



Reimagining Labor Market Information

A NATIONAL COLLABORATIVE FOR
LOCAL WORKFORCE INFORMATION

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A M E R I C A N E N T E R P R I S E I N S T I T U T E

Executive Summary

Profound changes in technology and climate, combined with the COVID-19 pandemic shock, have fundamentally changed the nature of work for firms and employees. And, because most labor markets are local, that change requires rethinking how data and evidence can be generated in a timely and actionable way to inform local decisions.

The emergence of new types of local data, new cloud-based platforms allowing state and local agencies to securely share de-identified confidential data, and new training programs to build state workforce capacity means that there is new potential for programs that are designed and shaped at the local level. A new workforce information system—a National Collaborative for Local Workforce Information

(NCLWI)—can be designed that is driven by local needs and that is timely, actionable, and responsive.

This report describes why and how such a system should be constructed. The approach, inspired by the successful National Agricultural Extension Program, is fundamentally local in nature. It should be federally funded but driven by state and local needs, networks, and decision makers. It should build on the success of multistate data collaboratives in sharing data across agency and state lines and partnering with local universities. The result will be bottom-up, locally generated projects that can be tested, improved, and scaled to become products that can be put into practice across the country.

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Profound changes in technology and climate, combined with the COVID-19 pandemic shock, have fundamentally changed the nature of work for firms and employees. Affected business owners, students, parents, incarcerated individuals, welfare recipients, and their elected representatives all need good data and evidence to make important decisions to ensure their future prosperity. Our current century-old labor market information system must be reimagined so that governments can efficiently allocate scarce resources, businesses can grow the economy, and workers can succeed.

A newly imagined workforce information system should be designed to reflect the constantly changing US economy. It should provide people and businesses with rich information about earnings, job dynamics, and opportunities where they live and work—from Austin, Texas, to Louisville, Kentucky, and from Buffalo, New York, to Hollywood, California. It should be based on timely data, complementing the current survey-based data collection that is sadly becoming slower and less reliable.¹ It should feature new, flexible measures and provide actionable information about job market dynamics customized to people’s differing educational and work experiences.² To achieve these goals, the system should be democratized so data users can create measures that are useful and useable for their needs.

The federal government has created such institutions in other contexts that have proven their worth

time and again. The National Oceanic and Atmospheric Administration’s (NOAA) National Weather Service has created a system of locally collected and disseminated but nationally funded and curated data to produce the familiar and successful local weather forecasts we use today.³ The US Department of Agriculture’s (USDA) National Institute of Food and Agriculture provides a cooperative model that serves farmers’ different local needs—ranging from how to raise longhorn cattle in Texas to how to grow apples in Wisconsin—using the land grant university system, which includes agricultural extension services that provide learning activities to rural communities (such as the 4-H program).⁴

This focus on local needs has thousands of examples of impact. Just to cite two from the USDA, the mining industry was transformed because Michigan researchers discovered how to pelletize fine powders and transport them, and Purdue University “Boilermakers” figured out how to make boilers, crucial technology for steam transport.⁵ The result of this systemic investment—a productivity boom in the agricultural sector with an economic rate of return over 40 percent—has fundamentally changed the US economy.⁶

This report recommends establishing a national collaborative grounded in the success of a set of regional collaboratives inspired by the Foundations of Evidence-Based Policymaking Act. The National Collaborative for Local Workforce Information (NCLWI)

would develop local, timely evidence to support state and local policymaking in using labor market data that support the American workforce. Its structure should be informed by the long-term success of the USDA and NOAA approaches and resourced to test, build, and scale new ideas, moving from projects to products to practice.⁷ It should be designed to (1) empower state and local stakeholders—such as government agencies, governors’ offices, education and training providers, and chambers of commerce—to identify and solve local problems; (2) foster innovation and build capacity through innovation sandbox training programs with local universities; and (3) produce high-value products for timely decision-making.

States are already moving to better connect and leverage their data to improve their state’s prosperity. Texas and Florida recently passed legislation to accomplish this by identifying and integrating additional data that can pinpoint and improve education and training programs’ impact on students and their families and ensure that employers have a workforce with job-essential skills.

The Context: Regional Collaboratives

The past five years have reinforced the importance of evidence and data for policymaking.⁸ The COVID-19 pandemic made the abstract real—and raised awareness of the need for and value of workforce data. At the pandemic’s start, state labor market information units were hammered with requests for information regarding what was going on, where job losses were occurring, and which industries were experiencing loss. After the first three to six months of the pandemic, the shift for evidence turned to questions on how fast jobs would be coming back and in what areas and industries. In other words, the pandemic raised awareness of the value of labor market data and evidence—and showed that state and local policymakers and elected officials lacked access to it.

Recent technological change has also prompted the emergence of state-centered regional collaboratives, transforming these states’ workforce information.

Three multistate data collaboratives—the MidWest, the Southern, and the Eastern Collaboratives—have formed, hosted by the National Association of State Workforce Agencies (NASWA) and supported by the State Higher Education Executive Officers Association.

They have leveraged state governance structures and cross-state and cross-agency data sharing agreements to develop a state-owned and -administered data environment in a secure remote-access facility hosted by the Coleridge Initiative. The Advisory Committee on Data for Evidence Building (ACDEB) highlighted this process in its report to the Office of Management and Budget.⁹ Each state links its de-identified data in the cloud with other states for agreed-on projects, controlling access to and use of the data through a well-developed data stewardship application.¹⁰ NASWA’s website provides a full description.¹¹

This approach’s key feature, and a major reason for its innovativeness and scalability, is that states maintain ownership of their data and approve any use of state data. A major accomplishment of this governance model is the trust generated among states and, importantly, across agencies in the same state. Rather than a hub-and-spoke model (in which control sits in Washington, DC), this system is a network model in which every state is its own node—of equal importance and voice and directly collaborating and communicating with peers.

States in these collaboratives have established a “project, product, practice” approach.¹² They identify *project*-level questions of high strategic importance and then work with universities to establish Applied Data Analytics training programs—a labor market analogous to agricultural extension programs—to answer those questions. In those programs, agencies across states collaborate to develop a portfolio of possible *products* that can scale to multiple states by defining common data models, developing new measures, and applying advanced methodologies to describe and capture cross-state flows. They then move the products into *practice*.

Two of these projects were identified as important use cases in the ACDEB’s report.¹³ The first practical

implementation was a portal for workforce boards and governors' offices that provided timely, local, and actionable measures of jobs and joblessness, led by Illinois. The second was a multistate education-to-workforce dashboard that developed useful measures of education and workforce credentials, matched to new measures of job quality that workers and firms can use to estimate the returns of training. (See the sidebar for an example of this approach.)¹⁴

States in these collaboratives have also developed a governance structure with an administrative center that can achieve these key goals: facilitate interstate collaboration on data, define a state-led data analytics infrastructure, build production-level technical capacity, address privacy concerns, establish a professional development curriculum, develop processes for the collective use of data for research and evaluation, and inform and shape the national evidence strategy.

The Approach

The NCLWI should be initially funded to address the two high-priority use cases identified in the ACDEB and then, if successful, scaled to suit demand. A third use case should also be considered that has risen to prominence because of recent federal investments to reshape the economy by supporting new and emerging technologies. These investments include the 2022 Creating Helpful Incentives to Produce Semiconductors (CHIPS) and Science Act and the National Artificial Intelligence (AI) Initiative. Both investments will require new ways of measuring and tracking how emerging technologies are reshaping local economies in order to guide strategic workforce investment decisions.

This next section uses those three use cases to illustrate how the NCLWI can create timely, local, and actionable information with a project, product, practice approach.

Joblessness and Reemployment. The US is an extremely dynamic and changing economy. It has also been subject to massive shocks to the system through

Project, Product, Practice—Ohio

Project: Many of Ohio's cities and towns are located on state borders, and students frequently migrate to neighboring states after graduation. Workers living in Ohio also commute to job sites in adjacent states, particularly Kentucky and Indiana. These interstate migration and commuting patterns pose important analytic challenges for several policy domains.

Product: A training class delivered at Ohio State University with participants from neighboring states examined connections between education and workforce; it focused on employment outcomes for community colleges or workforce training.

Practice: The Multi-State Postsecondary Report produces information crucial for institutions to determine programs' performance, as envisioned by proposed legislation, such as the College Transparency Act, and actual legislation, such as Kentucky's Students' Right to Know Act.

changing trade rules, global pandemics, and technological innovation. This use case illustrates the way in which data and evidence can be used to support workers who lose their jobs because of these shocks and to help them find new work.

Specific Rationale for Project. The COVID-19 pandemic illuminated the challenges of the existing approach to measuring labor market activity, which "emerged in the late 1930s from research conducted at the Works Progress Administration and the Census Bureau."¹⁵ At the onset of the pandemic, high-quality data were essential for determining extended benefits and allocating resources to workers in need. In response, Illinois launched an ambitious new project that used highly granular, timely, and local data to create new measures useful to governors and workforce boards.

Illinois's Department of Employment Services took several steps. The first step piloted new measures of

joblessness and reemployment. Survey-based measures of unemployment (whether respondents were actively looking for work in the survey week) and employment (whether respondents were paid at least one hour a week in the survey week) were too simplistic and static. Governors and workforce boards needed measures that were actionable and fluid enough to capture the duration and quality of jobs, the oscillation between jobs and joblessness, and the impact on workers' well-being—and businesses' survival.

The second step was establishing procedures to check these new measures. Survey-based measures were generating incorrect information for governors about their local labor markets—when correct data were most needed. From January to September 2021, for example, Michigan's reported unemployment rate was unrealistically low because of data errors in Detroit and an incorrect statistical correction by the federal government. As a result, the Michigan October unemployment rate, for example, had to be revised from 4.6 percent to 6.3 percent.¹⁶

Because unemployment is not directly measured at the local level but rather estimated for an entire region and then allocated to each state in the region, the revision affected other major states—Illinois, Indiana, Ohio, and Wisconsin. Illinois's governor was making decisions based on wrong data. Illinois's unemployment was much lower than reported. As the November 18, 2021, Illinois press release pointed out, the errors were identified when "Illinois and another East North Central Division state raised concerns about their monthly 2021 statewide labor force estimates."¹⁷

The third step was piloting the creation of detailed local information about which firms were hit worst and what types of workers were suffering most. Job seekers, employers, governors' offices, and legislators needed practical information to respond to the rapid and repeated shocks to the status quo; information needed to be detailed and local so that resource allocation could be informed by the uneven nature of the shock to different demographic groups and industries.

The pilot used data on joblessness from the Program for Measuring Insured Unemployed Statistics

files,¹⁸ which are collected by every state, including Illinois. Their practical value became immediately obvious. The data are extremely timely, since they are reported weekly, so policies can be developed in response to immediate needs. Governors and workforce boards could have the previous week's information within five days.

The sample size is generous—over 13 million data points repeated on over a million individuals at the peak of the COVID-19 pandemic—making it possible to construct both cross-sectional and longitudinal measures for each individual and aggregate to small geographies by race, sex, occupation, previous industry, and earnings. They are highly geographically granular so heterogeneity in spatial effects can be accounted for.

Finally, examining demographic heterogeneity is possible since, for each individual claimant, the dataset contains not only benefit details, such as total amount paid, but also claimant details, such as age, race, gender, educational attainment, and pre-separation occupation and industry. There are challenges, however. The data are collected from a different population than standard surveys, data are self-reported, and data discrepancies can be challenging to reconcile.¹⁹

Additionally, data on jobs, reemployment, and job quality can be derived from each state's quarterly Unemployment Insurance (UI) wage records.²⁰ These records comprise quarterly reports filed by employers for each individual in covered employment, which includes roughly 96 percent of private nonfarm wage and salary employment.²¹ The UI data provide less comprehensive coverage of agricultural employment and completely exclude federal government employees, self-employed individuals and independent contractors, and workers in the informal sector.

The wage record files also include information about quarterly wages²² for all UI-covered jobs in Illinois. These records are filed by employers and include roughly 96 percent of private nonfarm wage and salary employment.²³ They are not as timely,²⁴ but Illinois has the advantage of collecting monthly UI wage records with a one- to two-month lag. Like quarterly UI wage records, these records consist of monthly

reports filed by employers for everyone in covered employment for the first and second month of each quarter and could be replicated in each state.

Product. The development of Illinois’s product paralleled methods used in agricultural extension. Illinois partnered with the University of Chicago, Illinois State University, and New York University to create a new dashboard. That dashboard evolved from an intensive effort to transform weekly data on unemployment claims to data on the unemployment status of individual claimants and in turn to the patterns of jobs and joblessness of claimant cohorts over time. For example, considering employment status not just at a single point (e.g., paid at least one hour in a single week) but as a pattern greatly increases the detail captured even by this single state measure.

Consider, for example, the distinction between an individual who claims unemployment benefits for a single week, one who claims benefits every week for four consecutive weeks, and one who claims benefits every week for eight consecutive weeks. Or contrast an individual who is on unemployment benefits for eight consecutive weeks with one who receives four weeks of unemployment, is employed for six weeks, and then receives another four weeks of unemployment. The new product represented an advance over existing measures that characterize employment and unemployment using a single, binary, simplistic condition.

In keeping with the agricultural extension framework, the Department of Labor’s Employment and Training Administration supported four classes that trained over 100 labor market information staff from almost 30 states on how to work with the new data and develop products that could be used in their local area.²⁵ Multiple states then experimented with customizing the dashboard and their approach to their own local needs.

Practice. Those in charge of allocating resources practically for jobless individuals can now have much more information to meet their clients’ current needs from the *products* produced. They have access to information about the kinds of jobs available in a

local labor market to answer key questions: Which workers (by occupation, race, sex, or ethnicity) are unemployed for shorter durations? Which “oscillate” between employment and unemployment? Which are most likely to be reemployed in the same job or same industry after a spell of unemployment? Understanding employment and unemployment not as a singular condition but as a pattern of experiences allows for more nuanced program design and investment, particularly given new policies addressing equity and recent insights gained into how shifts in the economy affect specific subgroups.

Job Quality Measures and Returns to Education and Training. While getting a job is important, a major focus of employment policy is getting a “good” job. This use case shows how to build evidence about measures of good jobs that are grounded in available data and are useful to local education and training providers.

Rationale for Project. Education is a major pathway to high-wage jobs for individuals and a high-quality workforce for firms. Governments spend enormous amounts of money to support postsecondary education: The fiscal year 2023 appropriation for the Department of Education includes \$24 billion for student financial assistance; \$2 billion in career, technical, and adult education; and \$1.4 billion for the improvement of postsecondary education.²⁶ Student loans exceed \$1.6 trillion.²⁷

There is a dizzying array of choices. Credential Engine estimates that there are over one million different credentials in the US, offered by almost 60,000 providers.²⁸ And there is much waste: The three-year graduation rate of those who start a two-year degree at a community college is about 30 percent;²⁹ of those community college enrollees who transfer to a four-year institution, about 13 percent earned a bachelor’s degree within six years.³⁰

However, there is little evidence to identify what programs work best for different types of students or what types of investments work best.³¹ There are many reasons, but important reasons include that current measures of program performance are only

aggregate and descriptive and that job quality is poorly defined.

For state educational institutions located on state borders (such as Northern Kentucky University, which serves the greater Cincinnati area) whose graduates are more likely to get jobs in neighboring states, it is crucial to document the labor market outcomes of their students when determining the performance of programs, as envisioned by proposed legislation (such as the College Transparency Act) and actual state legislation (such as Kentucky's Students' Right to Know Act). Northern Kentucky University, for example, can measure the outcomes of almost twice as many of its graduates when it uses Ohio data as when only Kentucky data are used. It also can provide transparent information to students about credential opportunities linked to employment outcomes.³²

As state trainings continue, states are collaborating on more granular, common postsecondary measures, such as time to degree and failure to complete degrees within set periods. States are also developing improved employment metrics that capture information on employment stability, starting earnings, and earnings growth. Finally, states such as Texas are developing standard measures of the characteristics of firms that hire and employ their graduates so that states can characterize the demand for and the supply of postsecondary graduates, support the needs of businesses and workers in their states, and ensure that occupational education and training lead to a self-sufficient wage.

Further, a growing number of states—such as Florida, Texas, and Washington—are working to enhance employer wage records with occupation or job titles to better evaluate the targeting of education and training programs. Texas has even passed a law mandating that its Tri-Agency Workforce Initiative establish county-level self-sufficient wage standards and plan occupational education and training to lead to earnings that allow families to be self-sufficient.

Product. The product evolved out of a training course at Ohio State University (OSU).³³ A team of Kentucky Center for Statistics state analysts worked with Ohio data in that class to study education to workforce

transitions. Upon completing the class, they partnered with OSU and Ohio's state workforce and education agencies to develop a cross-state dashboard.

Every year, states' higher education departments receive detailed individual transcript information from every public institution of higher education and K-12. Since 2005, the Institute of Education Sciences has funded the building of many states' Statewide Longitudinal Data Systems (SLDS). The program has helped propel the successful design, development, implementation, and expansion of K-12 and early-learning-through-the-workforce longitudinal data systems. Ohio and Kentucky have SLDS and, after the course, can share data across state lines in a secure remote-access environment and build products that can inform decision-making.³⁴

One important result from the Kentucky and Ohio collaboration that has extended to other states is the Multi-State Postsecondary Report.³⁵ It represents the output of this cross-state, cross-agency effort to link individual level education data with employment outcomes to produce aggregate, local, timely, and actionable data for decision makers. The states involved—Arkansas, Indiana, Kentucky, New Jersey, Ohio, Tennessee, and Virginia—are expanding the current “qualifying employment” metric to a “quality employment” metric potentially in industries or occupations.

Practice. It is now possible to tell students and education providers what trajectories lead to improved, or at least stable, well-being—as measured by stable earnings, earnings growth, and earnings above local thresholds. Job quality measures can capture whether an individual has a single employer or is balancing multiple employers and whether they participate in seasonal work or otherwise have short-duration employment. The analytical foundation can also inform other emergent initiatives using state data, such as the extraordinarily ambitious Jobs and Employment Data Exchange initiative launched by the US Chamber of Commerce and the efforts of philanthropic foundations focused on learning and employment records and Credential Engine's credential schema.

Emerging Industries and Skills. This use case describes how data and evidence can inform the design of training programs to respond to new and emerging industries.

Rationale for Project. The economy and the labor market are clearly changing rapidly, because technological change is constantly changing the way US companies do business and their knock-on needs for labor skills. Innovation is seen as the “tool which allows society to escape the bonds of scarcity”³⁶ and create high-wage jobs. Federal government legislation to increase investment in research and development (R&D) explicitly intends to accelerate these trends.

The CHIPS and Science Act directs \$280 billion in spending over the next 10 years—primarily for scientific R&D and commercialization, tax credits for chip production, and semiconductor manufacturing, R&D, and workforce development. The National AI Initiative intendeds to foster US competitiveness in AI, and many other emerging technologies, such as quantum computing and synthetic biology, are on the horizon.³⁷

Yet spending in R&D is only the first step. The second step is to ensure that the workforce has the necessary skills to work in new technologies and that firms can hire the right kinds of skilled workers so research translates into innovation. The core building blocks are not in place for the second step.

When the Commerce Department issued its strategy regarding the CHIPS and Science Act, with its goal of creating high-wage jobs in semiconductor manufacturing, it claimed the industry had 185,000 jobs in 2020.³⁸ This number was drawn from state labor data but is almost twice the estimate from the Commerce Department’s own County Business Patterns of 96,000 jobs. The problem is that the industry classification system was developed in the 1990s and cannot keep up with swiftly changing technologies. Subsequently, the federal government cannot be sure how many firms and workers are currently involved in each industry, making it difficult to design a set of workforce investments that will ensure the maximal impact on economic growth.

The results could be dark. The founder of the National Science Foundation saw the bright side of science: “What we often forget are the millions of pay envelopes on a peacetime Saturday night which are filled because new products and new industries have provided jobs for countless Americans. Science made that possible, too.”³⁹ But others are less sanguine:

The technological revolution might soon push billions of humans out of the job market and create a massive new “useless class,” leading to social and political upheavals that no existing ideology knows how to handle. All the talk about technology and ideology might sound very abstract and remote, but the very real prospect of mass unemployment—or personal unemployment—leaves nobody indifferent.⁴⁰

Even if the aggregate impact of innovation and change is positive, the United States learned from the implementation of the North American Free Trade Agreement (NAFTA) and China’s accession to the World Trade Organization that innovation can have dramatically different effects on local job opportunities, available wages, prosperity, and different demographic groups.⁴¹ Building an understanding of the potential inequitable impacts of economic shocks, and designing proactive responses, will need highly granular and local labor market data.

Product. Developing proactive ways of identifying and responding to the labor market impact of science investments in universities to state-level jobs and businesses will require tracing how skills and knowledge are transmitted. The high-tech hubs surrounding universities in Boston, Silicon Valley, North Carolina’s Research Triangle, and Austin, Texas, are clear evidence that the “best way to send knowledge is to wrap it up in a human being.”⁴²

Again in the spirit of the agricultural extension model, the product combines the expertise of universities with the extensive data collected by workforce agencies. The University of Michigan’s Institute for Research on Innovation and Science (IRIS) has built an eminently scalable infrastructure that traces the impact of research project spending. It combines

university data on workers in research jobs and traces them to the private sector.⁴³ This has allowed hundreds of researchers at universities to access and use the underlying de-identified individual- and firm-level data to show economic impact. (See, for example, Tania Babina et al.)⁴⁴

The resulting product can trace the movement of university researchers to the private sector and thus identify the firms that employ research-trained workers. Initial work has shown that PhD recipients disproportionately take jobs at large and high-wage establishments in high-tech and professional service industries, and there is geographic clustering in employment near the universities that trained and employed the researchers.⁴⁵ It can also show economic impact of the firms that supply goods and services to universities for research projects, which are disproportionately in high-tech industries (including professional, scientific, electronic, and medical services and supplies) closer to universities, and linked to a stable market.⁴⁶

This work means that high-technology industries can be characterized by the knowledge and skill embodied in workers and the firms that employ them. Ohio specifically demonstrates how this can be done in the context of the CHIPS and Science Act and semiconductor investments. OSU ranks 12th among all US universities in terms of research expenditures, and its research expenditure data are hosted at the University of Michigan's IRIS. Ohio State University also hosts near-comprehensive UI Wages and Quarterly Census of Employment Wages (QCEW) data in the Ohio Longitudinal Data Archive (OLDA) and the Ohio Education Research Center.⁴⁷

Practice. Once research-intensive firms are re-identified, the links between education and workforce can be used to describe the firms' skill needs: The educational composition of occupations and industries is available from linked UI Wages-QCEW data with higher education data. The OLDA has already been used to develop demand-side estimates of employment for firms in 5G and broadband and estimates

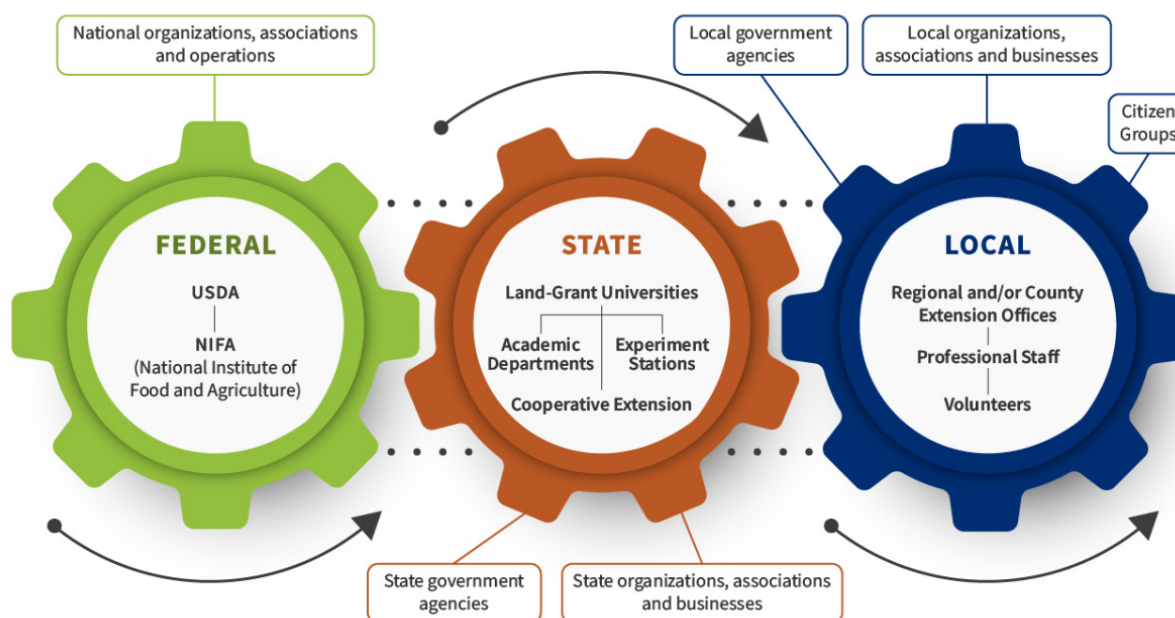
for economic development to identify training needs for skilled employment. These estimates are then disseminated in the OhioMeansJobs website, which workers and businesses in the state use.

The state-level data infrastructure described in the previous two use cases can be deployed to describe the basic workforce skills that firms need to produce cutting-edge technology—such as new types of semiconductors, AI-informed tools, electric vehicles, and bio-manufacturing-supportive technology. That evidence can inform policies such as increasing the completion rate of community college graduates in targeted majors or providing students with the necessary certificate trainings.

Some practical exemplars can be emulated. In the case of Ohio, OSU's 5G and Broadband Connectivity Center has assisted industry intermediaries and the state in organizing regional training opportunities throughout Ohio. The OLDA and related federal data have been used to identify occupations (e.g., telecommunications line workers) and site training programs at colleges with sufficient demand and monitor increases in investment across the state industry.

In addition, the data systems were used to argue for increased federal investment, which led to Intel announcing it would build two chip-making factories in Ohio.⁴⁸ Because Ohio was already investing in expanding training for related occupations, Intel and other companies can increase investment in engineering- and construction-related technologies. Furthermore, the investments have led to significant research initiatives at OSU for core areas such as technology, computer science and engineering, and data science.

The practical result would be developing local evidence that empowers local decision makers to quickly respond to changing technologies and design programs to equip authorities and workers in regional economies. The result would be a workforce infrastructure maximizing the impact of science investments, not leaving swaths of workers behind to relive NAFTA's impact on US workers in the 1990s and the resultant deaths of despair.⁴⁹

Figure 1. The Structure of the Cooperative Extension System

Source: National Institute of Food and Agriculture, “Cooperative Extension System,” US Department of Agriculture, <https://www.nifa.usda.gov/about-nifa/how-we-work/extension/cooperative-extension-system>.

Organizational Design

With the growing evidence of efficacy for the state and regional labor market information solutions discussed above, a clear need now exists for federal incentives to encourage other states and regions to design their own tailored solution. It will be crucial to adequately resource the state agencies through the NCLWI.

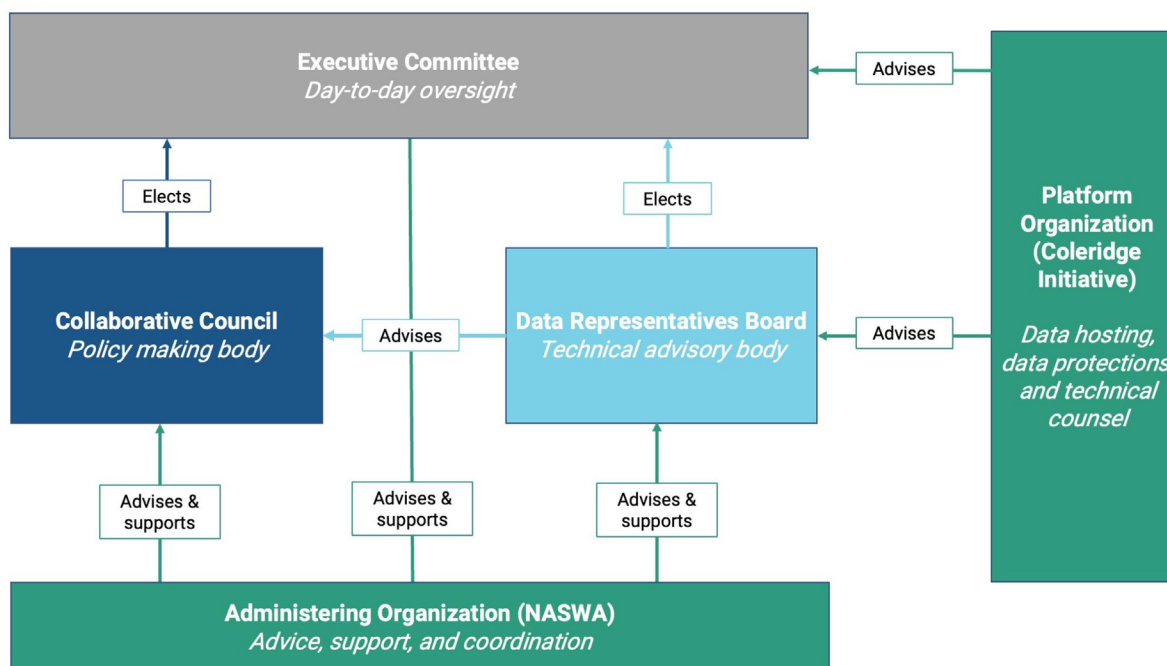
States and regions should exercise great care in designing the organizational structure so that line funding can flow from a core federal agency to the states without centralizing decision-making in Washington. A top-down, one-size-fits-all strategy cannot address all local labor market questions or meet local workforce needs; the system must be bottom-up, based on innovative projects that can scale from products to practice in and across states.

NCLWI could be established as an independent institution such as USDA’s National Institute for Food and Agriculture, which funds and manages the

Cooperative Extension System at the state and local levels.⁵⁰ The structure is described in Figure 1.

The governance structure could mirror that of the state regional collaboratives that jointly share education, training, and workforce data through a value-driven approach to building data infrastructures.⁵¹ The key components and features of the governance structure are described in Figure 2.

- Executive Committee.** The Executive Committee determines final approval on all policy recommendations and project proposals; it consists of state representatives from the Council and Data Stewards Board.
- Council.** The Council is the policymaking body for the collaborative. The Council’s goal is to not prevent states from doing what they wish with their own data but instead provide rules of engagement to allow states to work together more easily. The Council helps states focus

Figure 2. MidWest Collaborative Governance

Source: National Association of State Workforce Agencies, “Multi-State Data Collaboratives—About,” <https://www.naswa.org/partnerships/multi-state-data-collaboratives/about>.

on the core questions for educational workforce needs by providing a request-for-proposal approval process and standardized disclosure forms and by helping manage the review process for expedited access for states and researchers.

- Data Stewards Board.** The Data Stewards Board provides technical advice for the collaborative and comprises staff members who are subject matter experts regarding the data in the secure environment. The board additionally provides best practices for data use and advice on how to link datasets.
- Administering Organization (NASWA).** The administering organization engages states to communicate the value proposition of the regional collaborative and determine states’ needs. Other duties include enhancing inter-state collaboration, development, and implementation of governance arrangements.

- Platform Organization.** The platform organization provides and supports the Federal Risk and Authorization Management Program-certified environment built on Amazon Web Services’ GovCloud; its capabilities include data ingestion, data documentation, data analytic tools, and data stewardship. Authorized participants in the collaborative receive browser-based access to databases, file systems, and external websites.

The Role of Federal Agencies. While there should be a central administrative entity, such as the National Institute for Food and Agriculture, the federal system should be widely engaged to contribute resources to understanding local labor market outcomes consistent with their respective missions and their existing investments.⁵² For example, the Department of Labor clearly has a central role through the Employment and Training Administration and the Bureau of Labor Statistics.

However, the Department of Education has also been an important contributor to state workforce infrastructures through its Statewide Longitudinal Data Systems funding. A recent National Academies of Sciences, Engineering, and Medicine report effectively recommends a national extension program for education data—to build state capacity to link and share data, provide actionable information to state and local education agencies, establish state coordinators for the National Center for Education Statistics, and organize “a joint statistical research program that includes matching internal staff with highly qualified external researchers, statisticians, and data scientists to develop new data analyses, tools, and publications.”⁵³

Similarly, the Department of Justice has Statistical Analysis Centers—which collect, analyze, and report statistics on criminal justice⁵⁴—and the Department of Health and Human Services has an abiding interest in evaluating the impact of welfare recipients’ training. They can substantively contribute to socializing national data content models (projects) and sponsoring training (practice). In addition, they have a role down the line in incorporating new measures and practices into federal funding allocations to ensure the collaborative infrastructure’s sustainability and scalability.

The federal funding model for the NCLWI could follow a cooperative stewardship model, which is commonly used in high-capital-expenditure scientific user facilities and recommended for other related data infrastructures such as the National Secure Data Service.⁵⁵ While core facility funding would be allocated to the NCLWI lead agency, the NCLWI lead agency must be responsive to other agencies and the user community to achieve its goals. This could be done by allocating line funding to participating agencies within the relevant departments (such as the Departments of Education, Human Services, Justice, etc.) that wish to engage with the NCLWI to provide funding to states to support their respective missions.

The Role of Philanthropic Foundations. Philanthropic foundations are typically the engines of R&D and innovation. They are proving to be essential to

convening parties in solving common problems and working with individual organizations (e.g., states) to help them solve problems. Every state has the same basic data, questions, and similar problems, and they are each solving them alone. By investing in efforts in multiple advanced states that have ambition, vision, and stakeholder support, these foundations can encourage the creation of solutions (logic, rules, data models, governance, and even report templates) that can be used by others—by requiring that anything built with their money be shared with other public entities.

The Role of Universities and Training. The foundations for the land-grant equivalent exist throughout universities—funded by government and philanthropic foundations. Many universities already engage in an ad hoc process with state and local governments and aid in the effective use of federal, state, and local data. Linking with such emerging programs could dramatically scale up ongoing research and develop and test innovative policy pilots.

Because the proposed approach goes beyond the traditional reliance on statistical and social sciences to include the data and computer sciences, states have the potential to draw on rich experience in all parts of academe. Data scientists in particular are used to designing agile pilots that scale if successful.

In cancer research, for example, Robert L. Grossman of the University of Chicago created a National Institutes of Health data commons.⁵⁶ In astronomy, Alex Szalay of Johns Hopkins built SciServer, an open data resource for astronomers (built and supported by the Institute for Data Intensive Engineering and Science) that builds on and extends the SkyServer system of server-side tools that introduced the astronomical community to Structured Query Language and provides the Sloan Digital Sky Survey catalog data to the public. SciServer is particularly appealing because although it was designed to support astronomy research, it expanded to include several research and education tools that made access to hundreds of terabytes of astronomical data easy and intuitive for researchers, students, and the public.⁵⁷

Just as the 4-H model has a learning-by-doing component, the educational mission of universities could extend to learning-by-doing training programs for public sector agency staff. If properly resourced, the program could deliver data analytics certificate training for government agency staff, K–12 students, and two- and four-year colleges. Jeff Hammerbacher once remarked that the best minds of his generation were thinking about how to get people to click on ads; the goal of public-sector training programs would be to induce the best minds of the current generation to rise to the challenge of serving the needs of the economy, businesses, and workers.⁵⁸

Privacy and Ethics. Of course, privacy issues must be addressed, and states have protected privacy in practical ways. Traditional disclosure protection methods can reduce the utility of information for small geographies and demographic groups. However, the tiered access recommendations in the 2018 Evidence Act provide new flexibility with data release.

For example, in Illinois, unemployment and reemployment data have been primarily used by governor’s office staff (policymaking), state agency staff (program administration), and local workforce boards (strategic resource allocation). Illinois’s solution to increase data access while balancing privacy was to produce confidential summary tabulations that allowed the cell suppression rules to be relaxed to three individuals; the data was then released to target users only after they and their employer signed a nondisclosure agreement affirming they would not attempt to re-identify individuals. This approach, known as tiered access (because levels of access are “tiered” based on the need to know), complies with the Evidence Act, maximizes the contents of local data patterns, and protects against the disclosure of individuals’ personal information.

Illinois’s approach to making UI data available for decision-making while protecting claimant privacy can be contrasted with Texas’s approach. Texas has made its local workforce development boards responsible for timely claimant reemployment for nearly 20 years. Nearly all claimants are required to register in the state labor exchange system, and Texas has put

day-to-day management of that system and service to those registrants in the hands of its local workforce development boards.

Therefore, while Texas loved the Illinois tool, it didn’t meet a core Texas need. The tool illustrated what was happening regarding layoffs, closures, reemployment, and reopening, but it didn’t give the workforce development boards any information about who was unemployed or employed at any given point in time so they could reach out and assist. Texas took the basic Illinois dashboard concept and functionality and added to it the ability for local workforce development boards to securely download worker-level data on a limited, individually permissioned basis for outreach, service, and ultimately results.

The federal government can also contribute a great deal. The National Institute of Standards and Technology (NIST) and the International Organization for Standardization provide standards to protect privacy. These include sector-specific frameworks, such as the NIST Zero Trust Architecture⁵⁹ and the General Services Administration’s Federal Risk Authorization and Management Program, which is familiar to government entities and contractors.

Federal statistical agencies differentiate between public use and restricted access data to protect privacy. The Evidence Act recommends and the CHIPS and Science Act includes a provision to establish a National Secure Data Service (NSDS) demonstration project at the National Science Foundation, which will be informed by the recommendations of the ACDEB.⁶⁰ The NSDS has several core functions that can complement the NCLWI’s activities. These include

- Coordinating and supporting evidence-building efforts that cut across entities by facilitating linkage of, secure access to, and analysis of non-public data and providing capacity-building services for data users, data providers, and related communities of practice;
- Communicating the value and use of data for evidence-building and how the data are protected;

- Facilitating R&D and adoption of practices and methods that enhance privacy and confidentiality and improve record linkage quality; and
- Fostering and promoting data standardization to enable more efficient and high-quality linkage, access, and analysis.

The NSDS could also serve as a source of information for ethical data stewardship (such as its findable, accessible, interoperable, and reusable principles). Ethical guidelines established by the Neural Information Processing Systems’s hands-on tutorials, such as knowledge discovery and data mining, have been provided at multiple scientific conferences, and the American Association of Immunologists has multiple institutions, such as the University of Pittsburgh, that have well-developed protocols that could be emulated.⁶¹

Concluding Thoughts

The federal government can play an important role in producing national labor market information, particularly to agencies with a federal mission. It is, of course, responsible for producing internationally consistent national unemployment numbers on the first Friday of every month. But more must be done. A newly imagined labor market information system must be grounded in local data and local actors.

The project, product, practice approach is a proven way to innovate and effect new strategies. States have been remarkably effective in driving innovation in many domains. As far back as 1932, US Supreme Court Justice Louis D. Brandeis argued that states could be “laboratories” of experimentation—testing the effects of different policies, determining what worked and what didn’t, and leading the way to national programs.⁶² States have proven Justice Brandeis right

time and again, including Massachusetts’s experiment with health care reform, 1996 welfare reform built on various states’ experimentation, and California’s pollution controls.

The approach outlined in this report, to paraphrase Sen. Patty Murray (D-WA), shows that whether you think we need more government or less, it is possible to have better government.⁶³

About the Author

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