American Opportunity Index – Detailed Methodology

This section provides a detailed description of the methodology implemented to construct the American Opportunity Index (the Index). First, there will be an overview of the datasets leveraged for the Index, followed by a description of the methodology.

Datasets

Professional Profiles Dataset

The primary dataset examined for the Index is the 'Professional Profiles' dataset. The profiles dataset, provided by Lightcast, consists of individual work histories across multiple countries. There are over 40 million individual profiles in the US alone. Key features of information have been extracted and classified to organize the data into structured formats. This involved processes such as classifying individual work experiences into standardized occupations, industries, locations, and employers.

For the Index, we needed to isolate the top Fortune 250 employers and their US employees. As many of these employers are parent or holding companies, we also needed to account for their major subsidiaries. For example, Meta Platforms is the parent company of Instagram and WhatsApp. Therefore, we wanted to include the workforce information of these subsidiaries under the auspice of their parent companies. To do this, we first identified major subsidiaries within each of the Fortune 250 companies. We then developed a crosswalk that maps the raw employer names of subsidiaries and parent companies to their corresponding Fortune 250 standardized company name. This allowed us to select the profiles associated with a Fortune 250 employer and manage for slight variations in spelling to help maximize our sample.

Job Vacancies Dataset

We made use of Lightcast's Job Vacancies dataset to represent the share of occupations within an employer. Rather than using the Professional Profiles data, we chose to use the Job Vacancies dataset for this purpose because we believe the quality of the occupational distributions within employers to be higher quality and more consistent than in the Professional Profiles database. These occupational shares within employers were used as weights in the construction of the employer-level scores for each metric (more information on this further below).

Glassdoor Dataset

Data for the Wages metric is sourced from Glassdoor, an anonymous employer review jobs platform. The Glassdoor Research team generously provided access to the wage component of their dataset. Importantly for this research, these data include wage reviews by job title, occupation, employer, location, and date. This enabled us to identify median wages per occupation within an employer in 2021-2022. We again created a crosswalk that accounted for parent companies and subsidiaries that maps the Glassdoor employers to the standardized Fortune 250 employers.

Method

This section will first describe the overall methodological process implemented for all nine metrics. A description of the nine metrics and their specific parameters will then follow.

Selecting Worker Profiles to Include in Dataset

For each metric, we started by selecting the available Profiles (or user review observations in the Glassdoor dataset) by using the employer name crosswalks previously described. While timeframes and selection criteria vary within the nine metrics (described further below), sample selections were dependent on the employer name crosswalks. To maximize our sample of Profiles within employers, we applied a job title classification algorithm to classify unlabelled job titles into their standardized occupations, setting a confidence probability threshold 80% to help ensure quality. For the occupation labels, we made use of Lightcast's proprietary occupation ontology, which consists of 679 occupations. The advantages of using this occupation ontologies over others, such as O*NET or SOC, are the relative simplicity of the occupation titles for interpretability and its ability to capture more emerging job roles, such as 'Social Media Assistant'.

Filtering High-Educational Attainment Occupations

The focus of the Index is on worker opportunity and upward mobility, especially for the types of jobs where upward mobility is more challenging. Therefore, the Index is concentrated towards the experience of workers in jobs where 30 percent or more of workers lack a degree. To isolate these occupations, we first identified educational attainment distributions from the US Bureau of Labor Statistics.[1] Then, we qualitatively set an educational attainment threshold of >30% of jobs within an occupation that lack a Bachelor's degree. These are occupations with high educational attainment rates, such as 'Computer Scientists', 'Economists', and 'Tax Managers'. Last, we used a crosswalk to map the SOC 6-digit occupations to the Lightcast ontology. We then removed 183 high-educational attainment occupations and were left with 496 occupations for the Index. The Profiles that match any of these 496 occupation labels were included in the Index sample.

Assigning job-levels

Some of the metrics require organizing occupations into job-levels. To do this, we use the average years of professional experience for occupations from the Job Vacancies dataset as a proxy to sort occupations into standardized job-levels. The job-levels are organized into six standardized groups, in ascending level of experience and seniority:

- Level 1: 0 – 3.5 years of experience
- Level 2: 3.51 – 4.5 years of experience
- Level 3: 4.51 – 5.5 years of experience
- Level 4: 5.51 – 6.5 years of experience
- Level 5: 6.51 – 7.5 years of experience
- Level 6: >7.5 years of experiences

Occupation-level Scores

Once the sample of observations was selected, we then calculated occupation-level scores for each metric within their respective employer. For example, the retention rate for each occupation in an employer over five years; or the median wage for each occupation in an employer in 2021-22. After these occupation-employer scores had been calculated,

[1] https://www.bls.gov/emp/tables/educational-attainment.htm

we then converted these scores into quintiles, grouped by occupations. Here, we're aiming to compare labor outcomes for workers in the same occupation across the Fortune 250 employers. We acknowledge that there are nuanced differences between the skill and task requirements of the same occupation between employers (and industries more broadly), and that these nuances can influence the outcomes of the occupation-level scores and may contribute to some error in our measurement. However, there are also significant similarities and overlaps in skillset requirements between the same occupations across different employers. Therefore, rather than instituting an ordinal 'rank' of the occupational scores, we sorted the scores into quintiles. This allowed us to identify relative buckets of occupational performance across employers while not strictly ranking occupations with granular precision. We believe the quintile approach mitigates reporting errors from unmeasured differences in occupations between employers.

Occupational Distribution within Fortune 250 Employers

Naturally, the workforce composition of the Fortune 250 companies varies significantly. Certain occupations represent greater shares within firms than others. Therefore, we want to ensure that occupations that command high workforce shares within firms receive higher weights than occupations that have lower representation. To do this, we used the occupational distributions from the Job Vacancies dataset. We then merged across the occupational distributions for each occupation-employer pair in the metrics. As high-educational attainment occupations have been removed (see above), we adjusted the occupation shares by dividing each employer-occupation share by the sum of all remaining occupation shares within an employer. This adjusts the occupation shares to equate to 100% for each employer, while maintaining their original relative differences. The adjusted occupation shares were used as weights for calculating employer-level scores.

Employer-level Scores for the Metrics

Employer-level scores are simply the weighted average of the occupation quintiles within an employer, using the adjusted occupation shares as weights. This yields a decimal score out of 5 for each metric. As a final step, we converted these decimal scores into quintiles. Again, this conversion was so that we can compare relative performances between companies but not over inflate the precision of the ordinal rankings within the metrics.

Calculating the Overall Weighted Rank

The Overall Weight Rank, and the only ordinal measure in the Index, is a composite score across all nine metrics. The Overall Weighted Rank is calculated as the weighted average of the nine metrics (their quintile scores), applying two sources for weighting of the importance of the nine metrics. The two sources for developing the weighting of the nine metrics were: (1) a panel of 12 labor market experts, and (2) a sample of 500 randomly surveyed workers. The weighting for the nine metrics provided by both panels were given equal representation in the ranking model. Both set of respondents were asked to distribute value scores totalling 100 to each of the nine metrics regarding relative importance to employer opportunity for workers. We then took the mean of these weights from both respondent groups, averaged them together, and were left with weights for each of nine metrics with equal contributions from the expert and worker respondent groups. These weights were applied to their respective nine metric scores to yield the Overall Weighted Rank. The weightings of each respective group and the final applied weights are shown below.

Metrics	**Avg Expert Ratings**	**Avg Worker Ratings**	**Final Weights**
Barriers to Work	9.90	13.93	11.92
Entry-Level Hires	7.76	10.45	9.10
Wages	17.56	13.93	15.75
Job Level Advancement	11.72	10.95	11.33
Retention	11.09	6.97	9.03
Homegrown Leadership	8.50	10.95	9.72
Velocity of Growth	12.98	8.46	10.72
Promoting Out	9.39	11.44	10.41
Promoting Up	11.10	12.94	12.02

Representativeness and Handling of Missing Data

To maintain a strong baseline of quality, we excluded any companies that had fewer than 100 Profile observations for an employer per metric. As each metric has different calculation parameters, the sample of observations varied. Therefore, some metrics have results for more employers than others. We also did not want to calculate an Overall Weighted Score for employers who are missing scores for the majority of metrics. So, we instituted an overall threshold where an employer must have scores for a minimum of six metrics to register an Overall Weighted Score and rank. This overall threshold removed eight employers. For those employers missing fewer than four metrics but still recorded an Overall Weighted Score, we readjusted their weights to reflect their relative share, using the same process described above in the '*Occupational Distribution within Fortune 250 Employers*' section.

Descriptions of Metrics and Archetypes

Metric	Category	Timeframe	Metric Description
Barriers to Work	Access	2017-2021	This measures the extent to which a firm is employing workers with a bachelor's degrees (BA) in a given occupation. A higher share of bachelor's degrees relative to peers indicates less opportunity. For this metric, we calculated the share of workers in a given occupation with a BA relative to all the workers in the given occupation within an employer. The occupational score is calculated from 2017-2021. Sources: Lightcast Professional Profile and Job Postings Datasets
Entry-level Hires	Access	2017-2021	This measures what percentage of employees hired between the 2017-2021 time period were entry-level, as opposed to experienced hires. Specifically, we measure the percentage of employees in our sample who were at the first standardized job level with 0-3.5 years of experience when starting their Fortune 500 job. A higher percentage indicates more opportunity. Sources: Lightcast Professional Profile and Job Postings Datasets
Wages	Wage	2021-2022	The wages metric is calculated from the median wage of an occupation within a Fortune 250 employer from January 2021-April 2022. The data comes from employee reviews registered on the Glassdoor jobs platform. For data quality purposes, the wages registered above the 99th and below the 1st percentiles within an employer are trimmed to remove outliers and to help control from false reviews. Source: Glassdoor
Retention	Mobility	2013-2021	This component is based on the percentage of the workforce that is still at the same employer after five years. To calculate this sample, we start with all employees that started a job with a Fortune 250 employer between 2013-2016. We then count five years forward from their recorded start date and identify their employer. For example, if an employee started at Apple in January 2016, we would count forward to January

			2021 and observe their employer at this date. If the employee was still with Apple, then this would positively contribute to their retention score. For this metric, we are only concerned about retention within an employer as opposed to consistency of employment in the same occupation within the same employer. That is, if an employee has changed jobs multiple times within the same employer but is still employed by the same company after five years, this positively contributes to the company's retention score. The retention score is always attributed to the source (starting) occupation within an employer. Source: Lightcast Professional Profile Dataset
Job-level Advancement	Mobility	2013-2021	This metric calculates how far an employee has advanced after being at a company for five years. Specifically, we calculate the number of standardized job levels that employees within occupations have advanced after five years for each company. For this metric, we start with all employees that started a job with a Fortune 250 employer between 2013-2016. We then count five years forward from their recorded start date and identify their employer and occupation. Retention is a precondition of this metric. For those retained after five years, we calculate the average standardized job-level change between their source occupation of where they started and their destination role within the company five years later. Source: Lightcast Professional Profile Dataset
Velocity of Growth	Mobility	2013-2021	This component calculates how many days it takes on average for an employee to move up one standardized job level within the same company. Therefore, retention is a key characteristic of the metric. Similarly, we're interested in those workers who have held more than one job within the same employer and have moved up at least one job level. Again, we start with all employees that started a job with a Fortune 250 employer between 2013-2016. We then count five years forward from their

			recorded start date. Five years is the upper bound period to have moved up at least one job level. Once we isolate the sample of Profiles, we then calculate the average days to move up to a new role with at a higher job level within the same company. **Source: Lightcast Professional Profile Dataset**
Promoting Out	Mobility	2013-2021	This component measures the percentage of employees who receive a promotion upon leaving the company, highlighting where companies serve as effective career launchpads for their workers. This takes on the same setup as the Job-level Advancement metric, but instead examines the rate of employees who *left* the Fortune 250 company and weren't retained after five years. **Source: Lightcast Professional Profile Dataset**
Homegrown Leadership	Mobility	2017-2021	This component measures whether an employer is building its management team from promoting within its own ranks or hiring externally. For this component, we look at all profiles that worked at a Fortune 500 between 2017 and 2020 and had the keywords (or variation on keywords) "Director", "Vice President", "President" in their job title and it was their first title at this level. Then we divide the profiles into occupation groups and calculate the percentage of these employees that had their previous job at the last company. **Source: Lightcast Professional Profile Dataset**
Promoting Up	Mobility	2017-2021	This metric examines the percentage of Profiles that advance to an occupation from another occupation with a lower median wage within the firm. The rate is calculated relative to the total hires for the destination occupation. The timeframe for the metric is from 2017-2021 and the median occupational wages come from BLS wage data.

Archetypes

The Archetypes are composite indicators and assortments of the combined metrics. The combinations were created internally by BGI to showcase various motors of labor opportunity within employers. The archetypes scores were calculated by first taking the raw employer-level scores, normalizing them all to be on the same scale (creating z-scores), and then averaging the chosen assortment of normalized metric scores together. We only record archetype scores where all included metric values are available. As a final step, we calculate the top 50 per archetype (and for the Overall Weighted Rank).

Here is a description of each archetype:

Archetype	Metrics	Description
Career Launchpad	Entry-level opportunities + Promote-Out	Companies that have the best track record of hiring workers without experience, training them, and enabling them to move on to better positions elsewhere. These are companies where entry-level opportunities are plentiful and the professional experiences gained from these roles are positively recognized by other employers.
Career Stability	Retention + Wage	Companies that are most likely to offer good, well-paying jobs without significant churn.
Career Growth	Top Down + Internal and Upward Wage Mobility	Companies that are most likely to fill roles by promoting from within and whose leaders are mostly likely to have risen from within. Combines the promoting up and homegrown leadership measures. These are companies with established internal career development pathways to fill more senior roles.
Growing Talent	Entry-level + Velocity + Job-level Advancement	Companies that open their doors the widest to those without experience and then give them quick pathways for advancement within the firm. Combines the entry-level percentage, velocity of growth, and job level measures. The top ranked companies are those offering lots of entry-level roles with fast career advancement opportunities.
Advancement Without a Degree	Education Barriers + Internal and Upward Wage Mobility	Companies that are most likely to welcome those without degrees and to move them up the ladder.