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Issue Brief

What can federal data collection tell policymakers and researchers about artificial intelligence in the U.S. labor market?

August 2026 By Mary Beech

Key takeaways

- Federal data on unemployment, wages, and the availability of jobs in the U.S. labor market exist but are fragmented, often not timely, and difficult to link across sources.
- The adoption of artificial intelligence by individual firms is challenging to measure, and existing federal surveys are often binary, asking simple yes or no or true or false questions, as well as inconsistent and not connected to data on their workers' employment outcomes.
- Existing federal data sources cannot be used yet to conclusively show whether and how AI might be driving changes in the U.S. labor market.
- **What this means for growth:** Improving the infrastructure for federal data collection is essential for policymakers to understand how AI is reshaping the U.S. labor market and to design responses that are timely, comprehensive, and well-targeted. Economic growth from new technologies is not automatic; optimizing the talent in the U.S. economy requires knowing where and how the labor market is changing.

Overview

It is impossible to perfectly predict how artificial intelligence will affect the U.S. labor market. Policymakers and researchers are grappling with important questions around this topic, including what new opportunities may exist and what livelihoods might be eroded by AI? How will those countervailing forces net out, and which workers might be left behind? Will the quality of jobs be compromised in the process?

As the impacts from AI unfold, more and better data is an essential foundation for the design of policies, the implementation of programs, and future research. The federal government, researchers, and the public alike lack access to detailed, real-time, widely available, and impartial data on how AI is affecting workers, firms, and the broader U.S. economy—data that could inform social program design and participation, workforce development initiatives, and more.

There is a clear need to better understand and predict the effects of AI on employment and unemployment, job opportunities, wages, and earnings. The United States has faced labor market disruptions before. Trade shocks have displaced millions of workers over the past five decades, as have technological advancements such as the advent of the internet and increased factory automation, while the data and policy infrastructure to respond proved inadequate.[1] AI-driven disruption risks repeating those experiences at greater scale and speed.

This issue brief is the first in a three-part series that maps the federal data infrastructure through the lens of these questions about the increased adoption of AI in workplaces across the nation, examining the data related to unemployment, wages, job availability, and firm-level AI adoption, and where gaps in the data lie. The next two briefs will provide recommendations for improving the collection of federal data on AI and its impact on workers and how that data can be used to inform policymaking, program implementation, and research.

How do we know who is unemployed?

As the capabilities and applications of AI advance, AI tools in the workplace are likely to perform an increasing number of job-related tasks. To respond effectively, policymakers and researchers must understand to what extent the adoption of AI in workplaces causes workers to lose their jobs. This information is essential for designing effective policy responses, including social programs, workforce development and retraining efforts, and sector-specific approaches.

Answering this question requires first being able to determine exactly who is unemployed across the U.S. economy, which is surprisingly difficult to calculate precisely. Every month, the U.S. Bureau of Labor Statistics releases the official unemployment rate derived from the U.S. Census Bureau's Current Population Survey, along with demographic breakdowns by age, race, and gender. The unemployment rate in this household survey captures those who do not have a job in the relevant week of the survey and also have actively looked for work in the prior month. As such, the unemployment rate does not include those who have stopped looking for work or are underemployed.

Further, the monthly release can give general impressions about unemployment by industries, such as manufacturing or services, but is difficult to narrow further to track, for example, employment trends for occupations such as computer programmers. The survey response rate also has declined over the past decade, which may limit its representativeness.[2]

The U.S. Department of Labor's Employment and Training Administration releases weekly Unemployment Insurance claims data, which is a timely indicator but only captures those who file for UI benefits. Many workers are not eligible for benefits, including independent contractors, job-seekers who have not been recently employed, and those who have exhausted their benefits. The demographic information included in claims data also varies by state.

Employers are often required to inform workers about their eligibility for UI benefits, but this does not always happen, and many eligible workers do not file simply because they are unaware that they qualify.[3] In other cases, employers may actively deter workers from applying for benefits to reduce their tax obligations.[4] The Bureau of Labor Statistics estimates that in some years, most unemployed people did not apply for UI benefits.[5]

Additionally, both the unemployment rate and UI claims data can be affected by many other factors, including natural disasters, economic disruptions, and seasonal trends. As such, it is difficult to isolate and attribute changes in either statistic, particularly to diffuse trends related to the adoption of AI in many different kinds of workplaces across the U.S. economy.

Employers also submit quarterly wage records to state workforce agencies, which are then sent to the Census Bureau and processed into the Longitudinal Employer-Household Dynamics program. LEHD datasets link workers to employers using Social Security Numbers, with demographic information drawn in part from Social Security Administration administrative records. While these data have a 4- to 6-month lag, they allow researchers to link workers to specific employers over time, including tracking workers through periods of unemployment and into subsequent jobs. LEHD datasets include industry but not occupational details, which limits their usefulness for tracking which specific jobs are most affected by AI. Recognizing these gaps, a growing number of states have expanded their wage records to include additional information, such as job titles, total hours worked, and job location.[6]

UI claims and wage records data focus on "employees," a legal category defined differently across federal and state laws. Many workers are incorrectly classified as independent contractors by their employers and therefore cannot access Unemployment Insurance.[7] Independent contractors and platform workers make up a growing share of the U.S. workforce, so UI-focused data sources are likely to undercount the workers who are vulnerable to AI-driven disruptions.[8]

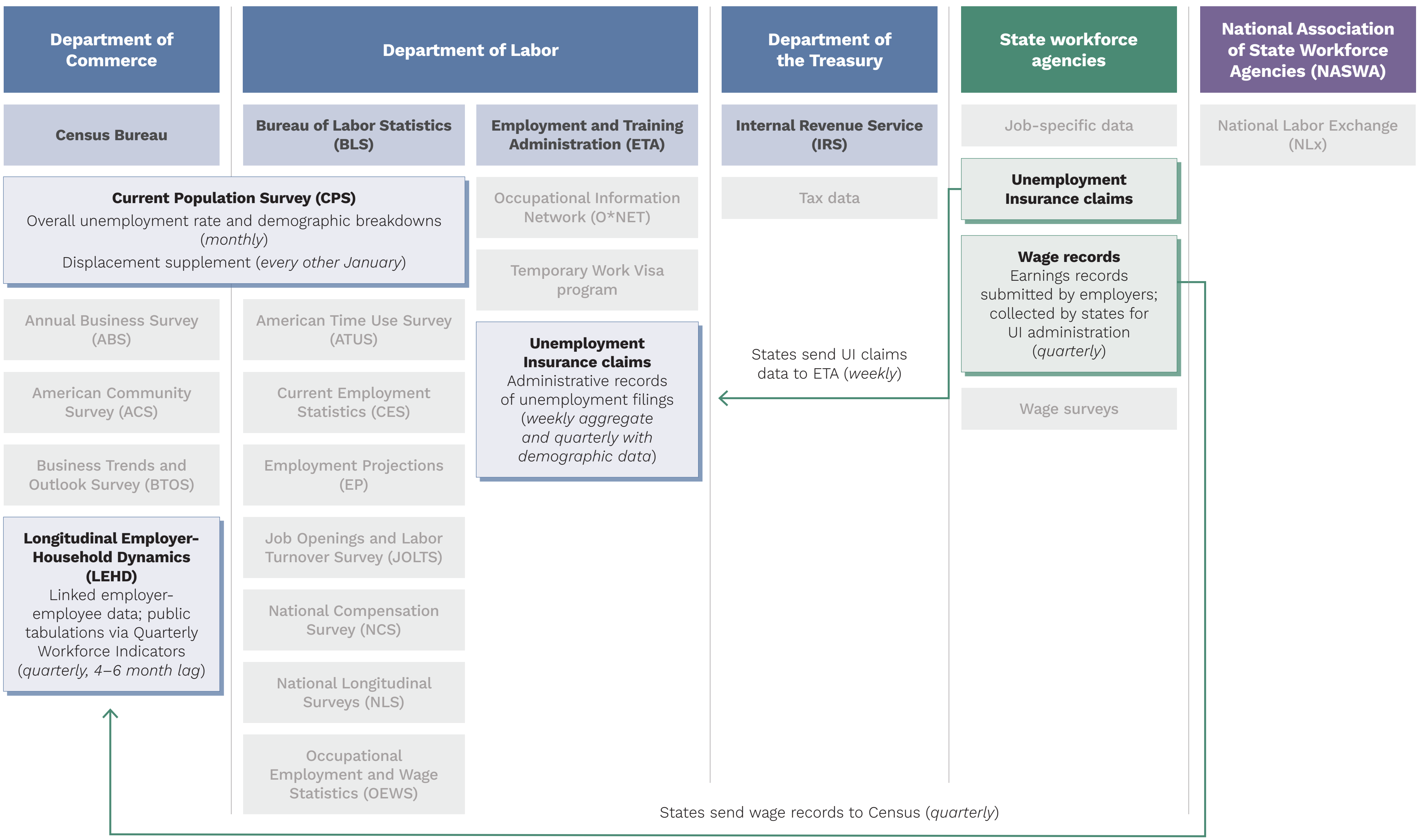
The Worker Adjustment and Retraining Notification, or WARN, Act requires larger employers to provide advance notice of mass layoffs and plant closures. [9] These data are shared with state and local governments to facilitate support services but are not shared with the federal government. They also exclude remote workers, workers at smaller employers, and independent contractors.

Studying unemployment broadly can reveal where labor market pain is concentrated, including which industries, occupations, and geographies are most affected. Yet attributing those changes specifically to the adpotion of AI remains difficult, given how many factors drive unemployment. (See Figure 1.)

Figure 1

Data sources for **unemployment** in the U.S. labor market

Federal State Association



Source: Author's descriptive analysis.

How do we know what is happening with wages and earnings?

Employment is only part of the U.S. labor market story. Understanding worker compensation and job quality is equally critical. AI has the potential to impact hours worked, salaries for different occupations, and pay for so-called platform, or gig, workers—including those engaged in ride-hailing and food-service delivery jobs, as well as in online digital freelance assignments. Understanding whose earnings are changing and how can reveal how income inequality may be exacerbated by AI and help to target programs to address the challenges ahead.

The Bureau of Labor Statistics releases information about earnings for a subset of the Current Population Survey sample on a quarterly basis, including demographic breakdowns by age, race, and gender. But these data are self-reported, and the ability to track a worker's earnings in the long term is limited. The survey also does not differentiate between employees and independent contractors, and it is difficult to identify or track pay dynamics, such as AI-driven wage pressures on specific occupations. Periodically, the agency conducts a Contingent Worker Supplement to the CPS data, which includes data on workers whose jobs are temporary and independent contractors.[10]

Each month, the Bureau of Labor Statistics also releases Current Employment Statistics, which includes information about average hourly earnings. Unlike the Current Population Survey, which surveys households and relies on self-reported earnings, CES data survey employers directly through payroll records, so it is a more precise measure of earnings for a given job. Yet the CES survey does not include data on demographics or occupation, which limits its usefulness for identifying or tracking trends among specific jobs or populations.

The Bureau of Labor Statistics also conducts the National Compensation Survey, which is used to generate data on pay and benefits by industry and occupation.[11] This survey does not cover independent contractors and has limited geographic and demographic detail.

Then, there are the BLS National Longitudinal Surveys, which gather information at multiple points in time on labor market activities for a cohort of individuals.[12] These surveys can show trends in education, training, and employment over the course of people's lives. By design, the surveys focus on one cohort, so it may be difficult to generalize findings to other generations.

The Census Bureau's LEHD program also includes earnings data, which allow for more longitudinal tracking. Similar to unemployment data, this has about a 4- to 6-month lag before it is publicly available. Despite this delay, LEHD data are one of the only sources that allows researchers to track how a specific worker's earnings change over time, including as they move between employers.

Each year, the Census Bureau releases the American Community Survey, which has more detailed demographic information. But because this survey asks respondents to report total income over the previous 12 months, it cannot capture within-year earnings trends. The Bureau of Labor Statistics also annually releases its Occupational Employment and Wage Statistics, which include wages by industry and occupation. The OEWS surveys employers, as opposed to workers, and does not capture those classified as independent contractors.

The Internal Revenue Service at the U.S. Department of the Treasury also gathers data about wages and earnings from tax filings. It can be a year or more before these data can be used for research, but data derived from IRS 1099 filings include information about income reported by independent contractors, making it an important resource, despite this delay.

More states have begun to require salary transparency on job postings. The National Labor Exchange, or NLx, a database of online job postings maintained by the National Association of State Workforce Agencies and Direct Employers Association, is updated daily and includes salary information for many of these listings. Yet the NLx database only captures jobs posted online and salary ranges do not necessarily reflect actual wages, which means these data provide an incomplete picture of wage and earnings compensation.

States also collect their own data about wages and earnings. The type of data collected varies considerably by state, and not all state wage survey data are shared with the federal government. This inconsistency makes it difficult to compare wage trends across states or build a national picture from state-level data alone.

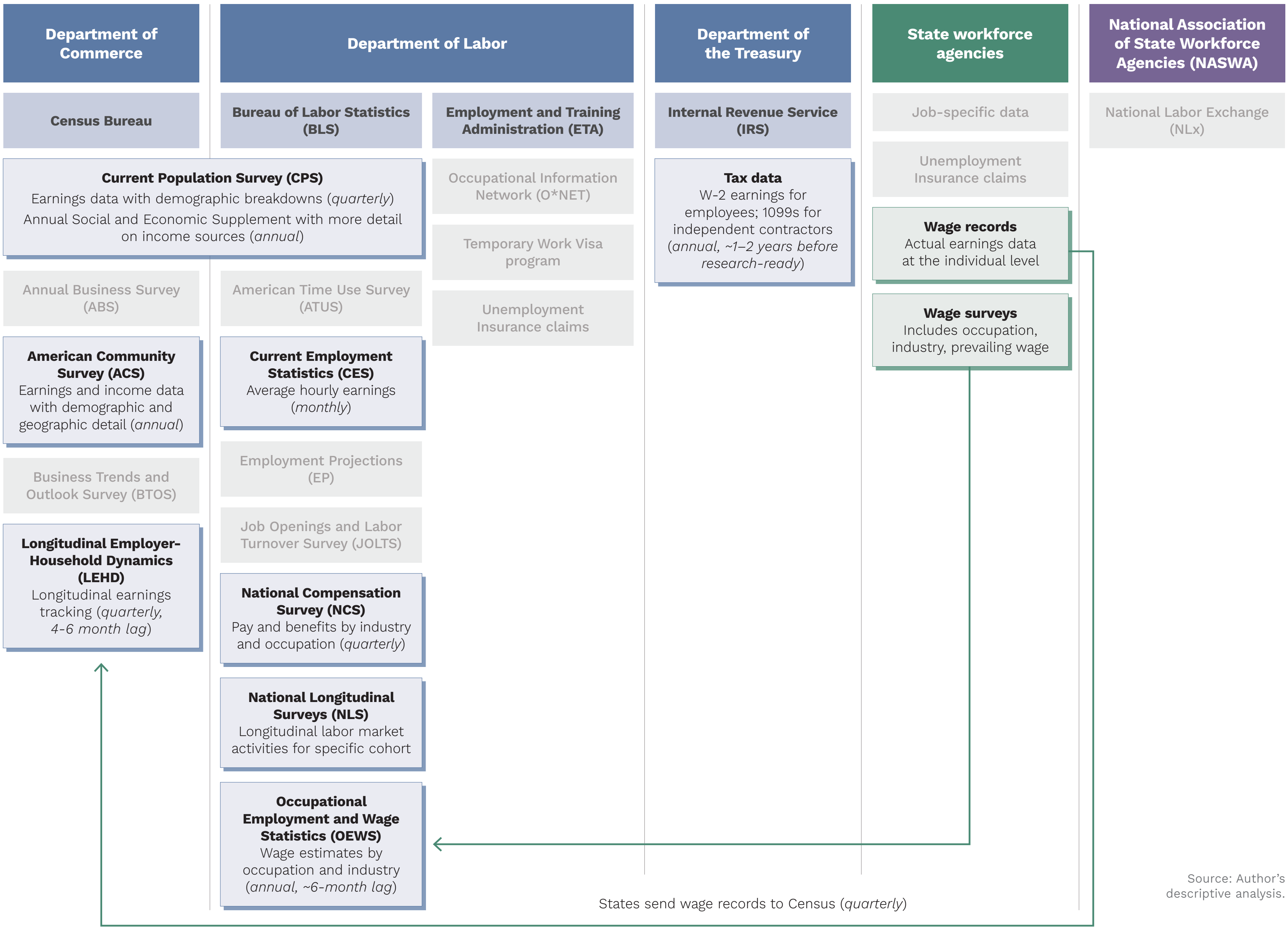
Many of these sources have limitations. Most sources lack hours worked, making it impossible to distinguish changes in earnings from wage rate cuts or reduced hours. Also, sources (except for the Current Population Survey's Annual Social and Economic Supplement[13]) do not capture nonwage compensation, such as health benefits and retirement contributions, and other important aspects of job quality. For these reasons, it can be difficult to get a holistic picture of worker compensation.

Moreover, these sources cannot easily be connected to paint a comprehensive picture of workers' compensation. They each use different methodologies, making individual-level linkage difficult. The Longitudinal Employer-Household Dynamics program offers the strongest foundation for tracking workers' earnings over time, but it can be difficult to access longitudinal data that are linked to CPS demographic detail, NLx postings, or tax records. These challenges make it difficult to identify whether the adoption of AI specifically is driving changes in compensation or to track how an individual worker's earnings evolve in response to AI-driven disruptions at their firms. (See Figure 2.)

Figure 2

Data sources for **wages and earnings** in the U.S. labor market

Federal · State · Association



Source: Author's descriptive analysis.

How do we know what jobs and opportunities exist?

As AI changes the nature of work, it is important to understand the universe of available jobs, including jobs available to workers who may lose their jobs or struggle to find new employment. Policymakers and workers need timely information about which firms are hiring and for which jobs.

The NLx is updated daily with real-time online postings, drawing directly from company websites and state job banks.[14] This is one of the best sources for workers to find currently available jobs but excludes jobs filled through referrals, internal promotion, word of mouth, or informal networks. Researchers have used these data alongside detailed occupational task datasets to extract structured information about skills, tasks, and tools from job postings at scale, and the data are accessible to researchers through the NLx Research Hub.[15]

The Bureau of Labor Statistics also releases its Job Openings and Labor Turnover Survey, which provides monthly estimates of industry-level job openings, hires, and separations, including by region and state. The JOLTS data, however, do not provide occupation-specific detail, and its sample of roughly 16,000 establishments is relatively small. The NLx Research Hub produces monthly job-opening estimates based on both JOLTS and NLx data.[16]

Understanding what jobs exist—not just what the current openings are—requires different data sources. The Current Employment Statistics survey provides monthly employment counts by industry based on employer payroll records. The CPS data complement this by providing monthly employment counts by occupation and demographic group. The American Community Survey provides similar occupational and demographic details on an annual basis, with richer geographic breakdowns that are useful for understanding where specific types of jobs are concentrated. For more detailed occupational data, the Occupational Employment and Wage Statistics survey provides annual employment counts by occupation and industry. Together, these sources can show where jobs are concentrated by industry, occupation, geography, and worker demographics, though no single source captures all these dimensions.

The U.S. Department of Labor also publishes data from temporary work-visa programs, including H-1B visas for specific occupations. These data include job titles, occupation codes, wages, and worksite locations. While publicly available and useful for understanding demand for high-skill specialty occupations, these data only cover positions for which employers sought workers and do not represent broader labor market demand.

The Bureau of Labor Statistics also releases annual Employment Projections, which forecast how occupations are expected to grow or shrink over a 10-year time horizon. This forward-looking view could be particularly valuable for workforce development programs, which aim to anticipate where opportunities will emerge rather than simply react to current conditions. As a projection rather than a real-time measure, however, these data are not designed to capture the pace or timing of AI-driven changes as they unfold.

As with wage and earnings data, the information collected by state workforce agencies about jobs varies by state. Registered apprenticeship programs, which states are required by law to report to the U.S. Department of Labor's Office of Apprenticeship, offer one of the more consistent sources of information. Some states collect their own job vacancy data through state-level surveys, but this information is not aggregated into a centralized federal database, limiting its usefulness for understanding national hiring patterns.

Private companies also compile and sell job-postings data. These datasets can be large and include structured information on skills, occupations, and wages, but they have significant limitations. Methods for collecting, cleaning, and structuring the data are typically proprietary and not available for independent verification. Increasingly, there are also challenges of ghost job postings—positions companies advertise but never intend to fill—which accounted for between 18 percent and 22 percent of online job listings in one 2024 analysis.[17]

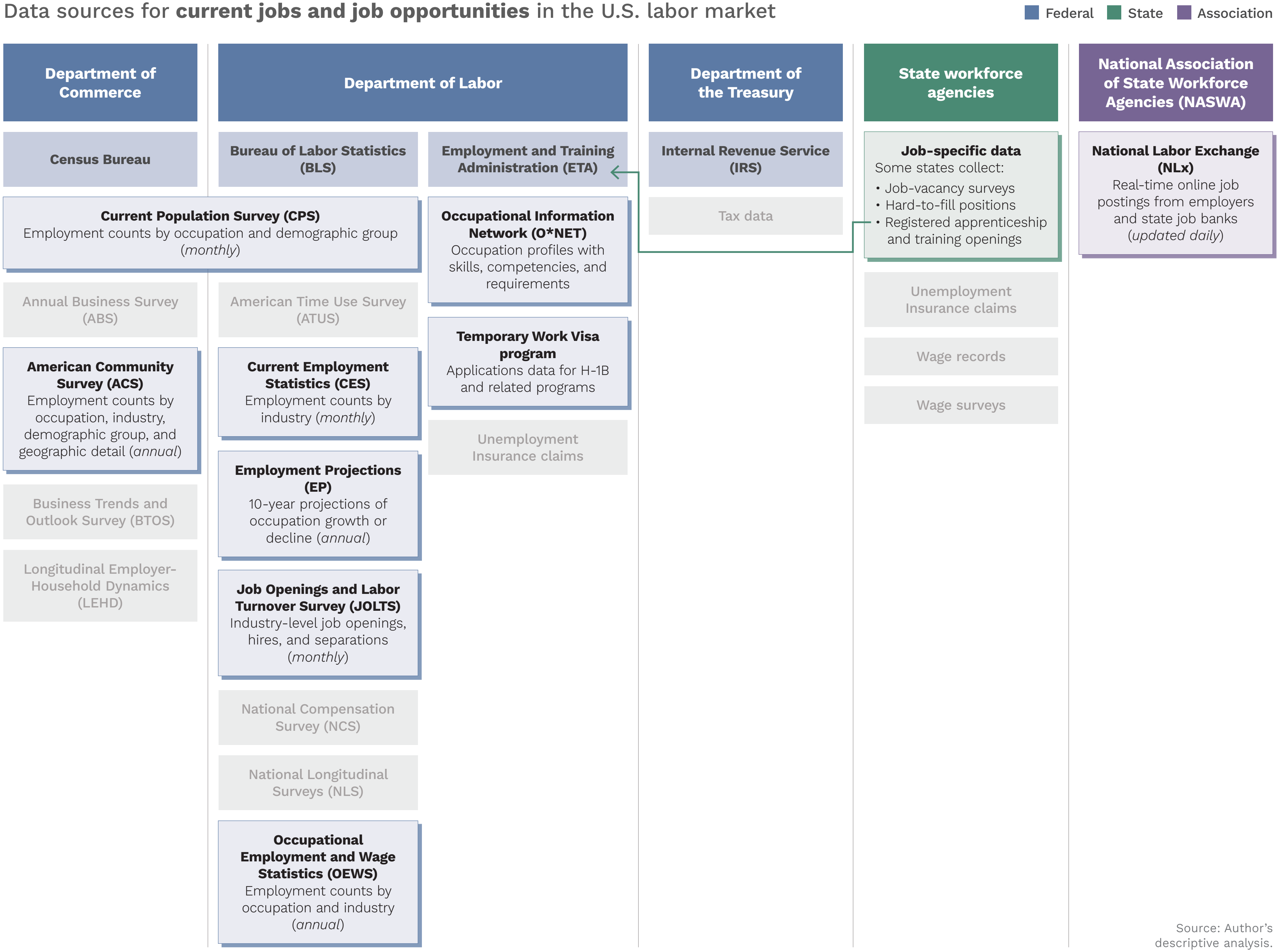
It is also important to understand the tasks that comprise these jobs so that workers can find opportunities that align with their skillsets, and workforce development initiatives can better target training and educational programs. The O*NET Program, sponsored by the U.S. Department of Labor's Employment and Training Administration, encompasses more than 900 occupation profiles and includes standardized skills, competencies, and occupational requirements.[18]

Researchers have used O*NET task descriptions to estimate which occupations and tasks could be most exposed to AI. Even if O*NET could be used to reliably make displacement predictions, O*NET has significant limitations for tracking AI-driven changes: Each occupation is updated infrequently, with an average sample of only 71 observations; the dataset is not designed for longitudinal research; and some data collection occurred as far back as 2006.[19]

Together, these sources can provide a picture of where hiring is happening and what skills employers are seeking. Yet no single source can reliably track how AI adoption is reshaping demand for specific occupations in real time or identify when firms are reducing jobs through attrition. (See Figure 3.)

Figure 3

Data sources for **current jobs and job opportunities** in the U.S. labor market



Source: Author's descriptive analysis.

What do we know about the adoption of AI by individual firms?

Understanding how AI adoption affects workers also requires knowing which firms have adopted AI and how they are using it. As it turns out, this is also difficult to measure well.

Job postings on NLx can give an indication of the needs of individual firms based on position descriptions that mention specific technologies or skills. This can be an important indicator, but it only captures the AI-related skills mentioned in job postings, which is an indirect signal that does not reflect a firm's full AI expenditures, adoption, or deployment plans.

Every other week, the Census Bureau releases the Business Trends and Outlook Survey, which asks firms a yes or no question about whether they have adopted AI and whether they plan to in the next year. Because this is a binary measure, it does not capture how or to what extent firms use AI.

Each year, the Census Bureau also releases the Annual Business Survey, which has recently included more detailed questions for firms about AI adoption. Yet these questions are inconsistent across cycles, which limits the longitudinal tracking of adoption for a specific firm. The 2023 Annual Business Survey asked firms whether technology adoption changed the number or skills of their workers but did not distinguish between different types of AI or automation, making it difficult to understand which specific technologies are driving workforce changes.[20]

Even where AI adoption data exist, they are not linked to worker-level outcomes such as employment or wages, making it nearly impossible to connect firm-level AI adoption with worker outcomes. The Business Trends and Outlook Survey and Annual Business Survey adoption data are not linked to the Longitudinal Employer-Household Dynamics data, wage records, or other worker-level outcomes, even though both datasets sit within the Census Bureau. NLx job postings data are also not linked to BTOS or ABS adoption responses, so a firm's self-reported AI use cannot be connected to its hiring activity.

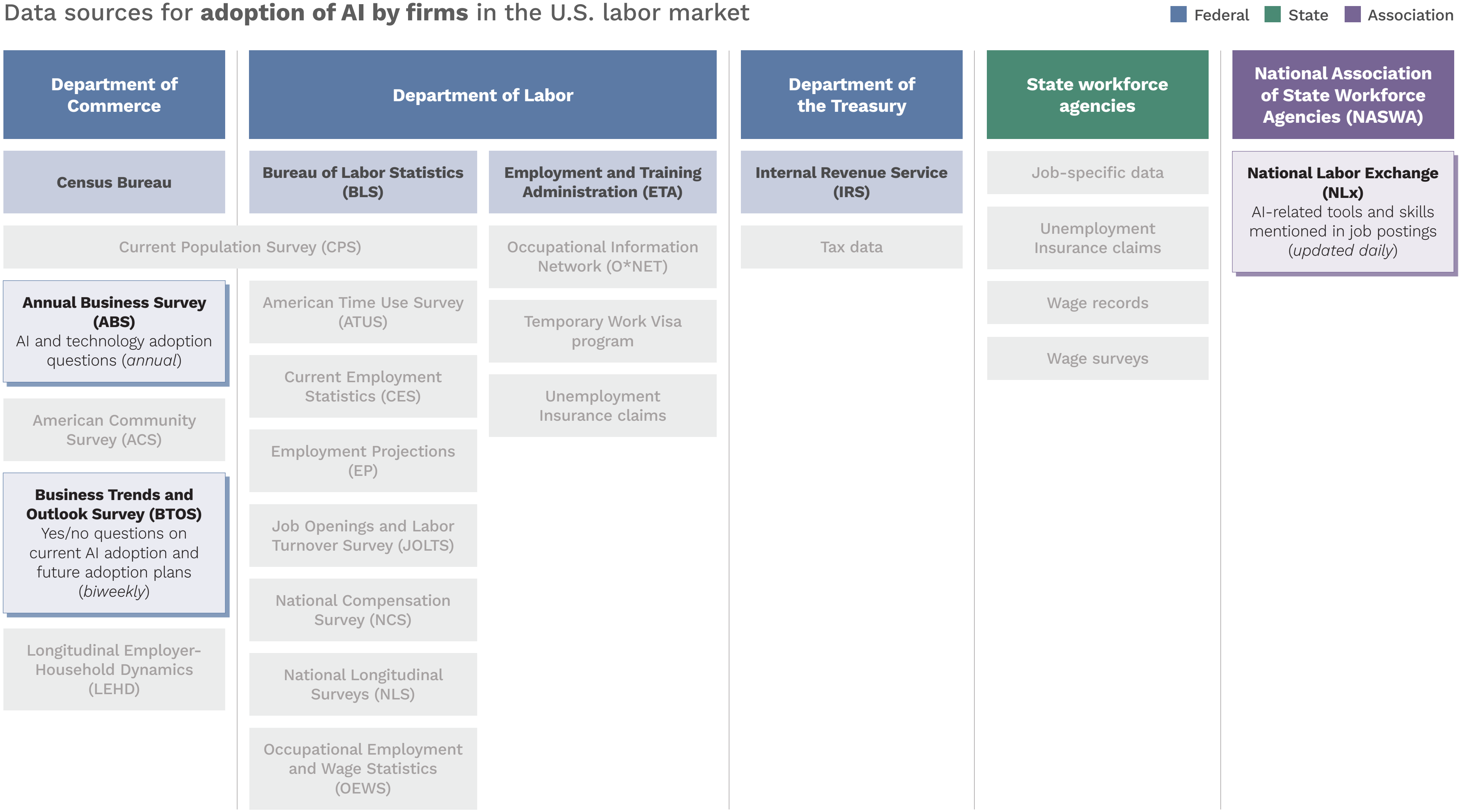
There are specific studies at the international level on the adoption of AI. A 2024 survey by the Organisation for Economic Co-operation and Development of more than 6,000 firms across six countries, including the United States, found that algorithmic management tools—software that partially or fully automates managerial functions such as giving instructions to workers and monitoring or evaluating them—are already widespread among U.S. firms, with 90 percent of those responding to the survey having adopted at least one such tool.[21]

Some companies also publish AI adoption surveys, but these use different methodologies, samples, and definitions, making comparisons nearly impossible. Private surveys may also reflect the interests of the companies conducting them, underscoring the importance of federal government data collection.

Researcher-led efforts—such as the Real-Time Population Survey, a survey by a consortium of U.S. universities of U.S. households that has run since 2020—have aimed to fill this gap.[22] The survey is designed to complement the Current Population Survey and the American Community Survey and, since 2024, has included questions about generative AI adoption in the workplace.[23] While the Real-Time Population Survey provides valuable worker-level information, this type of privately funded effort necessarily does not have the same scale as a government-administered survey. Additionally, even where workers are surveyed, they may not have a complete picture of the AI tools their employers have adopted, which can limit what worker surveys capture about firm-level decisions. (See Figure 4.)

Figure 4

Data sources for **adoption of AI by firms** in the U.S. labor market



Source: Author's descriptive analysis.

Conclusion

At the core of all the questions posed in this issue brief is causation. How does the adoption of AI by firms affect worker employment and unemployment, compensation, jobs lost, and job opportunities? As this brief demonstrates, no single data source can answer this question, federal or otherwise.

The gaps are significant and widely recognized. The Workforce Information Advisory Council, established under the Workforce Innovation and Opportunity Act of 2014 to advise the U.S. secretary of labor on workforce information needs, has called for improvements to federal infrastructure on U.S. labor market data.[24] The Department of Labor has announced plans to establish an AI Workforce Research Hub, in collaboration with the Bureau of Labor Statistics, the Census Bureau, and the U.S. Commerce Department's Bureau of Economic Analysis, to generate recurring analysis on the adoption of AI, jobs displaced by AI, and the wage effects of AI in the workforce.

The U.S. Congress also has taken notice. The proposed Workforce Transparency Act and the AI Workforce PREPARE Act are both bipartisan bills that would enact new federal data collection requirements on AI's labor market effects.

The next issue brief in this series will build on this landscape to provide concrete recommendations for improving federal data on AI and workers.

Mary Beech is a visiting fellow at the Washington Center for Equitable Growth and a policy consultant and fellow at Workshop, specializing in AI and emerging technologies. Previously, she served in the Biden administration as director of workers and technology policy at the U.S. Department of Labor, where she led initiatives to address the impact of AI and emerging technologies on workers' rights and livelihoods. Prior to that, she served as tech division chief of staff and senior policy advisor at the White House Office of Science and Technology Policy and as chief of staff of the Employee Benefits Security Administration at the U.S. Department of Labor.

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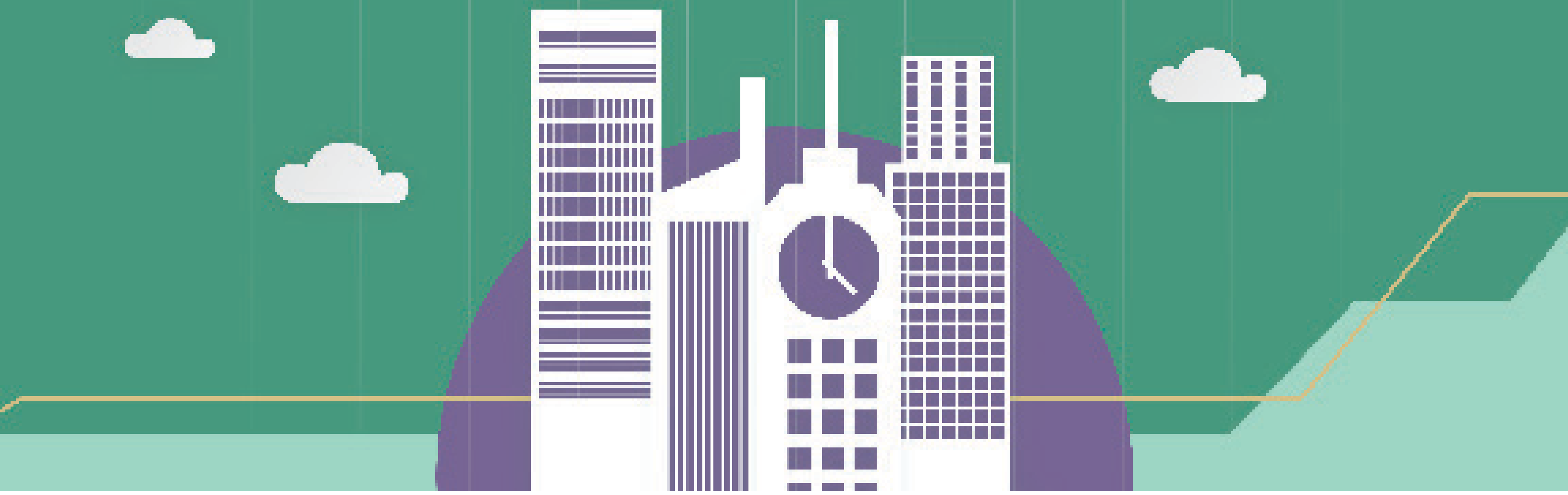

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