptive analyses for the outcome measures examined patterns in a single measure in a particular year.

The exploratory factor analysis indicates that 4 latent factors underlie the 26 outcome measures that were included:



**Human Capital Production**



**Reputation in Knowledge Production**



**Economic Development of Knowledge and Science-Intensive, High-Technology Industries**



**Racial and Gender Diversity in Labor Force Development**

Promax rotation provided the best-defined factor structure where all measures in the analysis had primary loading greater than 0.5, and only one measure had a cross-loading greater than 0.5.<sup>68</sup> Exhibit 7.2 shows the results of the factor analysis on the contextual measures. The four factor labels—human capital production; reputation in knowledge production; economic development of knowledge and science-intensive, high-tech industries; and racial and gender diversity in labor force development—were selected as the measures in each factor aligned with the appropriate logic model domains and/or AREC framework. More details are presented in Appendix D.

For the **human capital production factor**, there are two main underlying sub-factor constructs:

1. Student Enrollment and Degree Completion
  - a. EPSCoR helps jurisdictions to develop or improve their S&E research and education programs at their universities and colleges, thereby increasing the number of S&E graduates and doctorates. The main loading in this sub-factor construct includes number of SEH graduate students, number of S&E doctorates, and number of SEH postdoctoral students.
2. Workforce Education Level
  - a. This sub-factor measures the jurisdictions' S&E workforce. EPSCoR aims to increase jurisdiction-level S&E workforce by strengthening the jurisdictions' ability to retain and attract S&E graduates. The top two loadings in this sub-factor include percentage of population with a doctorate and proportion of workers who earned a bachelor's, master's, or PhD in S&E.

<sup>68</sup> Three items—Rate of Research Proposals Given NSF Funding, Percentage Distribution of Asian Workers, and State's Relative Performance in Generating Fast-Growing High-Tech Enterprises—were eliminated because no measure failed to meet a minimum criterion of having a primary factor loading of greater than 0.5 or cross-loadings between 0.3 and 0.4. However, only one measure, Percentage of Workforce Composed of S&E Occupations, had cross-loading values which were similar to the primary factor loading. This measure was kept in the final stage analysis.

For the **reputation in knowledge production factor**, there are two main underlying sub-factor constructs:

1. Institutional Reputation in Knowledge Production
  - a. EPSCoR plays a vital role in funding research at the jurisdictions' universities and increasing their research competitiveness. This sub-factor includes highest score on papers published in *Nature* or *Science* for any institution in the jurisdiction, highest score on papers indexed in science and social science fields for any institution in the jurisdiction, highest score on per capita academic performance for any institution in the jurisdiction, and highest score on highly cited researchers for any institution in the jurisdiction.
2. Jurisdictional Reputation in Knowledge Production
  - a. EPSCoR intends to help jurisdictions improve their academic reputations. This sub-factor measures that intention and includes number of NAI fellows in the jurisdiction, number of SBIR program awards, and number of utility patents issued to jurisdiction residents.

For the **economic development of knowledge and science-intensive, high-tech industries factor**, the main factors are number of Inc. 500 companies in the jurisdiction, concentration of high-tech industries, and percentage of businesses that are defined as high-tech.

For the **gender and racial diversity in labor force development factor**, there are two underlying sub-factor constructs:

1. Gender Diversity in S&E Workforce Development
  - a. EPSCoR focuses on broadening participation of women in S&E. This sub-factor measures that intention and includes percentage of female full-time S&E graduate students, as well as percentage of women employed in professional, scientific, and technical services.
2. Racial Diversity in S&E Workforce Development
  - a. EPSCoR intends to broaden participation of URM's in S&E. This sub-factor measures that intention and includes percentage of racial minority full-time S&E graduate students, and percentages of Black workers and Hispanic/Latino workers in professional and business services.

Internal consistency for the factors was examined using Cronbach's alpha.<sup>69</sup> The overall Cronbach's alpha was 0.95. The alphas for the first three factors were high: 0.94 for factor 1 (9 items), 0.90 for factor 2 (8 items), and 0.93 for factor 3 (7 items). The Cronbach's alpha was moderate for factor 3 (0.66; 3 items). No *substantial* increases in alpha for any of the scales could have been achieved by eliminating items. Overall, this analysis indicated that four distinct factors were underlying the outcome measures and that these factors were internally consistent.

<sup>69</sup> Average interitem correlation values are greater than 0.25 for all four factors. Overall, the average interitem correlation was 0.37.

## EXHIBIT 7.2 EXPLORATORY FACTOR ANALYSIS FOR OUTCOME MEASURES AT THE JURISDICTION LEVEL

	Human Capital Production	Reputation in Knowledge Production	Economic Development of High-Tech Industry	Gender and Racial Diversity
Number of S&E Doctorates Awarded per Resident	<b>0.94</b>			
Number of SEH Graduate Students per Resident	<b>0.90</b>			
Proportion of Workers Who Earned Bachelor's, Master's, or PhD in S&E	<b>0.86</b>			
Number of Employed Doctorates in SEH per Resident	<b>0.84</b>			
Number of SEH Postdoctorates per Resident	<b>0.83</b>			
Percentage of Population Age 25 and Older with Doctorate	<b>0.80</b>			
Percentage of Population Age 25 and Older with Bachelor's Degree	<b>0.70</b>			
Percentage of Population Age 25 and Older with Master's Degree or Higher	<b>0.69</b>			
Number of NAI Fellows in Each Jurisdiction		<b>0.84</b>		
Utility Patents Issued to Jurisdiction Residents		<b>0.82</b>		
Number of SBIR Awards		<b>0.71</b>		
Highest Score for Highly Cited Researchers for a Doctoral University		<b>0.70</b>		
Highest Score for Papers Published in <i>Nature</i> or <i>Science</i> for a Doctoral University		<b>0.60</b>		
Highest Score for Staff Winning Nobel Prizes and Fields Medals for a Doctoral University		<b>0.58</b>		
Highest Score for Papers Indexed in Science or Social Science Fields for a Doctoral University		<b>0.57</b>		
Percentage of Minority Full-Time S&E Graduate Students†		<b>0.60</b>		
Total Number of Inc. 500 Companies Per 10,000 Business Establishments			<b>0.73</b>	
Concentration of High-Tech Industries			<b>0.66</b>	
Percentage of Businesses Defined as High-Tech			<b>0.64</b>	
Number of High-Tech Industries with Employment Growing Faster than the U.S. Average			<b>0.59</b>	
Percentage of Employment in High-Tech Industries			<b>0.57</b>	
Percentage of Workforce Composed of S&E Occupations	<i>0.53</i>		<b>0.55</b>	
Percentage of Women in Professional, Scientific, and Technical Services employment in 2016††			<b>0.54</b>	
Percentage of Female Full-Time S&E Graduate Students				<b>0.60</b>
Percentage Distribution of Hispanic/Latino Workers				<b>0.59</b>
Parity Ratio of Number of Minority-Owned S&E Businesses				<b>0.50</b>

Notes: Extraction method: principal axis factoring. Rotation method: Promax with Kaiser normalization.

Factor loading < 0.5 are suppressed. Variables with secondary loadings of lower value than the primary loadings are italicized.

† This measure is discussed with the Diversity factor, even though the exploratory factor analysis aligns it with the Reputation in Knowledge Production factor.

†† This measure is discussed with the Diversity factor, even though the exploratory factor analysis aligns it with the Economic Development factor.

## Key Outcome Factors that Vary Across EPSCoR Jurisdictions

This section addresses RQ 3b: To what extent and in what ways does the variability in context and strategy across EPSCoR jurisdictions influence the identification of relevant indicators of research competitiveness?

### Human Capital Production

#### Summary



- Compared to non-EPSCoR jurisdictions, a majority of EPSCoR jurisdictions produce low numbers of graduate students in S&E (relative to their populations) except for states with at least one highly reputed research-intensive doctoral university.
- Compared to non-EPSCoR jurisdictions, a majority of EPSCoR jurisdictions have a low percentage of their workforce with postsecondary education relative to their populations.

Postsecondary education provides a worker with the advanced skills needed to excel in a competitive, technology-focused workforce. In particular, graduate-level S&E education provides workers with valuable research skills that facilitate innovation and adaptability to change. Fostering the development of professional skills increases a jurisdiction's ability to attract potential employers by promising a steady flow of skilled, highly educated workers, as employers' value for talented workforce has increased over time. Employers' value for professional skill has especially increased in technology-focused industries. In addition to attracting technology firms, the presence of a large S&T graduate workforce can create positive externalities for jurisdictions by forming informal networks of researchers, facilitating knowledge dissemination, and increasing the adoption of new technology.

#### *Student Enrollment and Degree Completion*

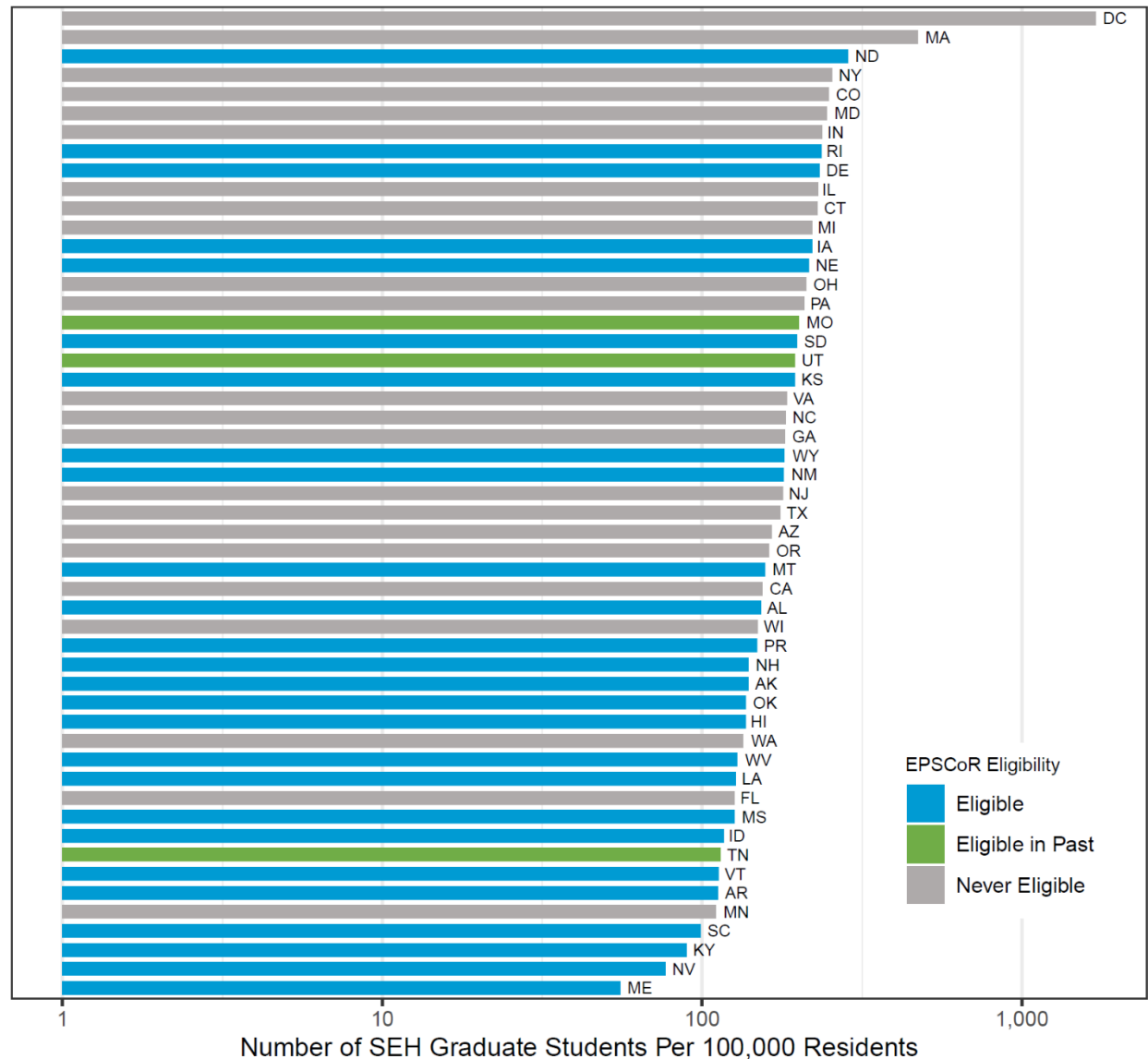
In 2015, U.S. academic institutions awarded nearly 3.8 million associate, bachelor's, master's, and doctoral degrees, 25 percent of which were in S&E fields.<sup>70</sup> However, each jurisdiction varies in its population size and number of S&E graduates. As a result, the study team standardized the measures of graduate students, doctorates awarded, and postdoctoral students by the number of residents in the jurisdiction. Exhibits 7.3, 7.4, and 7.5 indicate that several EPSCoR jurisdictions (Delaware, Iowa, Nebraska, North Dakota, and Rhode Island) have produced a significant number of highly educated S&E students relative to their population sizes. Each of these five states has at least one highly reputed R1 doctoral university. However,

<sup>70</sup> National Science Board. (2018). *Science and engineering indicators 2018* (NSB-2018-1). Alexandria, VA: National Science Foundation. Retrieved from <https://www.nsf.gov/statistics/indicators/>



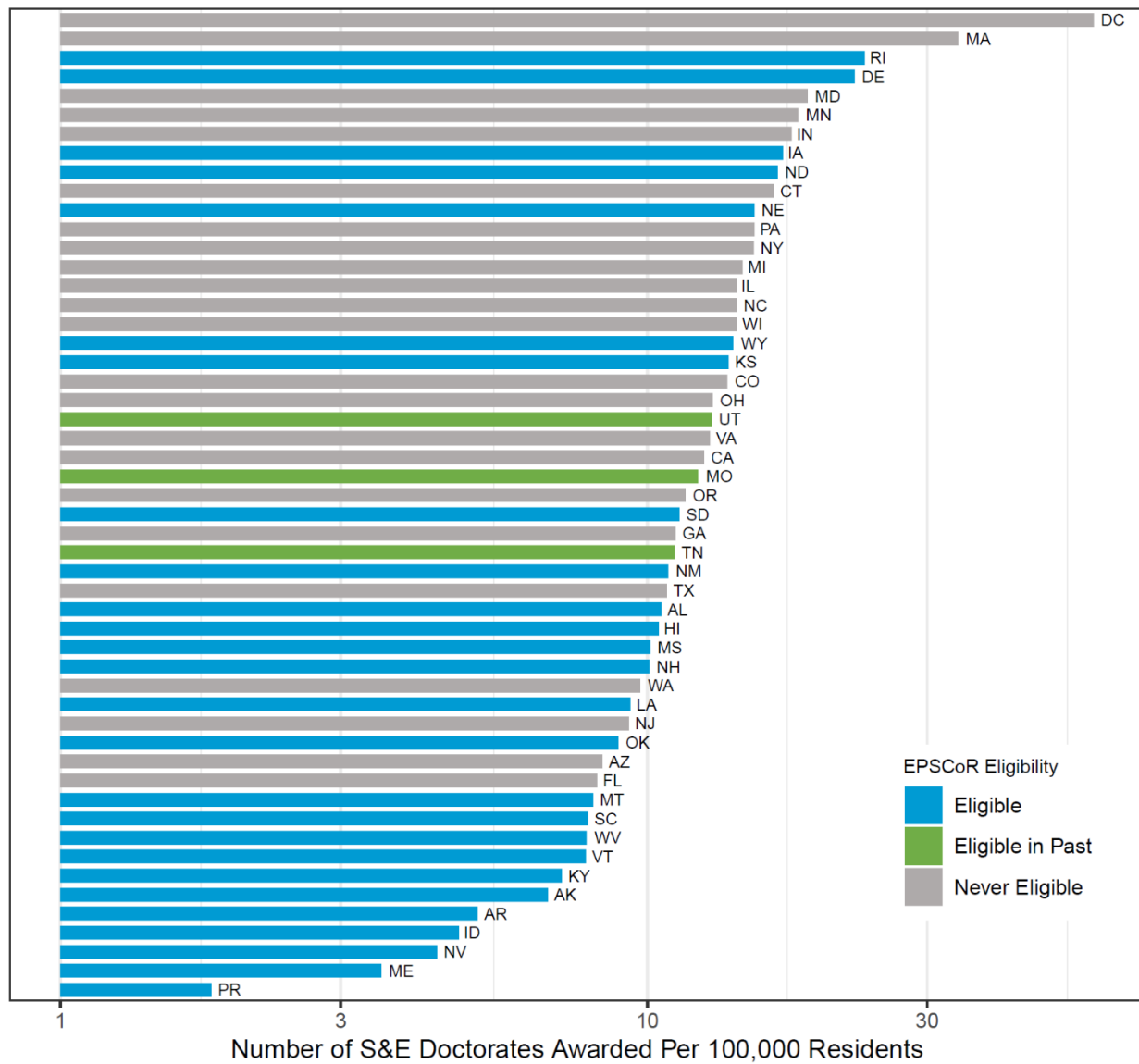
most EPSCoR jurisdictions seem to have lower numbers of graduate students, doctorates awarded, and postdoctoral students than non-EPSCoR jurisdictions. In particular, EPSCoR jurisdictions such as Alaska, Arkansas, Nevada, and Maine produce low numbers of S&E workers relative to their population sizes. Each of these four states has a low-ranking research-focused doctoral university (in terms of academic reputation).

### EXHIBIT 7.3 NUMBER OF SEH GRADUATE STUDENTS PER 100,000 RESIDENTS IN 2016



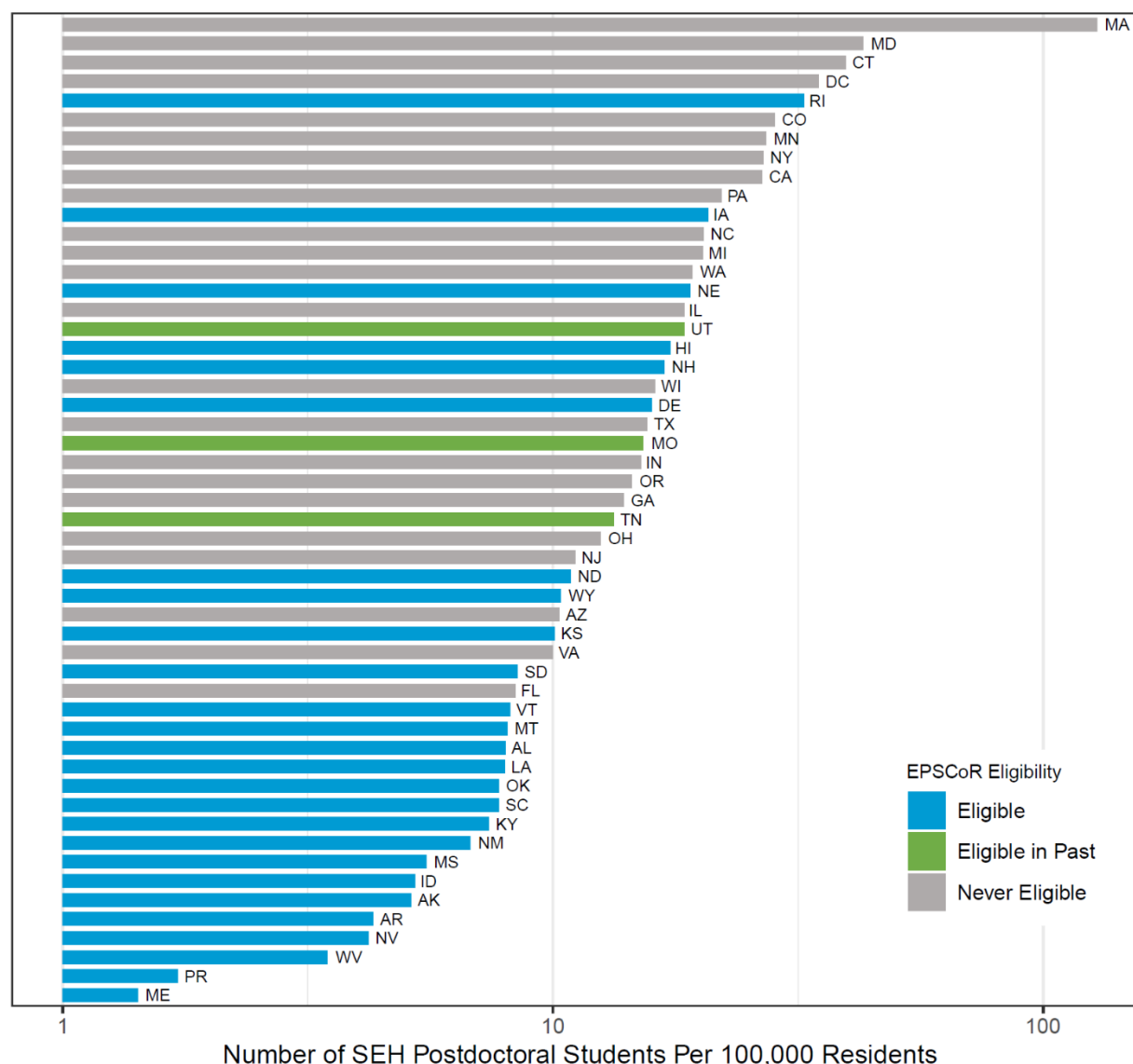
Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands.

## EXHIBIT 7.4 NUMBER OF S&E DOCTORATES AWARDED PER 100,000 RESIDENTS IN 2017



Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands.

## EXHIBIT 7.5 NUMBER OF SEH POSTDOCTORAL STUDENTS PER 100,000 RESIDENTS IN 2016



Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands.

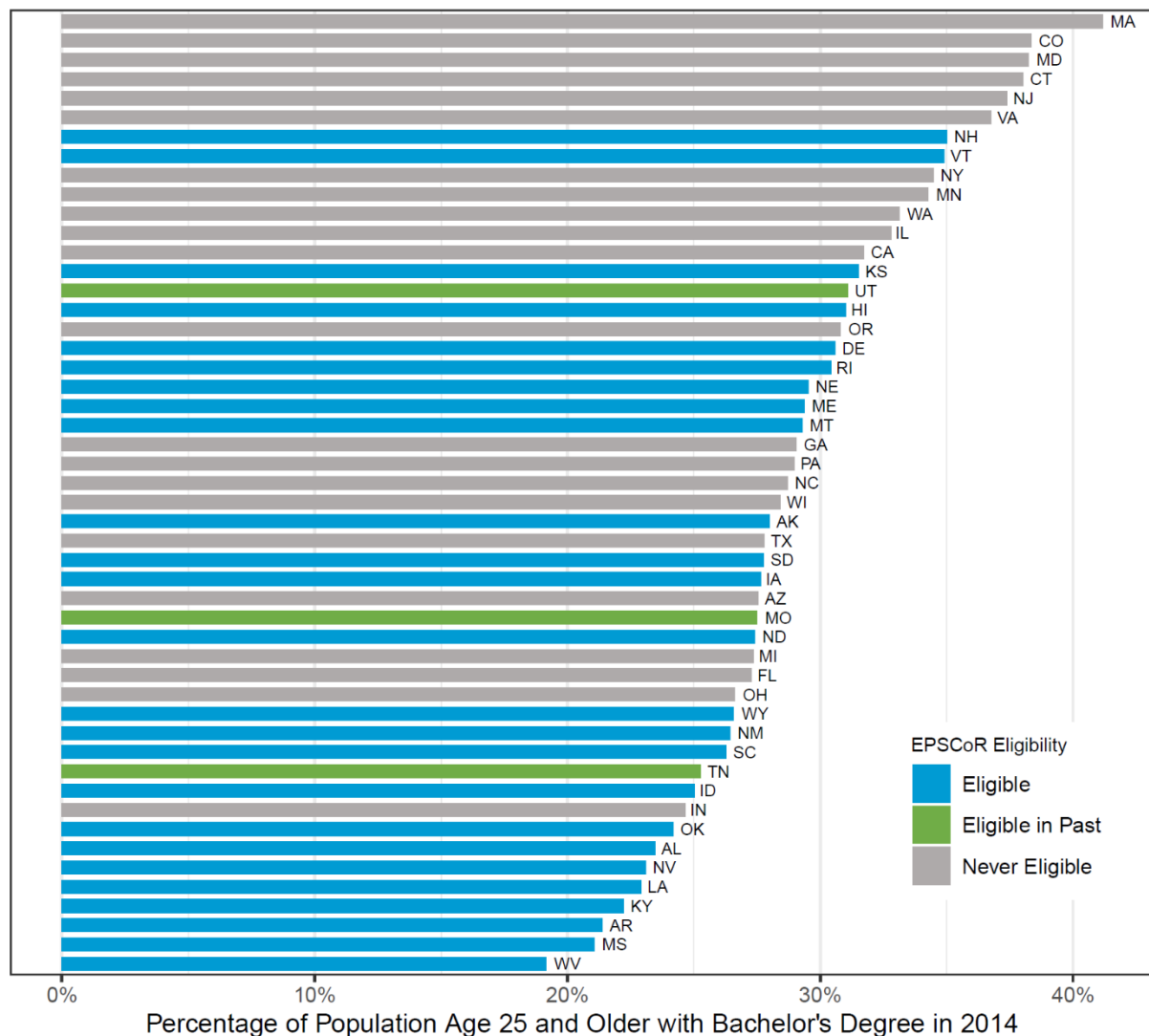
### Workforce Education Level

The number of graduate and doctoral degrees awarded in a jurisdiction is a useful measure of human capital production, but it is not a reliable measure of human capital stock due to the high interjurisdiction mobility of graduate students. For example, more than half of U.S. citizens who receive doctoral degrees in one state are subsequently employed in another state.<sup>71</sup> Jurisdiction retention of these postsecondary graduate and doctoral students is important since

<sup>71</sup> National Science Foundation, National Center for Science and Engineering Statistics. (2019). *Doctorate recipients from U.S. universities: 2018* (Special Report NSF 20-301). Alexandria, VA. Retrieved from <https://nces.nsf.gov/pubs/nsf20301/>

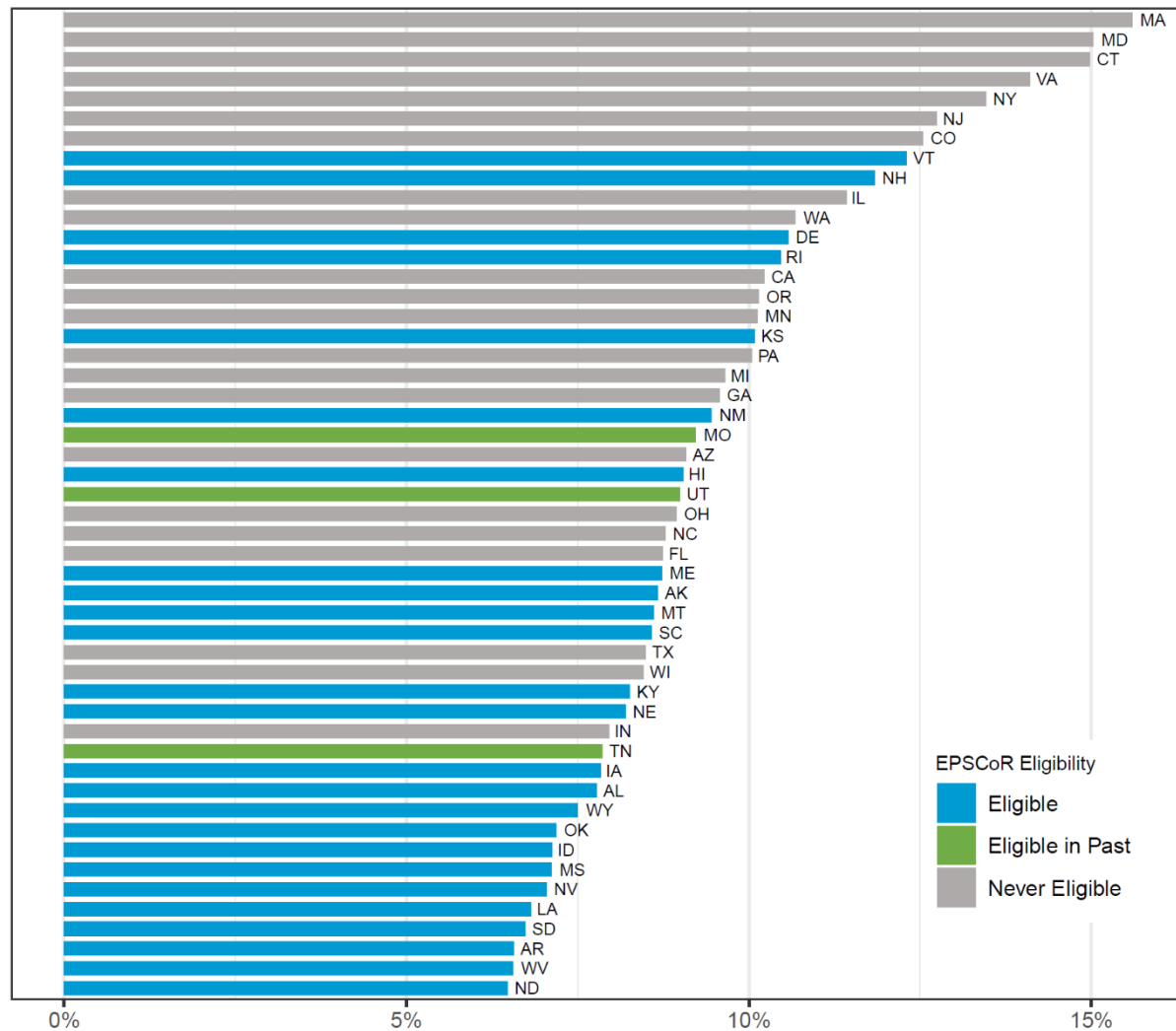
they can be critical to a jurisdiction's progress. These graduates are generally involved in creating and sharing new knowledge, leading innovation, starting new businesses, and improving the standard of living in the communities where they live. In addition, they also are responsible for teaching the next generation of students. Even though the number of doctoral recipients from a university in a jurisdiction is a measure of investment in human resources, the percentage of workforce in the jurisdiction with a graduate degree is a clearer indicator of the capacity of knowledge creation and innovation in the jurisdiction. Exhibits 7.6–7.8 examine the percentages of the workforce with different postsecondary degrees. New Mexico, Rhode Island, Delaware, New Hampshire, and Vermont have higher percentages of the workforce with postsecondary educations relative to their populations.

#### EXHIBIT 7.6 PERCENTAGE OF POPULATION AGE 25 AND OLDER WITH A BACHELOR'S DEGREE IN 2014



Note: Data are not available for District of Columbia, Guam, Puerto Rico, and the U.S. Virgin Islands.

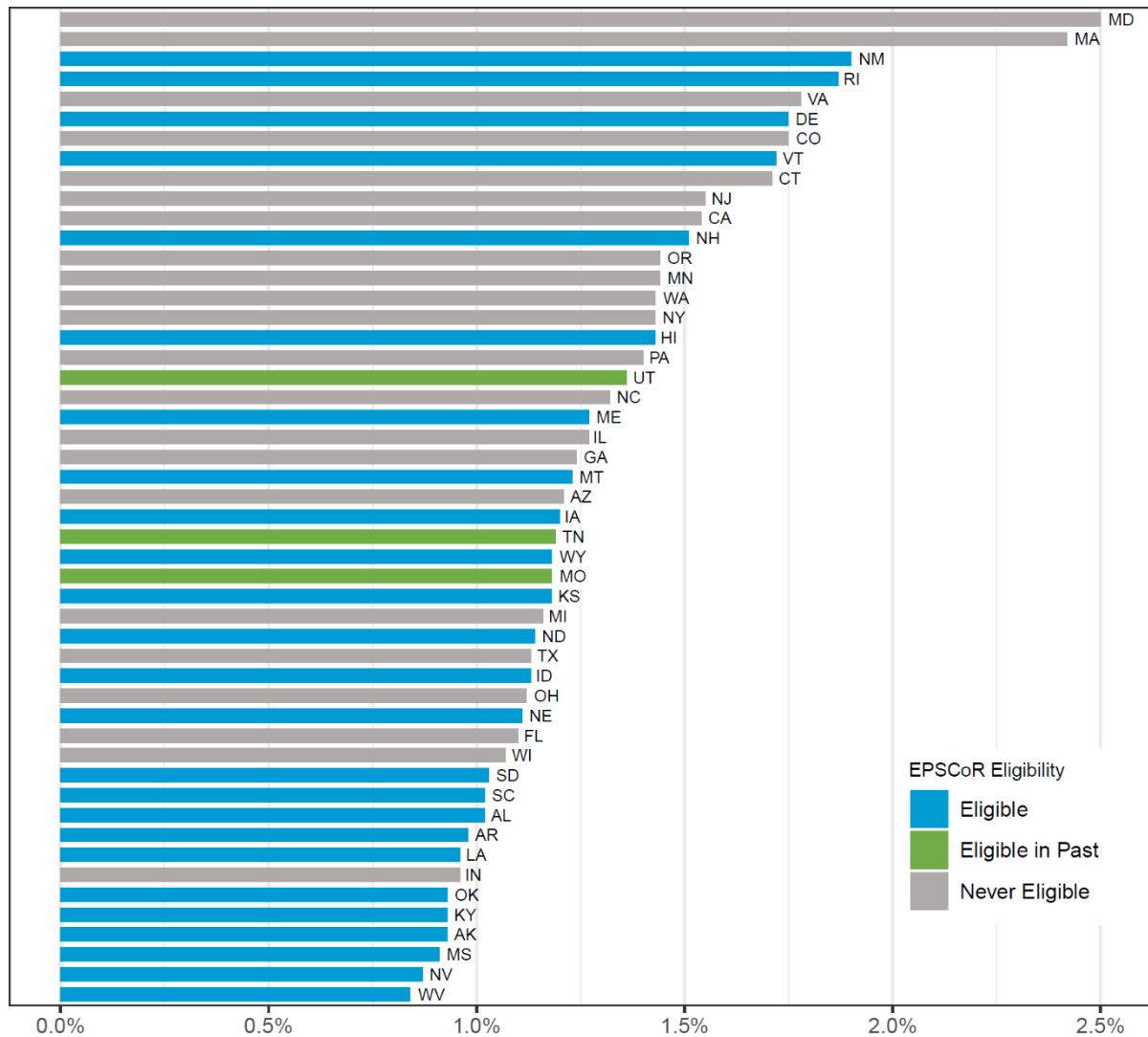
## EXHIBIT 7.7 PERCENTAGE OF POPULATION AGE 25 AND OLDER WITH A MASTER'S DEGREE IN 2014



Percentage of Population Age 25 and Older with Master's Degree in 2014

Note: Data are not available for District of Columbia, Guam, Puerto Rico, and the U.S. Virgin Islands.

## EXHIBIT 7.8 PERCENTAGE OF POPULATION AGE 25 AND OLDER WITH A DOCTORATE IN 2014

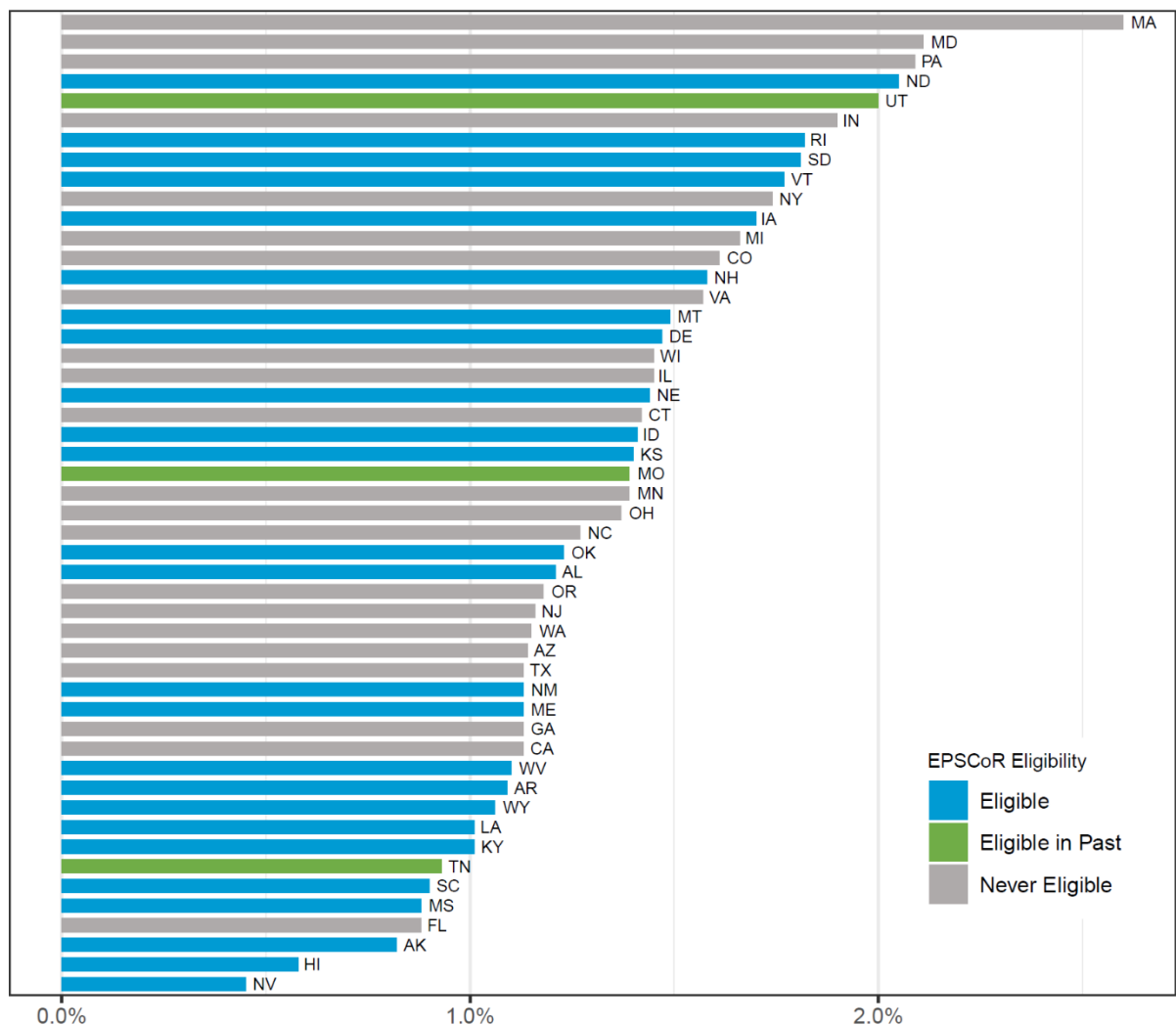


Percentage of Population Age 25 and Older with a Doctorate in 2014

Note: Data are not available for District of Columbia, Guam, Puerto Rico, and the U.S. Virgin Islands.

Exhibit 7.9 examines the proportion of the workforce with a postsecondary education in S&E. EPSCoR jurisdictions like North Dakota, Utah, Rhode Island, and South Dakota have high proportions of workers with S&E degrees, which is in line with these states producing higher numbers of S&E graduate students (see Exhibits 7.3–7.5).

EXHIBIT 7.9 PROPORTION OF WORKERS WHO EARNED A BACHELOR’S, MASTER’S, OR PHD IN S&E IN 2014



Proportion of Workers who Earned Bachelor's, Master's, or PhD in S&E in 2014

Note: Data are not available for District of Columbia, Guam, Puerto Rico, and the U.S. Virgin Islands.

## Reputation in Knowledge Production

### Summary:



- The highest-ranking institution in most EPSCoR jurisdictions tends to have a lower national ranking in research capability and reputational measures compared to non-EPSCoR jurisdictions.
- Jurisdictional indicators of high reputation in knowledge production, such as NAI Fellows, SBIR program awards, and issued patents, are less prevalent in EPSCoR jurisdictions compared to non-EPSCoR jurisdictions.
- Past EPSCoR jurisdictions tend to perform better on reputation in knowledge production measures than current EPSCoR jurisdictions.

A jurisdiction's human capital production in part depends on the number of S&E graduate students who choose to enroll in higher education institutions within the jurisdiction. Further, prospective students' choices for graduate school enrollment in part depend on institutions' research reputation, particularly in S&E disciplines. As a result, the presence of reputable, research-focused universities plays a vital role in jurisdictional research competitiveness. Universities with good reputations and high knowledge outputs benefit jurisdictions by conducting research and publishing in high-quality journals such as *Nature* or *Science*, attracting talent, and leveraging their reputations to obtain research/grant funding. Each of these university components is critical in improving jurisdiction economies in order to attract workers and firms, anchor regional communities, and foster innovation. It is evident that a jurisdiction's identity and economy are both significantly tied to the performance of its research ecosystem—one in which research universities play a unique and crucial role.

### *Institutional Reputation in Knowledge Production*

The United States hosts world-class academic institutions that regularly dominate the global university rankings. However, U.S. institutions demonstrate substantial variation in research competence across jurisdictions. The study team measured institutional contributions to a jurisdiction's reputation in knowledge production by examining several institutional measures aggregated to the jurisdiction level:<sup>72</sup>

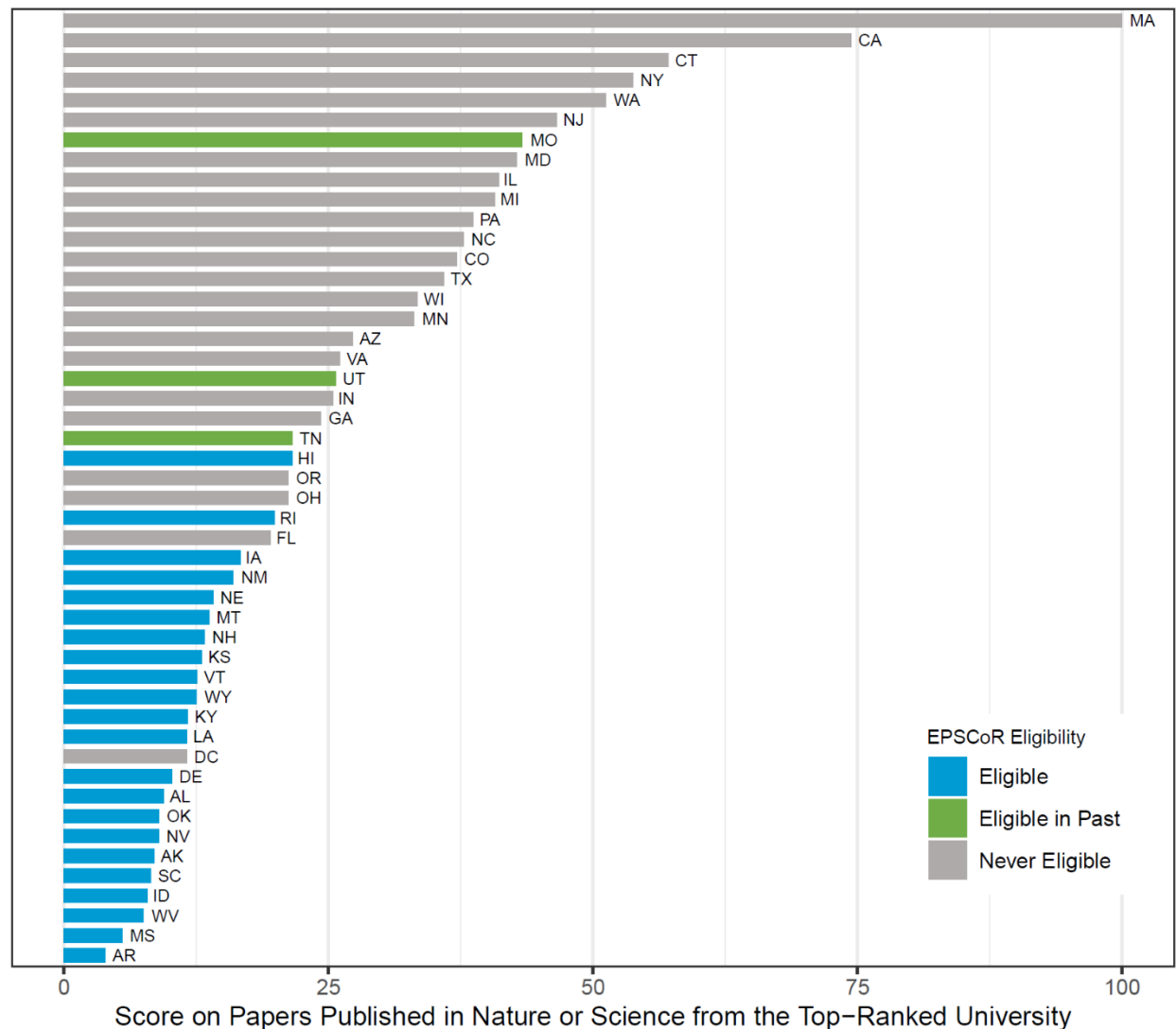
- Highest score for papers published in *Nature* or *Science* of any institution in the jurisdiction
- Highest score for papers indexed in science and social science fields of any institution in the jurisdiction
- Highest score on per capita academic performance of any institution in the jurisdiction
- Highest score for highly cited researchers in any institution in the jurisdiction

<sup>72</sup> No institution in Maine, North Dakota, or South Dakota has any score across these four measures. This may imply that either there is missing information or no university in these states met the criteria for being ranked by ARWU. For more information, see <http://www.shanghairanking.com/ARWU2016.html>



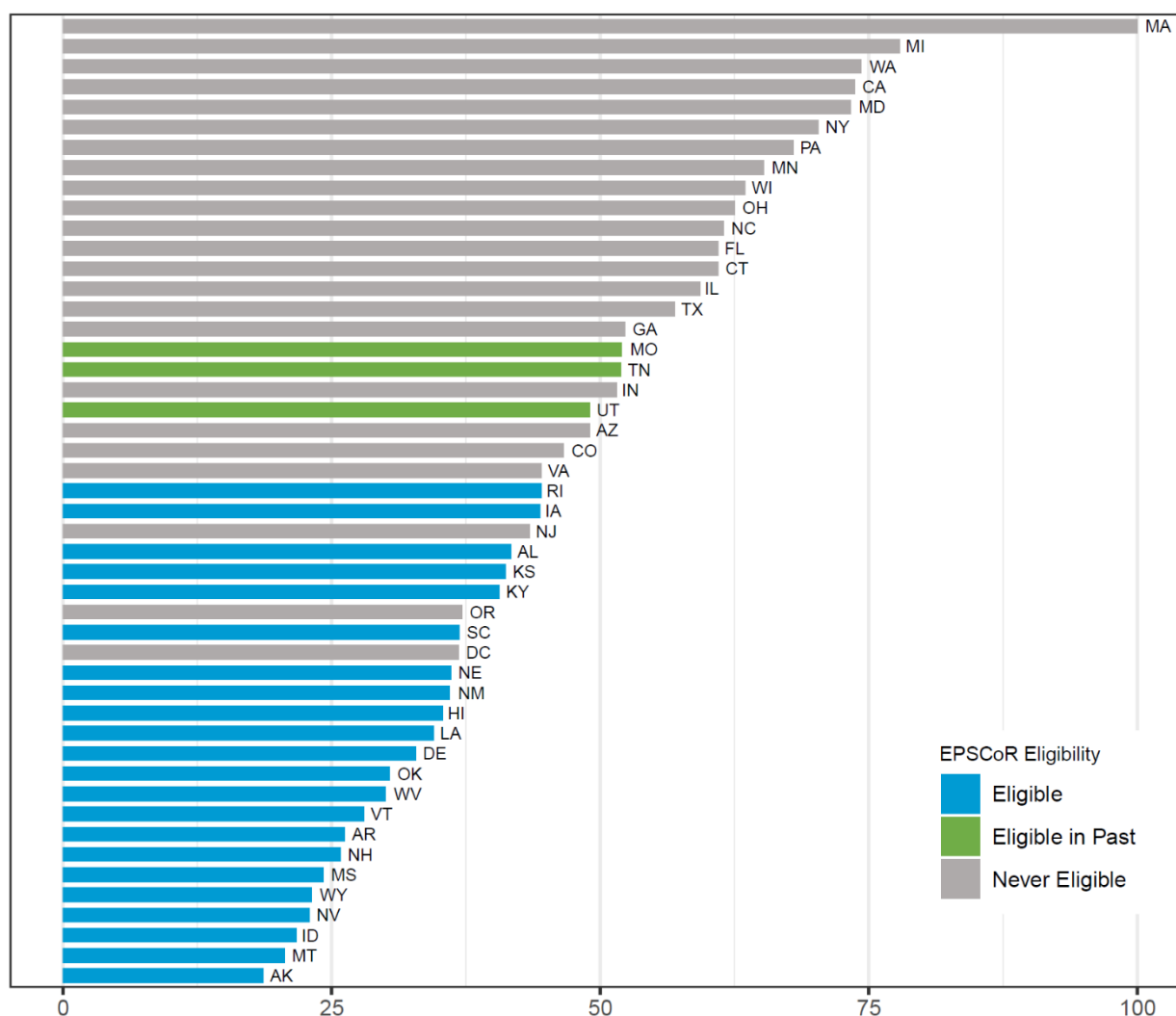
Examining the highest-ranking institution in a jurisdiction across the four scores that measure an institution's research capabilities and reputation revealed that most EPSCoR jurisdictions cluster at the lower end of the rankings. Past EPSCoR jurisdictions Missouri, Tennessee, and Utah tend to perform much better than the current EPSCoR jurisdictions across the four institution-level measures signaling the reputational scores of the top doctoral university in the state.

#### EXHIBIT 7.10 SCORES ON PAPERS PUBLISHED IN *NATURE* OR *SCIENCE* FROM THE TOP-RANKED UNIVERSITY IN THE JURISDICTION IN 2017



Note: No institutions in Maine, North Dakota, Puerto Rico, and South Dakota have ranking scores. Guam and the U.S. Virgin Islands have no doctoral university.

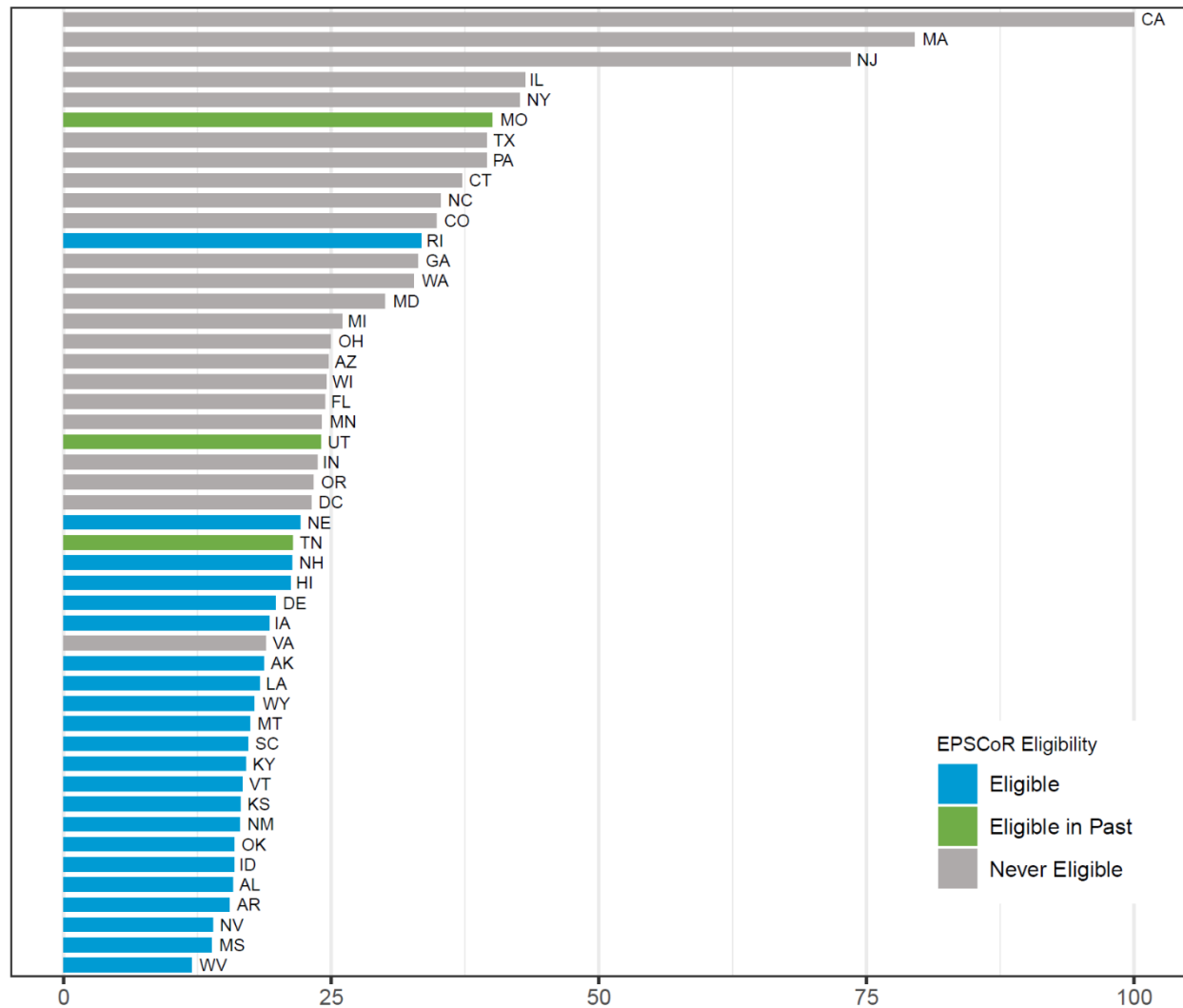
## EXHIBIT 7.2 SCORE ON PAPERS INDEXED IN SCIENCE OR SOCIAL SCIENCE FIELDS FROM THE TOP-RANKED UNIVERSITY IN THE JURISDICTION IN 2017



Score on Papers Indexed in Science or Social Science Fields from the Top-Ranked University

Note: No institutions in Maine, North Dakota, Puerto Rico, and South Dakota have ranking scores.  
Guam and the U.S. Virgin Islands have no doctoral university.

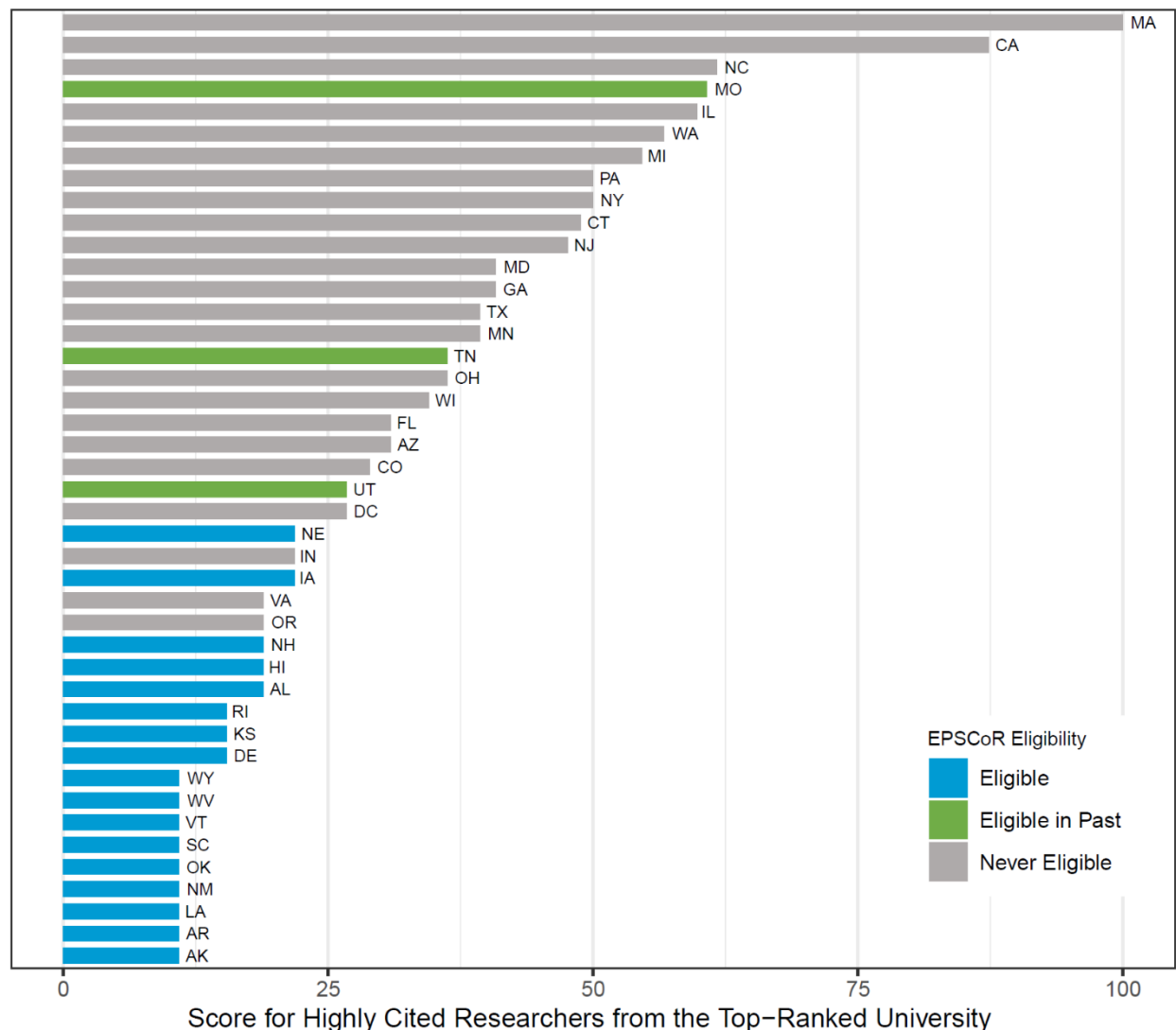
## EXHIBIT 7.3 SCORE ON PER CAPITA ACADEMIC PERFORMANCE FROM THE TOP-RANKED UNIVERSITY IN 2017



Score of State Institution for Per Capita Academic Performance from the Top-Ranked University

Note: No institutions in Maine, North Dakota, Puerto Rico, and South Dakota have ranking scores. Guam and the U.S. Virgin Islands have no doctoral university.

## EXHIBIT 7.13 SCORE FOR HIGHLY CITED RESEARCHERS FROM THE TOP-RANKED UNIVERSITY IN 2017



Note: No institutions in Idaho, Kentucky, Maine, Mississippi, Nevada, North Dakota, Puerto Rico and South Dakota have ranking scores. Guam and the U.S. Virgin Islands have no doctoral university.

### *Jurisdictional Reputation in Knowledge Production*

There are several jurisdictional measures that also relate to reputation in knowledge production that leads to additional research funding:

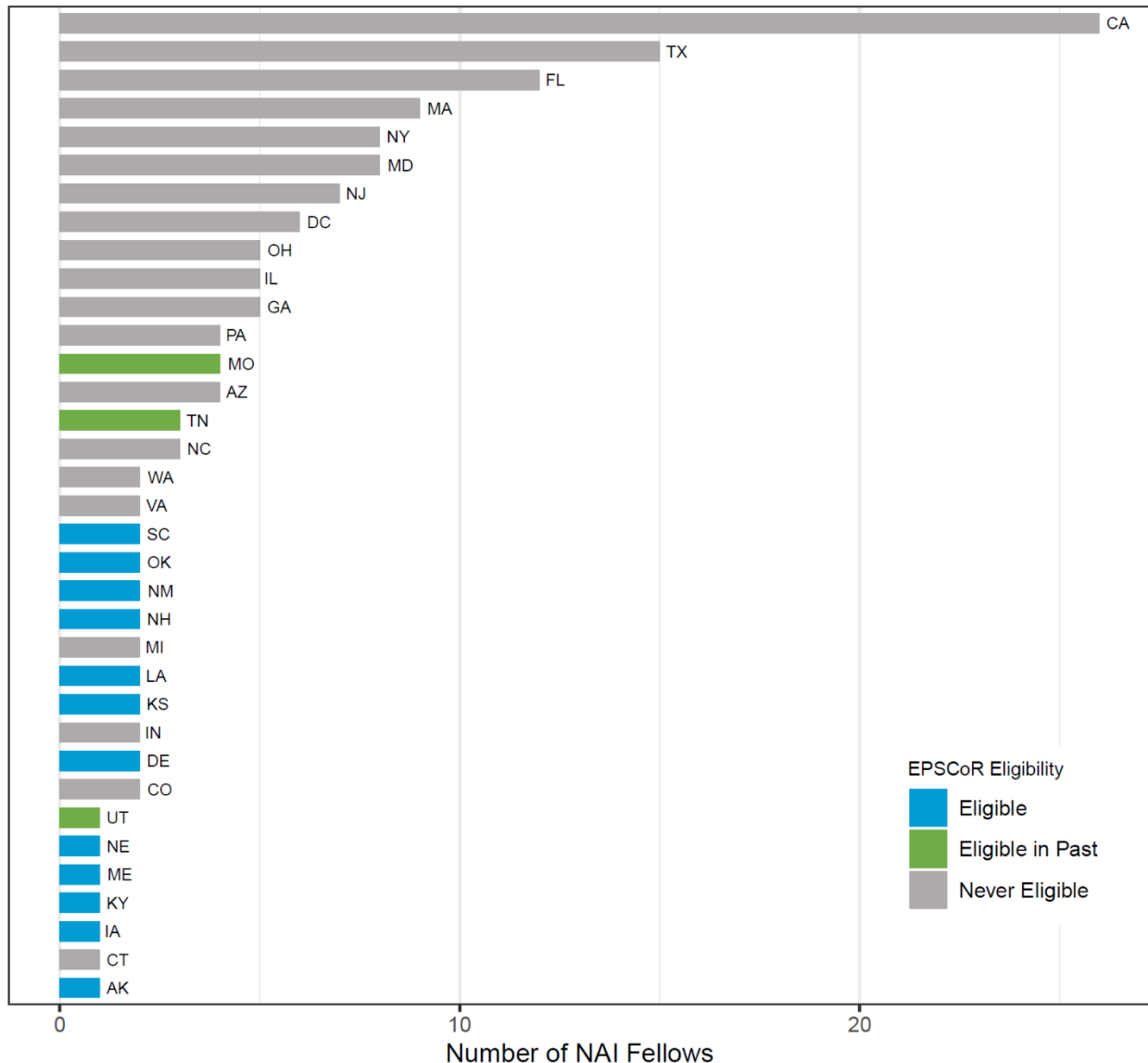
- Number of NAI Fellows in the Jurisdiction
- Number of SBIR Program Awards
- Number of Utility Patents Issued to Jurisdiction Residents

As with the institutional reputation measures in knowledge production, most EPSCoR jurisdictions tend to fall at the lower end of jurisdictional measures. All past EPSCoR jurisdictions have at least one NAI Fellow, with Missouri and Tennessee housing more than five

Fellows (Exhibit 7.14). The presence of these academic innovators could potentially attract state, federal, and private grant funding, as seen by the number of SBIR program awards (Exhibit 7.15) and utility patents (Exhibit 7.16) issued in these jurisdictions.

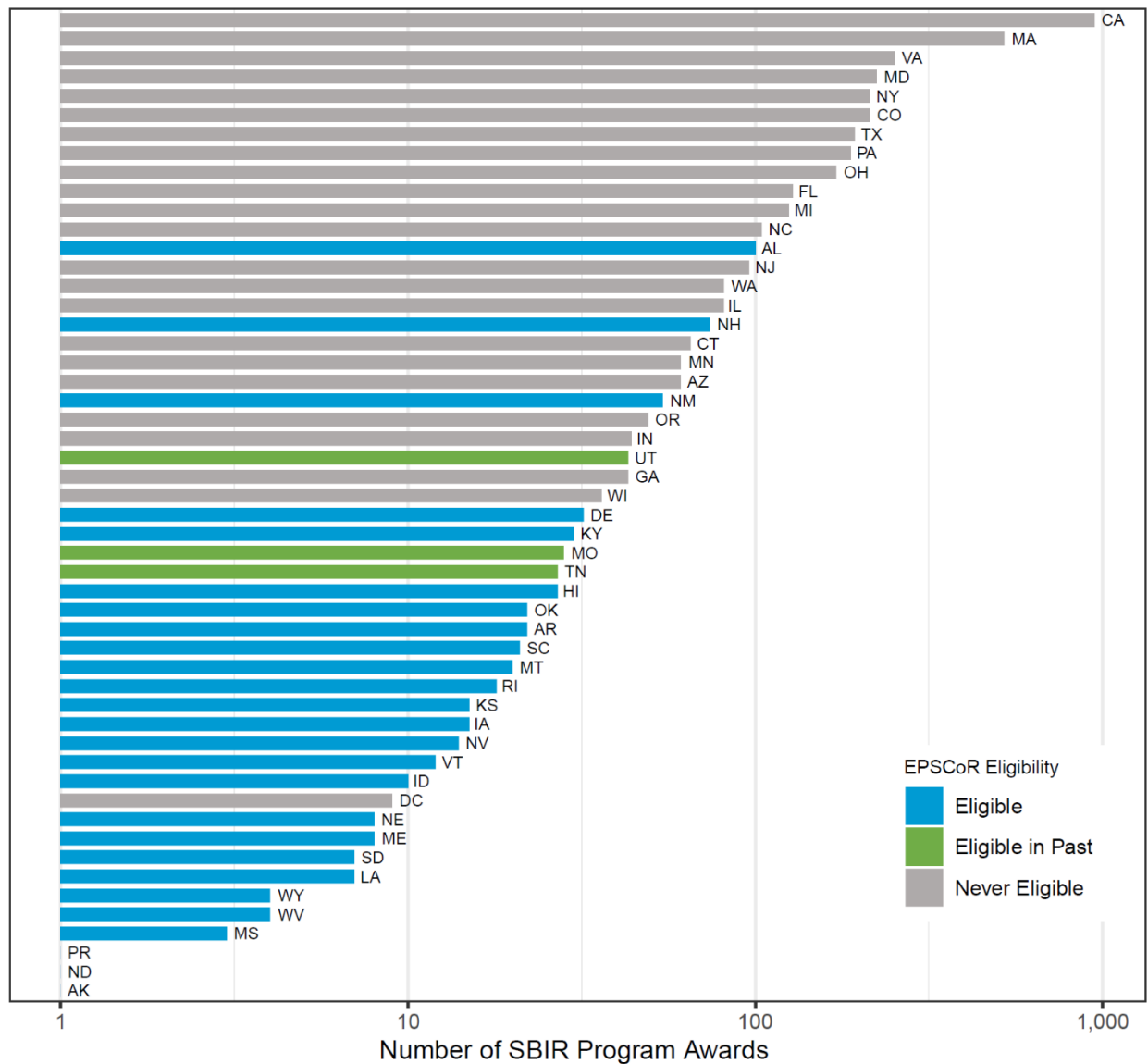
Notably, Alabama, New Hampshire, and New Mexico were awarded a high number of SBIR awards compared to other current EPSCoR jurisdictions. This could be due to federal labs or a specific state program.

#### EXHIBIT 7.14 NUMBER OF NAI FELLOWS FOR EACH JURISDICTION IN 2015



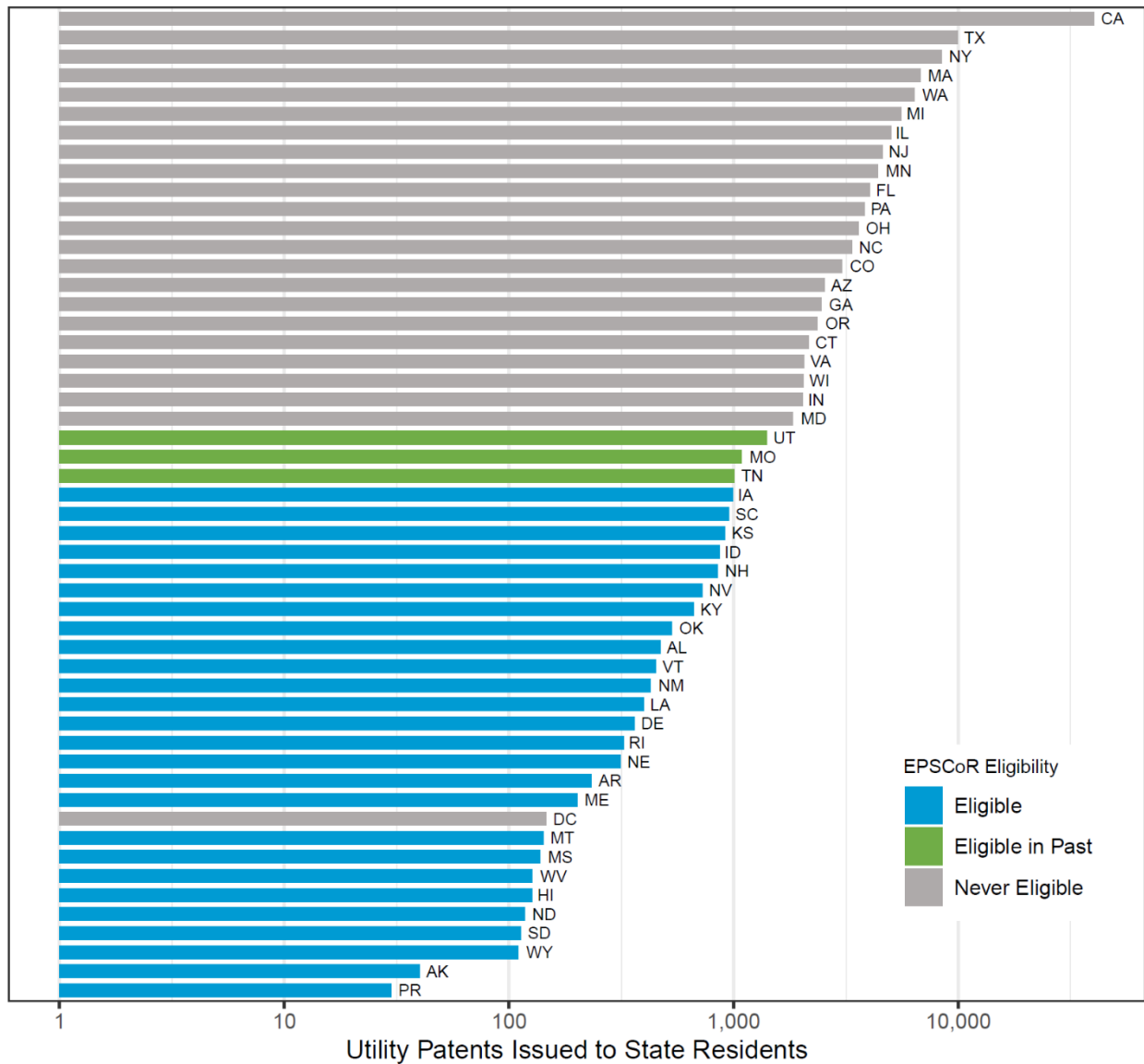
Note: States not displayed in the exhibit have zero NAI Fellows.

## EXHIBIT 7.15 NUMBER OF SBIR PROGRAM AWARDS FOR EACH JURISDICTION IN 2015

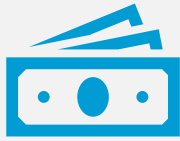


Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands.

## EXHIBIT 7.16 UTILITY PATENTS ISSUED TO STATE RESIDENTS IN 2015



Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands.



## Economic Development of Knowledge and Science-Intensive, High-Technology Industries

### Summary

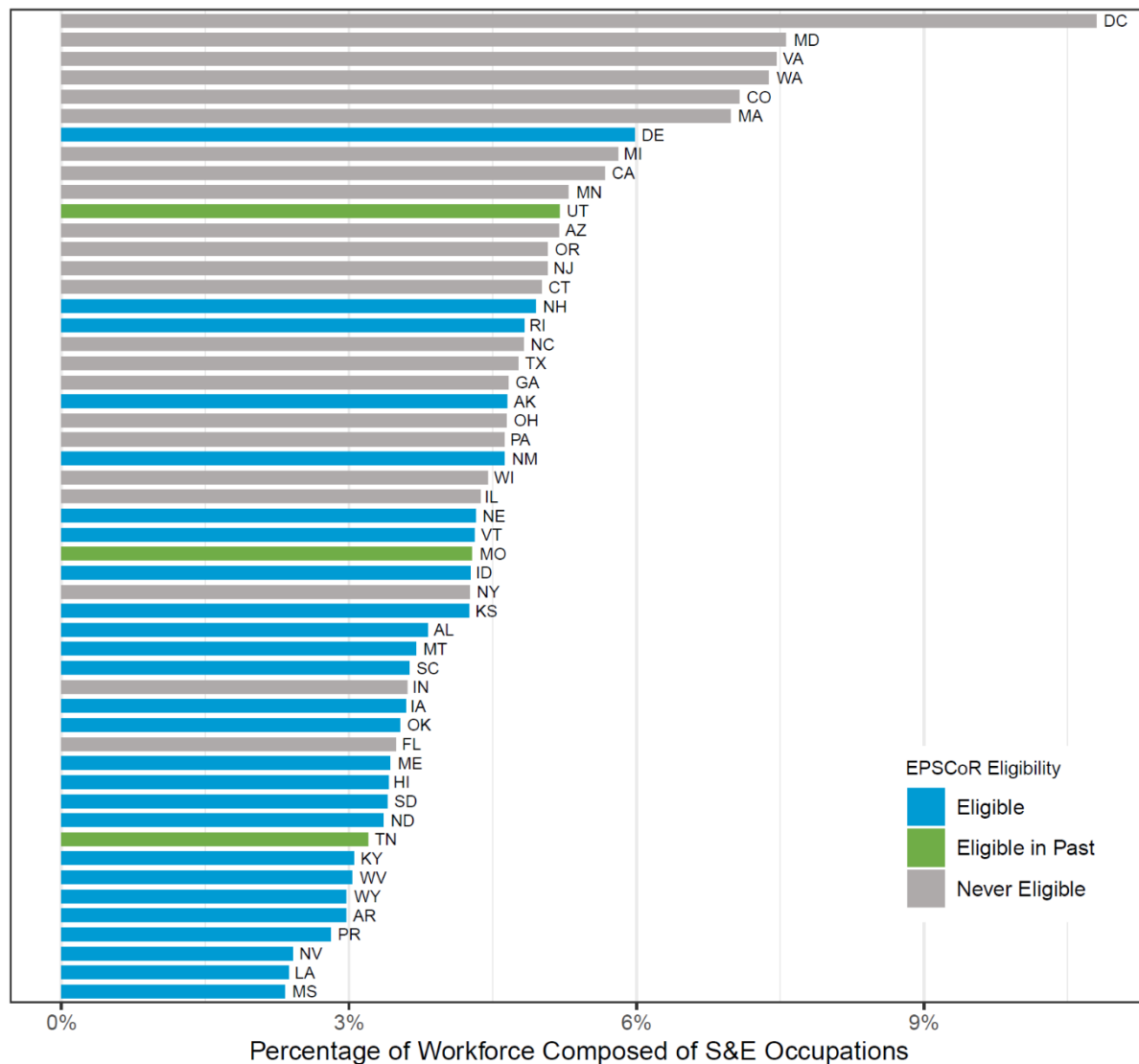
- Compared to non-EPSCoR jurisdictions, nearly all EPSCoR jurisdictions' economies present relatively limited opportunities for S&E graduates because the jurisdictions generally lag in the development of high-tech industries, with the exception of Utah.

S&E employment in the United States has grown more rapidly than in the overall workforce, representing 5 percent of available jobs.<sup>73</sup> Most EPSCoR jurisdictions have S&E employment rates below the national average. However, there are a few exceptions that have a high percentage of S&E jobs, such as Delaware, New Hampshire, and Rhode Island. Utah has also seen tremendous growth in the nation's high-tech sector (at 4.3 percent from 2016 to 2018) due to the increase in the number of high-tech businesses in that jurisdiction. These data also suggest that the current economic structure of an EPSCoR jurisdiction presents relatively limited opportunities for S&E graduates, and that many educated at highly research-focused universities in jurisdictions such as Iowa, North Dakota, and Nebraska (with high numbers of graduate students) may be leaving the jurisdiction to find employment elsewhere that is commensurate with their qualifications.

<sup>73</sup> National Science Board, National Science Foundation. (2020). *Science and engineering indicators 2020: The state of U.S. science and engineering*. NSB-2020-1. Alexandria, VA. Retrieved from <https://nces.nsf.gov/pubs/nsb20201/>



## EXHIBIT 7.17 PERCENTAGE OF WORKFORCE COMPOSED OF S&E OCCUPATIONS IN 2017

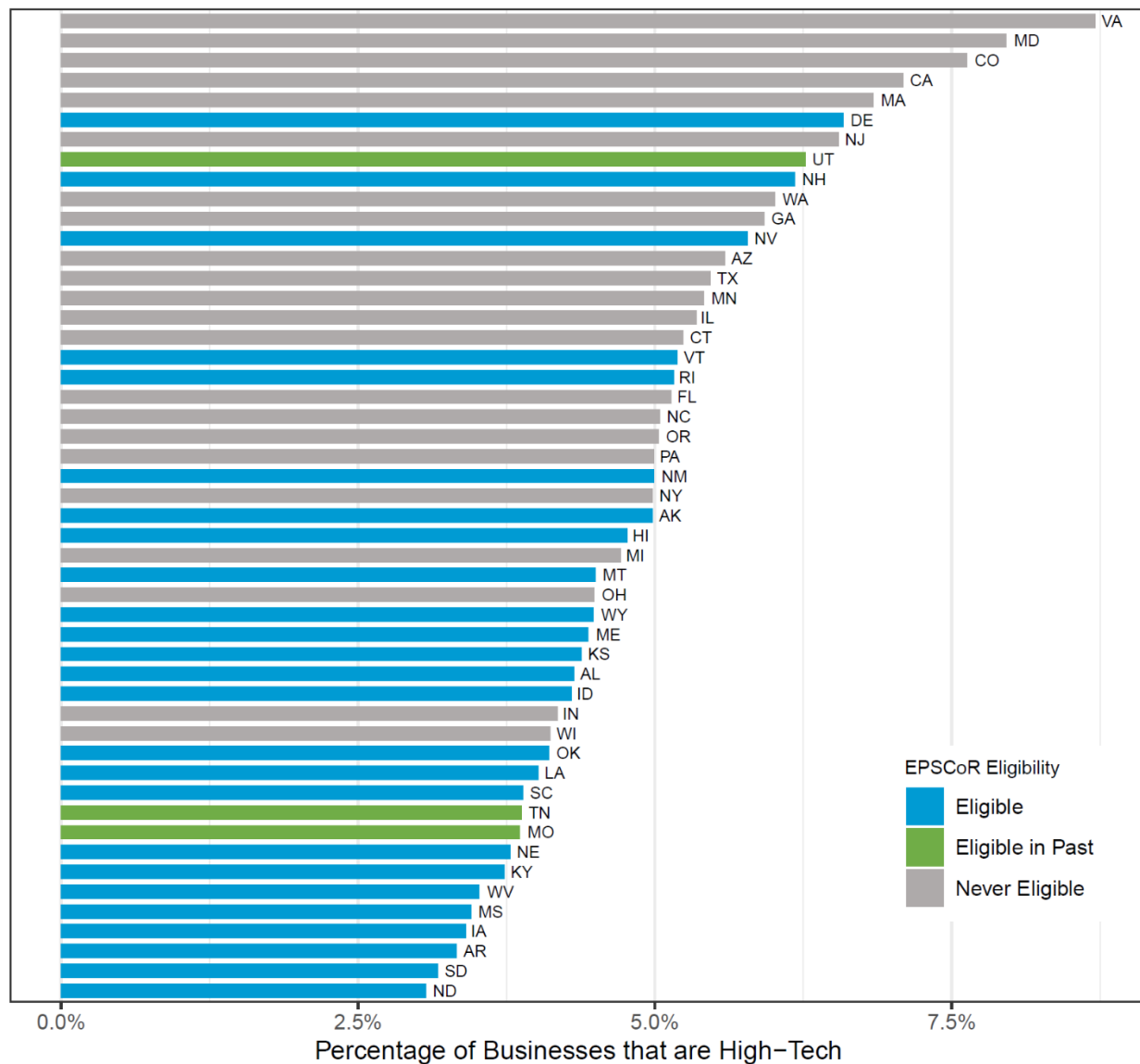


Note: Data are not available for Guam and the U.S. Virgin Islands.

Exhibits 7.18 to 7.21 show several measures that align with the development of high-tech industry in a jurisdiction. Only a few EPSCoR jurisdictions in the Northeast (New Hampshire, Vermont, Delaware, and Rhode Island) and Utah have developed a high-tech sector or attracted companies that employ high-tech workers. As Exhibit 7.18 demonstrates, only four EPSCoR jurisdictions—Delaware, Utah, New Hampshire, and Nevada—have a high-tech industry percentage greater than the national average (5.6 percent). The scale of high-tech employment ranges from 10.5 percent for Washington to 2.3 percent for Wyoming, with only a few EPSCoR jurisdictions (Utah, New Hampshire, New Mexico, and Kansas) having a percentage greater than the 6 percent national average (Exhibit 7.19). Two EPSCoR jurisdictions, Utah, and New Hampshire, also rank highly on the two other measures of high-tech industry development: state's relative performance in generating fast-growing high-tech enterprises (Exhibit 7.20) and

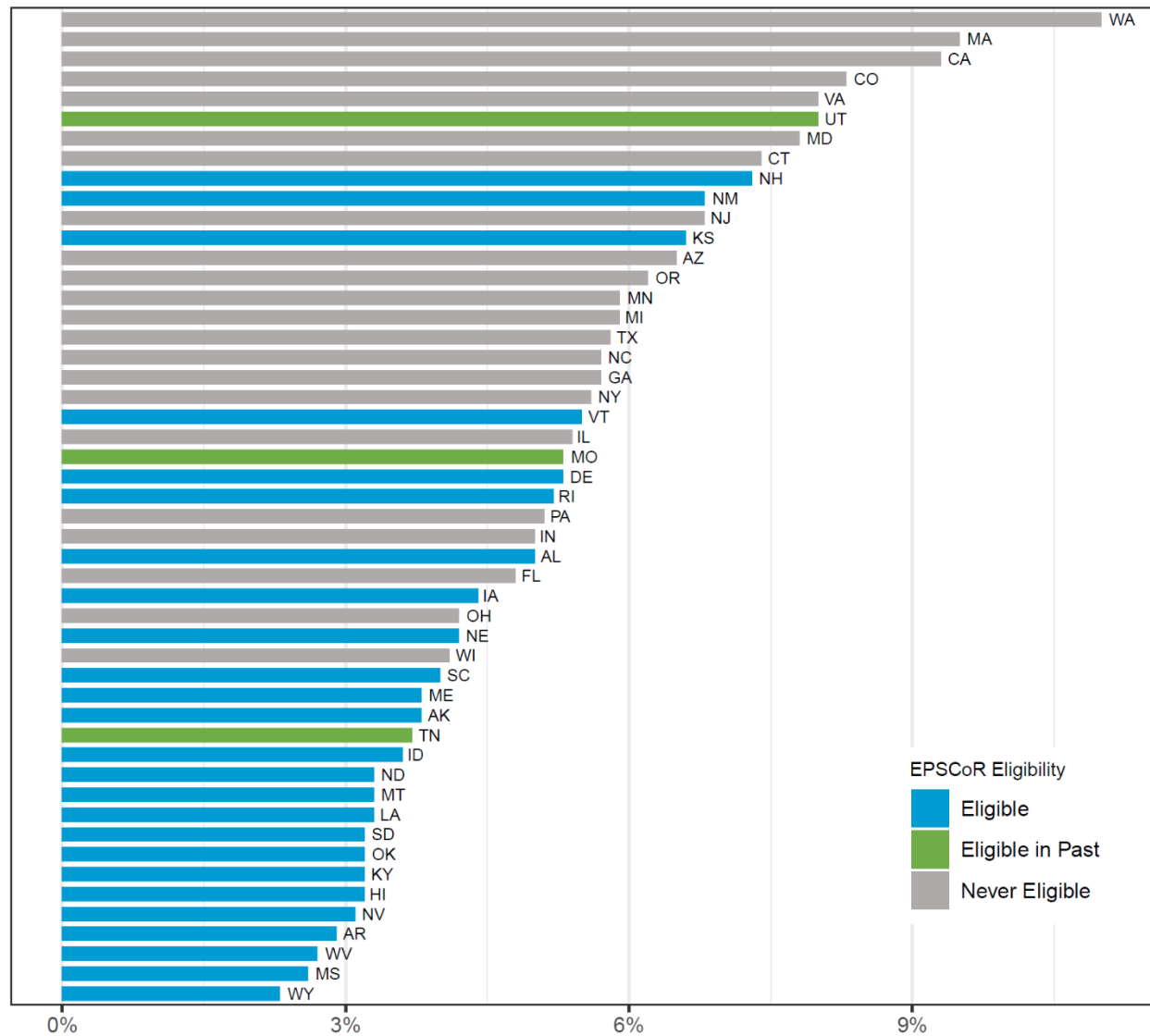
concentration of high-tech industries in the jurisdiction (Exhibit 7.21). On the other hand, EPSCoR jurisdictions in the South and Mountain West consistently appear at the lower end of the distribution of these measures aligned with the development of high-tech industries.

#### EXHIBIT 7.18 PERCENTAGE OF BUSINESSES THAT WERE HIGH-TECH IN 2014



Note: Data are not available for District of Columbia, Guam, Puerto Rico, and the U.S. Virgin Islands.

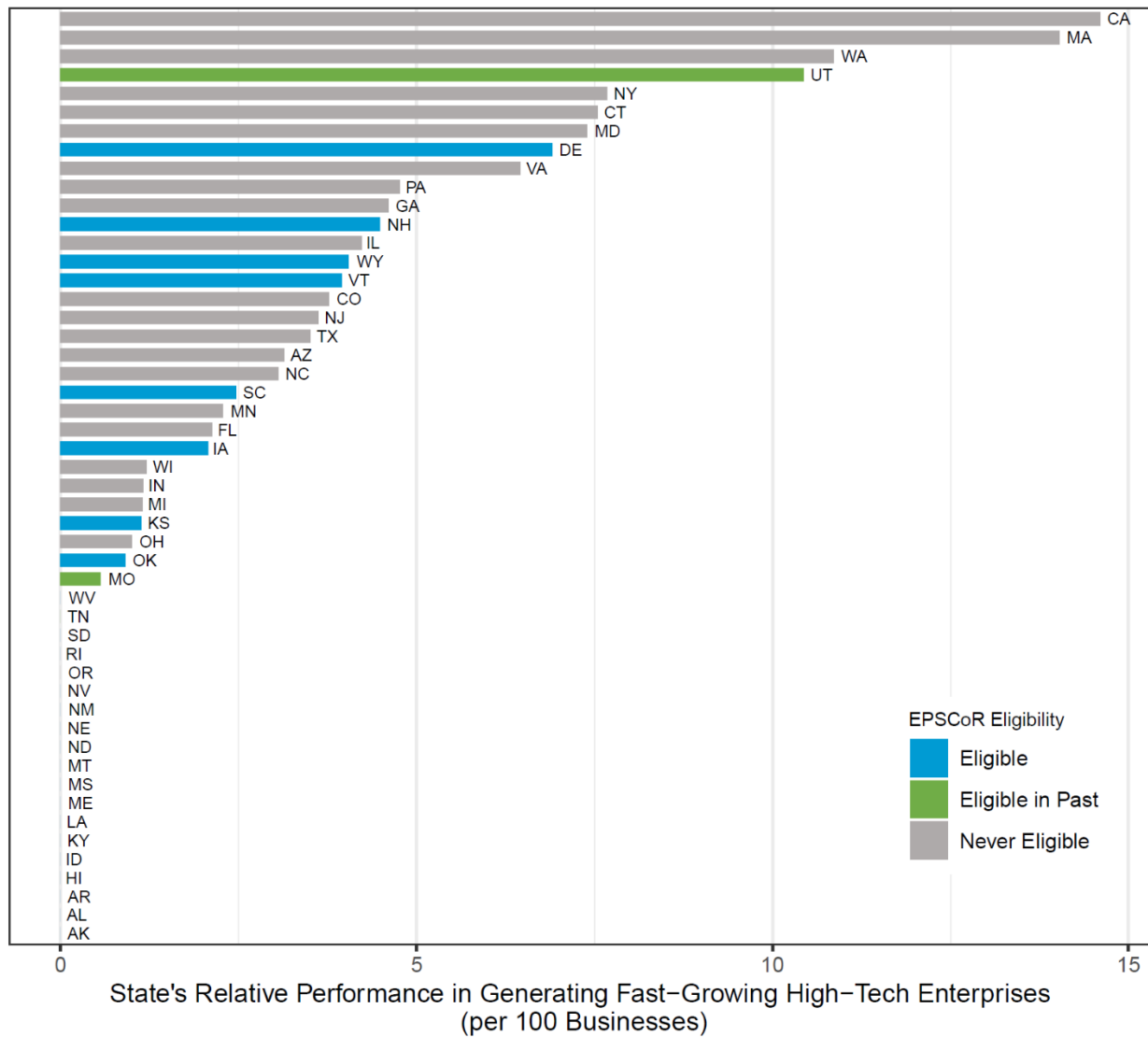
## EXHIBIT 7.4 PERCENTAGE OF EMPLOYMENT IN HIGH-TECH INDUSTRIES IN 2015



Percentage of Employment in High-Tech Industries

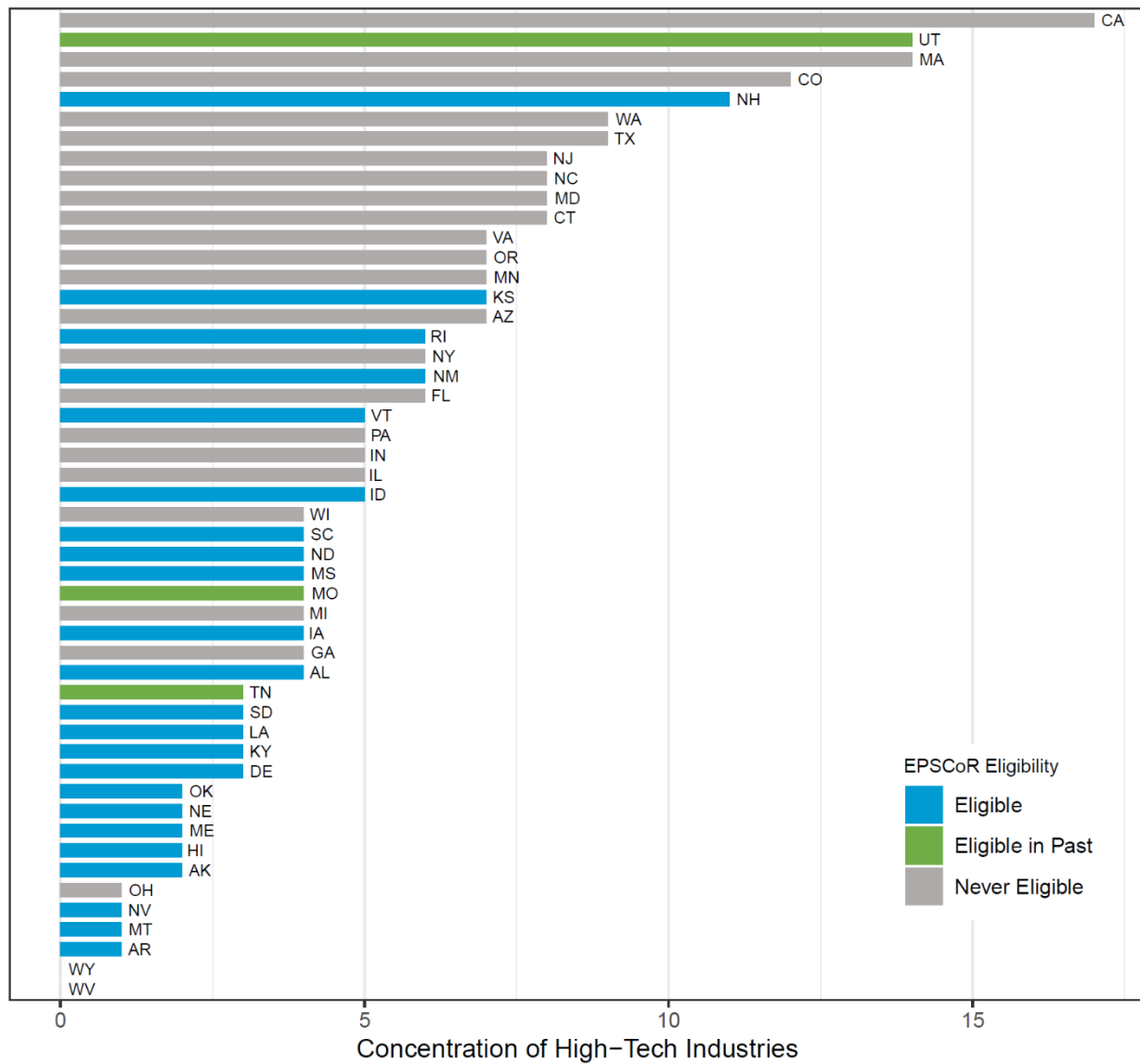
Note: Data are not available for District of Columbia, Guam, Puerto Rico, and the U.S. Virgin Islands.

## EXHIBIT 7.20 JURISDICTIONS' RELATIVE PERFORMANCE IN GENERATING FAST-GROWING HIGH-TECH ENTERPRISES IN 2015



Note: Data are not available for District of Columbia, Guam, Puerto Rico, and the U.S. Virgin Islands.

## EXHIBIT 7.21 CONCENTRATION OF HIGH-TECH INDUSTRIES IN 2015



Note: Data are not available for District of Columbia, Guam, Puerto Rico, and the U.S. Virgin Islands.



## Gender and Racial Diversity in Labor Force Development

### Summary

- Compared to non-EPSCoR jurisdictions, EPSCoR jurisdictions tend to have similar numbers of women participating in S&E graduate education and workforce to the numbers in non-EPSCoR jurisdictions, but they also tend to have lower participation by minorities in S&E graduate education and workforce.

One objective of EPSCoR is to broaden participation of diverse individuals in S&E research. Graduate education in S&E is an important step toward S&E research employment and contributes to a jurisdiction's research competitiveness by producing the highly skilled workers needed for a high-tech economy. As a result, the study team examined gender and racial diversity in both graduate education and the workforce.

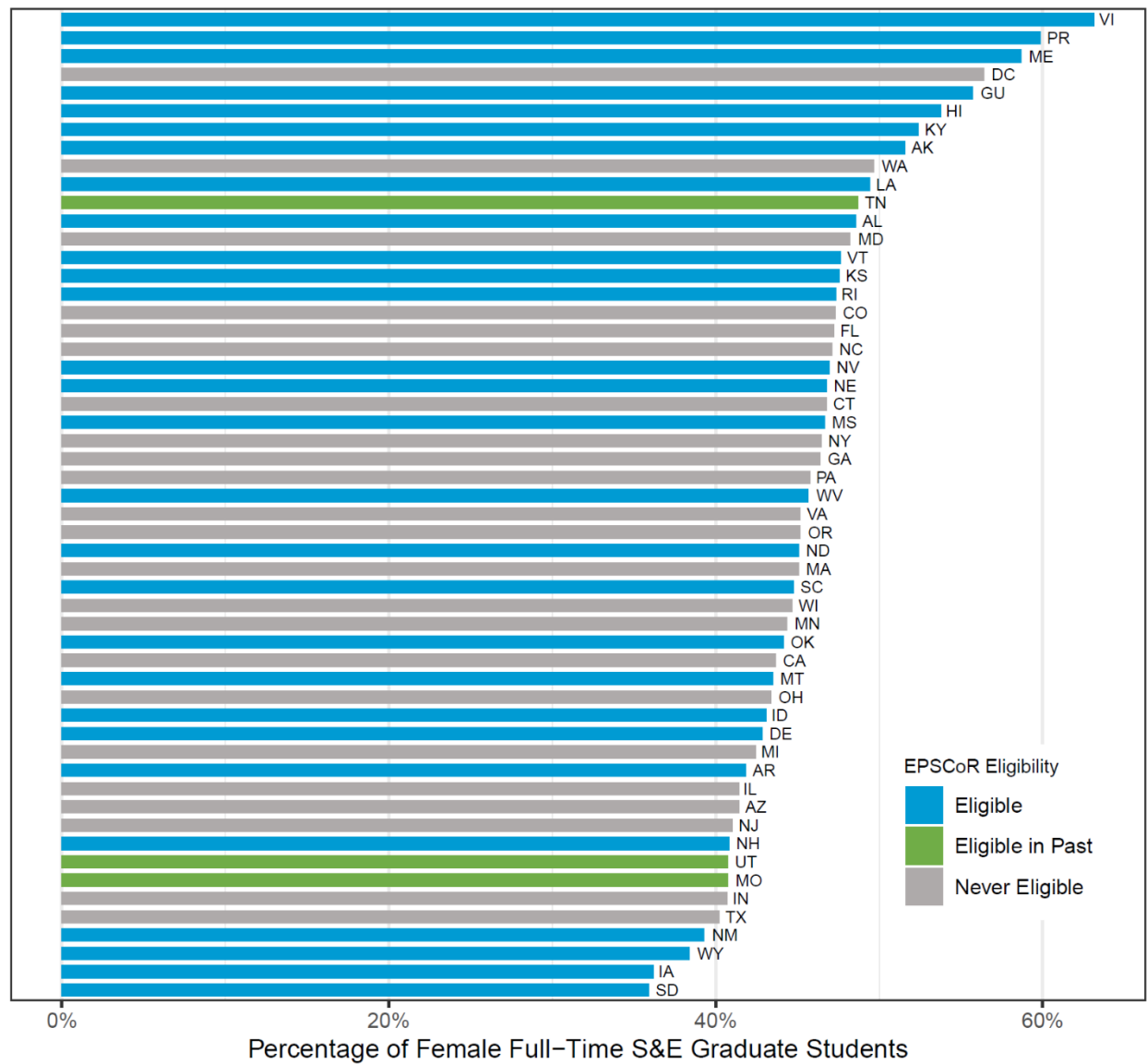
### *Gender Diversity in S&E Labor Force Development*

Although women have reached parity with men in terms of number of S&E bachelor's degree recipients—half of S&E bachelor's degrees were awarded to women in 2016—they are still underrepresented in S&E graduate education and S&E occupations. Among students enrolled in full-time graduate school in S&E fields, women make up approximately 47 percent.<sup>74</sup> The proportion of women in S&E fields varies across and within broad fields of study, with the share highest in social sciences and biosciences and lowest in computer science and engineering.<sup>75</sup> The proportion of women in S&E fields also varies across jurisdictions and institutions. Some EPSCoR jurisdictions have a greater proportion of women enrolled in S&E graduate programs than others (Exhibit 7.22). The majority of EPSCoR jurisdictions have a greater proportion of women working in professional, scientific, and technical services than non-EPSCoR jurisdictions (Exhibit 7.23). Both measures provide insight into how some jurisdictions like Maine are better able to broaden participation of women in S&E and provide career opportunities that enable women to find employment in S&E fields within their states.

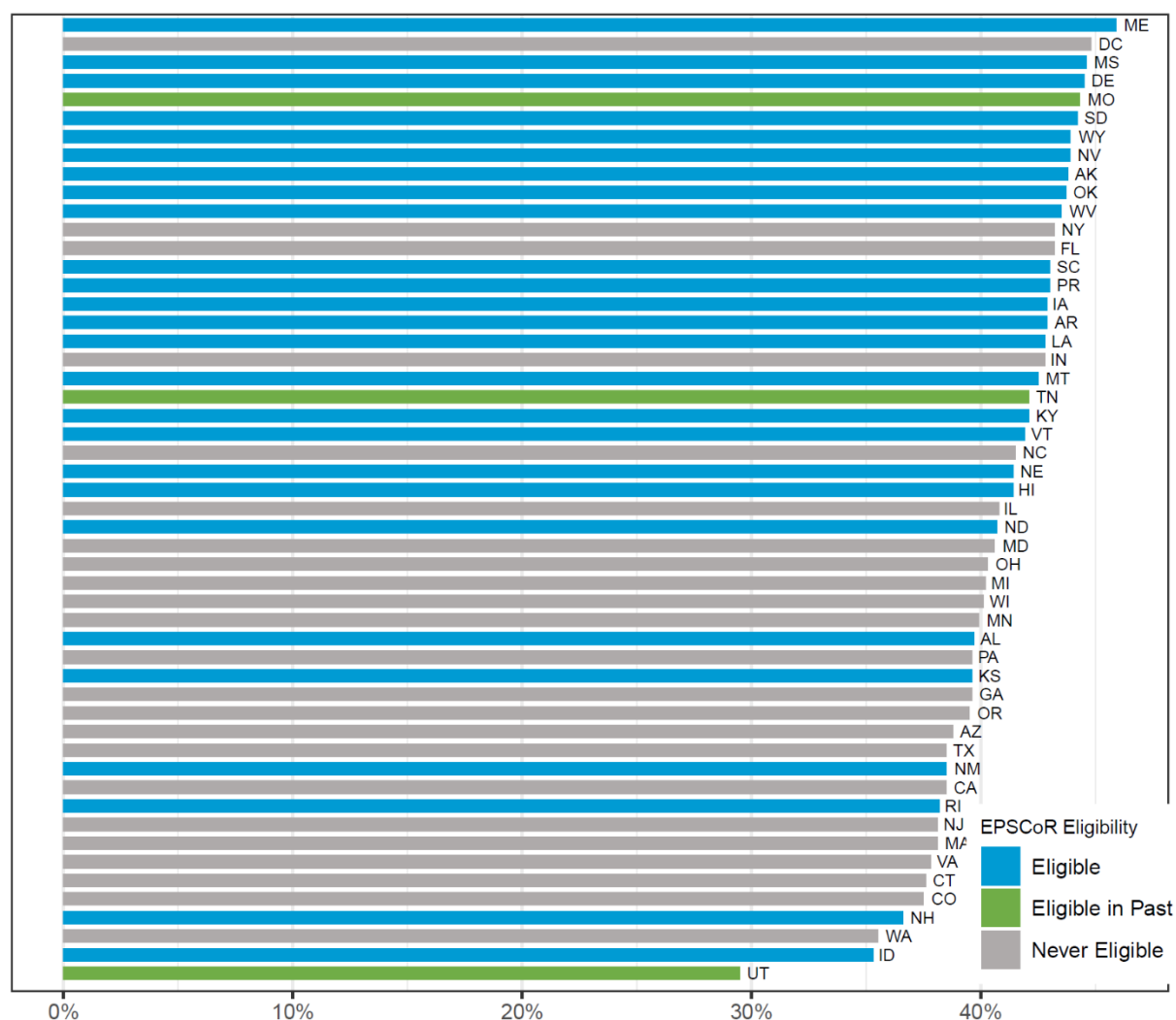
<sup>74</sup> National Science Foundation, National Center for Science and Engineering Statistics. (2019). *Women, minorities, and persons with disabilities in science and engineering: 2019* (Special Report NSF 19-304). Alexandria, VA. Retrieved from <https://www.nsf.gov/statistics/wmpd>

<sup>75</sup> National Science Foundation, National Center for Science and Engineering Statistics. (2019). *Women, minorities, and persons with disabilities in science and engineering: 2019* (Special Report NSF 19-304). Alexandria, VA. Retrieved from <https://www.nsf.gov/statistics/wmpd>

## EXHIBIT 7.5 PERCENTAGE OF FEMALE FULL-TIME S&E GRADUATE STUDENTS IN 2015



## EXHIBIT 7.23 PERCENTAGE OF WOMEN EMPLOYED IN PROFESSIONAL, SCIENTIFIC, AND TECHNICAL SERVICES IN 2016



Percentage of Women Employed in Professional, Scientific, and Technological Services

Note: Data are not available for Guam and the U.S. Virgin Islands.

### Racial Diversity in S&E Workforce Development

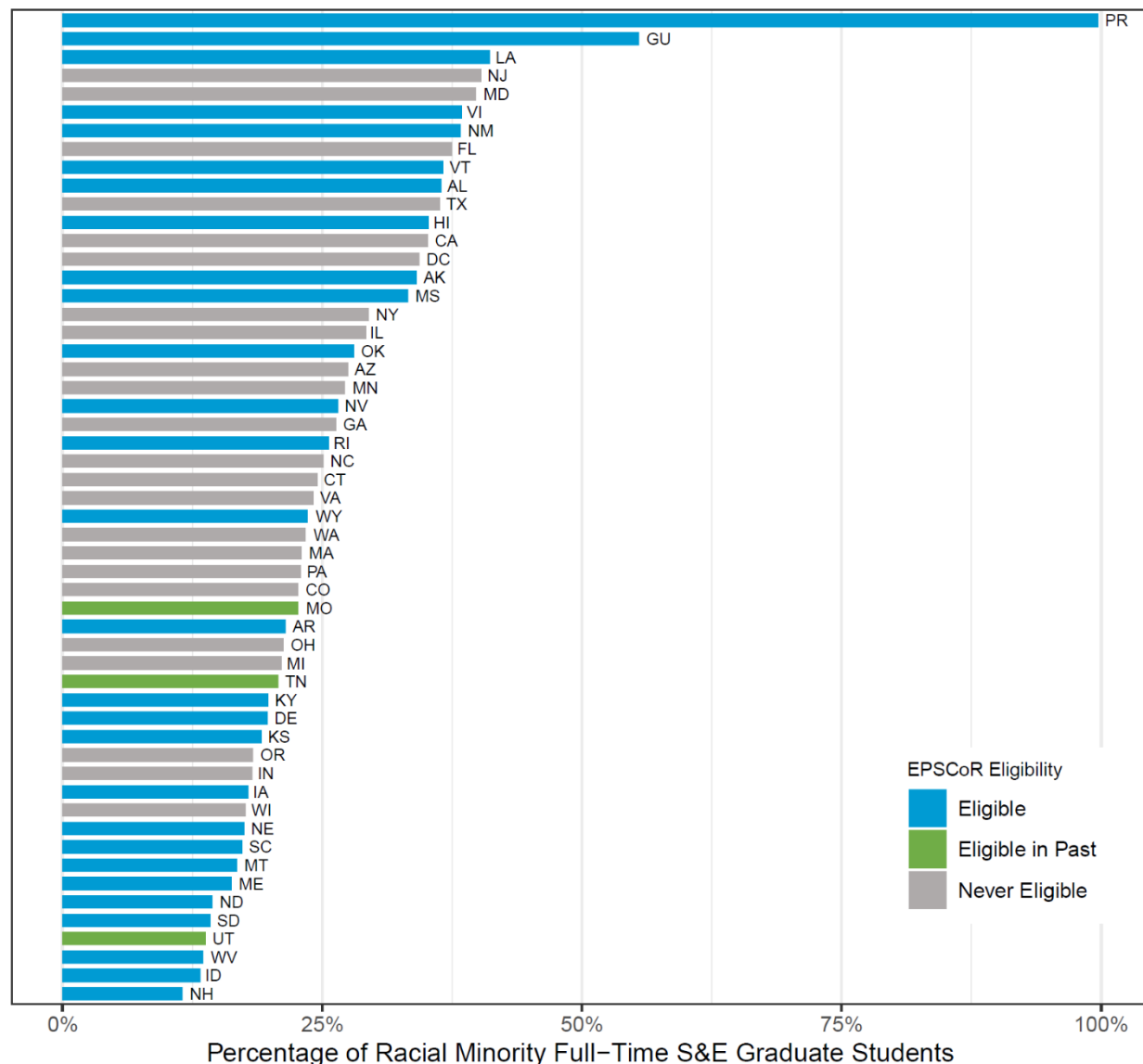
Although considerable progress has been made by racial minorities in increasing their share of S&E graduate degrees, they still remain underrepresented in S&E educational attainment and S&E occupations. Among students enrolled in full-time graduate school in S&E fields, racial minorities make up approximately 28 percent. Minority women perform academically slightly better than minority men (31 percent vs. 25 percent).<sup>76</sup> However, the proportion of minority S&E graduate students varies across jurisdictions. In a majority of the EPSCoR jurisdictions—

<sup>76</sup> National Science Foundation, National Center for Science and Engineering Statistics. (2019). *Women, minorities, and persons with disabilities in science and engineering: 2019* (Special Report NSF 19-304). Alexandria, VA. Retrieved from <https://ncses.nsf.gov/pubs/nsf19304/>



New Hampshire, Idaho, West Virginia, Utah, South Dakota, and North Dakota—less than 15 percent of graduate students in S&E fields are URM (Exhibit 7.24). This number reflects that these EPSCoR jurisdictions have a low percentage of minorities in their total populations. However, Vermont is an exception to this trend, as the jurisdiction has a high percentage of minority graduate students in S&E fields due to those enrolled in the University of Vermont medical school.<sup>77</sup>

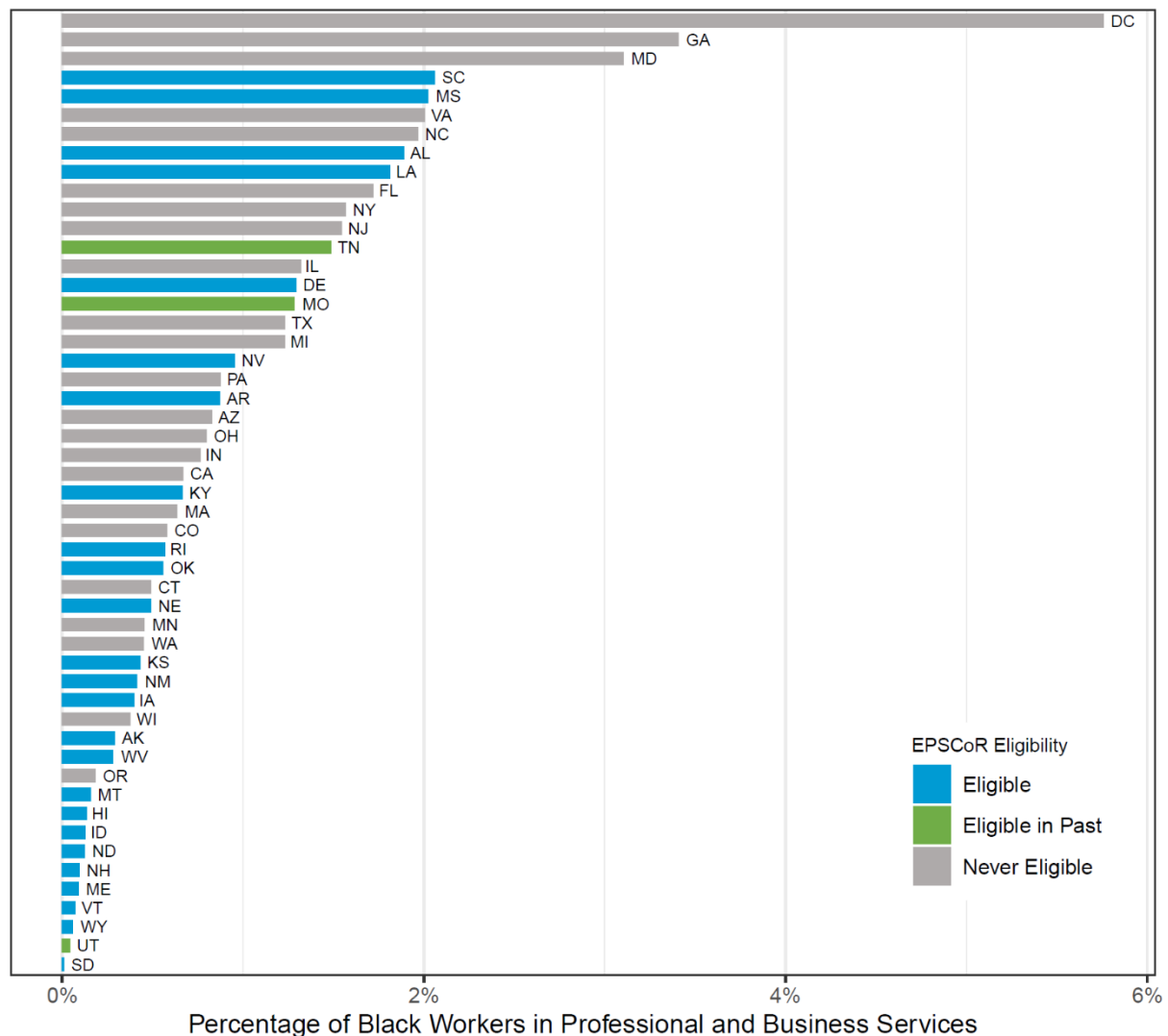
#### EXHIBIT 7.24 PERCENTAGE OF RACIAL MINORITY FULL-TIME S&E GRADUATE STUDENTS IN 2015



<sup>77</sup> Thirty-two percent of medical students at the University of Vermont are people of color. The percentage of non-medical minority graduate students is 10 percent, which is in line with the percentage of minorities in the state. University of Vermont. (n.d.). *UVM facts*. Retrieved from [https://www.uvm.edu/uvm\\_facts](https://www.uvm.edu/uvm_facts)

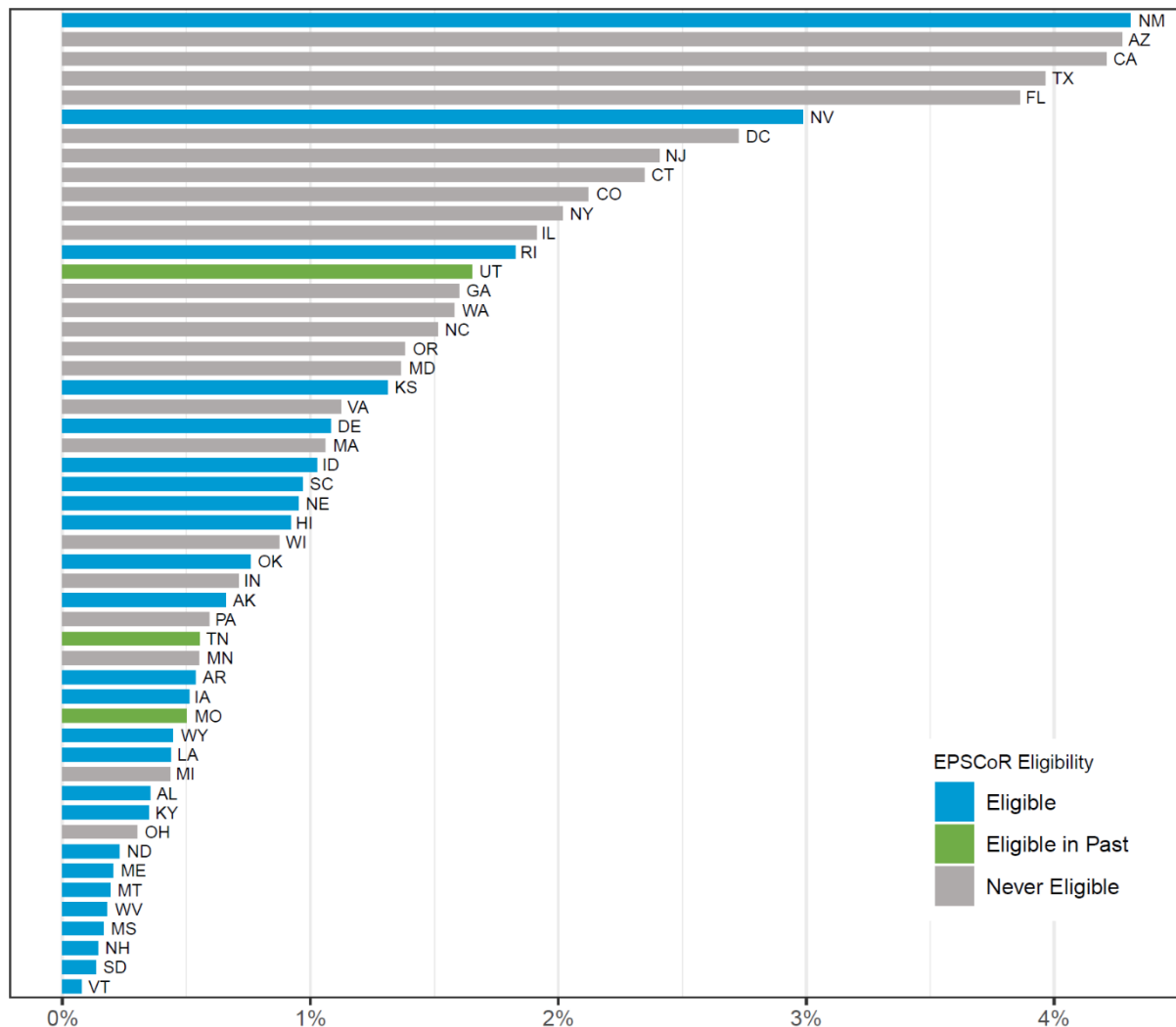
Only a few EPSCoR jurisdictions with higher minority populations have greater proportions of racial minorities working in professional and business services occupations than do non-EPSCoR jurisdictions, as shown in Exhibits 7.25 and 7.26.

### EXHIBIT 7.25 PERCENTAGE OF BLACK WORKERS IN PROFESSIONAL AND BUSINESS SERVICES IN 2016



Note: Data are not available for Guam, Puerto Rico, and the U.S. Virgin Islands.

## EXHIBIT 7.6 PERCENTAGE OF HISPANIC/LATINO WORKERS IN PROFESSIONAL AND BUSINESS SERVICES IN 2016



Percentage of Hispanic/Latino Workers in Professional and Business Services

Note: Data are not available for Guam, Puerto Rico, and the U.S. Virgin Islands.

Combined, these measures provide complex insights into how EPSCoR jurisdictions with significant minority populations may be better able to broaden participation of URMs in S&E and provide S&E career opportunities within their jurisdictions.

## Cluster of Jurisdictions with Common Outcome Measures

**The section addresses RQ 3c: Are there any clusters/groups of jurisdictions with common context and/or strategy characteristics that can be used to understand variability in research competitiveness?**

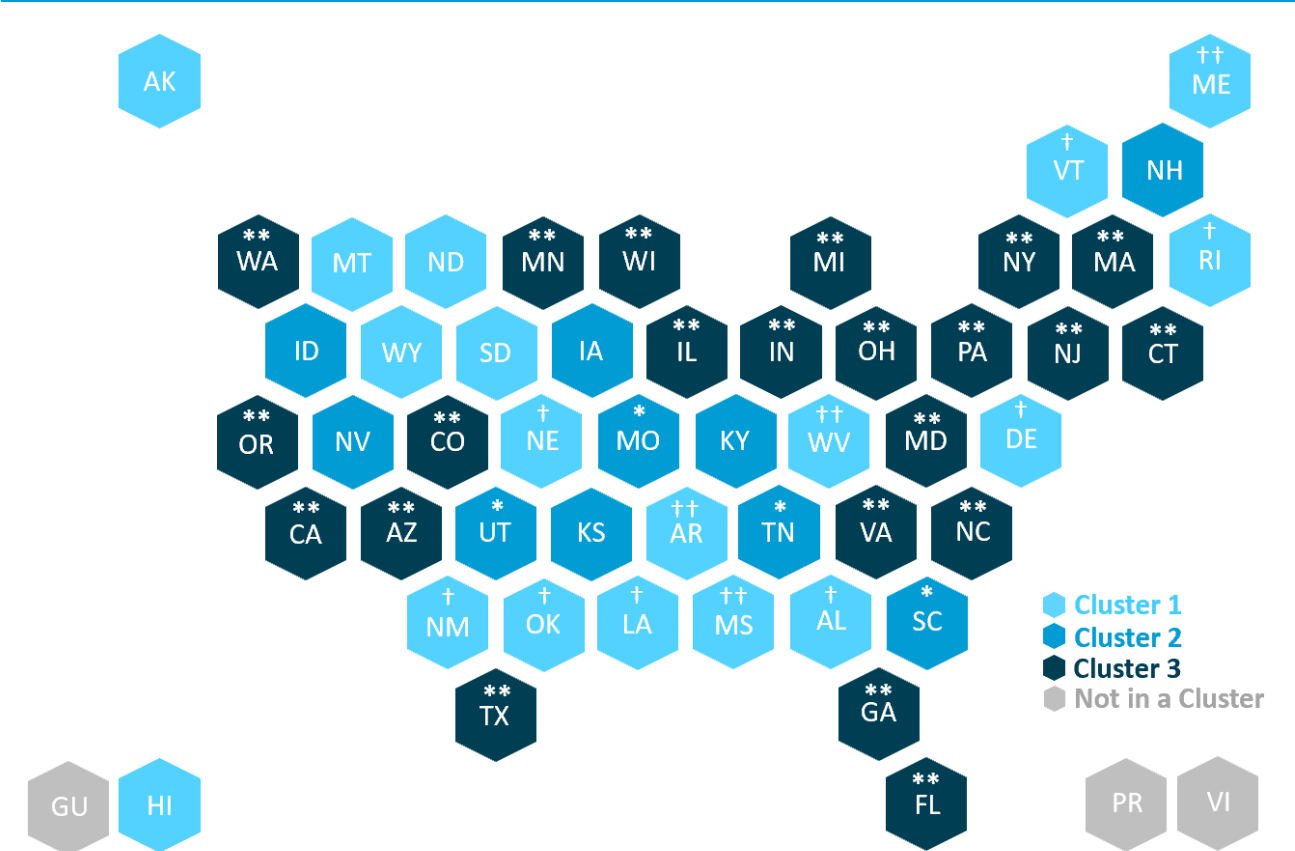
The exploratory factor analysis indicates that there are 4 factors underlying the 30 outcome measures. Using these outcome measures, the study team conducted an exploratory cluster analysis to group jurisdictions with common outcome measures (see details in Appendix D). As the emphasis is on grouping EPSCoR jurisdictions, the additional clusters of non-EPSCoR jurisdictions have been combined to form Cluster 3. Jurisdictions that are similar across these outcome measures were identified and are presented in Exhibit 7.27 (\*\*- indicates past EPSCoR jurisdictions)

- Cluster 1 – Alabama, Alaska, Arkansas, Delaware, Hawaii, Louisiana, Maine, Mississippi, Montana, Nebraska, New Mexico, North Dakota, Oklahoma, Rhode Island, South Dakota, Vermont, West Virginia, Wyoming
- Cluster 2 – Iowa, Idaho, Kansas, Kentucky, Nevada, New Hampshire, Missouri, \*\* South Carolina, Tennessee, \*\* Utah\*\*
- Cluster 3 – All Non-EPSCoR Jurisdictions (not listed)

**Notably, the grouping of clusters aligns closely with the NSF eligibility criteria for EPSCoR.**

Cluster 2 includes those jurisdictions that were eligible for EPSCoR in the past and others like Iowa, Kansas, South Carolina and New Hampshire that are close to the EPSCoR eligibility cut-off criteria.

## EXHIBIT 7.7 GROUPING OF JURISDICTIONS BY OUTCOME MEASURES



Note: \* indicates eligible for EPSCoR in the past. \*\* indicates never eligible for EPSCoR. Data are not available for Guam, Puerto Rico, and the U.S. Virgin Islands and as a result they are not in a cluster.

Cluster 1 could be further broken down into two more groups. The second group is denoted by †. The third group is denoted by ††. However, this was not the optimal number of groups according to the preset criteria laid out by the study team.

## Summary of Outcome Variability Findings

### EPSCoR jurisdictions vary along several measures in four outcome domains.

#### Human Capital Production



Compared to non-EPSCoR jurisdictions, a majority of EPSCoR jurisdictions

- produce low numbers of graduate students in S&E (relative to their population) except for jurisdictions with at least one highly reputed research-intensive doctoral university, and
- have a low percentage of their workforce with postsecondary education relative to their populations.

#### Reputation in Knowledge Production



The highest ranking institution in most EPSCoR jurisdictions tends to have lower national ranking in research capability and reputational measures compared to non-EPSCoR jurisdictions.

Jurisdictional Indicators of high reputation in knowledge production, such as NAI Fellows, SBIR program awards, and issued patents, are less prevalent in EPSCoR jurisdictions compared to non-EPSCoR jurisdictions.

Past EPSCoR jurisdictions tend to perform better on reputation in knowledge production measures than current EPSCoR jurisdictions.

#### Economic Development



Compared to non-EPSCoR jurisdictions, nearly all EPSCoR jurisdictions' economies present relatively limited opportunities for S&E graduates because the jurisdictions generally lag in the development of high-tech industries, with the exception of Utah.

#### Diversity in Labor Force



EPSCoR jurisdictions tend to have numbers of women participating in S&E graduate education and workforce that are similar to the numbers in non-EPSCoR jurisdictions, but they also tend to have lower participation by minorities in S&E graduate education and workforce.

Jurisdictions of similar EPSCoR status tend to cluster together around outcome measures.

#### Cluster 1

Alabama	Maine	Oklahoma
Alaska	Mississippi	Rhode Island
Arkansas	Montana	South Dakota
Delaware	Nebraska	Vermont
Hawaii	New Mexico	West Virginia
Louisiana	North Dakota	Wyoming

#### Cluster 2

Iowa	South Carolina
Idaho	Missouri
Kansas	Tennessee
Kentucky	Utah
Nevada	
New Hampshire	

#### Cluster 3

All non-EPSCoR jurisdictions

Note: Current EPSCoR Jurisdictions, Past EPSCoR Jurisdictions, Non-EPSCoR Jurisdictions

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## 8. FINDINGS RELATED TO EFFECTIVENESS AND INSTITUTIONALIZATION

This chapter addresses primary RQs 4 and 5, which focus on effectiveness and institutionalization. With the available data, the study team could partially address primary RQ 4. The study team also provides guidance for NSF regarding how consistent data can be captured while addressing primary RQ 5.

**This section addresses RQ 4a: What differences and similarities exist with respect to implementation strategies and levels of research competitiveness, as defined for this study, for EPSCoR jurisdictions?; and RQ 4c: What career pathways have been developed? To what extent are these career pathways diverse and inclusive, especially for early career researchers?**

The study was not able to address primary RQ 4a for the following reasons:

1. Thoroughly understanding the differences and similarities related to implementation strategies and levels of research competitiveness requires a deep dive into each jurisdiction's activities, which was not within the scope of this study. After agreement with NSF, the study team focused on publicly available data, so we were able to gain a high-level understanding of EPSCoR awardees' strategies through their final reports. However, the extent to which each awardee presented a comprehensive picture of their project varied greatly. Awards had varying focuses, jurisdictional contexts, and levels of reporting detail, which made it difficult to connect awardees' strategies to improvements in research competitiveness. In addition, the variation in the strategies is at the award level, as seen in Chapter 6, and not at the jurisdiction level—the level at which the AREC outcomes are available. It was not feasible for the study team to accurately account for jurisdictions with common implementation strategies because most jurisdictions implemented strategies to varying degrees. Determining the degree of implementation of a particular activity or strategy was beyond the scope of this study. Furthermore, reporting inconsistencies present within awardee final reports impeded the study team's efforts to consistently measure or analyze strategic activities across all jurisdictions.
2. The study captures the jurisdictions' research competitiveness at one point in time. Assessing the levels of research competitiveness and how those levels relate to implementation strategies requires measuring research competitiveness before and after strategies are implemented by jurisdictions.

3. Jurisdictions may have received earlier awards that use the same implementation strategy or activity as recent awards. However, the study team only reviewed the most recent award reports. As a result, if the earlier awards implemented the same strategies as recent rewards, then the effect of the strategy will also be underreported.
4. The reality of linking jurisdictions' implementation strategies to the levels of research competitiveness for EPSCoR jurisdictions is complicated due to the nature of the awards. The awards represent a maximum of \$20 million across 5 years, and there are other externalities that these awards may attract that will not be captured succinctly in the analysis.

In order to successfully analyze specific implementation strategies and combinations of these strategies that can strongly increase jurisdictions' research competitiveness, the study team suggests conducting implementation studies of some jurisdictions. To thoroughly examine the jurisdictions' efforts to improve research competitiveness, these implementation studies should conduct stakeholder interviews, key informant interviews, and document analysis, which will capture and verify the breadth of strategies implemented. In addition, these future studies can use the research framework developed in the current study to examine the change in AREC outcomes over time due to these strategies. We also suggest analyzing current EPSCoR-eligible jurisdictions that are just below the eligibility cut-off and previously EPSCoR-eligible jurisdictions that are just above the eligibility cut-off. The differences in implementation strategies across these two types of jurisdictions and their contributions toward research competitiveness will provide some exploratory evidence regarding which strategies seem to be influential.

The study team was not able to address primary RQ 4c because the study did not collect data across the 31 current and previously EPSCoR-eligible states to explore the career pathways developed by the institutions in these jurisdictions, especially for early career researchers. This information is not consistently captured in a publicly available dataset and would require considerable effort to be captured consistently across the several institutions in each jurisdiction.

**This section addresses RQ 4b: Are there specific strategies or combinations of strategies with evidence of stronger influence or contribution toward research competitiveness than others? For example, how do EPSCoR and non-EPSCoR institutions in similar Carnegie Classification currently compare with respect to research competitiveness as defined for the study?**

This study is not able to answer the fundamental question asked by RQ 4b regarding the specific strategies or combination of strategies that contribute to jurisdictional research competitiveness. However, the study team is able to compare a part of research competitiveness as captured by reputation in knowledge production in the main institution of



higher education across EPSCoR and non-EPSCoR jurisdictions. This explicit comparison is presented in Chapter 7 in the section on Institutional Reputation in Knowledge Production.

**This section addresses RQ 5: What ongoing evaluation processes, practices, and structures—in particular those related to stakeholder engagement, data collection, and analysis—are feasible to support and sustain the current and future implementation of a longitudinal program-level evaluation with common measures and a consistent yet flexible analytic approach?**

To implement the AREC framework and the associated logic models presented in Chapter 2, the study team relied entirely on publicly available extant datasets. The study team identified existing data and developed a dataset to provide evidence accounting for potential impacts across all AREC elements. However, assessment of the available data in Chapter 3 underscores the significant data challenges because the data coverage of the AREC framework and resulting logic models is incomplete, as described in the study limitation section in Chapter 4. While the compiled data enabled some exploration of the distribution of AREC across jurisdictions and the relationship between AREC variables in Chapters 5–7, it also revealed critical gaps in data that limit analysis. Lack of consistent data across all jurisdictions restricts the evidentiary base for program planning, design, operation, and evaluation. Additional data analysis using identifiable data that allow for linking across projects, institutions, and jurisdictions can shed more light on factors that differentiate research activities and the diverse set of AREC outcomes. In particular, the evaluation processes, practices, and structures—especially related to data collection and analysis—will be greatly enhanced by creating consistent data collection and reporting requirements.

*Common Data Requirement.* EPSCoR staff can create a standardized reporting form designed to capture the context, strategies, and outcomes consistently, and in more detail, without reporting the technical aspects of the project. This standardized reporting form can help build stronger evidence for understanding the variability across the strategies used by jurisdictions and how they affect research competitiveness of the jurisdiction, as well as provide EPSCoR staff with the ability to track whether projects meet the objectives of their awards. In addition, the jurisdiction EPSCoR staff can aggregate this award-level information to the jurisdiction level.

*EPSCoR Baseline Evaluations.* The AREC framework provides a grounding structure for guiding the evaluation of the EPSCoR portfolio of awards. However, these awards vary considerably in disciplinary focus, collaborations with institutions within the jurisdiction, and expected impacts. Each EPSCoR award has external evaluation requirements, and these processes may be leveraged to capture improved jurisdiction- and institution-level data by incorporating required AREC elements in the specific project evaluations. At the same time, it is important to allow

tailoring of the award-level evaluative approaches to account for unique characteristics; the AREC framework and baseline data elements can inform the identification of priority elements in jurisdictions and strengthen the EPSCoR evaluation portfolio by providing approaches for all EPSCoR evaluations. The study team suggests NSF include in all award evaluations the following baseline set of questions as part of the preparation of the Year 1 data in their evaluation plans, as shown in Exhibit 8.1. Importantly, these data should be part of the external evaluator scope and should not pose additional burden to jurisdictional EPSCoR staff. These baseline questions build context into existing evaluations and strengthen evaluation processes, as well as the quality and appropriateness of their findings and recommendations.

*EPSCoR Longitudinal Data.* The framework, reporting form, baseline data, and compiled dataset will provide a foundation for the development of a data consortium and repository for EPSCoR projects. Coordination and communication across jurisdictions can improve the collection of consistent data to capture and track the components of AREC in each EPSCoR jurisdiction. These data can be captured using a dashboard that can help track the progress made by ongoing evaluation processes, practices, and structures to support and sustain a longitudinal program-level evaluation with common measures and a consistent yet flexible data collection approach. The study team recommends the development of a more robust dataset based on AREC-relevant variables to provide a more complete understanding of the capacities and complexities within jurisdictions. We recommend that NSF continue to identify and integrate additional data sources that could be mapped to the AREC framework developed by this study. The data inventory compiled for this study provides a foundation for ongoing work in this area.

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**TABLEAU DASHBOARD:** *The study team developed a Tableau dashboard to facilitate the exploration of the various AREC measures at the jurisdiction level. The dashboard has two features, one to view a single measure collected at one point in time and another for viewing two measures simultaneously. This dashboard displays the measure in two ways: as a tile map and an ordered bar chart. Currently, the study team has programmed all the contextual and outcome measures, which can be accessed using the dropdown menu located at the top of the dashboard. The dashboard provides an additional feature that enables the user to select jurisdictions based on their EPSCoR eligibility statuses. In addition, specific values of the measures for a particular jurisdiction can be viewed by hovering over the specific bar in the ordered bar chart. Finally, an image can be downloaded using the “download” icon at the bottom of the dashboard. Similarly, the dashboard can be used to create a scatterplot for two measures using the dropdown menus for the X- and Y-axis, respectively. In this case, each point represents a jurisdiction. All other features are similar to the single-measure dashboard. One important feature of the two-measure dashboard is the ability to identify clusters of jurisdictions that are similar on these measures. This dashboard can be used to longitudinally track these outcomes to observe progress along the measures and is a feasible and sustainable method to track common measures that can be used for eligibility, as well as evaluation of EPSCoR.*

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## EXHIBIT 8.1 BASELINE CHARACTERISTICS TO INCLUDE IN EVALUATION



### JURISDICTION AND PROJECT LEADERSHIP STRUCTURE

- EPSCoR office structure: For R1 institutions, how is the EPSCoR office organized? For example, does the office have a permanent administrative head or staff?
- Is the principal investigator a scientist, university administrator, or professional staff person?



### JURISDICTION CHARACTERISTICS

- How has jurisdiction support for education and research changed in the 5 years prior to the project? What is the budget health jurisdiction-wide and in the project institutions?
- What are the types of postsecondary institutions in the jurisdiction? What are the characteristics of partner institutions in the jurisdiction, including their prior research grant activities?
- What baseline conditions are evident in the jurisdiction and partner institutions in terms of workforce/faculty/student diversity, and characteristics of URM populations in the project disciplines?
- What industry base and opportunities/trends exist in the jurisdiction that are relevant to project external partnerships?



### INSTITUTIONAL CAPACITY AND CHARACTERISTICS

- What ties exist between project partner schools (e.g., joint degrees, student educational pathways)?
- For PUIs, what existing Office of Sponsored Program staff and grant administration capacities do these institutions have? If commercialization is an aspect of the project, what technology transfer office resources are available?
- What existing outreach and education resources are available on partner institution campuses?
- What is the structure and availability of proposal submission data at partner institutions? Which data are tracked?
- For all institutions, what are faculty teaching loads and buyout policies at the institutional level and in the project-affiliated departments?
- How important is undergraduate research for the college or universities? How is undergraduate research integrated in PUI curricula? What level of federal grant experience have PUIs had in the past?



### TEAM CAPACITY AND CHARACTERISTICS

- For R1 and R2 institutions, what is the baseline science and research capacity of the project? What is the baseline level of prior research collaboration among all partners and disciplines? What is the interdisciplinary and cross-institutional experience of the project team?
- To what extent is the research team using existing facilities, and how much will the facilities and/or equipment supported by the EPSCoR project represent new resources on campus?

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## 9. CONCLUSION AND RECOMMENDATIONS

This section addresses RQ 6: What insights can be drawn from the evidence compiled to address RQs 1 through 5 that can be used to inform programmatic strategic directions?

EPSCoR is a federally funded research program to enrich jurisdictional research capacity and ultimately improve the research competitiveness of jurisdictions that have historically received little federal R&D funding. EPSCoR's mission is to build research capacity in order to enable competitiveness by providing research funding to academic institutions in eligible jurisdictions. Because the development and sustainability of research excellence and competitiveness occurs within such a complex institutional and environmental context, it is critical to recognize the different dimensions of research achievement and the structural characteristics of the research system that advances or constrains it. This study was motivated by the desire of NSF to inform communication and representation of EPSCoR and provide input and tools for portfolio planning and management. The main purpose of this study was to articulate a framework that clearly identifies the multiple dimensions of research capacity and competitiveness, as well as to examine empirically how those dimensions demonstrate variations, strengths, and weaknesses relevant to improving competitiveness in the jurisdictions. This study has made significant conceptual, theoretical, and empirical progress toward identifying the relevant elements and factors that constitute academic research competitiveness. An important aspect of this approach is that it does not view research activities or competitiveness without context; instead it uses a systems perspective to demonstrate the nested nature of academic research within institutions and jurisdictions.

More specifically—

- The **conceptual AREC framework** and the systems approach that links the logic models at the jurisdiction, university, and project levels provide an initial formulation of a comprehensive treatment of AREC in the U.S. context.
- The compiled **data inventory** provides a foundation of existing evidence for testing and implementing the AREC framework for program management and evaluation. The study has also revealed critical data gaps and opportunities for NSF to develop further guidance for EPSCoR evaluation.
- The **data analysis** illustrates (when data are available) similarities and differences across jurisdictions according to elements identified in the AREC framework. Connections across AREC levels also demonstrate the nested, multilayered system in which academic research (and EPSCoR-funded activities) operates.

It is important to note that this study is not an evaluation. Rather, its purpose is to develop comprehensive knowledge of the key factors that contribute to jurisdictional AREC, as well as

the jurisdictional variability in these key factors. The study operationalizes this knowledge in order to answer six primary RQs related to *contextual variability*, *strategic variability*, *outcome variability*, *effectiveness*, *institutionalization*, and *improvement*. Specifically, the analyses presented in this study demonstrate how publicly available data can be used to assess the progress of each jurisdiction along the key contextual, strategic, and outcome measures.

Furthermore, the use of a jurisdiction-wide NSF funding acquisition metric for EPSCoR does not capture the multidimensionality of research competitiveness. In particular, the metric does not address the complex environment in which academic scientific research and related activities take place: Research is nested in institutions that have varied research cultures and resources, and in jurisdictions that differ considerably in contextual factors relevant to STEM workforce, economies, and priorities. A single jurisdiction-level measure may not support strategic program planning and portfolio management in ways that are actionable and reflective of the variation in capacity and competitiveness across the jurisdiction.

The exploratory factor analyses indicate that the following three latent factors underlie several contextual measures that were collected for this study:



**Environment and Institutional Capacity**



**Research Capacity**



**Jurisdiction-Level Financial Resource Capacity**

and four latent factors underlie the several outcome measures that were included:



**Human Capital Production**



**Reputation in Knowledge Production**



**Economic Development of Knowledge and Science-Intensive, High-Technology Industries**



**Racial and Gender Diversity in Labor Force Development**

Descriptive analysis of jurisdictional contextual measures show that compared to non-EPSCoR jurisdictions, a majority of EPSCoR jurisdictions are different in terms of these key contextual measures. One significant contextual difference is that these EPSCoR jurisdictions tend to have much smaller numbers of research-intensive universities, which may help explain EPSCoR jurisdictions' lower level of research competitiveness for R&D funding. Moreover, examining jurisdictions that are closely aligned on contextual measures shows that they are most similar to each other in their population sizes. To account for the contextual differences in population sizes, it is important to standardize outcome measures. The study also found substantial contextual variation across jurisdictions, even after standardizing the measures to account for differences in population size.

Using the logic model developed with the AREC framework for this study and literature review, the study team identified that the most common activities undertaken across the funded tracks were related to **research**, **education**, and **outreach and engagement**. Specifically, the EPSCoR funding mostly supported the following strategic activities:

- Building cyberinfrastructure
- Building state or local programs
- Funding undergraduate and graduate students or existing faculty
- Creating instructional or curricular materials
- Holding workshops, camps, or seminars
- Supporting collaborative relationships within a jurisdiction

These activities are related to implementation strategies used by a jurisdiction to improve its level of research competitiveness. However, EPSCoR awards had varying focuses, jurisdictional contexts, and levels of reporting detail, which made it difficult to connect awardees' strategies to improve research competitiveness. This challenge meant that the study team was unable to achieve a higher understanding of the EPSCoR awardees' strategies—resulting in the study team's inability to comprehensively explain why awardees' strategies varied widely across jurisdictions and award tracks. This variability highlights the diversity in awardees' reporting mechanisms, investigators' interpretations of the Solicitations, and jurisdictions' baseline needs or capacity.

Finally, the descriptive analysis of the jurisdictional outcome measures shows that, compared to non-EPSCoR jurisdictions, a majority of EPSCoR jurisdictions have low measures of human capital production. These low measures stem from a lack of reputed, research-intensive doctoral universities, which limits opportunities for S&E graduates because these jurisdictions lag in the development of high-tech industries. Specific jurisdictions, such as Utah, have been able to create pathways programs that support collaborative efforts between the private and public sectors, which allows the jurisdiction to address industry workforce needs as the state continues to build its S&E workforce by attracting new, reputed faculty.

Our findings show that jurisdictions similar on contextual measures have different values on outcome measures, suggesting a need for an in-depth investigation of jurisdiction-specific programs, policies, and practices that could be driving these differences. Various contextual and outcome measures can be used to classify the EPSCoR jurisdictions into groups that are similar,

and these groups can be used to understand how different strategies result in differences in measures that represent research competitiveness. An exploratory cluster analysis of the jurisdictions using the outcome measures reveals that the grouping aligns closely with the NSF eligibility criteria for EPSCoR (see Exhibit 7.27).

## **LIMITATIONS**

Despite its contributions to understanding the research competitiveness variability, this study has limitations that are differentiated by the overall use of the framework and conceptual and data-related aspects of the study.

### **Limitations Regarding Implementation of Concepts**

This study has articulated a framework based on a wide range of literature and empirical studies in the EPSCoR context. The availability of data for fully testing the framework, combined with the varied political and institutional cultures in the jurisdictions, means that applying the framework and accompanying logic models to a specific project and jurisdictional context should be tailored to those specific contexts.

While this study has helped move closer to an improved set of indicators that may depict EPSCoR jurisdiction research capacity, given the data limitations for a fuller examination of the AREC framework, it is premature to suggest one or more new metrics for EPSCoR eligibility at this time. However, this study has revealed some of the unique aspects of jurisdictions that are critical for research competitiveness, as well as some aspects that may pose limiting factors. For example, findings show that jurisdictions near the EPSCoR eligibility cutoff margin (on both sides) may benefit (in terms of overall grant acquisition statistics) from the presence of a federal research center, but the findings may not reflect the research capacity of the jurisdiction's institutions.

### **Data-Related Limitations**

Given data availability (or lack thereof), the study team suggests using caution while using the findings of this study, especially when making significant programmatic decisions. Rather, the study team believes the AREC framework will be helpful in the program planning and communication stages. The data inventory presented in this study can inform EPSCoR management regarding the progress made by each of the jurisdictions over the years, even though it cannot be used to draw causal conclusions about how to increase research competitiveness. These caveats aside, the AREC framework and the corresponding data inventory provide theoretical underpinnings and data assessments that demonstrate the potential for application and substantial use for NSF in the future.

## Recommendations

The results of this study lend themselves to two groups of recommendations. First, the study team presents recommendations on how the AREC framework and resulting observations can inform program conceptualization and communication. These recommendations are based on the conceptual work for the AREC framework (Chapter 2) and results of the data inventory (Chapter 3). Second, the study team presents actionable recommendations specific to EPSCoR implementation and operation. These recommendations are based on the analyses (Chapters 5–8) while understanding the limitations of the data inventory (Chapter 3).

### 1. RECOMMENDATIONS FOR COMMUNICATING, REFINING, AND IMPLEMENTING AREC FOR EPSCoR

Research excellence and competitiveness has long been understood to be operationalized in the federal research policy environment as success in obtaining grant funding. Yet, EPSCoR projects are distinctive within the larger NSF funding portfolio because of their emphasis on many AREC elements across different program tracks: scientific excellence and productivity, research capacity, workforce development, education and workforce diversity, early career engagement, education and outreach, stakeholder interaction and impacts, institution-level research culture and capacity. The AREC framework offers an opportunity for NSF to capture and articulate research competitiveness and align the broad range of these interconnected EPSCoR priorities to NSF's capacity development and research competitiveness goals. The AREC framework also provides a basis for communication and engagement with ongoing project leadership, EPSCoR evaluators, and other policy stakeholders.

*Recommendation 1.1: Solicit EPSCoR Community Input to Communicate and Refine the AREC Framework.* The AREC framework is based on a broad foundation of interdisciplinary literature and empirical research. Because the intention is to apply this framework to programmatic activities, it is critical to solicit the feedback and reaction from the target community. **We recommend that the NSF EPSCoR office organize EPSCoR project investigators' and officers' community meetings where the framework can be addressed and refined if needed.** This is important in the future use of the framework for communication and application to project evaluation or other activities.

*Recommendation 1.2: Implement AREC Elements in EPSCoR.* Because several elements of the AREC framework already exist as part of EPSCoR's capacity-building program objectives, this framework provides a foundation for further linking and demonstrating how program objectives relate to research excellence and competitiveness. **We recommend that the vetted AREC framework be refined and consciously structured for use as a guide to evaluating EPSCoR projects.** For example, NSF EPSCoR could develop concise guidance and explanation of the AREC framework. Guidance could include the development of written materials and other online media for EPSCoR teams and leadership, NSF EPSCoR evaluators, and external review committees. Such a structured approach would produce a common language and shared concepts that could enable standardizing elements while also allowing for the tailoring of evaluation components to specific projects/jurisdictions.



## 2. RECOMMENDATIONS FOR CHANGES IN EPSCoR PROGRAMMATIC ELEMENTS FOR FUTURE EVALUATIONS

While this study was not an evaluation, the findings and the limitations of this study have led the study team to make the following recommendations for changes in EPSCoR programmatic elements that can aid future evaluations.

*Recommendation 2.1: Create a Common Data Repository.* The work conducted in this study identifies significant data challenges. Specifically, the data inventory developed by this study underscores the existing data's limitations in regard to providing evidence that accounts for potential impacts across all AREC elements. The lack of consistent data across all jurisdictions limits the evidentiary base for program planning, design, operation, and evaluation—especially in the territories, which might experience the most significant impacts as a result of the EPSCoR program. Given EPSCoR's mission, ***we recommend the development of a more robust data repository based on AREC-relevant elements to provide a more complete understanding of the research capacities and complexities within jurisdictions.*** In order to facilitate the creation of this dataset, we recommend creating a common data repository through the following steps:

1. Create a standardized reporting form designed to capture the context from the EPSCoR jurisdictions' perspectives. The reporting form should emphasize the details of the strategies used that are aligned with the refined EPSCoR logic model without covering the technical aspects of each specific project (especially for Track-3 awards). This standardized reporting form can also collect critical outcome information, especially outcomes aligned with the domains highlighted in this study: human capital production, reputation in knowledge production, economic development of knowledge and science-intensive, high-technology industries, and racial and gender diversity in labor force development. These outcome measures can be collected at the award level but can also be aggregated to the jurisdiction level for further reporting.
2. Create a longitudinal database of the key contextual and outcome measures—at least within the domains highlighted in the study, but also using new data that might become publicly available.

The standardized reporting form, along with the longitudinal data, can help build a stronger understanding of the variability across the jurisdictions' contexts and strategies used, and the outcome measures. The reporting form and the longitudinal data can also provide EPSCoR staff with the ability to track whether projects successfully meet the objectives of the EPSCoR award. The AREC framework, reporting form, and data inventory will provide a foundation for the development of a data consortium and repository. In addition, we suggest NSF EPSCoR staff coordinate and communicate with jurisdictions to improve the collection of consistent data elements to capture and track the various components/domains of AREC in EPSCoR jurisdictions.

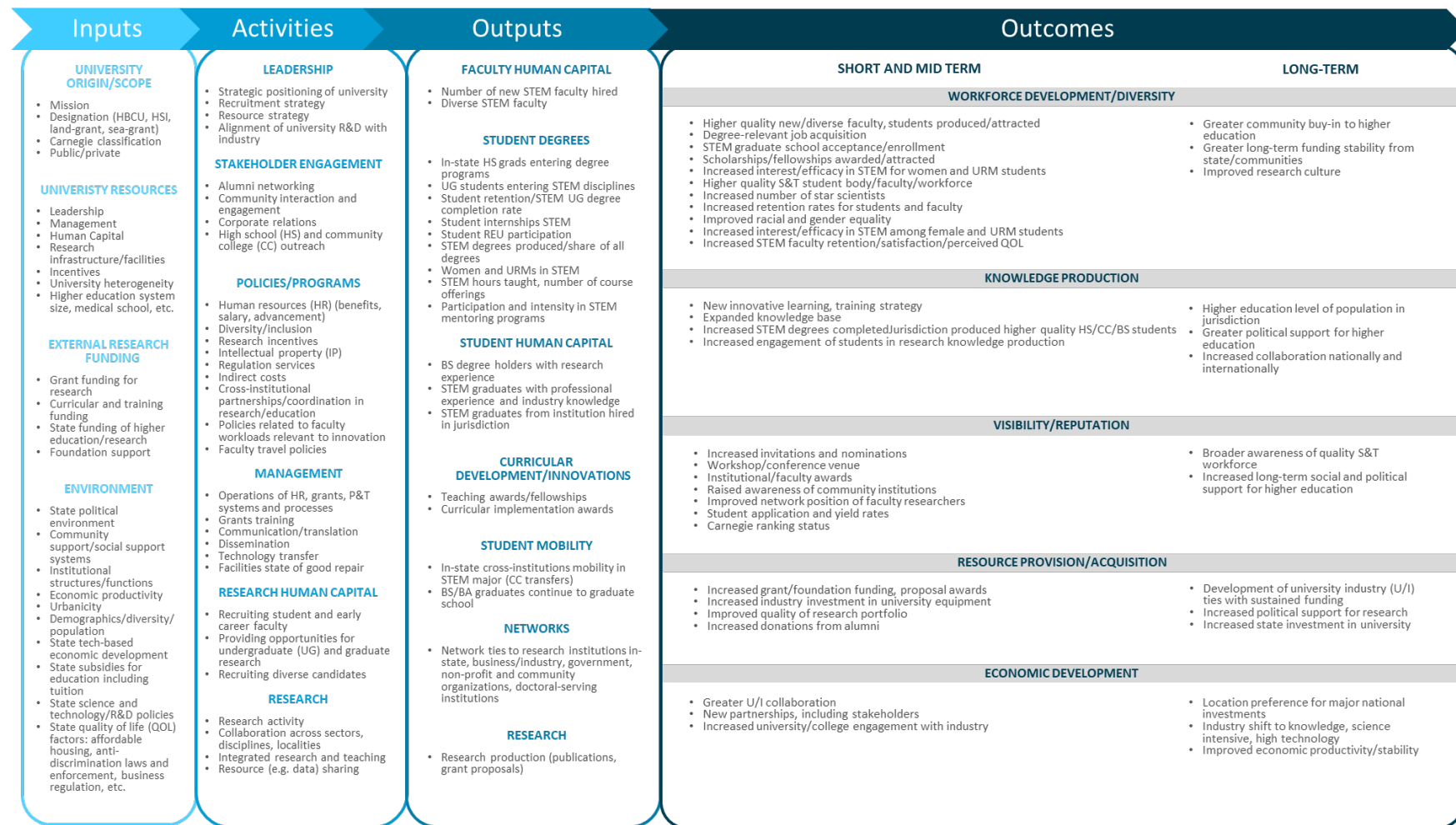
*Recommendation 2.2: Conduct Future EPSCoR Evaluations.* ***We recommend small, focused implementation studies be conducted, focusing on similar clusters of jurisdictions to thoroughly examine the jurisdictions' efforts to improve research competitiveness.*** These implementation studies should include stakeholder interviews, key informant focus groups, and

document analysis, which will capture and verify the breadth of strategies implemented, as well as the reason for implementing these strategies. In addition, these future studies can use the AREC framework developed in this study to guide evaluation and examine the change in AREC outcomes over time due to these strategies. We highly recommend including current EPSCoR-eligible jurisdictions that are just below the eligibility cutoff and previously EPSCoR-eligible jurisdictions that are just above the eligibility cutoff in one of these possible studies. The differences in implementation strategies across these two types of jurisdictions and their contributions toward research competitiveness will provide some exploratory evidence regarding which strategies/activities seem to be influential in improving research competitiveness and can be incorporated across other EPSCoR jurisdictions.

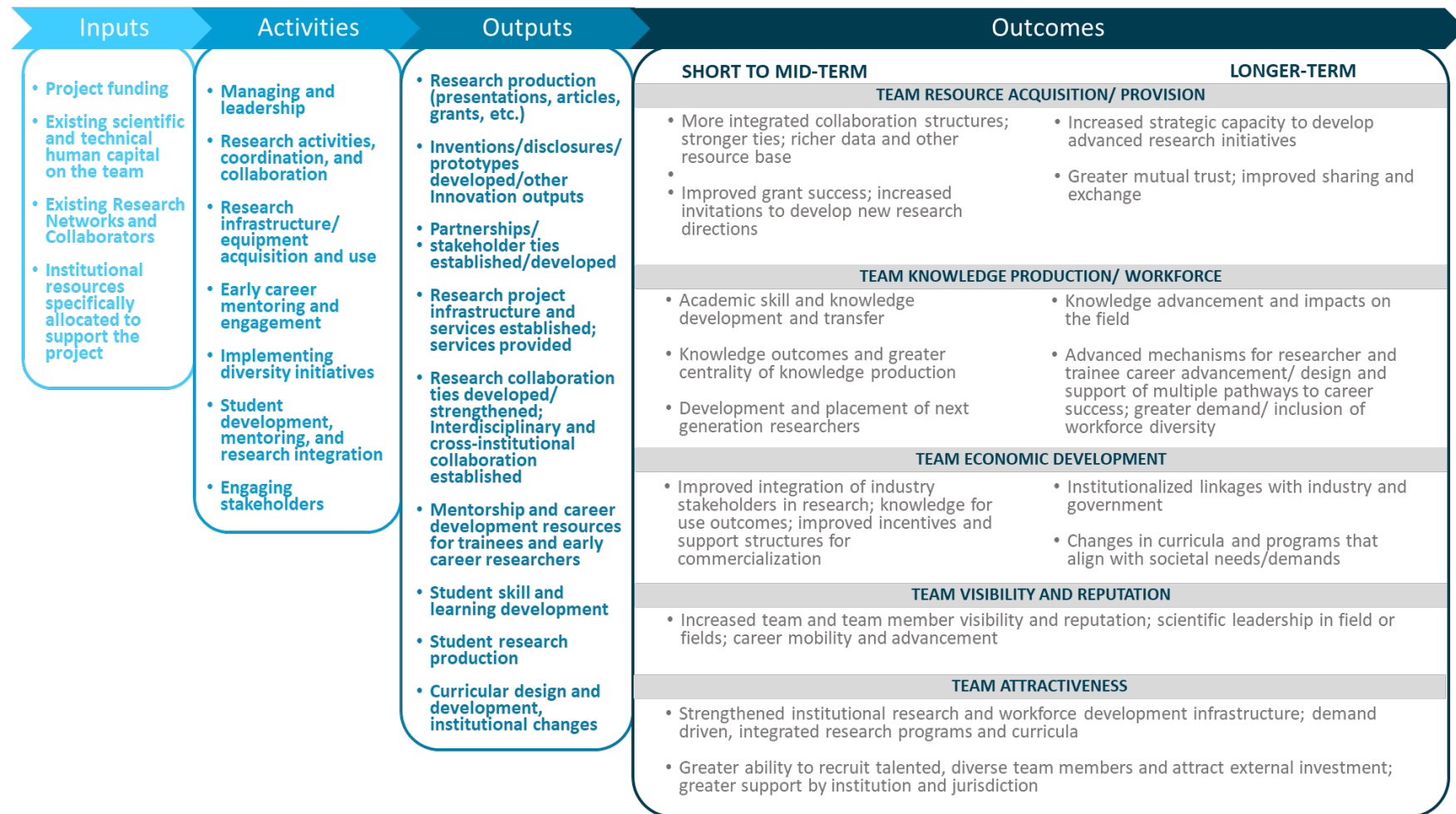
*Recommendation 2.3: Standardize the Measures Used for Evaluation.* A minor but consequential finding of the study is that significant variation exists in jurisdiction size, which makes it difficult to meaningfully compare measures across jurisdictions. Our recommendation for NSF is to standardize the evaluation measures.

## APPENDIX A. ADDITIONAL LOGIC MODELS

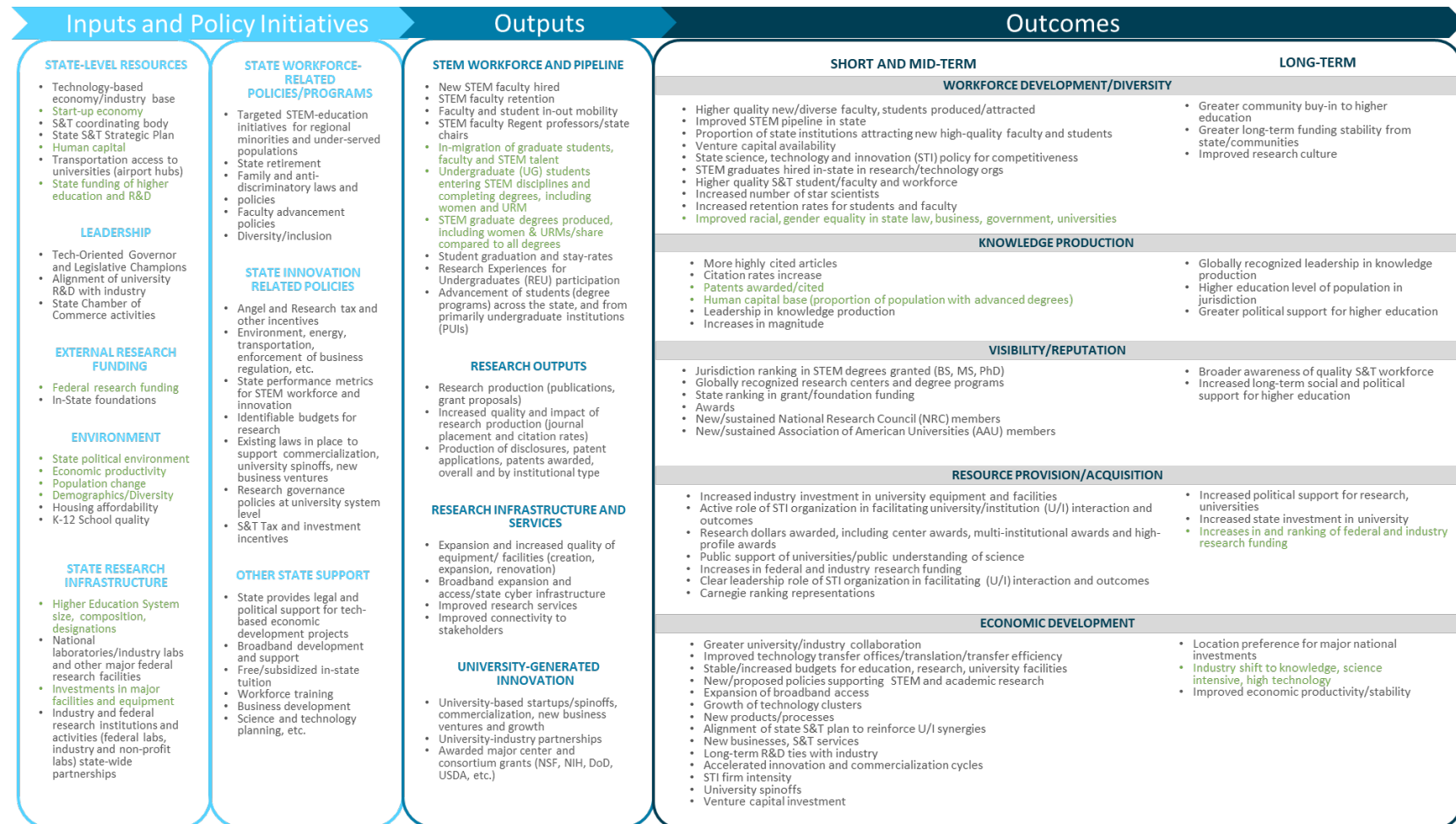
### EXHIBIT A.1 LOGIC MODEL FOR NONDOCTORAL INSTITUTIONS



## EXHIBIT A.2 LOGIC MODEL FOR PROJECT/CENTER LEVEL (NOT IN AN EMBEDDED SYSTEM)

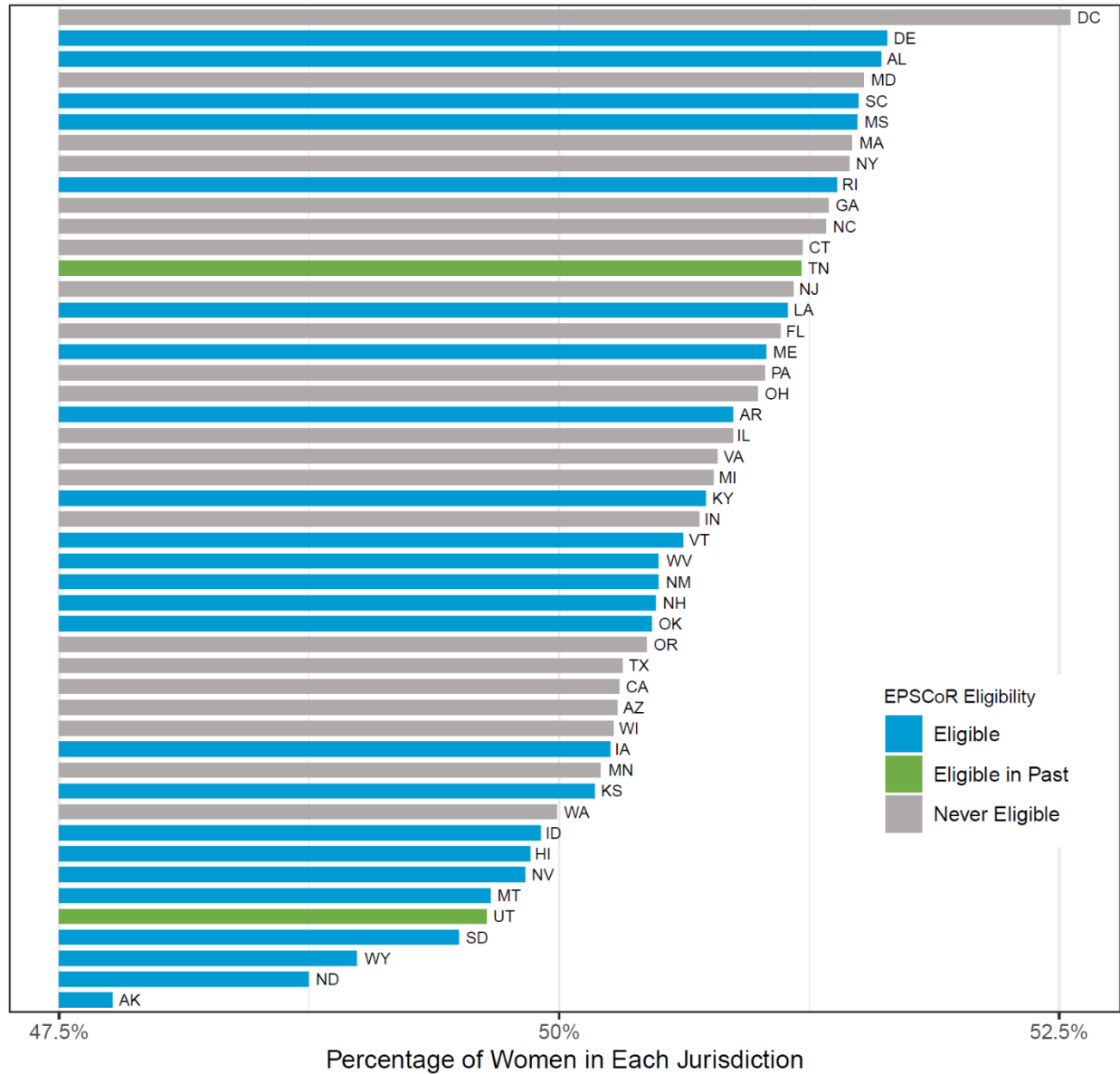


## EXHIBIT A.3 DATA AVAILABILITY FOR JURISDICTIONAL-LEVEL MEASURES



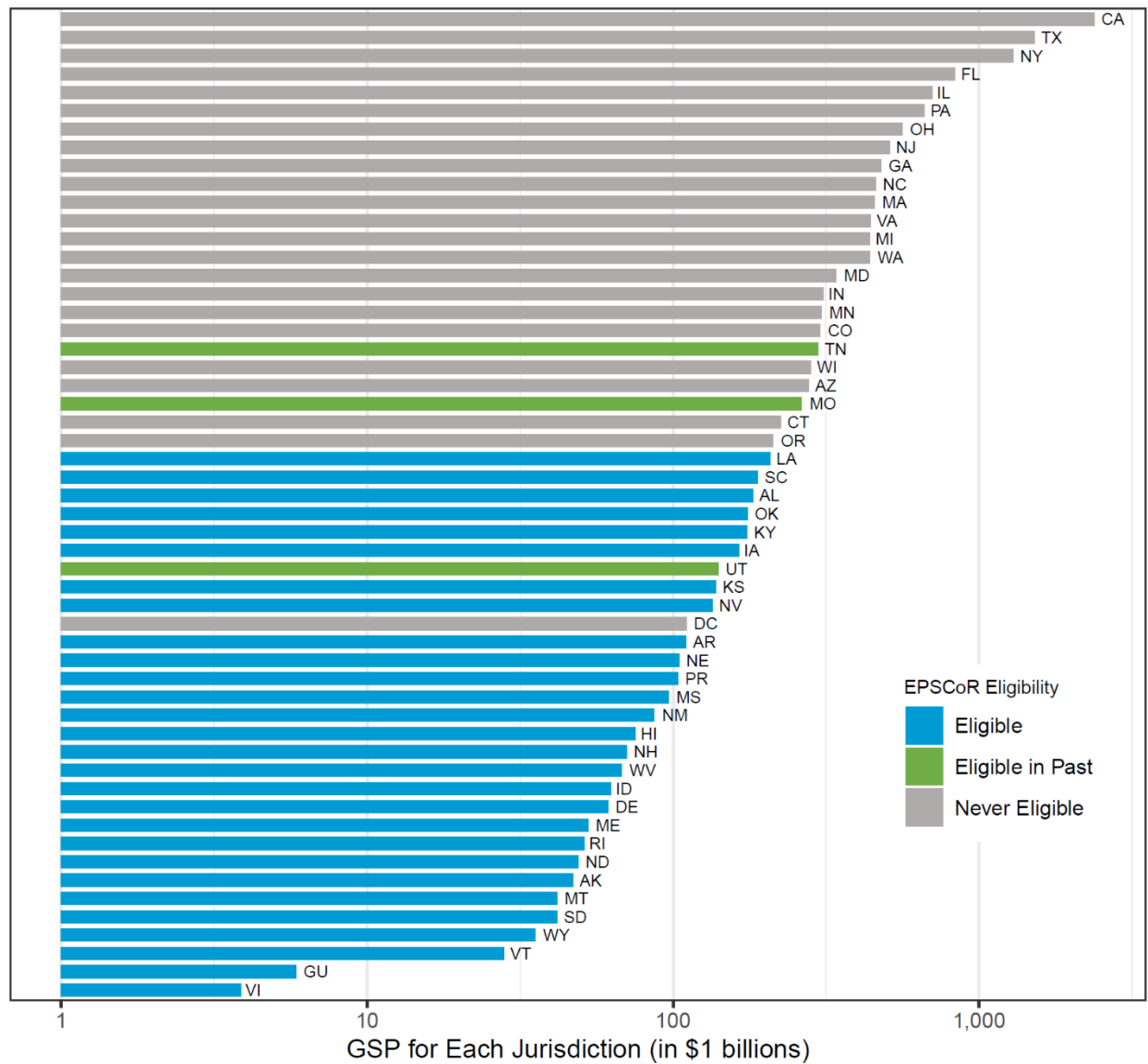
## APPENDIX B. UNSTANDARDIZED CONTEXTUAL MEASURES

### EXHIBIT B.3 PERCENTAGE OF WOMEN IN EACH JURISDICTION IN 2017



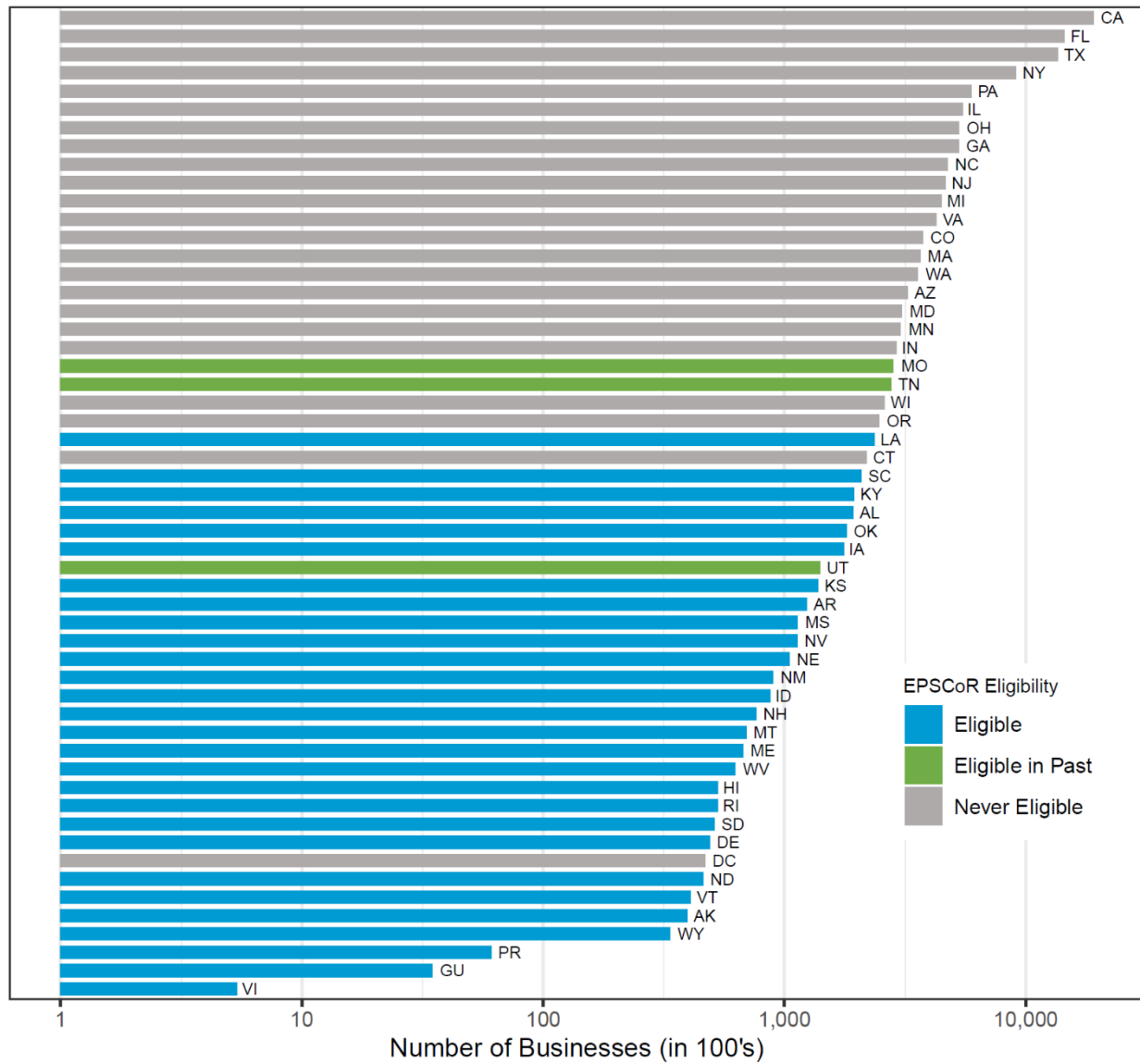
Note: Data are not available for Guam, Missouri, Nebraska, Puerto Rico, and the U.S. Virgin Islands.

## EXHIBIT B.2 GSP IN 2017



Note: In log scale.

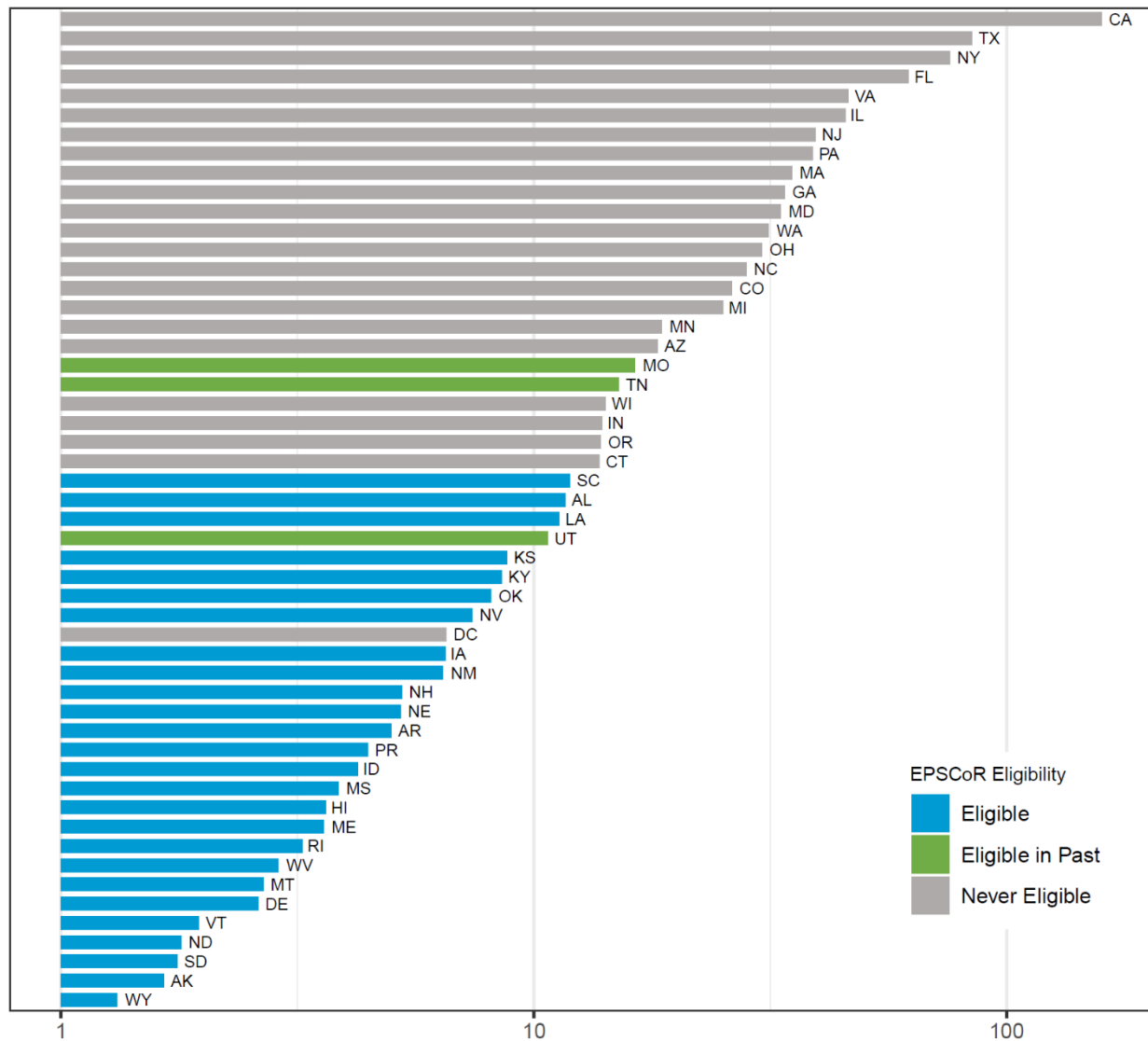
## EXHIBIT B.3 TOTAL NUMBER OF BUSINESSES IN 2017



Note: In log scale.



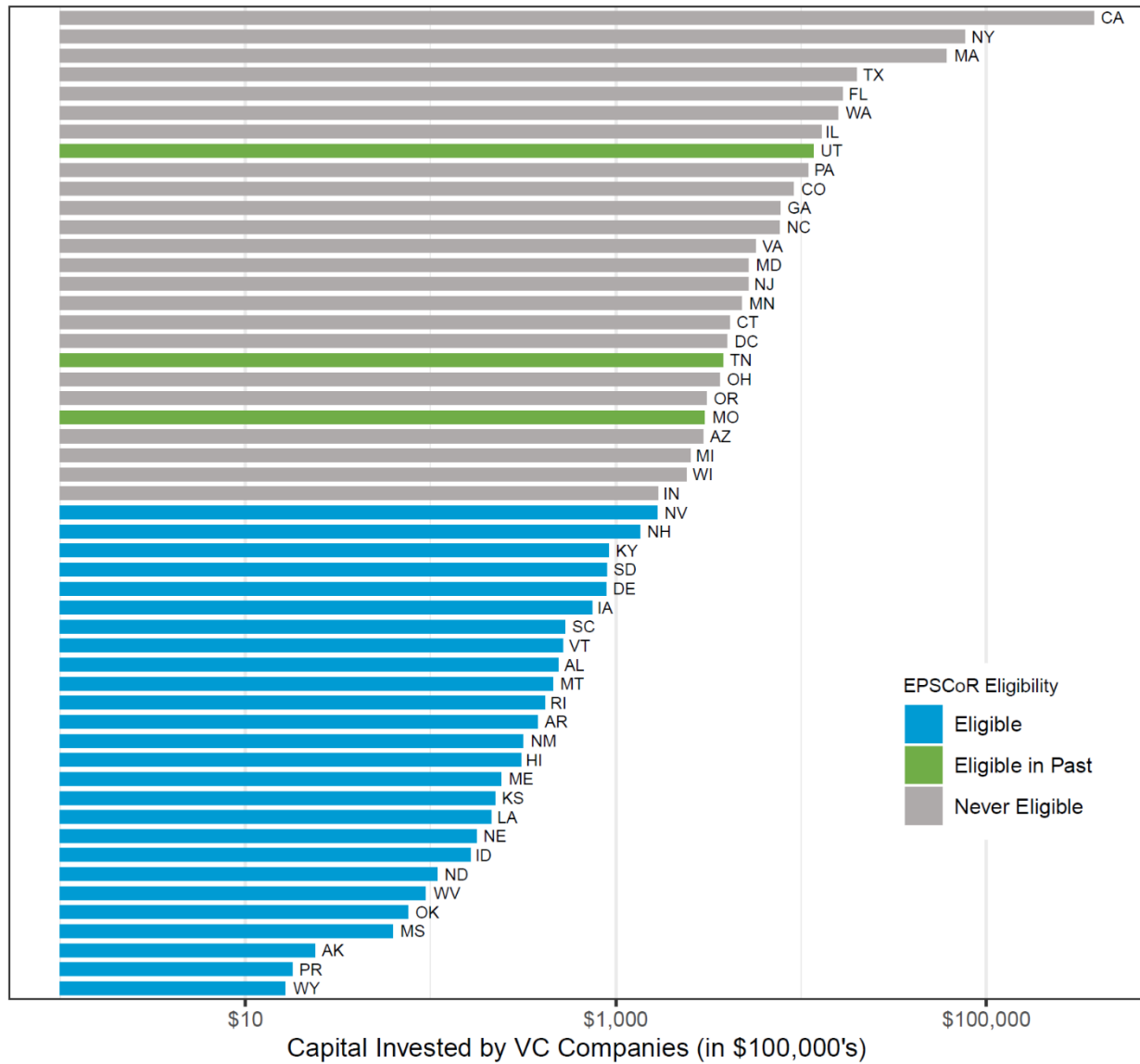
## EXHIBIT B.4 TOTAL NUMBER EMPLOYED IN PROFESSIONAL, SCIENTIFIC, AND TECHNICAL SERVICES IN 2016



Total Number Employed in Professional, Scientific, and Technical Services in 2016 (in 10,000s)

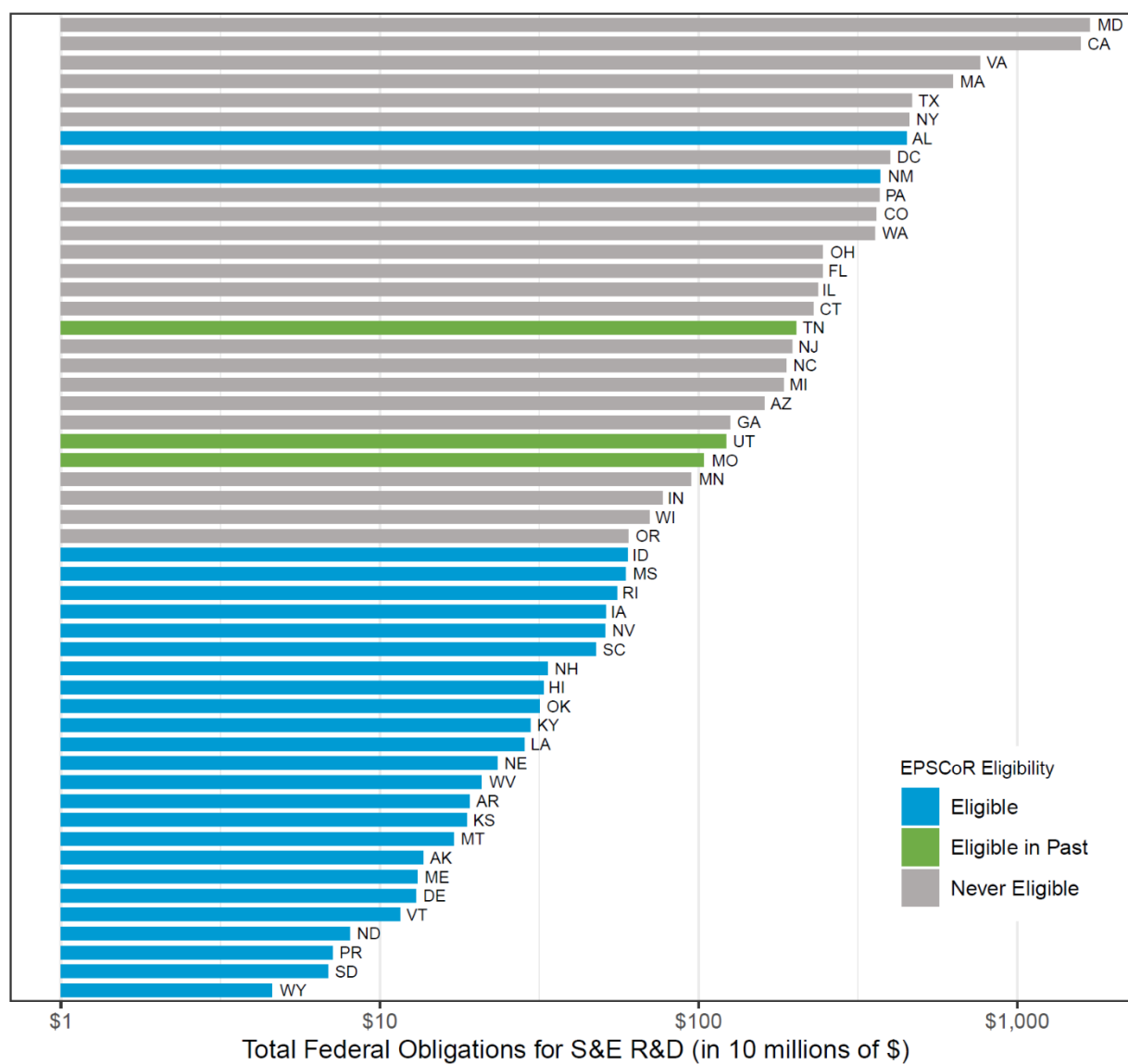
Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands.

## EXHIBIT B.5 CAPITAL INVESTED BY VC COMPANIES IN 2016



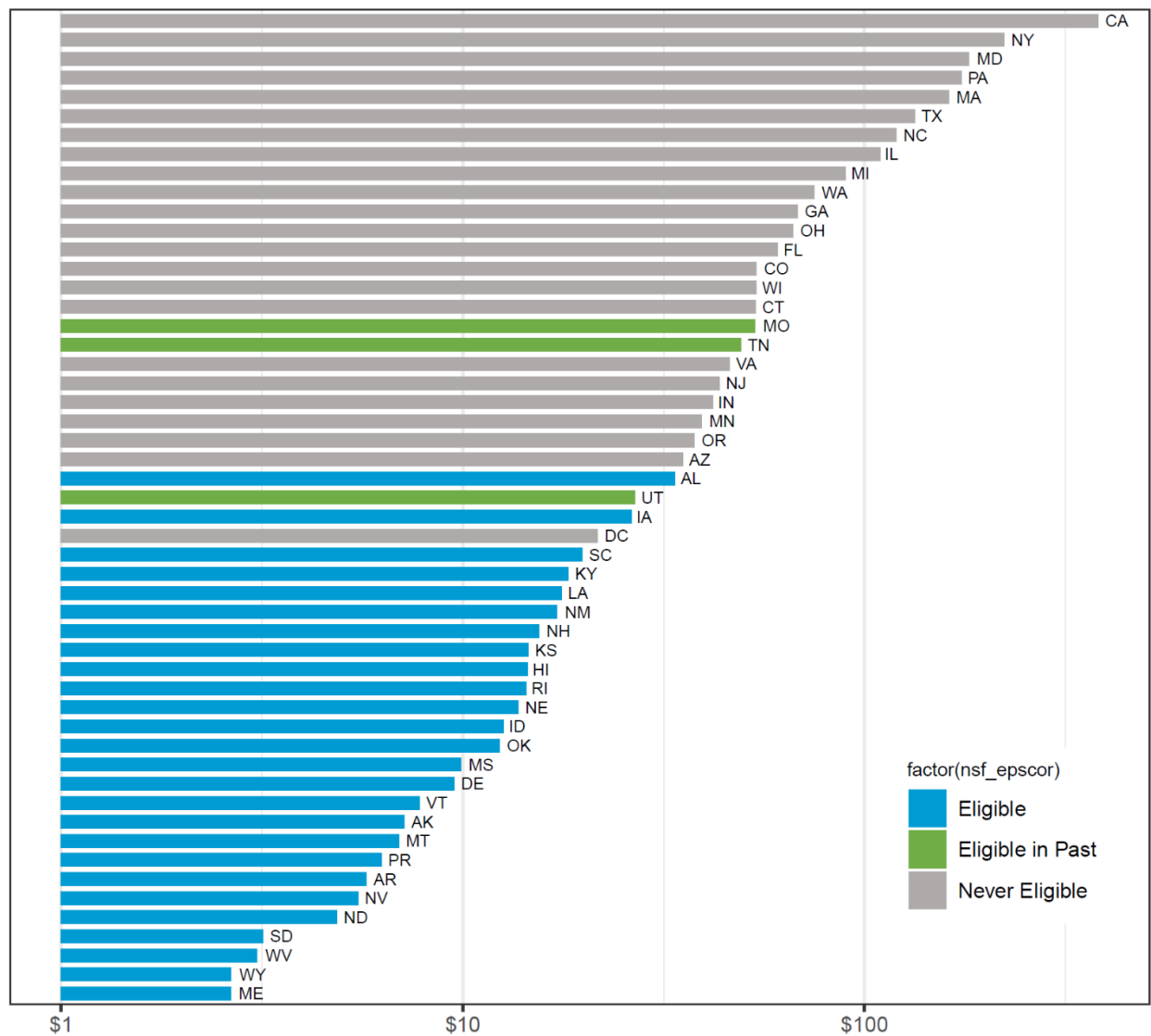
Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands.

## EXHIBIT B.4 TOTAL FEDERAL OBLIGATION FOR S&E R&D IN 2014



Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands.

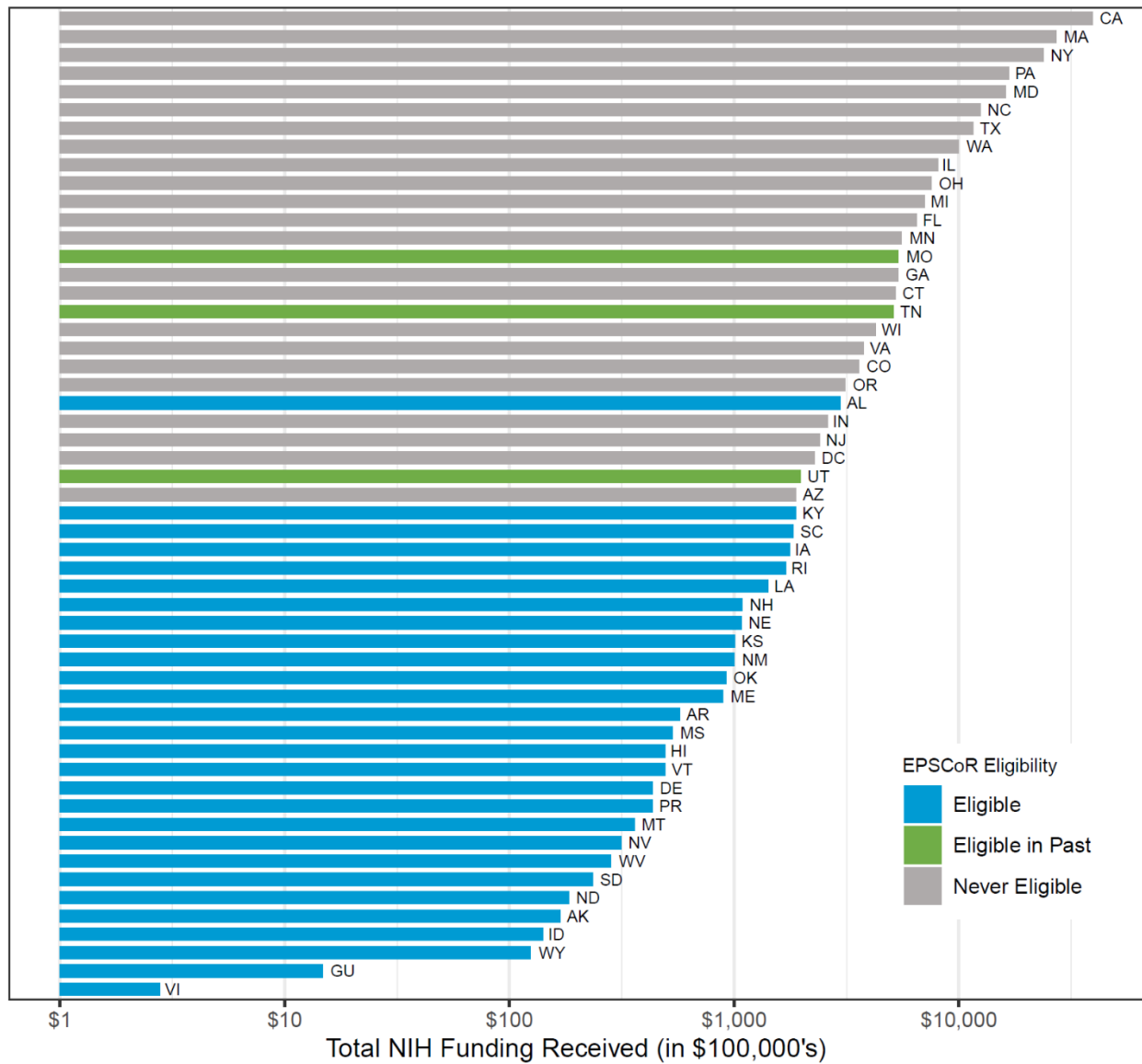
## EXHIBIT B.5 TOTAL FEDERAL OBLIGATIONS FOR S&E R&D FUNDING TO UNIVERSITIES IN 2014



Total Federal Obligations for S&E R&D Funding to Universities (in 10 millions of \$)

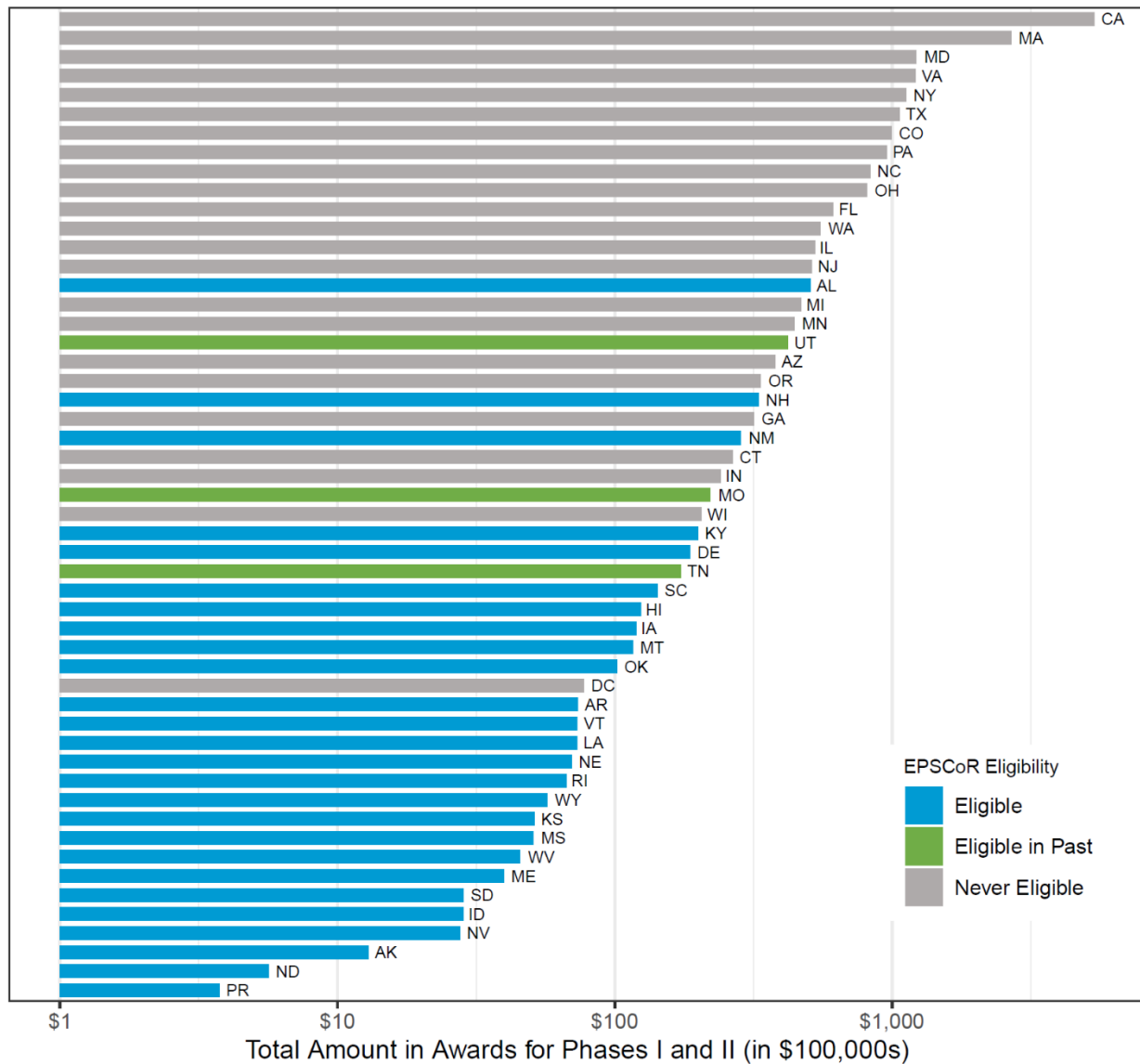
Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands.

## EXHIBIT B.8 TOTAL NIH FUNDING RECEIVED IN 2017



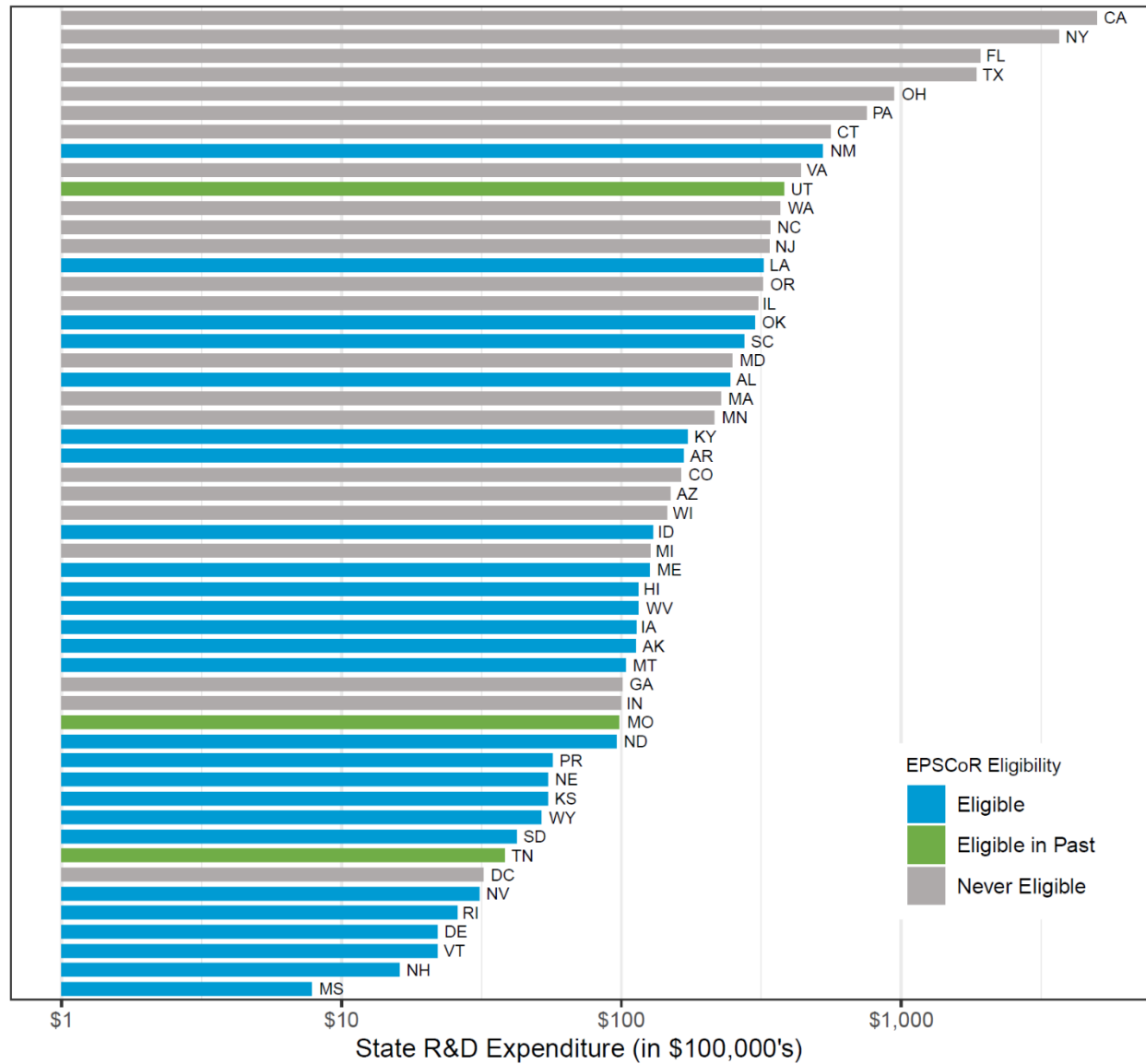
Note: In log scale.

## EXHIBIT B.9 TOTAL SBIR AWARDS FOR PHASE I AND II IN 2017



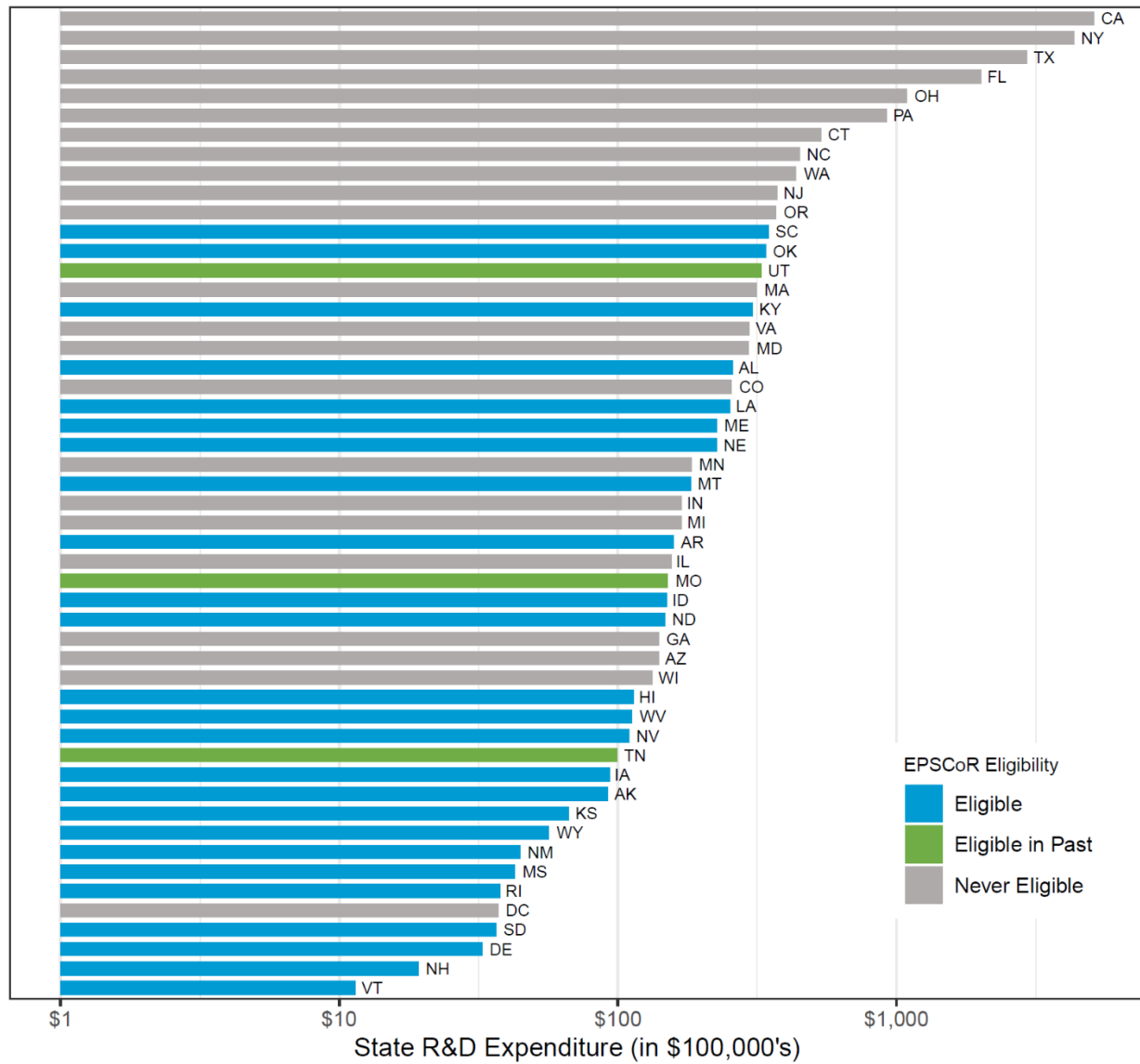
Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands.

## EXHIBIT B.10 STATE R&D EXPENDITURE IN 2015



Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands.

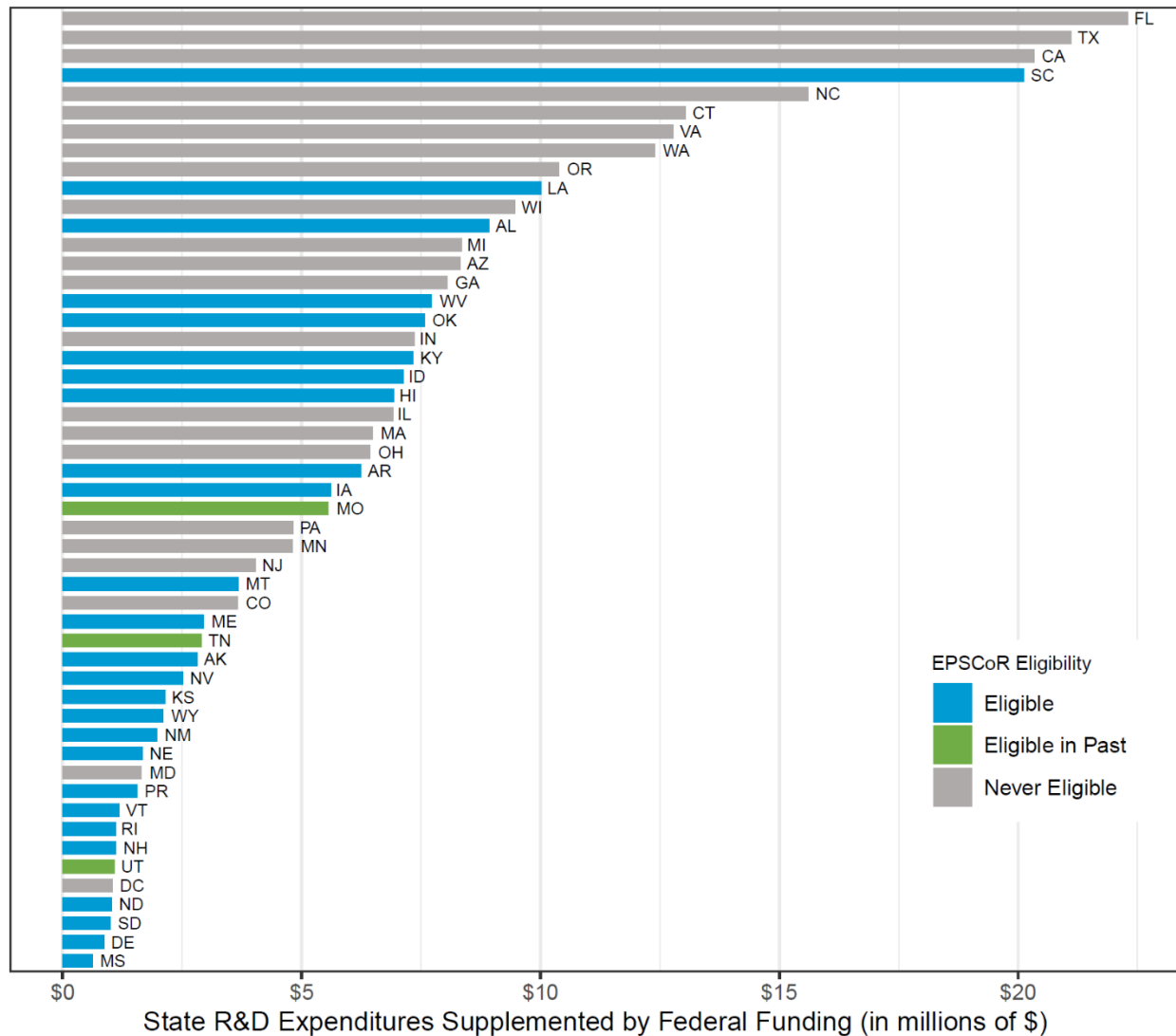
## EXHIBIT B.11 STATE R&D EXPENDITURE IN 2017



Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands.



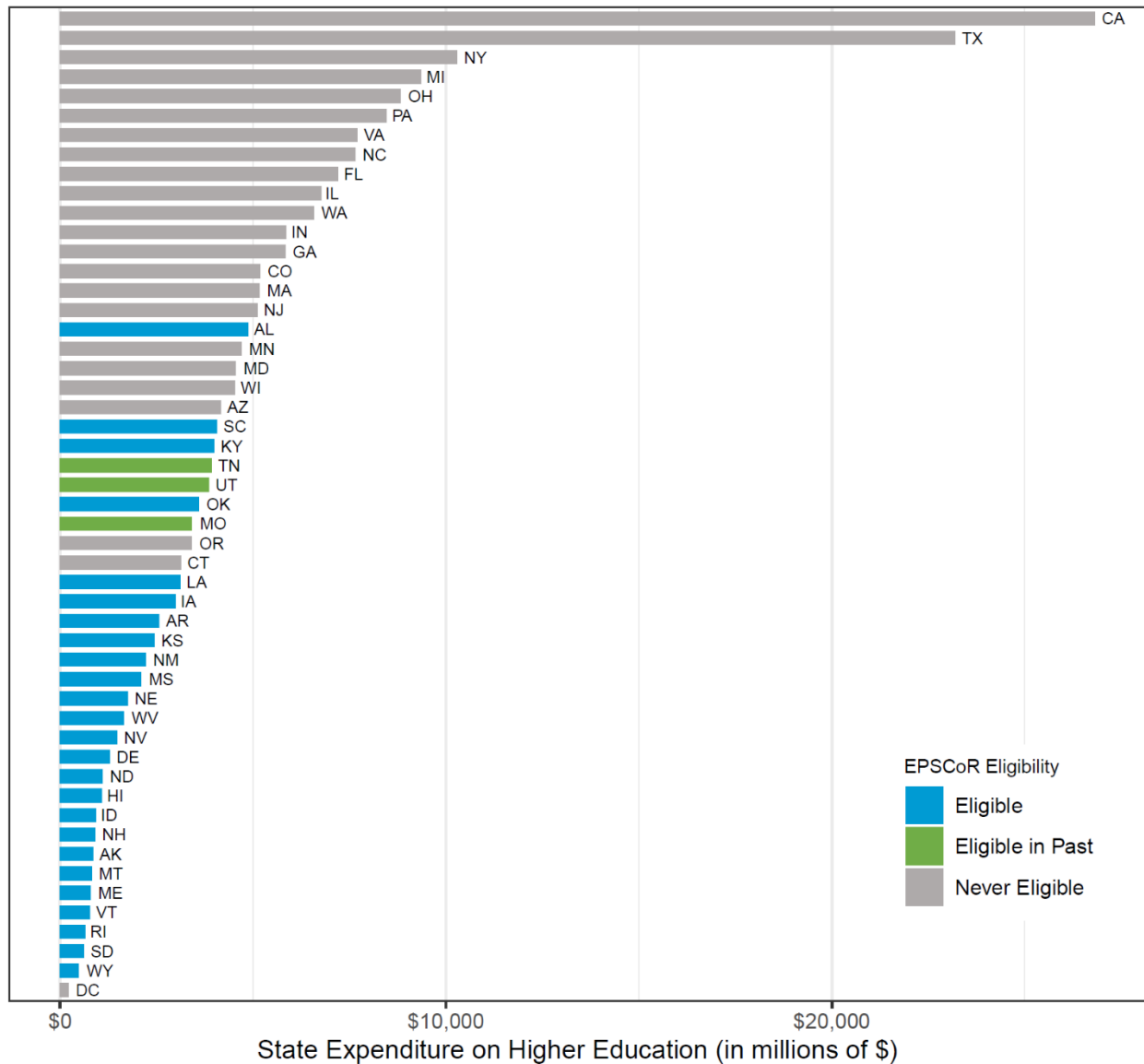
## EXHIBIT B.12 STATE R&D EXPENDITURE SUPPLEMENTED BY FEDERAL FUNDING IN 2015



Note: Data are not available for Guam and the U.S. Virgin Islands.

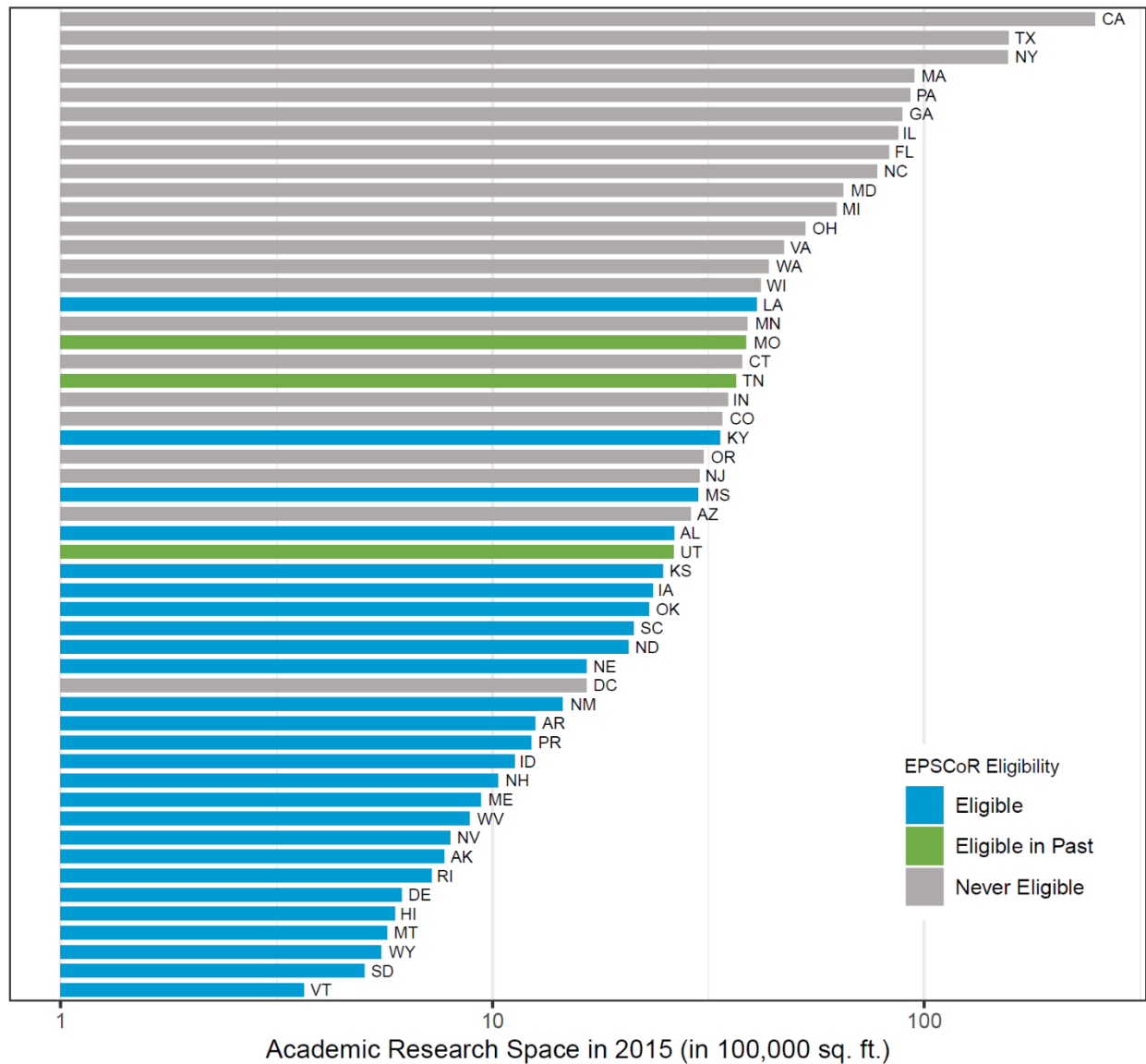
NY (not displayed) = State R&D expenditure of \$151 million Supplemented with Federal Funding.

## EXHIBIT B.13 STATE EXPENDITURE ON HIGHER EDUCATION IN 2015



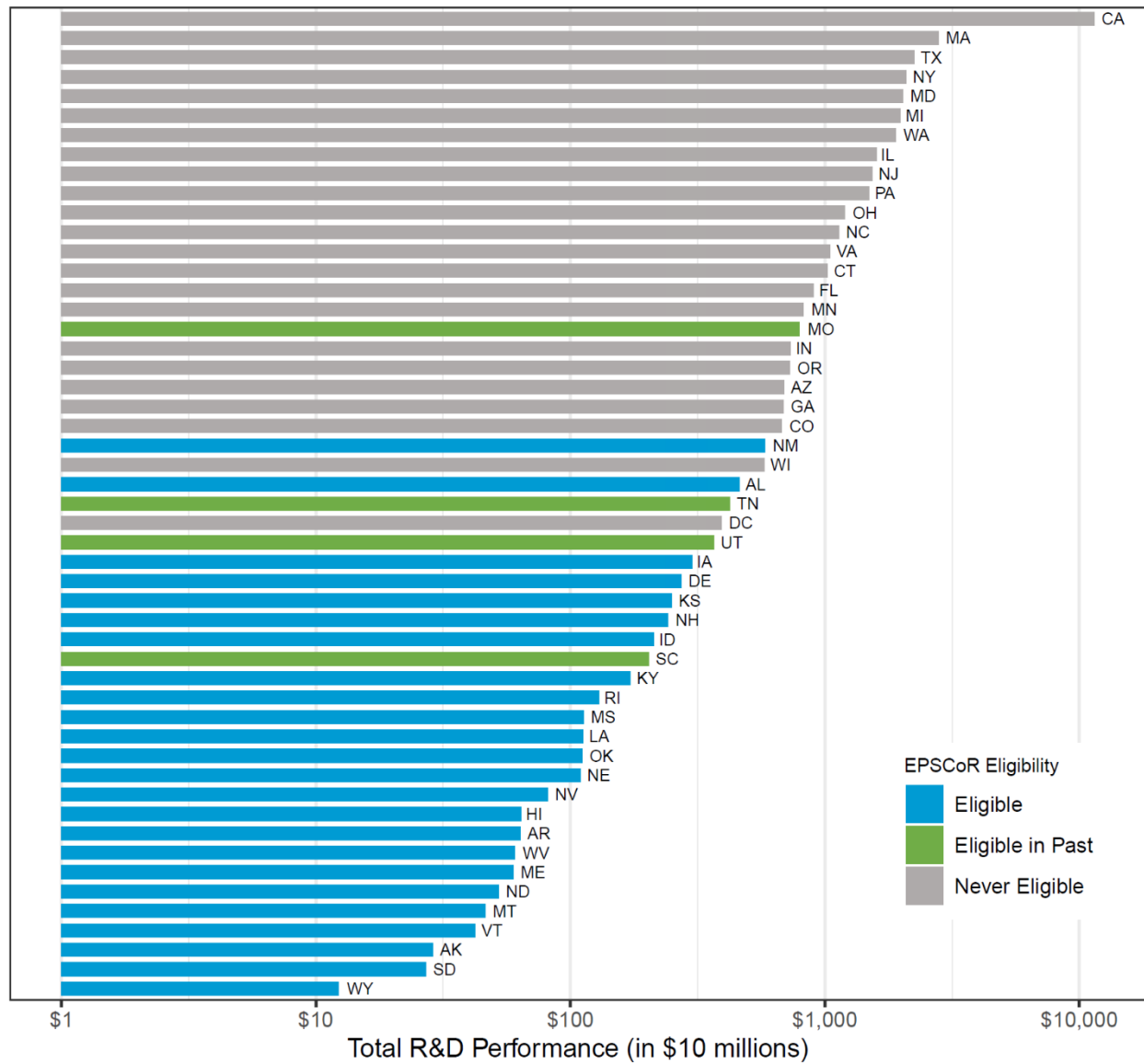
Note: Data are not available for Guam, Puerto Rico and the U.S. Virgin Islands.

## EXHIBIT B.14 STATE ACADEMIC RESEARCH SPACE IN 2015



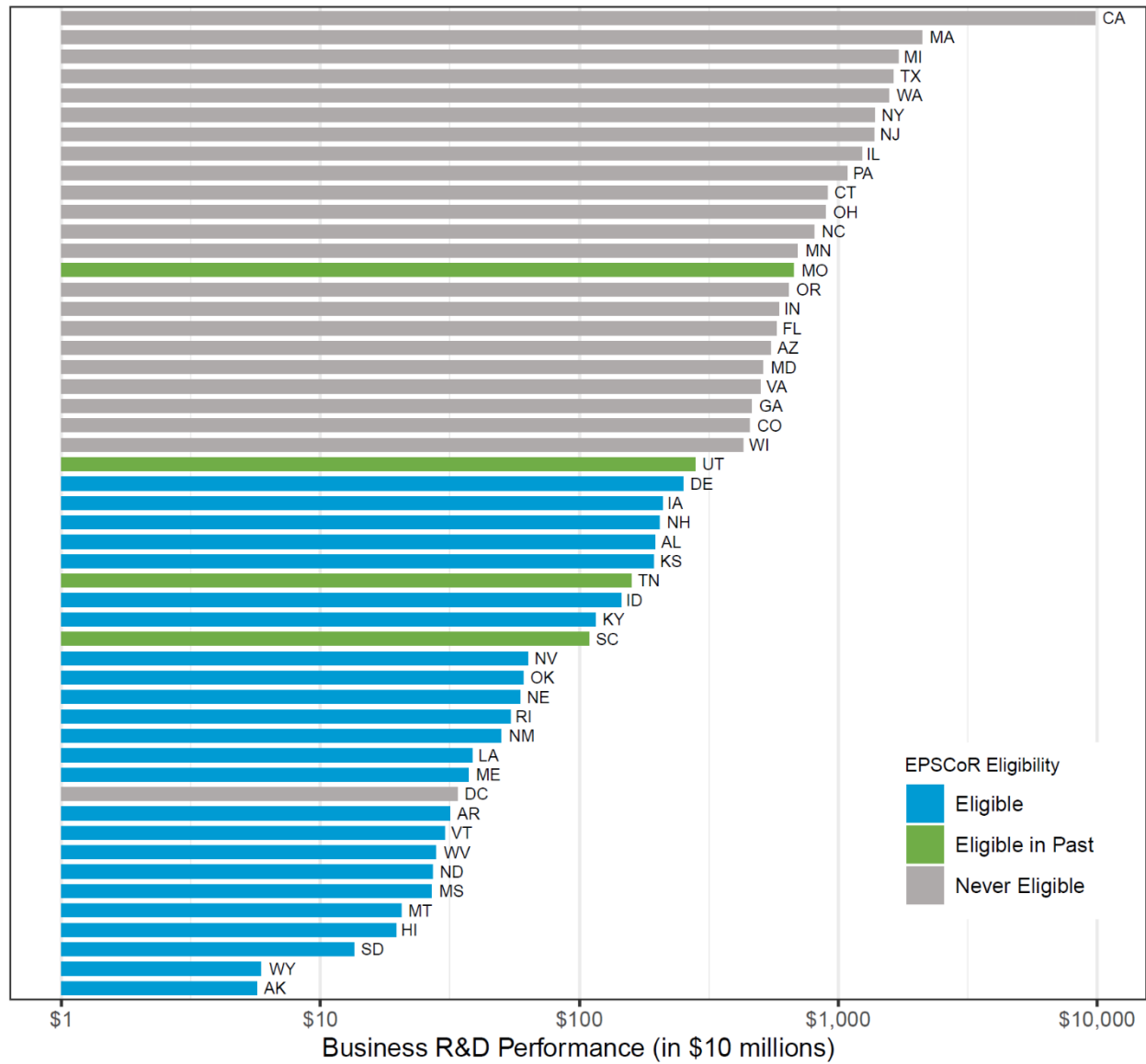
Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands.

## EXHIBIT B.15 TOTAL R&D PERFORMANCE IN 2014



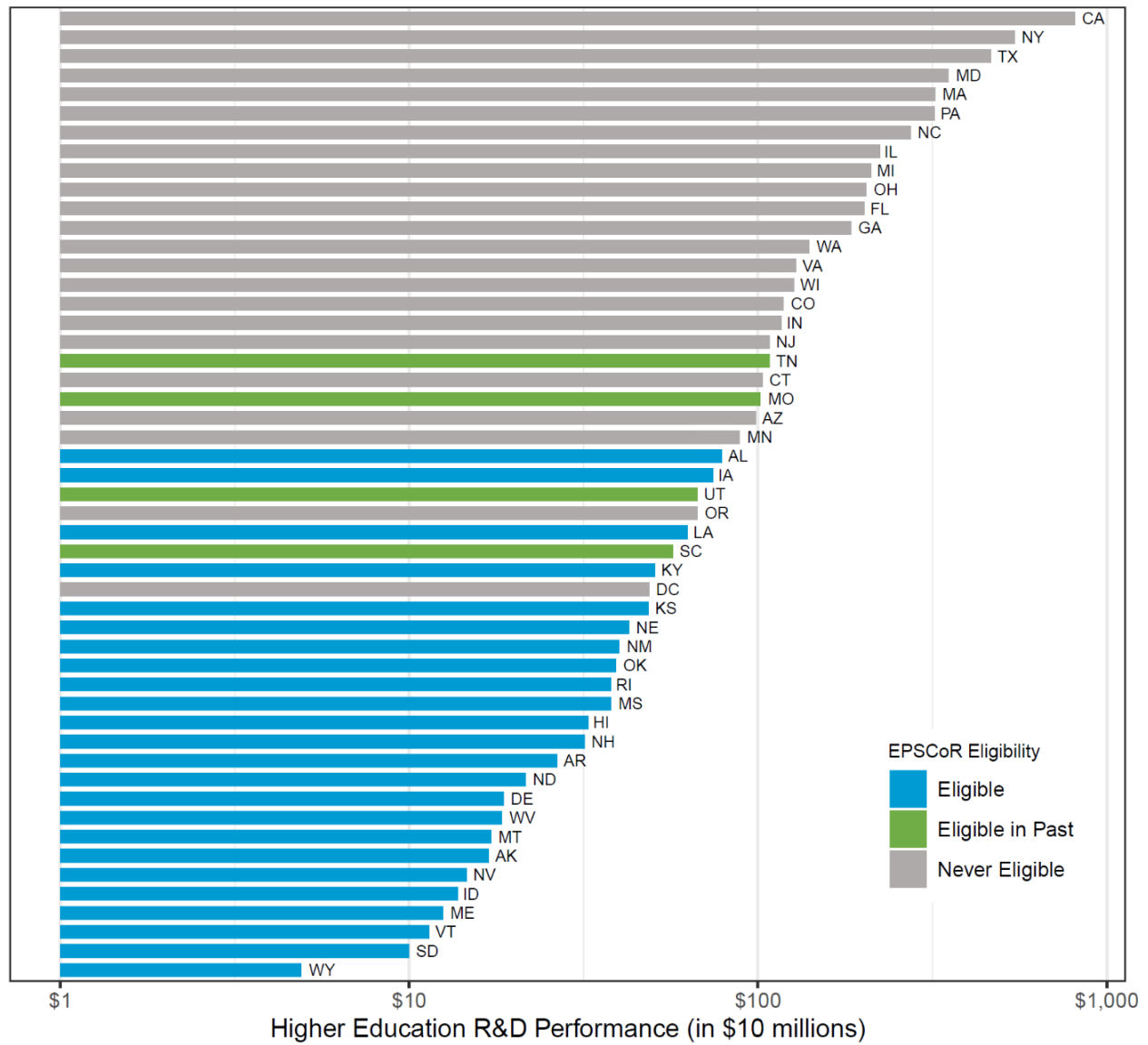
Note: In log scale.

## EXHIBIT B.16 BUSINESS R&D PERFORMANCE IN 2014



Note: In log scale.

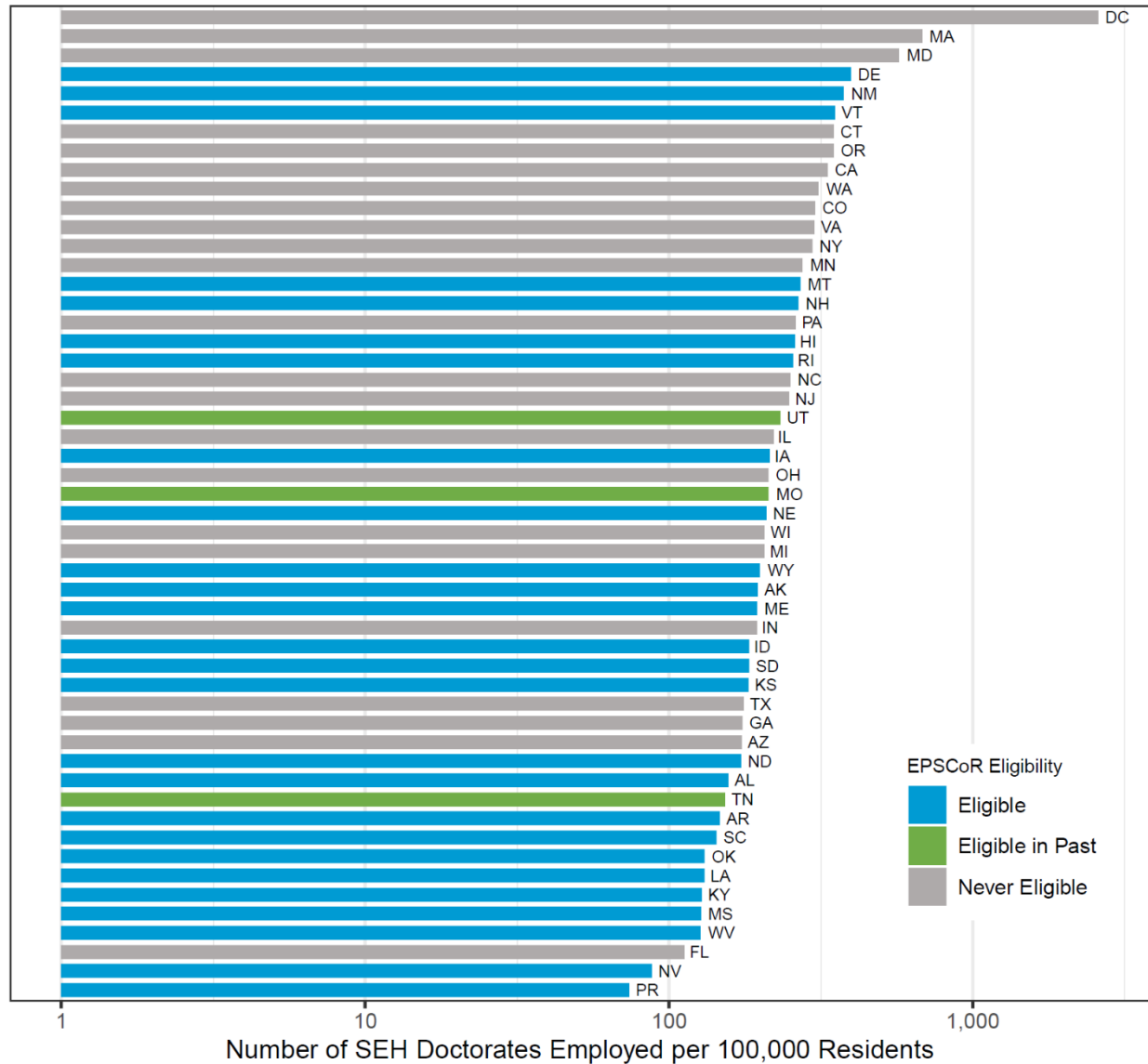
## EXHIBIT B.17 HIGHER EDUCATION R&D PERFORMANCE IN 2014



Note: In log scale.

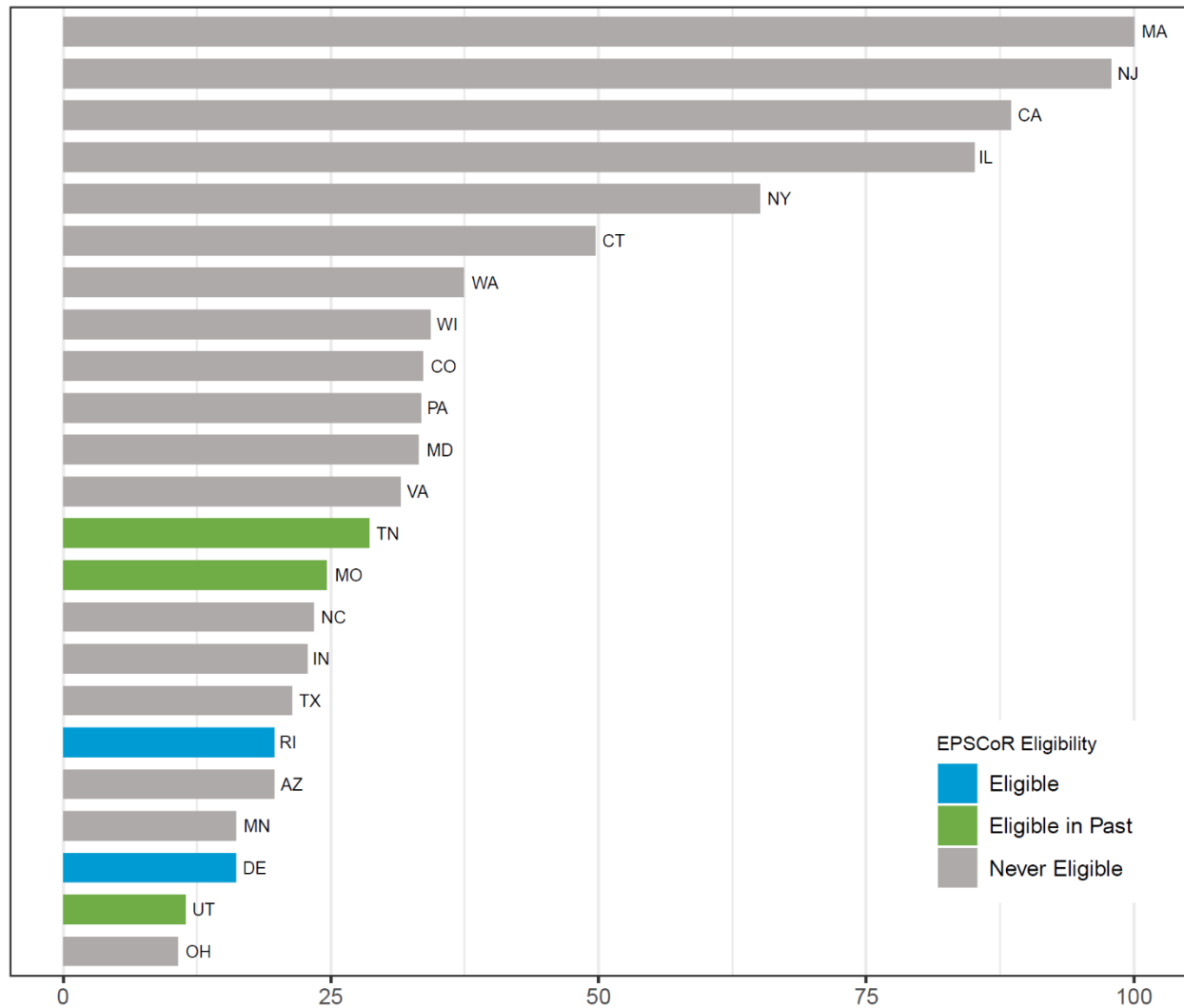
## APPENDIX C. ADDITIONAL OUTCOME MEASURES EXAMINED

### EXHIBIT C.6 NUMBER OF EMPLOYED DOCTORATES IN SEH IN 2017



Note: In log scale. Data are not available for Guam and the U.S. Virgin Islands.

## EXHIBIT C.7 SCORE OF STAFF WINNING NOBEL PRIZES AND FIELDS MEDALS FROM THE TOP-RANKED UNIVERSITY IN 2017

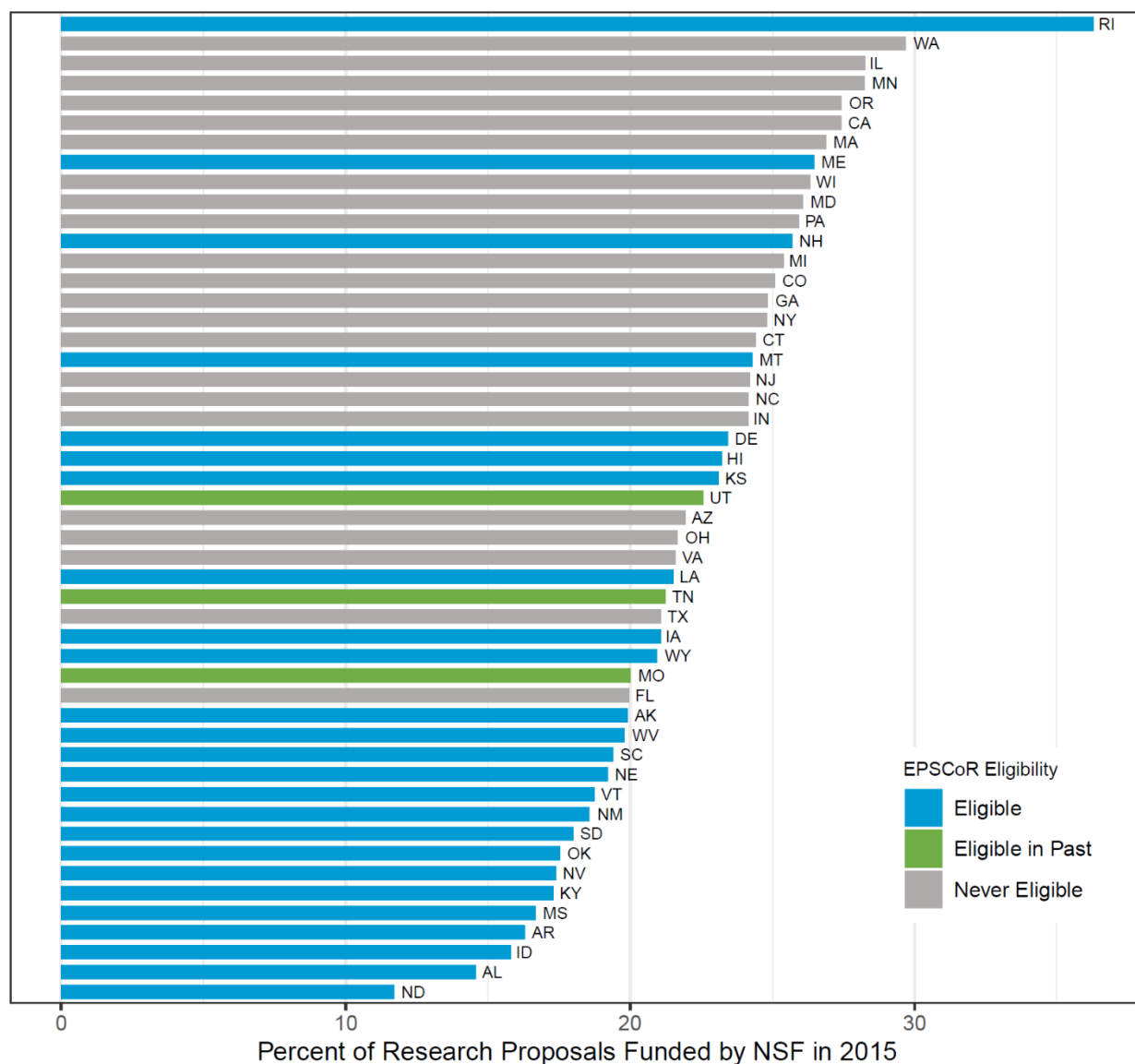


Score for Staff Winning Nobel prizes and Fields Medals from the Top-Ranked University

Note: No institutions in other states have a ranking scores.  
Guam and the U.S. Virgin Islands have no doctoral university.

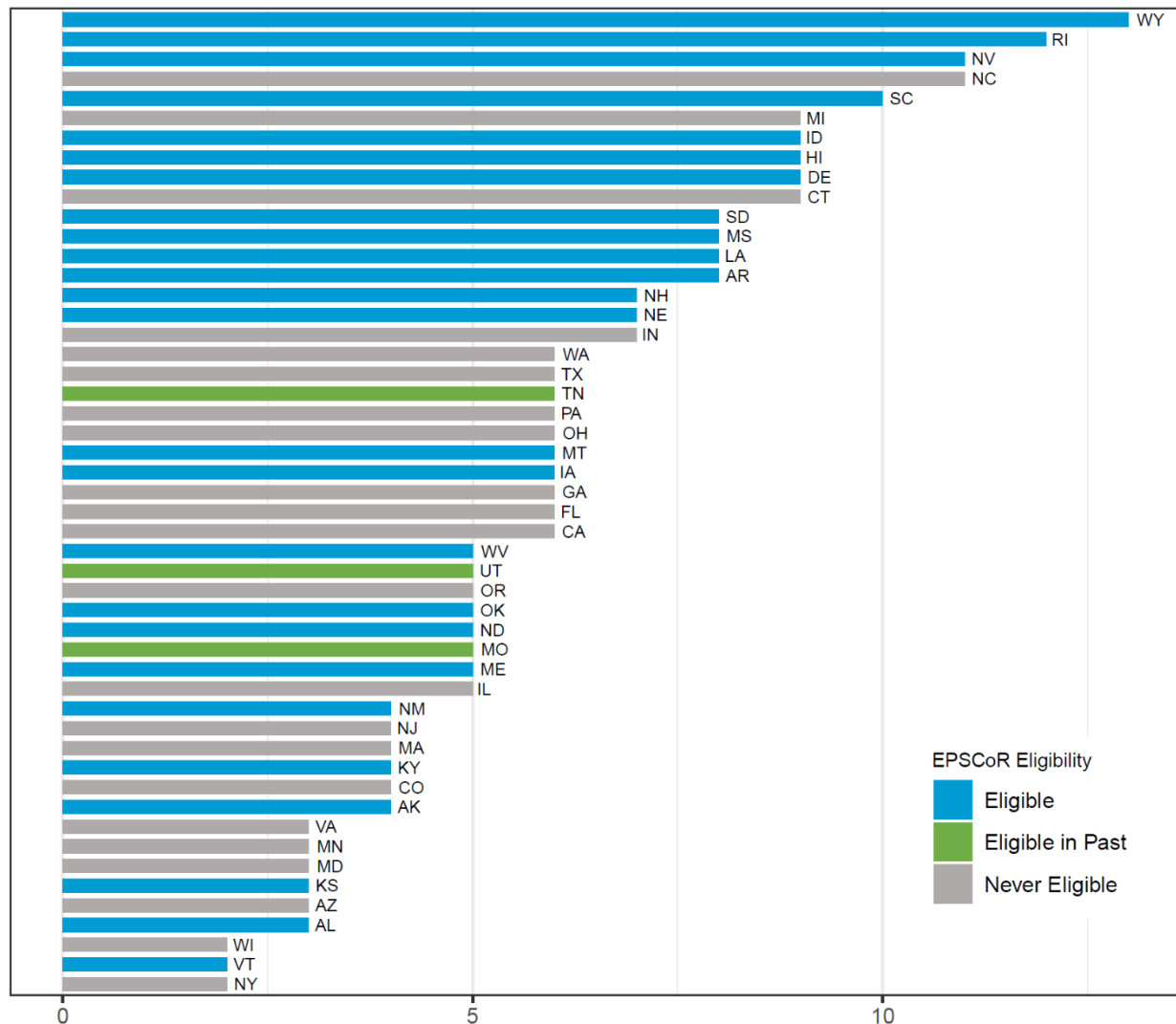


## EXHIBIT C.8 PERCENTAGE OF RESEARCH PROPOSALS FUNDED BY NSF IN 2015



Note: Data are not available for District of Columbia, Guam, Puerto Rico, and the U.S. Virgin Islands.

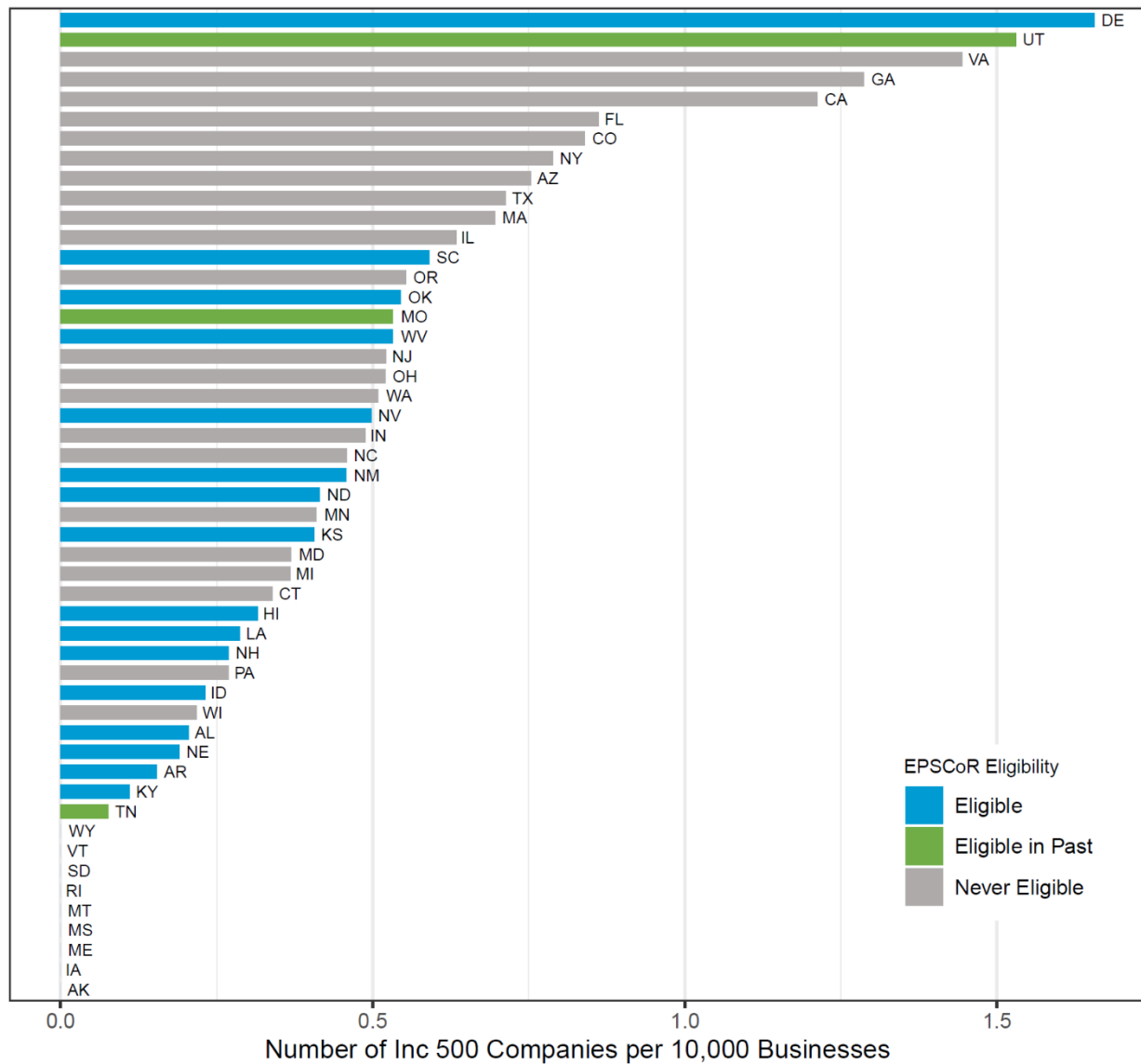
## EXHIBIT C.9 NUMBER OF HIGH-TECH INDUSTRIES WITH EMPLOYMENT GROWING FASTER THAN U.S. AVERAGE IN THE PAST 5 YEARS



Number of High-Tech Industries with Employment Growing Faster than U.S. Average

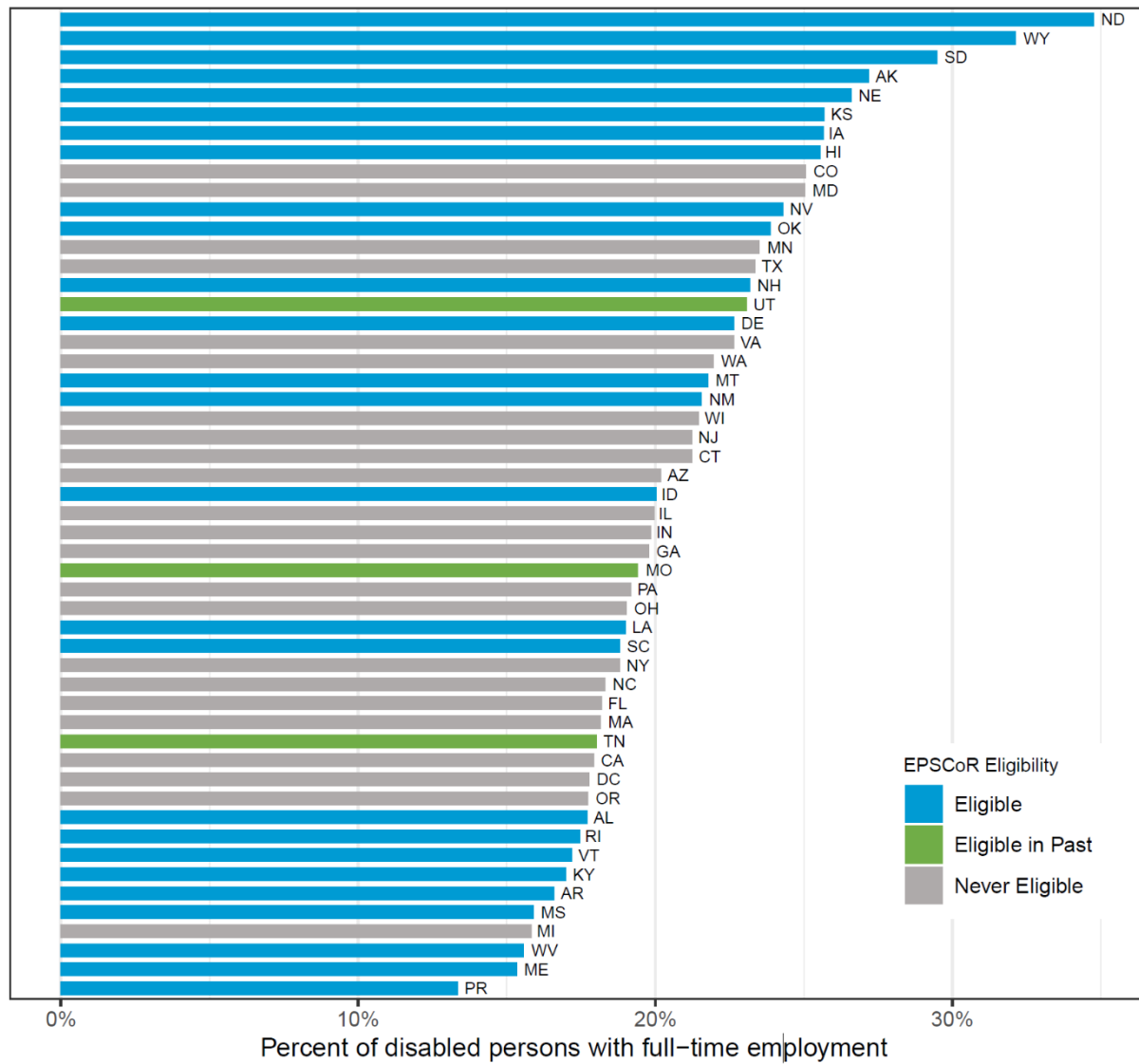
Note: In log scale. Data are not available for District of Columbia, Guam, Puerto Rico, and the U.S. Virgin Islands.

## EXHIBIT C.10 TOTAL NUMBER OF INC. 500 COMPANIES PER 10,000 BUSINESSES IN 2015



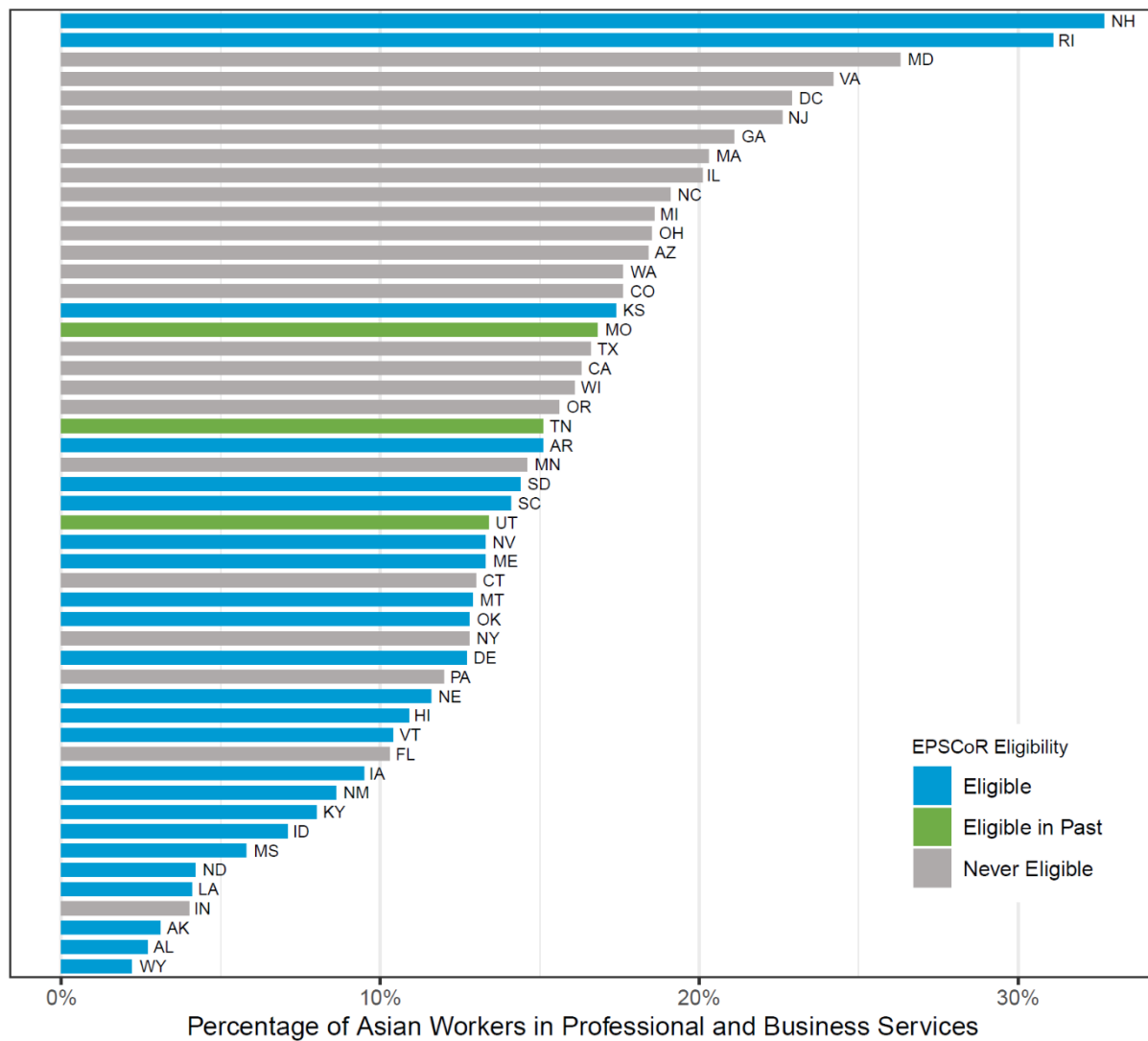
Note: In log scale. Data are not available for District of Columbia, Guam, Puerto Rico, and the U.S. Virgin Islands.

## EXHIBIT C.11 PERCENTAGE OF DISABLED PERSONS WITH FULL-TIME EMPLOYMENT IN 2013



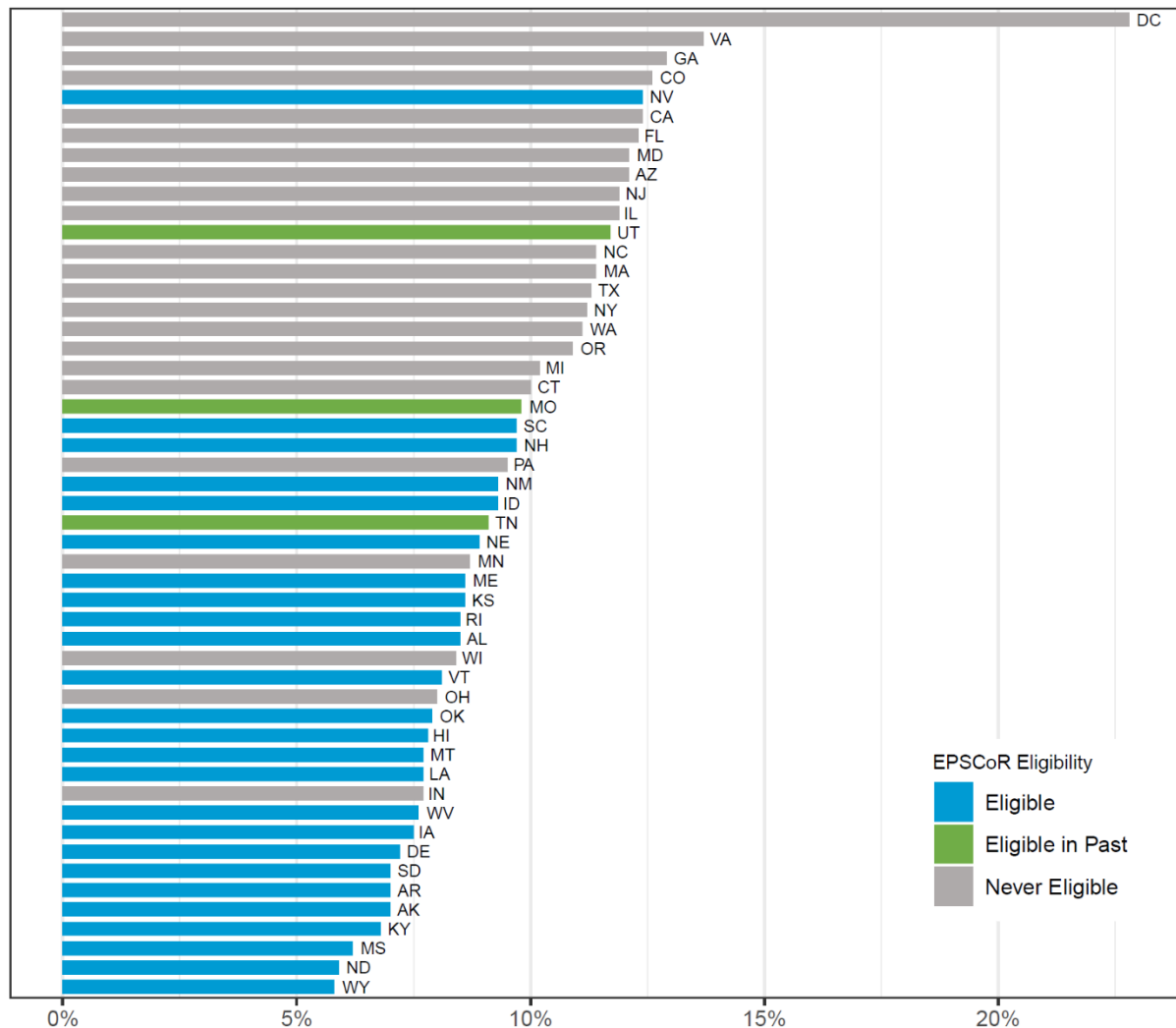
Note: Data are not available for Guam and the U.S. Virgin Islands.

## EXHIBIT C.12 PERCENTAGE OF ASIAN WORKERS IN PROFESSIONAL AND BUSINESS SERVICES IN 2016



Note: Data are not available for Guam, Puerto Rico, and the U.S. Virgin Islands.

## EXHIBIT C.13 PERCENTAGE OF FEMALE WORKERS IN PROFESSIONAL AND BUSINESS SERVICES IN 2016



Percentage of Women Employed in Professional and Business Services

Note: Data are not available for Guam, Puerto Rico, and the U.S. Virgin Islands.

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## APPENDIX D. TECHNICAL APPENDIX FOR EXPLORATORY FACTOR AND CLUSTER ANALYSES

### Exploratory Factor Analysis for Contextual Measures

Factor analysis is a statistical method used to describe variability among many observed, correlated variables that reflect a smaller number of unobserved/underlying latent variables called factors. Essentially, a factor is a construct that is a condensed statement of the relationships between a set of similar variables. Factor analysis is used to examine the relationships between the contextual measures and find the underlying latent variable that these measures represent.

The study team started with the following list of measures that represent the jurisdiction context (data sources listed in parentheses):

- *Capital Invested by VC Companies Per S&E Worker in 2016* (NVCA)
- *Real GSP Per Capita for 2017* (BEA)
- *Total Number of Businesses Per Capita in 2017* (NAICS)
- *Total Employment in Professional, Scientific, and Technical Services Per Capita in 2016* (Census)
- *Percentage of Bachelor's Degrees in S&E Disciplines* (STSI)
- *State R&D Expenditures Per S&E Worker in 2015* (SESP)
- *State Expenditure on Higher Education Per Capita in 2015* (Census)
- *Total R&D Expenditures Per S&E Worker by State with Funding from the Federal Government in 2015* (SGRD)
- *Total Amount in Awards Per S&E Worker for SBIR-STTR Phases I and II Combined in 2015* (SBIR-STTR)
- *Total NSF Research Funding Per S&E Worker in 2015* (STSI)
- *Total NIH Funding Per S&E Worker Received in 2017* (NIH)
- *Total Federal Obligations for S&E R&D Per S&E Worker in 2014* (SESP)
- *Total Federal Obligations for S&E R&D to Universities and Colleges Per S&E Worker in 2014* (SESP)
- *Academic Research Space Per S&E Worker in 2015* (SESP)
- *Total Population in 2017* (Census)
- *Percent of URM in 2017* (Census)
- *Number of Very High Research Doctoral Granting (R1) Institutions* (Carnegie)
- *Number of High Research Doctoral Granting (R2) Institutions* (Carnegie)
- *Number of Moderate Research Doctoral Granting (R3) Institutions* (Carnegie)
- *Number of Associates' Granting Institutions* (Carnegie)

Exhibit D.1 shows the correlation across the contextual measures for the jurisdictions.<sup>78</sup> Several well-recognized criteria from the literature for the factorability of a correlation were used. First,

<sup>78</sup> The squared multiple correlations between each variable and all other variables were high (range: 0.5 to 0.96). This is the theoretical lower bound for communality or an upper bound for uniqueness.

it was observed that 19 of the 20 measures correlated at least 0.3 with at least 1 other item, suggesting reasonable factorability (see Exhibit D.1). Secondly, the Kaiser-Meyer-Olkin measure of sampling adequacy was 0.65, above the commonly recommended value of 0.6, and Bartlett's test of sphericity was significant (Chi-squared [190] = 664.1,  $p = 0.00$ ). Finally, the communalities (1-uniqueness) were above 0.3 for most variables (see Exhibit D.3), further confirming that the measure shared some common variance with other measures. Given these indicators, factor analysis was deemed suitable with all 20 measures.



## EXHIBIT D.14 CORRELATION BETWEEN CONTEXTUAL MEASURES AT THE JURISDICTIONAL LEVEL

### Environment and Institutional Capacity

	Total population	Percent of URM	Number of R1s	Number of R2s	Number of R3s	Number of associate institutions	VC invested
Total population	1						
Percent of URM	0.468	1					
Number of R1s	0.847	0.364	1				
Number of R2s	0.51	0.203	0.439	1			
Number of R3s	0.93	0.39	0.782	0.409	1		
Number of associate institutions	0.898	0.407	0.775	0.425	0.857	1	
VC invested	0.583	0.132	0.713	0.202	0.544	0.571	1

### State-Level Financial Resource Capacity

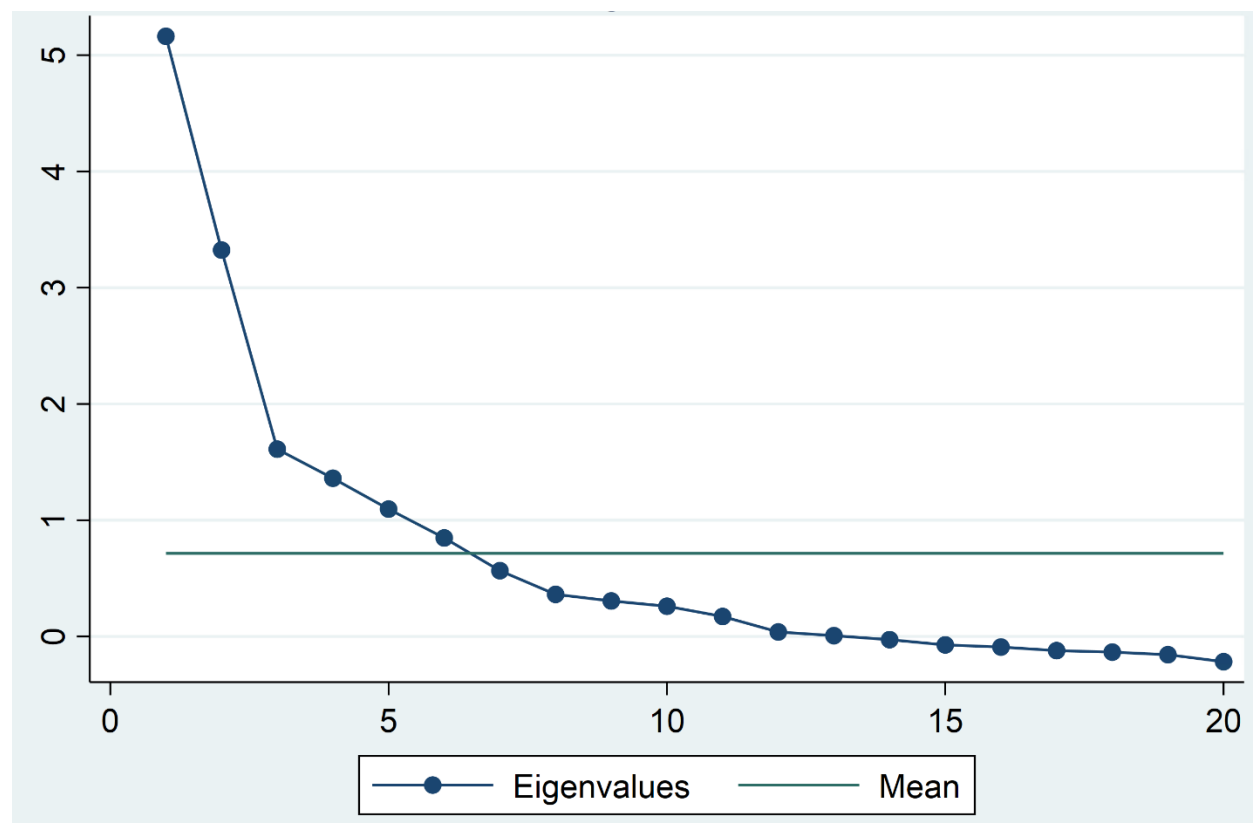
	R&D Expenditures	Expenditure on higher education	R&D expenditures with federal funding	Academic research space
R&D Expenditures	1			
Expenditure on higher education	0.309	1		
R&D expenditures with federal funding	0.53	0.054	1	
Academic research space	0.276	0.423	0.111	1

### Research Capacity

	State GDP	Number of businesses	Number of S&E workers	Percentage of population with bachelor's degree in S&E	Federal obligations for S&E R&D	Federal obligations for S&E R&D to universities and colleges	NSF research funding	NIH research funding	SBIR-STTR award amount
State GDP	1								
Number of businesses	0.348	1							
Number of S&E workers	0.546	0.322	1						
Percentage of population with bachelor's degree in S&E	0.658	0.491	0.892	1					
Federal obligations for S&E R&D	-0.04	-0.15	0.335	0.152	1				
Federal obligations for S&E R&D to universities and colleges	0.351	0.082	0.173	0.328	0.351	1			
NSF research funding	0.354	0.274	0.552	0.594	0.396	0.518	1		
NIH research funding	0.299	0.021	0.384	0.434	0.282	0.684	0.438	1	
SBIR-STTR award amount	0.272	0.182	0.374	0.419	0.346	0.381	0.464	0.379	1

Principal-factor method was used to analyze the correlation matrix.<sup>79</sup> Initial eigenvalues indicated that the first three factors explained 36 percent, 23 percent, and 11 percent of the total variance, respectively. The fourth and fifth factors had eigenvalues just over 1 and explained 10 percent and 8 percent of the total variance. Solutions for three, four, and five factors were each examined using varimax, oblimin, and promax rotations of the factor loading matrix. The three-factor solution, which explained 75.2 percent of the total variation (after the promax oblique rotation),<sup>80</sup> was preferred because of (a) theoretical support, (b) the “leveling off” of eigenvalues on the scree plot after three factors<sup>81</sup> (see Exhibit D.2), and (c) the insufficient number of primary loadings and difficulty of interpreting the fourth factor and subsequent factors. There was little difference between the three-factor varimax, promax, and oblimin solutions; all solutions were examined before deciding to use promax rotations for the final solution.

#### EXHIBIT D.15 SCREE PLOT DISPLAYING THE EIGENVALUES FOR EACH FACTOR FOR CONTEXTUAL FACTOR ANALYSIS



<sup>79</sup> The principal component factor model was found inappropriate. The model assumes that the uniquenesses are 0, considerable uniqueness was found—considerable variability left over after the three factors.

<sup>80</sup> The promax rotation with power of 3 and Kaiser normalization was used. Oblique rotations allow the rotated factors to be correlated and often yield more interpretable factors due to the simpler pattern matrix. Varimax rotation and oblimin rotation with Kaiser normalization got similar results with the factor loadings varying slightly.

<sup>81</sup> The scree plot has two inflection points—one at 3 and the other at 8.

No items were eliminated as no measure failed to meet a minimum criterion of having a primary factor loading of 0.35 or lower. “Total Number of Businesses Per Capita” has a factor loading of 0.4 and “Total Federal Obligations for S&E R&D Per S&E Worker” has factor loading between 0.3 and 0.4. “VC Capital Invested Per S&E Worker” and “Total Number of S&E Workers” have cross-loading of 0.4 and 0.36, respectively (see Exhibit D.3).

#### EXHIBIT D.16 FACTOR LOADINGS AND UNIQUENESS FOR THE CONTEXTUAL MEASURES

	Population and Institutions Structure of the State	Jurisdiction Competitiveness	State Funding for R&D	Uniqueness
VC Capital Invested Per S&E Worker	<b>0.61</b>	<i>0.40</i>		0.41
Real GSP Per Capita		<b>0.64</b>		0.43
Total Number of Businesses Per Capita		<b>0.40</b>		0.83
Total Number of S&E Workers		<b>0.62</b>	<i>-0.36</i>	0.34
Percentage of Bachelor’s Degrees in S&E		<b>0.67</b>		0.53
State Expenditure on Higher Education Per Capita			<b>0.42</b>	0.62
Total R&D Expenditures Per S&E Worker by State with Funding from the Federal Government			<b>0.58</b>	0.59
State R&D Expenditures Per S&E Worker			<b>0.77</b>	0.43
Total Amount in SBIR-STTR Awards Per S&E Worker		<b>0.65</b>		0.56
Total NSF Research Funding Per S&E Worker		<b>0.57</b>		0.56
Total NIH Funding Per S&E Worker		<b>0.62</b>		0.49
Total Federal Obligations for S&E R&D Per S&E Worker		<b>0.36</b>		0.84
Total Federal Obligations for S&E R&D to Universities and Colleges Per S&E Worker		<b>0.70</b>		0.51
Academic Research Space Per S&E Worker			<b>0.49</b>	0.69
Total Population	<b>0.99</b>			0.04
Percent of URMs	<b>0.47</b>			0.77
Number of R1 Institutions	<b>0.89</b>			0.17
Number of R2 Institutions	<b>0.48</b>			0.73
Number of R3 Institutions	<b>0.93</b>			0.16
Number of Associate’s Institutions	<b>0.91</b>			0.18

**Notes:** Extraction Method: Principal Axis Factoring. Rotation Method: Promax with Kaiser Normalization. Factor loading < 0.35 are suppressed. Variables with secondary loadings of much lower value than the primary loadings are italicized.

These four measures were kept in the final stage analysis. Promax rotation provided the best-defined factor structure where all measures in the analysis had primary loading over 0.35 and

only two measures had a cross-loading of above 0.35. The factor loading matrix for this final solution is presented in Exhibit D.3.

The factor labels were selected as the measures in each factor aligned with the appropriate logic model domains and/or AREC framework. Internal consistency for each of the scales was examined using Cronbach's alpha.<sup>82</sup> The alphas for the first two factors were high: 0.89 for factor 1 (7 items), 0.81 for factor 2 (10 items), and moderate for factor 3 (0.61; 5 items). No substantial increases in alpha for any of the scales could have been achieved by eliminating more items.

Composite scores were created for each of the three factors using a regression scoring method. Higher scores indicated greater resources available for each factor. Although an oblique rotation (promax) was used, only small correlations between each of the composite scores existed: 0.15 between factors 1 and 2, -0.24 between factors 1 and 3, and -0.05 between factors 2 and 3.

Overall, these analyses indicated that 3 distinct factors were underlying the 20 contextual measures and that these factors were internally consistent. Using these factors, the jurisdictions can be preliminarily grouped in four buckets as shown in Exhibit D.4.

#### EXHIBIT D.17 PRELIMINARY GROUPING OF JURISDICTIONS

	Below F3 Mean	Above F3 Mean	
Below F2 Mean	Alabama Kansas Mississippi Nevada Missouri* Tennessee*	Arkansas Idaho Kentucky Louisiana Maine Nebraska	Oklahoma South Dakota West Virginia South Carolina Indiana**
Above F2 Mean	New Hampshire Rhode Island Colorado** Minnesota** Wisconsin**	Alaska Delaware Hawaii Iowa Montana North Dakota	New Mexico Vermont Wyoming Utah* Connecticut** Oregon**

**Notes:** \* indicates eligible for EPSCoR in the past. \*\* indicates never eligible for EPSCoR.

All the jurisdictions that have F1 Above Mean are jurisdictions that have never been eligible for EPSCoR.

<sup>82</sup> Average interitem correlation values are greater than 0.3 for all three factors.

## Exploratory Cluster Analysis for Contextual Measures

Next, the study team verified the grouping of jurisdictions using an exploratory cluster analysis, a more sophisticated method to identify jurisdictions with similar contextual measures. Identifying these groups enables comparison of the strategies used—and to some extent—the comparison of outcomes that might be best suited to each group. Although many different methods of cluster analysis have been developed, the literature focuses almost exclusively on two types: hierarchical agglomerative methods<sup>83</sup> and iterative partitioning methods.<sup>84</sup> Hierarchical clustering was selected as it is most used in the literature. Any differences that occur are discussed using partitioning methods.

There are four decisions involved in this procedure:

- *Measuring* distance between observations – using Euclidean distance method<sup>85</sup> to measure similarity
- *Measuring* distance between groups – using the average linkage as it is reasonably robust
- *Selecting* the observable variables –the variables in the factor analysis are included
- *Selecting* the optimal number of groups – using the two stopping rules<sup>86</sup>: the Caliński and Harabasz pseudo-F index and the Duda-Hart  $Je(2)/Je(1)$  index with the associated pseudo- $T^2$

Using these criteria, the jurisdictions were divided into eight groups.<sup>87</sup> However, the last five groups had few jurisdictions in each group and these jurisdictions are not eligible for EPSCoR. We merged these jurisdictions into one group. This reduced the number of clusters to four (see Exhibit D.5). The clusters are stable across different measures, methods, and stopping rules.<sup>88</sup> Exhibit D.6 graphically presents the information concerning which jurisdictions are grouped together at various levels of (dis)similarity. At the bottom of the tree, each jurisdiction is

<sup>83</sup> Hierarchical agglomerative cluster analysis involves a series of steps, whereby individual cases (people) begin as individual clusters and step-by-step the most similar clusters are joined, eventually resulting in one cluster containing all cases. Each step is irreversible, so clusters joined at one step cannot be separated later in the clustering process. Hierarchical clustering procedures result in the same number of cluster solutions as there are entities to cluster.

<sup>84</sup> Iterative partitioning methods (e.g., K-means cluster analysis) begin by dividing the entities into the required number of clusters, calculating the cluster centroids, and relocating the entities to their nearest cluster centroid. The process of calculating the new cluster centroids and relocating entities continues until all the entities are closer to their own cluster centroid than any other and the solution is therefore stable. Iterative partitioning techniques differ from hierarchical methods in two key ways. First, the number of clusters is specified by the researcher before the analysis takes place, and therefore only one cluster solution is given. Second, cases can be moved from one cluster to another during the clustering process to optimize the cluster solution.

<sup>85</sup> Squared Euclidean distance was used as the value of the measures is more important than the pattern of the measures across time.

<sup>86</sup> Distinct clustering is signaled by a high Caliński and Harabasz pseudo-F index, as well as by a large  $Je(2)/Je(1)$  index associated with a low pseudo- $T^2$  surrounded by much larger pseudo- $T^2$  values

<sup>87</sup> The Caliński and Harabasz pseudo-F index was 729.7 and the Duda-Hart  $Je(2)/Je(1)$  index was 0.29 with the associated pseudo- $T^2$  of 29.4.

<sup>88</sup> Cluster analysis was done using Stata/MP 16.0.

considered its own cluster. Vertical lines extend up for each jurisdiction, and at various (dis)similarity values, these lines are connected to the lines from other observations with a horizontal line.<sup>89</sup> The observations continue to combine until all jurisdictions are grouped together at the top of the tree.

#### EXHIBIT D.18 GROUPING OF JURISDICTIONS BY CONTEXTUAL MEASURES

Cluster 1	Cluster 2	Cluster 3	Cluster 4
Alabama† Kentucky† Louisiana† Missouri* South Carolina Colorado** Maryland** Minnesota** Wisconsin**	Arkansas Iowa Kansas Mississippi Nevada Oklahoma Utah* Connecticut** Oregon**	Alaska Delaware Hawaii Idaho Maine Montana Nebraska New Hampshire New Mexico†† North Dakota Rhode Island South Dakota Vermont West Virginia Wyoming	Georgia** Illinois** Michigan** New Jersey** North Carolina** Ohio** Pennsylvania** Virginia**  California** Florida** New York** Texas**
Tennessee* Arizona** Indiana** Massachusetts** Washington**			

**Notes:** \*indicates eligible for EPSCoR in the past. \*\* indicates never eligible for EPSCoR.

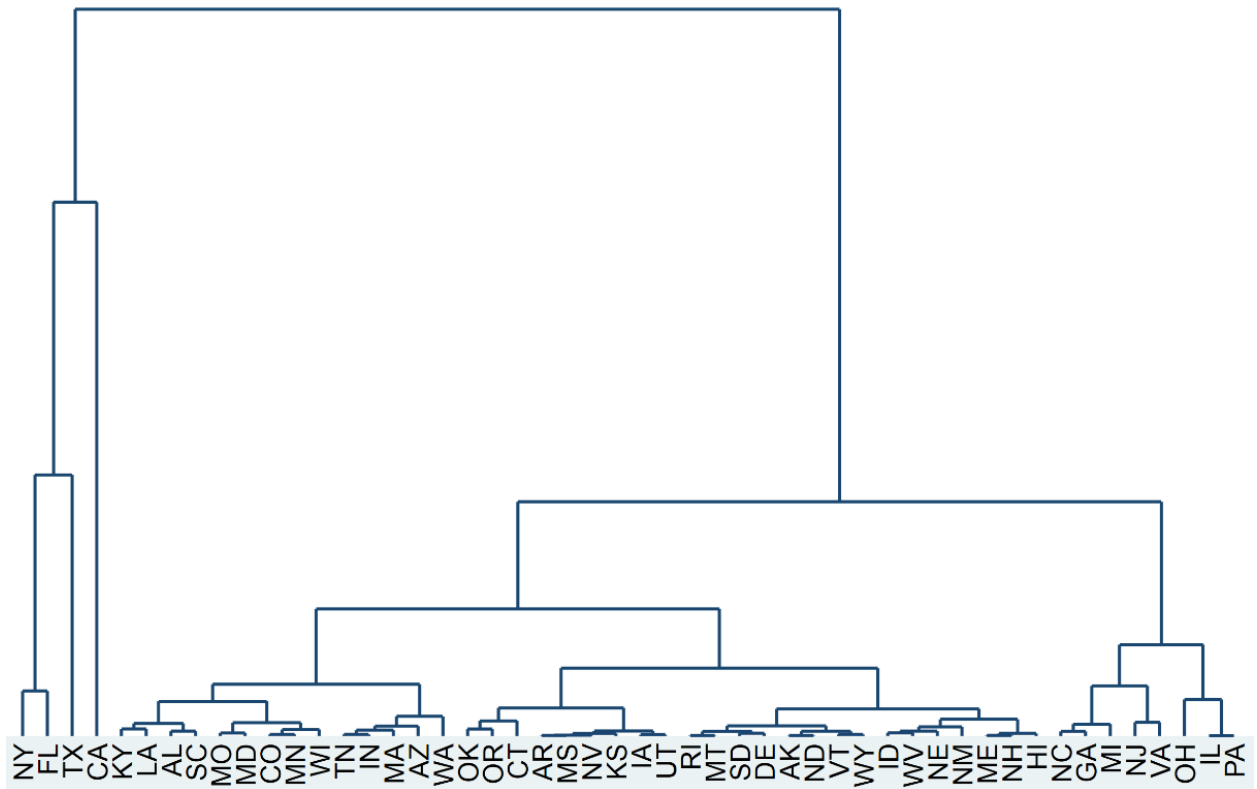
†Alabama, Kentucky, and Louisiana were in Cluster 2 in some of the sensitivity tests.

††New Mexico was in Cluster 2 in one of the sensitivity tests.

Cluster 1 could be further broken down into two groups with Tennessee, Arizona, Indiana, Massachusetts, and Washington forming the new group. However, this was not the optimal number of groups.

<sup>89</sup> Long vertical lines indicate more distinct separation between the groups. Shorter lines indicate groups that are not as distinct.

**EXHIBIT D.19 A TREE GRAPHICALLY DEPICTING THE VARIOUS LEVELS OF SIMILARITY USING CONTEXTUAL MEASURES**



## Exploratory Factor Analysis for Outcome Measures

This analysis begins with the following list of jurisdictional outcome measures (data sources listed in brackets):

- Number of SEH Graduate Students in 2016 (SESP)
- Number of S&E Doctorates Awarded in 2017 (SESP)
- *Number* of SEH Postdocs in 2016 (SESP)
- *Number* of Employed Doctorates in SEH in 2017 (SESP)
- *Percentage* of Population in State Age 25 and Older with Bachelor's Degree in 2014 (STSI)
- *Percentage* of Population in State Age 25 and Older with Master's Degree or Higher in 2014 (STSI)
- *Percentage* of Population in State Age 25 and Older with Doctorate in 2014 (STSI)
- *Proportion* of Workers Who Earned Bachelor's, Master's, or Doctorate in S&E in 2014 (STSI)
- *Percentage* Minority of Full-Time S&E Graduate Students in 2015 (SGSPSE)
- *Percentage* of Female Full-Time S&E Graduate Students in 2015 (SGSPSE)
- *Percentage* Distribution of Asian Workers (BLS)
- *Percentage* Distribution of Hispanic/Latino Workers (BLS)
- *Percentage* Distribution of Female Workers (BLS)
- *Percentage* of Women in Professional, Scientific, and Technical Services Employment in 2016 (Census)
- *Parity* Ratio of Number of Minority-Owned S&E Businesses (MBDA)
- *Percentage* of Workforce Composed of S&E Occupations (NSF State Indicators)
- *Number* of High-Tech Industries with Employment Growing Faster than the U.S. Average (STSI)
- *Total* Number of Inc. 500 Companies Per 10,000 Business Establishments (STSI)
- *Percentage* of Business Establishments in a State Defined as High-Tech (STSI)
- *Percentage* of Employment in a State in One of the High-Tech Industries (STSI)
- *State's* Relative Performance in Generating Fast-Growing High-Tech Enterprises (STSI)
- *Concentration* of High-Tech Industries in 2015 (STSI)
- *Utility* Patents Issued to State Residents in 2015 (SESP)
- *Number* of NAI Fellows in Each State in 2015 (NAI)
- *Rate* at Which State's Research Proposals were Given NSF Funding in 2015 (STSI)
- *Number* of Small Business Innovation Research Program Awards in 2015 (SESP)
- *Score* on Papers Published in *Nature* or *Science* from 2017 (ARWU)
- *Score* on Papers Indexed in Science and Social Science Fields from 2017 (ARWU)
- *Score* on Highly Cited Researchers from 2017 (ARWU)
- *Score* of Staff Winning Nobel Prizes and Fields Medals from 2017 (ARWU)



Exhibit D.7 show the correlation across the contextual measures for the jurisdictions.<sup>90</sup> Several well-recognized criteria in the literature for the factorability of a correlation were used. First, it was observed that all 30 measures correlated at least 0.3 with at least 1 other item, suggesting reasonable factorability (see Exhibit D.7).<sup>91</sup> Secondly, the Kaiser-Meyer-Olkin measure of sampling adequacy was 0.72, above the commonly recommended value of 0.6, and Bartlett's test of sphericity was significant (Chi-squared (465) = 1800.99,  $p = 0.00$ ). Finally, the communalities (1-uniqueness) were above 0.3 for most variables (see Exhibit D.9),<sup>92</sup> further confirming that the measure shared some common variance with other measures. Given these indicators, factor analysis was deemed suitable with all 31 measures.

Principal-factor method was used to analyze the correlation matrix.<sup>93</sup> Initial eigenvalues indicated that the first four factors explained 49 percent, 12 percent, 9 percent, and 6 percent of the total variance, respectively. The fifth and sixth factors had eigenvalues just over 1 and explained 5 percent and 4 percent of the total variance. Solutions for three, four and five factors were each examined using varimax, oblimin, and promax rotations of the factor loading matrix. The four-factor solution, which explained 75.6 percent of the total variation (after the promax oblique rotation)<sup>94</sup> was preferred because of (a) theoretical support, (b) the "leveling off" of eigenvalues on the scree plot after three factors<sup>95</sup> (see Exhibit D.8), and (c) the insufficient number of primary loadings and difficulty of interpreting the fifth factor and subsequent factors. There was little difference between the four-factor varimax, promax, and oblimin solutions; all solutions were examined before deciding to use promax rotations for the final solution.

<sup>90</sup> The squared multiple correlations of each variable with all other variables was high (range: 0.67 to 0.98).

<sup>91</sup> *Percentage distribution of Black workers in professional & business services in 2016 (BLS)* and *Average yearly growth of high-tech industries for each year 2010–2015 (STSI)* and are not correlated with other variables and were removed from the factor analysis but included in the exploratory cluster analysis.

<sup>92</sup> State's relative performance in generating fast-growing high-tech enterprises has a value of 0.1 for communality (1-uniqueness).

<sup>93</sup> The principal component factor model was found inappropriate as the model is based on the assumption that the uniquenesses across the variables are 0. However, considerable uniqueness was found after the four factors.

<sup>94</sup> The promax rotation with power of 3 and Kaiser normalization was used. Oblique rotations allow the rotated factors to be correlated and often yield more interpretable factors due to the simpler pattern matrix. Varimax rotation and oblimin rotation with Kaiser normalization got similar results with the factor loadings varying slightly.

<sup>95</sup> The scree plot has two inflection points—one at 2 and the other at 4.

## EXHIBIT D.20 CORRELATION BETWEEN OUTCOME MEASURES AT THE JURISDICTIONAL-LEVEL

### Human Capital Production

	Number of SEH graduate students	Number of S&E doctorates	Number of SEH postdocs	Number of employed PhDs in SHE	Percentage of population with bachelor's degree in S&E	Percentage of population with master's degree in S&E	Percentage of population with doctorate in S&E	Proportion of workers who earned degrees in S&E
Number of SEH graduate students	1							
Number of S&E doctorates	0.862	1						
Number of SEH postdocs	0.779	0.8	1					
Number of employed PhDs in SEH	0.631	0.661	0.768	1				
Percentage of population with bachelor's degree in S&E	0.511	0.503	0.603	0.764	1			
Percentage of population with master's degree in S&E	0.507	0.496	0.625	0.792	0.909	1		
Percentage of population with doctorate in S&E	0.554	0.61	0.672	0.923	0.81	0.841	1	
Proportion of workers who earned degrees in S&E	0.757	0.698	0.59	0.581	0.5	0.458	0.535	1

### Reputation in Knowledge Production

	Utility patents issued	NAI fellows	SBIR-STTR program awards	Score for papers published in Nature or Science	Score for papers indexed	Score for highly cited researchers	Score for staff awards	Percentage minority of S&E graduate students
Utility patents issued	1							
NAI fellows	0.862	1						
SBIR-STTR program	0.892	0.836	1					
Score for papers published in Nature or Science	0.604	0.606	0.721	1				
Score for papers indexed	0.468	0.523	0.569	0.854	1			
Score for highly cited researchers	0.615	0.639	0.683	0.935	0.871	1		
Score for staff awards	0.573	0.583	0.639	0.852	0.625	0.793	1	
Percentage minority of S&E graduate students	0.257	0.421	0.257	0.237	0.25	0.221	0.255	1

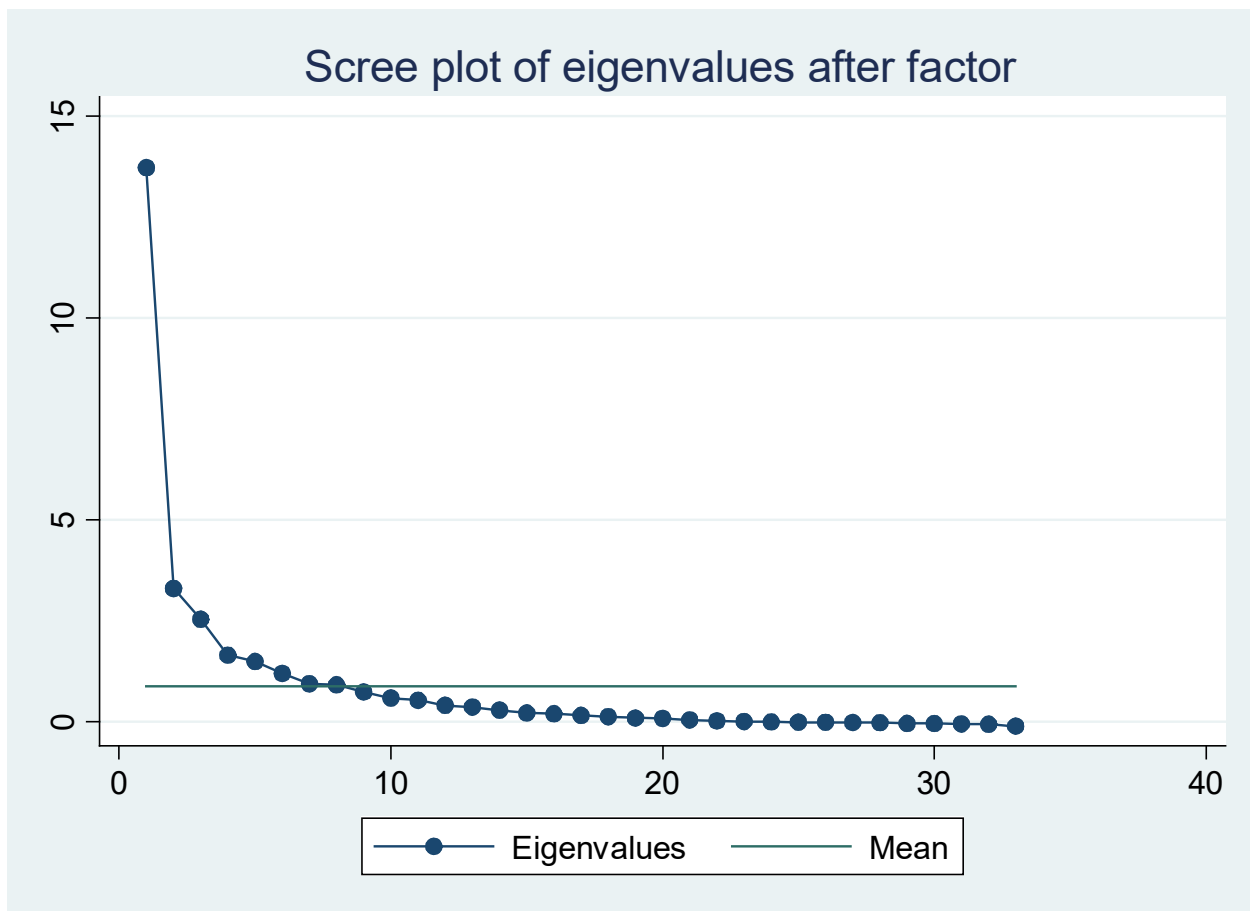
## Economic Development

	Percentage of workforce composed of S&E occupations	Percentage of businesses defined as high tech	Percentage of employment in high-tech industries	Concentration of high-tech industries	Relative performance in generating fast-growing high-tech enterprises	High-tech industries growing faster than average	Inc 500 companies	Percentage of women in professional, scientific, and technical services employment
Percentage of workforce composed of S&E occupations	1							
Percentage of businesses defined as high tech	0.814	1						
Percentage of employment in high-tech industries	0.865	0.763	1					
Concentration of high-tech industries	0.658	0.654	0.861	1				
Relative performance in generating fast-growing high-tech enterprises	0.663	0.687	0.781	0.753	1			
High-tech industries growing faster than average	-0.31	-0.21	-0.33	-0.25	-0.15	1		
Inc 500 companies	0.489	0.622	0.51	0.474	0.582	-0.16	1	
Percentage of women in professional, scientific, and technical services employment	-0.54	-0.57	-0.61	-0.54	-0.45	0.226	-0.3	1

## Diversity in Workforce

	Percentage of female S&E graduate students	Percentage distribution of Hispanic/Latino workers	Parity ration of number of minority-owned S&E businesses
Percentage of female S&E graduate students	1		
Percentage distribution of Hispanic/Latino workers	0.259	1	
Parity ration of number of minority-owned S&E businesses	0.282	0.188	1

**EXHIBIT D.21 SCREE PLOT DISPLAYING THE EIGENVALUES FOR EACH FACTOR FOR OUTCOME FACTOR ANALYSIS**



Three items—Rate of Research Proposals Given NSF Funding, Percentage Distribution of Asian Workers, and State’s Relative Performance in Generating Fast-Growing High-Tech Enterprises—were eliminated as no measure failed to meet a minimum criterion of having a primary factor loading of greater than 0.5 or cross-loadings between 0.3 and 0.4. However, only one measure, Percentage of Workforce Composed of S&E Occupations, had cross-loading values which were similar to the primary factor loading. This measure was kept in the final stage analysis. Promax rotation provided the best-defined factor structure where all measures in the analysis had primary loading over 0.5 and only one measure had a cross-loading above 0.5. The factor loading matrix for this final solution is presented in Exhibit D.9.

## EXHIBIT D.22 FACTOR LOADINGS AND UNIQUENESS FOR THE OUTCOME MEASURES

	Human Capital Production	Reputation in Knowledge Production	Economic Development of High-Tech Industry	Diversity	Uniqueness
Number of SEH Graduate Students Per Resident	<b>0.90</b>				0.15
Number of S&E Doctorates Awarded Per Resident	<b>0.94</b>				0.15
Number of SEH Postdocs Per Resident	<b>0.83</b>				0.20
Number of Employed Doctorates in SEH Per Resident	<b>0.84</b>				0.20
Proportion of Workers Who Earned Bachelor's, Master's, or PhD in S&E	<b>0.86</b>				0.33
Percentage of Population Age 25 and Older with Doctorate	<b>0.80</b>				0.17
Percentage of Population Age 25 and Older with Bachelor's Degree	<b>0.70</b>				0.16
Percentage of Population Age 25 and Older with Master's Degree or Higher	<b>0.69</b>				0.15
Utility Patents Issued to State Resident		<b>0.82</b>			0.17
Number of SBIR Awards		<b>0.71</b>			0.21
Number of NAI Fellows in Each State		<b>0.84</b>			0.20
Highest Score for Papers Published in <i>Nature</i> or <i>Science</i> for a Doctoral University		<b>0.60</b>			0.09
Highest Score for Papers Indexed in Science or Social Science Fields for a Doctoral University		<b>0.57</b>			0.22
Highest Score for Highly Cited Researchers for a Doctoral University		<b>0.70</b>			0.12
Highest Score for Staff Winning Nobel Prizes and Fields Medals for a Doctoral University		<b>0.58</b>			0.30
Percentage of Minority Full-Time S&E Graduate Students		<b>0.60</b>			0.60
Percentage of Workforce Composed of S&E Occupations	<i>0.53</i>		<b>0.55</b>		0.18
Percentage of Businesses Defined as High-Tech			<b>0.64</b>		0.13
Percentage of Employment in High-Tech Industries			<b>0.57</b>		0.19
Concentration of High-Tech Industries			<b>0.66</b>		0.22
Total Number of Inc. 500 Companies Per 10,000 Business Establishments			<b>0.73</b>		0.15
Number of High-Tech Industries with Employment Growing Faster than the U.S. Average			<b>0.59</b>		0.56
Percentage of Women in Professional, Scientific, and Technical Services employment in 2016			<b>0.54</b>		0.28
Percentage of Female Full-Time S&E Graduate Students				<b>0.60</b>	0.64
Percentage Distribution of Hispanic/Latino Workers				<b>0.59</b>	0.50
Parity Ratio of Number of Minority-Owned S&E Businesses				<b>0.50</b>	0.72

**Notes:** Extraction method: principal axis factoring. Rotation method: promax with Kaiser normalization.

Factor loading < 0.5 are suppressed. Variables with secondary loadings of lower value than the primary loadings are italicized.

The factor labels were selected as the measures in each factor aligned with the appropriate logic model domains and/or AREC framework. Internal consistency for each of the scales was examined using Cronbach's alpha.<sup>96</sup> The overall Cronbach's alpha was 0.95. The alphas for the first three factors were high: 0.94 for factor 1 (9 items), 0.90 for factor 2 (8 items), and 0.93 for factor 3 (7 items). The Cronbach's alpha was moderate for factor 4 (0.66; 3 items). No *substantial* increases in alpha for any of the scales could have been achieved by eliminating more items.

Composite scores were created for each of the four factors using a regression scoring method. Higher scores indicated greater resources available for each factor. The use of an oblique rotation (promax) was justified as the correlations between the composite scores was from 0.22–0.42 (see Exhibit D.10).

#### EXHIBIT D.23 CORRELATION BETWEEN THE COMPOSITE FACTORS

	Factor 1	Factor 2	Factor 3	Factor 4
Factor 1	1			
Factor 2	0.41	1		
Factor 3	0.38	0.31	1	
Factor 4	0.26	0.42	0.22	1

Overall, these analyses indicated that 4 distinct factors were underlying the 31 outcome measures and that these factors were internally consistent. Using these factors, the jurisdictions can be preliminarily grouped in nine buckets as shown in Exhibit D.11.

#### EXHIBIT D.24 PRELIMINARY GROUPING OF JURISDICTIONS

Above Mean				States
Factor 1	Factor 2	Factor 3	Factor 4	
				Arkansas, Alaska, Alabama, Idaho, Louisiana, Mississippi, Montana, North Dakota, Oklahoma, South Dakota, Wyoming
			X	Hawaii, Kentucky, Maine, West Virginia, South Carolina
		X	X	Tennessee*
	X		X	Nevada
X				Iowa, Kansas, Nebraska
X			X	Rhode Island
X		X	X	Missouri*, Illinois**, Michigan**, Pennsylvania**, Wisconsin**
X	X			Delaware, New Mexico, Utah*
X	X		X	New Hampshire, Vermont, Colorado**, Maryland**, Minnesota**, Oregon**, Virginia**

**Note:** \* indicates eligible for EPSCoR in the past. \*\* indicates never eligible for EPSCoR. All the jurisdictions that have F1 Above Mean are jurisdictions that have never been eligible for EPSCoR.

<sup>96</sup> Average interitem correlation values are greater than 0.25 for all four factors. Overall, the average interitem correlation was 0.37.

## Exploratory Cluster Analysis for Outcome Measures

Next, the study team grouped jurisdictions using an exploratory cluster analysis to identify jurisdictions with similar outcome measures. The study team applied following hierarchical cluster analysis using the following criteria:

- *Measuring* distance between observations – Euclidean distance method
- *Measuring* distance between groups – the average linkage
- *Selecting* the observable variables – variables in the factor analysis are included but two measures—*Percentage distribution of Black workers in professional and business services in 2016 (BLS)* and *Average yearly growth of high-tech industries for each year 2010–2015 (STSI)* were excluded
- *Selecting* the optimal number of groups – two stopping rules<sup>97</sup>: the Caliński and Harabasz pseudo-F index and the Duda-Hart  $Je(2)/Je(1)$  index with the associated pseudo- $T^2$ .

Using these criteria, the jurisdictions were divided into 12 groups.<sup>98</sup> However, the nine groups had few jurisdictions in each group and all jurisdictions in these nine groups are not currently eligible for EPSCoR. The study team merged these jurisdictions into one group. This reduced the number of clusters to three (see Exhibit D.12). The clusters are stable across different measures, methods, and stopping rules.<sup>99</sup> Exhibit D.13 graphically presents the information concerning which jurisdictions are grouped together at various levels of (dis)similarity.

### EXHIBIT D.25 A GROUPING OF JURISDICTIONS BY OUTCOME MEASURES

Cluster 1†		Cluster 2		Cluster 3	
Alabama†	Nebraska†	Iowa	New Hampshire	Arizona**	Minnesota**
Alaska	New Mexico†	Idaho	Missouri*	California**	New Jersey**
Arkansas††	North Dakota	Kansas	South Carolina	Colorado**	New York**
Delaware†	Oklahoma†	Kentucky	Tennessee*	Connecticut**	North Carolina**
Hawaii	Rhode Island†	Nevada	Utah*	Florida**	Ohio**
Louisiana†	South Dakota			Georgia**	Oregon**
Maine††	Vermont†			Illinois**	Pennsylvania**
Mississippi††	West Virginia††			Indiana**	Texas**
Montana	Wyoming			Maryland**	Virginia**
				Massachusetts**	Washington**
				Michigan**	Wisconsin**

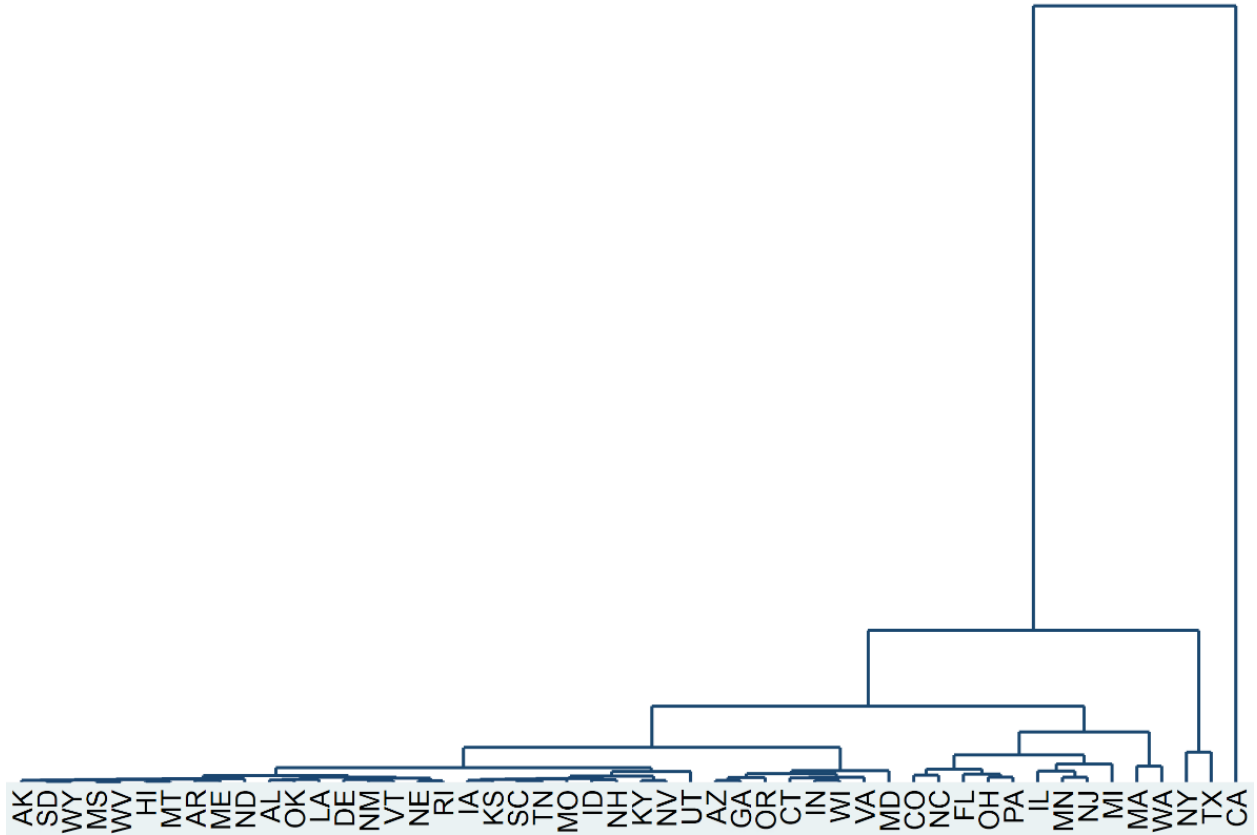
**Notes:** \* indicates eligible for EPSCoR in the past. \*\* indicates never eligible for EPSCoR. Cluster 1 could be further broken down into two more groups. The second group is denoted by †. The third group is denoted by ††. However, this was not the optimal number of groups according to the pre-set criteria laid out.

<sup>97</sup> Distinct clustering is signaled by a high Caliński and Harabasz pseudo-F index, as well as by a large  $Je(2)/Je(1)$  index associated with a low pseudo- $T^2$  surrounded by much larger pseudo- $T^2$  values.

<sup>98</sup> The Caliński and Harabasz pseudo-F index was 729.7 and the Duda-Hart  $Je(2)/Je(1)$  index was 0.29 with the associated pseudo- $T^2$  of 29.4.

<sup>99</sup> Cluster analysis was done using Stata/MP 16.0.

EXHIBIT D.26 GRAPHICAL DEPICTION OF THE VARIOUS LEVELS OF SIMILARITY USING OUTCOME MEASURES





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## APPENDIX E. EXPLORATORY ANALYSIS TO EXPLORE PATHWAYS BETWEEN MEASURES OF AREC LOGIC MODEL CONTEXT, INPUTS, OUTPUTS, AND OUTCOMES

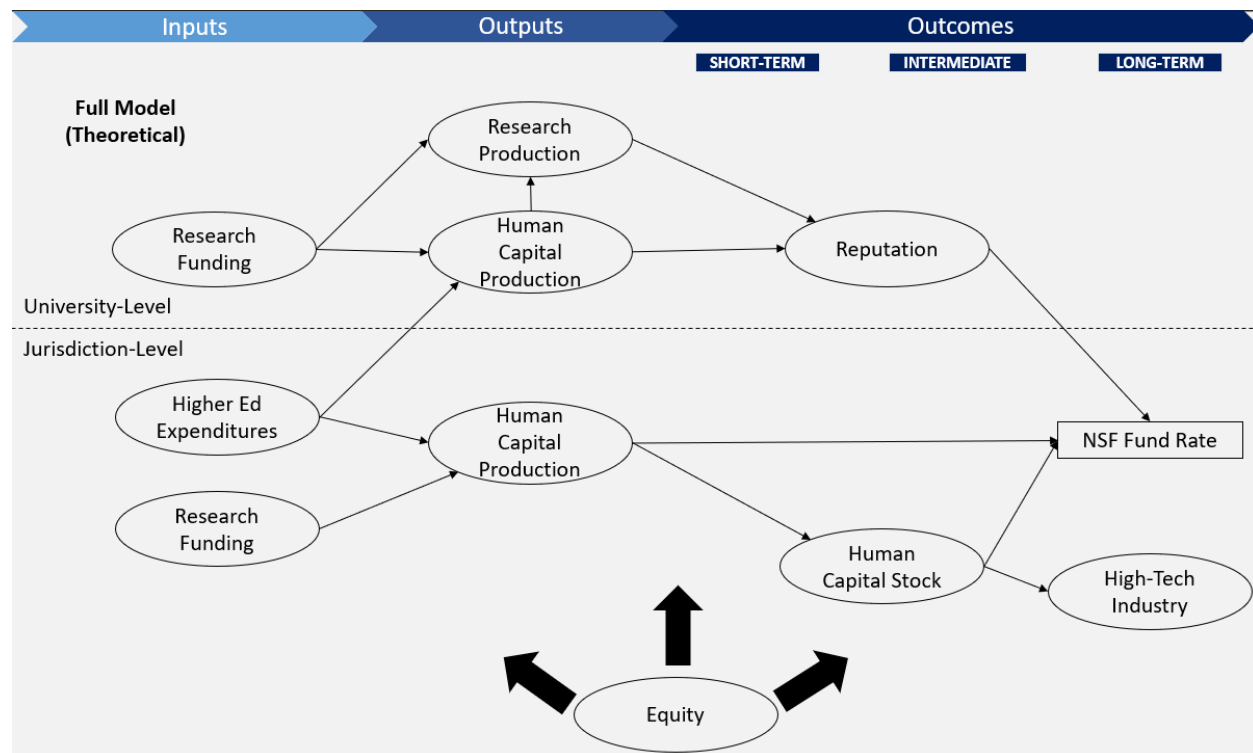
Using measures mapped to the AREC logic models in Chapter 3, the study team conducted structural equation modeling (SEM) to explore preliminary pathways between measures of AREC logic model contexts, inputs, outputs, and outcomes. The analyses in this appendix are subject to substantial caveats. As noted earlier in Chapter 3, large portions of the AREC logic models are not adequately covered by existing publicly accessible measures, so the analyses necessarily provide only a partial picture of AREC framework. In particular, the structural equation models are limited to available data and therefore include only a fraction of the possible pathways between inputs, outputs, and outcomes described in Chapter 4. The activities measures are only available for EPSCoR jurisdictions, which will reduce the number of observations. As a result, activities measures were not incorporated. Additionally, many of the accessible measures are coarse metrics that may not be sensitive to small changes in AREC induced by particular programs or policies. Finally, the relatively small number of U.S. jurisdictions (55) makes it difficult to estimate complex statistical models at the jurisdiction-level. The remainder of this appendix includes the preliminary SEM analyses that address the pathway RQ.

To demonstrate how AREC can be put into practice, the study team used SEM<sup>100</sup> to test pathways connecting inputs, outputs, and outcome constructs from the AREC logic models that map to available measures (see Exhibit E.1). As a caveat, this analysis is only used to test whether relationships in the model correlated as expected and should not suggest that short-term initiatives may produce rapid change. To reduce complexity, a larger set of measures was grouped into a smaller number of theoretical latent constructs (pictured in ovals).<sup>101</sup> The study team then hypothesized pathways between these constructs, illustrated by arrows.

<sup>100</sup> SEM combines path analysis with factor analysis, allowing researchers to explore theories around complex processes. Path analysis allows researchers to estimate multiple regressions simultaneously, and factor analysis allows researchers to create latent variables for complex constructs.

<sup>101</sup> Confirmatory factor analysis was performed in SAS to test whether the measures theoretically associated with each latent construct actually hang together empirically. When they did not, one measure was selected to represent the construct. Measures appear as rectangles.

## EXHIBIT E.27 FULL STRUCTURAL EQUATION MODEL

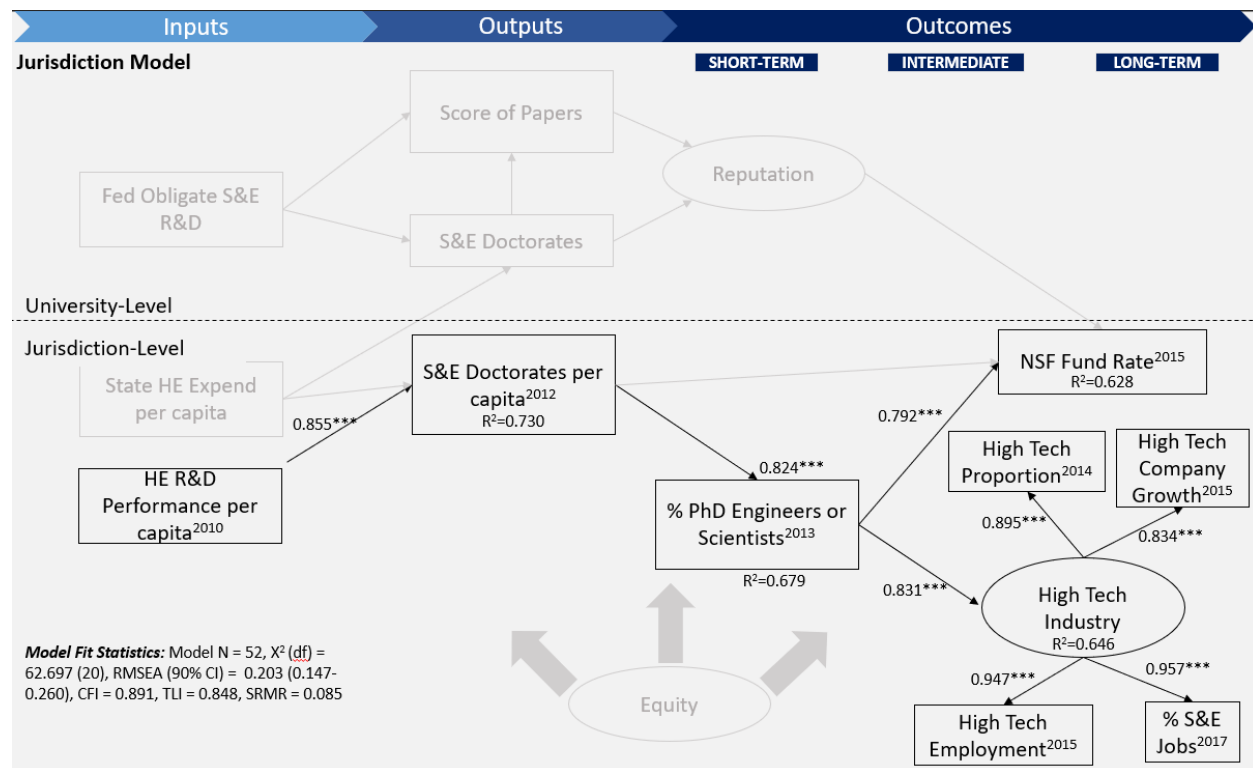


SEM is a useful analytic tool, but it does not provide causal evidence of the impact of inputs on outcomes. Because AREC measures are fairly stable over time, the analysis might detect relationships rather than effects even when inputs, outputs, and outcomes are temporally ordered. In addition, since the testable model is limited by available measures, it does not include all the AREC pathways suggested by the logic models. For example, the long-term outcomes in the theoretical model (NSF funding rate and high-tech industry) are important AREC constructs, but they by no means encompass the breadth of long-term outcomes across the five AREC elements described in the logic models.

The study team tested theoretical pathways separately at the jurisdiction and university levels.<sup>102</sup> At the jurisdiction-level, for example, the study team explored the relationships between higher education expenditures, research funding, demographics, human capital production, human capital stock, NSF funding rate, and high-tech industry (Exhibit E.2). High-tech industry is a complex construct that the study team operationalized as a latent factor, including percentage of businesses that are high-tech, percentage of employment that is in high-tech industries, number of fast-growing high-tech industries, and percentage of jobs in S&E.

<sup>102</sup> The relatively small sample size of jurisdictions limited the complexity of the structural equation models the study team could estimate. The study team attempted to fit a cross-level model, but it failed to converge.

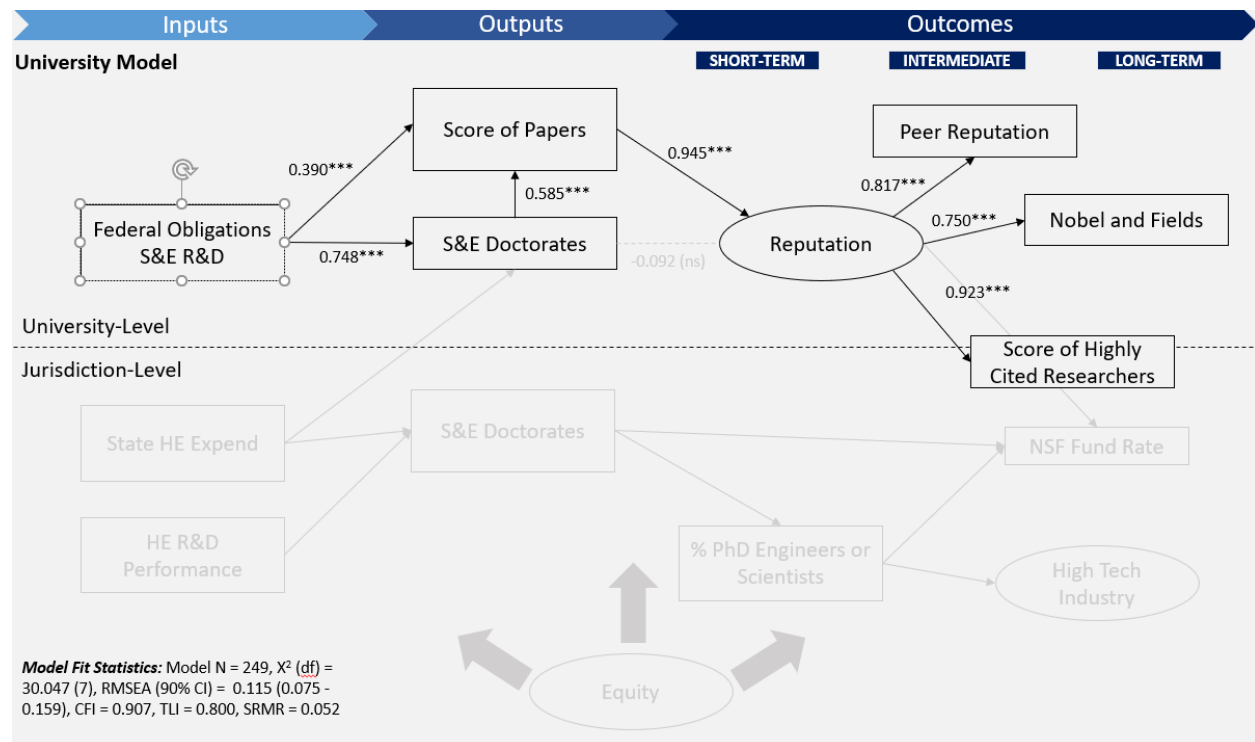
## EXHIBIT E.28 JURISDICTION-LEVEL STRUCTURAL EQUATION MODEL



The study team found that higher education R&D performance is positively associated with per capita award of S&E doctorates (standardized coefficient of 0.855),<sup>103</sup> but state higher education expenditures per capita are not. In addition, the number of S&E doctorates per capita is positively associated with the proportion of S&E doctorates in the workforce (standardized coefficient of 0.824). Finally, the number of S&E doctorates in the workforce is positively associated with NSF funding rate and high-tech industry. Contrary to the study team's expectation, there is no direct relationship between production of S&E doctorates and NSF funding rate. As noted earlier, doctorate recipient mobility is relatively high, so success in winning research funding is likely to be affected by the ability of a given jurisdiction to attract and retain doctoral recipients.

<sup>103</sup> Because the variables in the models are on different scales, the study team reported standardized coefficients, which range from 0 (no association) to 1 (one-to-one association). This coefficient can be interpreted to mean that a 1-standard-deviation difference in higher education R&D performance is associated with a 0.855-standard-deviation difference in per capita award of S&E doctorates. There is some variability across the model fit statistics reported—rule of thumb is Tucker–Lewis index (TLI)  $\geq .95$ ; Comparative fit index (CFI)  $\geq .95$ ; and standardized RMR (SRMR)  $\leq .08$ . Using these statistics, the model fit is a poor fit. This is also related to small sample size issue as discussed earlier.

## EXHIBIT E.29 UNIVERSITY-LEVEL STRUCTURAL EQUATION MODEL



At the university level, the study team explored the relationships between research funding, human capital production, research production, and institutional reputation (Exhibit E.3), where institutional reputation was defined as peer reputation, number of Nobel Prizes and Fields Medals earned by an institution's faculty, and a score of highly cited researchers at the institution. The data revealed that human capital production partially mediates the relationship between research funding and research production, and research production fully mediates the relationship between human capital production and institutional reputation. This means that a large part of the association between federal R&D obligations and publications flows through production of S&E doctorates, and all of the association between S&E doctorates and institutional reputation flows through publications.<sup>104</sup>

<sup>104</sup> There is some variability across the model fit statistics reported—rule of thumb is Tucker–Lewis index (TLI)  $\geq .95$ ; comparative fit index (CFI)  $\geq .95$ ; and standardized RMR (SRMR)  $\leq .08$ . Using these statistics, the model fit is a marginal fit.