Research Article

Balancing Artificial Intelligence Innovation and Job Preservation: A U.S. State-Level Policy Index Using Artificial Intelligence Exposure

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ABSTRACT

Artificial intelligence (AI) has been reshaping how work is performed across states, while creating changes for both growth and concerns about job loss. Leaders are currently in a situation where they need to make a clear yet fair rule to support innovation, while preserving jobs for workers. This study particularly asks whether it is possible for a simple, single dataset-based rule can help leaders balance artificial intelligence with job preservation. This study hypothesized that a rule rewarding higher artificial intelligence task exposure with gentle penalty on extreme exposure would keep the national portfolio clustered at a national mean, while maintaining priorities on high-potential places. Using one publicly available dataset with the score of exposure to artificial intelligence from the Brookings Institution (standardized state artificial intelligence exposure, 2017), this study analyzed 50 states with the District of Columbia. Exposure scores were calculated to have the average of -0.007 (SD 0.044), with Hawaii the lowest (-0.115) and Indiana the highest (0.065). According to ± 1 standard deviation bands, this study classified 10 innovation-max states, 33 balanced states, and 8 job-preservation support states. With an equal-weight index of a=0.5 to rank states, the top five states were Indiana, Kentucky, Michigan, the District of Columbia, and Washington. This ranking stayed unchanged when shifting weights towards innovation (a=0.7) or to job protection (a=0.3) through sensitivity analysis. Results in this study supported the hypothesis in this study about how most states remained clustered around the center, while maintaining priorities on high-potential places. The method taken in this study was transparent, offering a practical initiative for policy design.

Keywords: Artificial intelligence; artificial intelligence exposure; innovation policy; job preservation; place-based policy; state-level analysis; workforce reskilling

INTRODUCTION

Artificial intelligence (AI) has been shaping how people live and work. Artificial intelligence has been helping firms make new products, improve services, and raise productivity in an efficient way. However, there is a possibility for artificial intelligence to change jobs in an unprecedented way, moving tasks from people to machines and tools. Because of this possibility, many leaders have been wishing for policies to support AI innovations while protecting jobs and supporting workers to learn new skills. This paper aims to build a simple way to guide balanced decisions by using a publicly available excel file.

Many articles explain why artificial intelligence and digital tools are both powerful and disruptive at

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the same time. Studies suggest that productivity and growth tend to improve when new technologies are introduced with workers transitioning to higher-value tasks (1, 2). However, as different occupations involve different levels of tasks that are either more easily or more difficulty computerized than others, risks are uneven (3). According to empirical researches, automation shocks, including robotics, tend to decrease manufacturing employment in some regions (4). More importantly, since outcomes of employing new technologies depend on adoption, demand, and how tasks are reorganized, exposure tends not to be the same as job loss (5, 6). The mix of tasks, wages, and labor shares may be altered by technology, reinforcing growth but making challenge to worker adjustment (7). Therefore, it tends to lead to a productivity paradox that lagging productivity is seen with tangible technology change when firms adopt new technologies and reorganize (8). The importance of lifelong learning, social protection, and active labor-market policies has been stressed by policy groups to support transitions (9-12). In addition, it has been highlighted by researchers that impacts may vary across states and industries as they may have different local skill bases, data availability, and management practices (13-15). There are evidences that there would be mismatches between artificial intelligence-related skills and occupational structures that cause disruption (16). Putting all of them together, these findings emphasize that major potential may be brought by artificial intelligence, but the effects of it may not be even with a potential of creating a need for balanced policy frameworks.

Beyond measurement, theory and policy analysis raise an issue related to fairness and distribution of artificial intelligence. There is a study arguing that an issue of inequality may be raised by artificial intelligence when gains flow mainly to capital or to highly skilled worker without properly corresponding policies (17). Other studies ask what it means for machines to learn about work, pointing out that many tasks are mixed with the ones to be automated with the ones that are still best done by people (18).

Despite the extensive literature dealing with artificial intelligence, labor market, and automation, most of studies focus on complex models with multiple datasets and advanced economic techniques, making it difficult for policyholders to audit or reproduce results (7, 17). Only a few works indicate how a single and transparent dataset rule may be applied to a decision making process in state-level for reproducible and interpretable outcomes. This literature gap creates the need to make a policy tool to balance innovation with job preservation by using publicly available data. This study specifically asks whether a simple and reproducible index from a single credit dataset may guide state-level policy by balancing the innovation of artificial intelligence with job protection. This study hypothesized that a rule focusing on higher exposure of artificial intelligence but gentle penalization on extremes will create a portfolio of states clustered around the national average with priority on high-potential places for innovation.

METHODS AND MATERIALS

Using one publicly available dataset from the Brookings Institution, this study built a clear and reproducible policy guide as a cross-sectional research. The goal was to balance artificial intelligence innovation and job preservation with a rule presented. Particularly, this study used AI_Appendices_v2_BrookingsMetro_20200505 file from the Brookings Institution. This file contained several sheets, but this study mainly focused on the “States” sheet that listed a standardized artificial intelligence exposure score for each U.S. state (and the District of Columbia). This exposure came from the original Brookings Institution, showing how closely tasks in each place overlapped with what artificial intelligence could do at the time of their study. The score was standardized around the national average.

This study focused on state-level values, removing missing values or non-state rows from the “State” sheet, while leaving a total of 51 units (the 50 states with the District of Columbia). With one consistent level for the states, the analysis was kept simple and clear. In the modeling process, four variables were used. Here, E = exposure score of a state; m = national mean of exposure; a = policy weight ($0 \leq a \leq 1$); P = policy index score. Exposure (E) was used as the standardized artificial intelligence score from the Brookings Institution for each state. The higher the values were, the stronger the potential for artificial intelligence was to change tasks in that particular state. Mean exposure (m) was the average of exposure scores of all states. Policy weight (a) was a value between 0 and 1, setting how well the innovation was rewarded (higher exposure) versus how much it was to protect jobs when exposure was extreme. In the analysis, this study used $a = 0.5$ (equal balance). In addition, simple sensitivity check was performed by testing $a = 0.3$ and a = 0.7. Lastly, policy index (P) was used as a single rule to mix the goals.

MATH MODEL

This study defined a one-line score for each state with variables as follows.

$$P = a \cdot E - (1 - a) \cdot (E - m)^2$$

Where P was the policy index for a state (the higher, the better it was for receiving innovation support under a balanced strategy), E was the exposure score of that state, m was the national average exposure across states, and a was the policy weight between 0 and 1. The first part of $a \cdot E$ rewarded the potential of innovation that the higher the exposure, the more positive push it received. The second part of $-(1 - a) \cdot (E - m)^2$ added a small penalty when a state exposure score was far from the national average, in either direction. This played a role of protecting jobs by discouraging over-concentration in places with a potential of high disruption, while avoiding over-using innovation funds to places with very low exposure with limited impact. In this study, a=0.5 was used as a default for the equal balance, valuing artificial technology innovation and job protection the same.

While translating the single index into action, this study grouped states using their exposure (E) compared to the average (m) and one standard deviation (s). Without any extra calculations, this study only performed this step with descriptive cutoffs. First of all, innovation-max was relevant to states with exposure above the national average by at least one standard deviation ($E \geq m + s$). Job-preservation support was relevant for states with exposure below the national average by at least one standard deviation ($E \leq m - s$). These were places with priority with career services, reskilling, and careful adoption plans. Balanced was relevant to all other states with exposure within one standard deviation from the national average. This was for a dual-track plan to mix innovation support and worker support. With these steps, this study reported descriptive statistics for the distribution of exposure to artificial intelligence (mean, standard deviation, minimum, and maximum), the number of states in each policy category (innovation-max, job preservation support, and balanced), the top and bottom states with P under a=0.5, and a short sensitivity note for a=0.3 and a=0.7. The choice of ± 1 standard deviation provided a symmetric rule around the national mean. Percentiles or quartiles were also considered. However, modest variation was provided by the standardized Brookings data. Therefore, ± standard deviation assured both tails indicating the meaningful outliers, while keeping most states in the balanced group.

RESULTS

Among the 51 state-level units (50 states + DC), the average exposure (m) of artificial intelligence was calculated to be around -0.007, with a standard deviation around 0.044. The lowest exposure to artificial intelligence was Hawaii (-0.115), and the highest one was Indiana (0.065). These values indicated a modest spread around the national mean as expected since the exposure score of artificial intelligence were standardized by design. For some states, the exposure score was notably above the national average in artificial intelligence task exposure, and some were notably below. However, most states turned out to be near the national average. A simple histogram of state exposure to artificial intelligence confirmed this pattern (Figure 1). Most states clustered around the national average, with only fewer states in the tail areas. This supported the plan of this study to use the average and one standard deviation as a valid cutoff for the program design.

Using the ± standard deviation rule on exposure to artificial intelligence, this study found the following

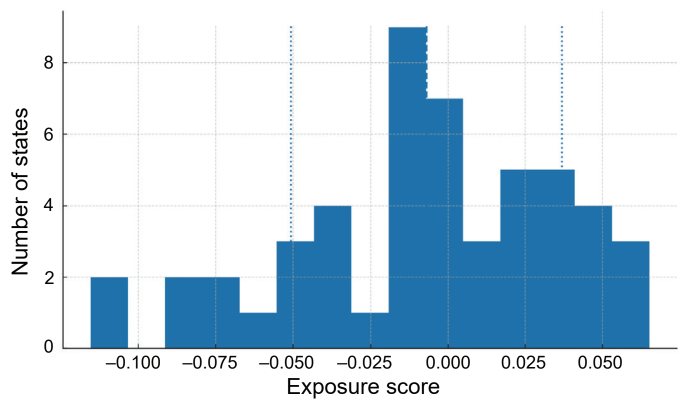

Figure 1. Histogram of state-level artificial intelligence exposure (Brookings Standardized Score, 2017). This shows the distribution across 50 U.S. states and the District of Columbia related to the national mean around -0.007 and standard deviation around 0.044.

counts. There were 10 states for innovation-max, 33 states for balanced, and 8 states for job-preservation support (Figure 2). This meant that most states fell into the middle "balanced" group. This made sense for a national program that mixed innovation and worker support. Only a smaller portion of states were either above or below the national average, helping target more intensive interventions as needed the most. States in the innovation-max group (high exposure to artificial intelligence) included Indiana, Kentucky, Michigan, the District of Columbia, and Washington. They had score well above the national average on exposure to artificial intelligence. By contrast, job-preservation support group had states (low exposure to artificial intelligence) included Hawaii, Nevada, Montana, New Mexico, Maine, New York, South Dakota, and Florida. They had the score below national average and may benefit from stronger interventions, up-skilling programs, and cautious sequence of artificial intelligence adoption.

Policy Index Ranking (a = 0.5)

When applying the policy index with the equal weight of a = 0.5, the top of the ranking stayed consistent with the high-exposure group, but moderated by the small penalty for extremely large deviations from the national mean. The top five by P were Indiana (highest exposure, strong innovation case, still balanced by the penalty), followed by Kentucky, Michigan, the District of Columbia, and Washington (Figure 3). At the bottom of the P ranking were states with low exposure far from the national mean, lowering their P in spite of the symmetric share of penalty. These included particularly Hawaii and Nevada, among others. For these states, the balanced rule suggested that focus needed to be placed on job-preservation supports rather than pushing spending for innovation. From this ranking, it turned out that the penalty was gentle without erasing the advantage of higher exposure but rather trimming extremes for the national portfolio to be stable. The order was intuitive that states with strong potential remained strong, and states with extremely low exposure to artificial intelligence were flagged for protective programs with priority (Table 1).

Sensitivity Checks (a = 0.3 and a = 0.7)

This study shifted the weight a to test how well the top end of the ranking was appropriately calculated. With a=0.3, more weight was on the penalty, and the top five states did not change. It was in an order of Indiana, Kentucky, Michigan, the District of Columbia, and Washington. At a = 0.7, more weight was on exposure, and the same top five states held. This sensitivity check indicated that the top ranked states were stable under reasonable weight choices. In terms of policy, this was useful for leaders to consider the exact balance between innovation and job protection without particularly overturning the main priorities.

Putting them all together, innovation-max group of states were ready for research and development grants, or startup support. Innovation funds may move quickly with task structures lined up with artificial intelligence. Balanced group of states were in need of receiving dual-track support with moderate innovation funding and strong worker support programs. Job-preservation

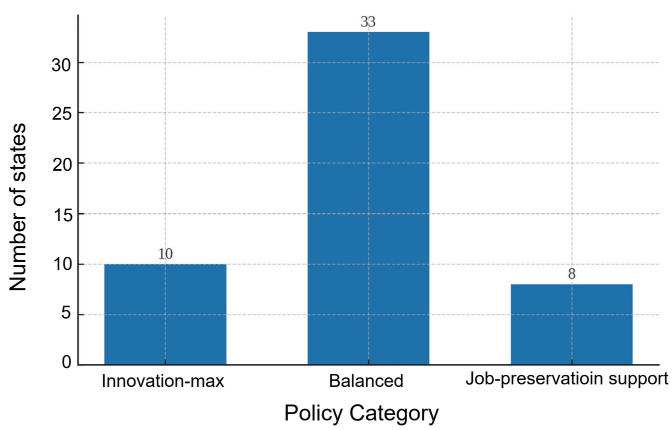

Figure 2. Distribution of states by program category with innovation-max, balanced, and job-preservation support with ± 1 standard deviation cutoff around the national mean. Innovation-max was E ≥ m + SD; job-preservation support = E ≤ m-SD; Balanced = otherwise.

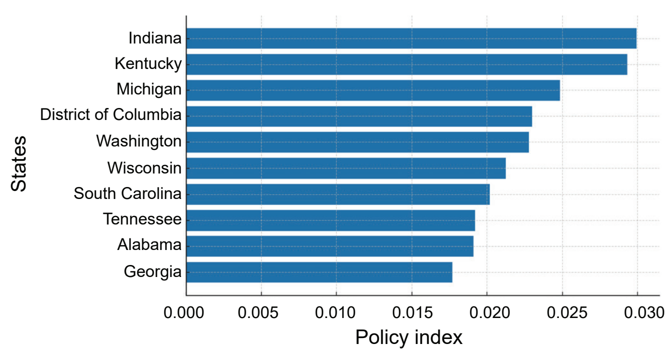

Figure 3. Top 10 states ranked by policy index (a = 0.5). Higher values show stronger case for the support of innovation under balanced strategy.

support group of states were in need of starting with career services and careful artificial technology adoption planning. Care needed to be taken on worker transition and local capacity when adopting artificial intelligence for innovation.

Table 1. Top 10 and bottom 10 U.S. states ranked by policy index (a = 0.5)

State	Exposure	Policy Index	Policy Focus
Indiana	0.065	0.030	Innovation-max
Kentucky	0.064	0.029	Innovation-max
Michigan	0.053	0.025	Innovation-max
District of Columbia	0.049	0.023	Innovation-max
Washington	0.049	0.023	Innovation-max
Wisconsin	0.045	0.021	Innovation-max
South Carolina	0.043	0.020	Innovation-max
Tennessee	0.041	0.019	Innovation-max
Alabama	0.040	0.019	Innovation-max
Georgia	0.037	0.018	Innovation-max
Alaska	-0.044	-0.023	Balanced
Louisiana	-0.045	-0.023	Balanced
Florida	-0.054	-0.028	Job-preservation support
South Dakota	-0.063	-0.033	Job-preservation support
New York	-0.069	-0.036	Job-preservation support
Maine	-0.072	-0.038	Job-preservation support
New Mexico	-0.082	-0.044	Job-preservation support
Montana	-0.087	-0.047	Job-preservation support
Nevada	-0.114	-0.063	Job-preservation support
Hawaii	-0.115	-0.064	Job-preservation support

Higher values show stronger suitability for the support of innovation in a balanced strategy. Lower values show stronger need for the support of job-preservation. The full ranking of all 51 units (50 states + DC) is provided in Appendix.

DISCUSSION

This study investigated a simple rule built from publicly available dataset from the Brookings Institution to help leaders balance artificial intelligence innovation with job preservation. This study used state exposure score from the Brookings as a single input while creating a policy index that rewarded higher exposure to artificial intelligence with gentle penalty on extreme values. The main pattern shown in this dataset was straightforward. Exposure scores of most states turned out to be near the national average exposure (mean ≈ -0.007, SD ≈ 0.044). A smaller set of states were either above or below the center. Using ± standard deviation, this study found 10 innovation-max states, 33 balanced states, and 8 job-preservation support states. When ranking states with the index at equal weight of a=0.5, the top five turned out to be Indiana, Kentucky, Michigan, the District of Columbia, and Washington. This top tier stayed stable when shifting the weight toward protection (a=0.3) or toward innovation (a=0.7) in sensitivity analysis.

The findings in this study supported the hypothesis established in this study, indicating that a rule rewarding higher exposure to artificial intelligence but penalizing extremes would generate a balanced selection to keep the overall national portfolio centered near the national average, while still maintaining priority on strong innovation potential. First, the category counts indicated that most states fell within the balanced range (33 within ± 1 standard deviation). Therefore, the national portfolio remained centered rather than towards the tails. Second, the index still lifted places with high potential to the top, including Indiana and Kentucky, even with slight penalty in places that confirmed how innovation leaders remained priorities. Third, sensitivity checks (a=0.3 and a=0.7) left the top five states unchanged, indicating that the rule established in this study was stable to plausible shifts in preference between innovation and job protection. Putting all of them together, these findings aligned with the hypothesis, indicating that the approach taken in this study balanced rather than towards to one side.

However, this study has limitations. First, exposure was not regarded as an impact. The score used in this study signaled where task could change without considering net job gains or losses, wages, or productivity. Second, the measures calculated in this study reflected the period particularly when the Brookings study took place. Recent artificial intelligence advances or adoption may have different exposure over time. Third, there was only one indicator considered in this study without adding wages, education, industry mix, or adoption rates. In addition, this study maintained ± standard deviation bands and equal weight to make them transparent, but different reasonable choices may move a few states across categories. Lastly, exposure was standardized, making the differences modest. The index needed to guide not fixed dollar amount but ranking and program mix.

CONCLUSION

This study showed that a clear and reproducible rule in balancing artificial intelligence innovation with job preservation could be produced by a single publicly available dataset. Using the exposure scores of states from the Brookings Institution (mean -0.007; SD 0.044), this study grouped states into innovation max (10), balanced (33), and job-preservation support (8). In an equal-weight index of a=0.5, the top five states turned out to be Indiana, Kentucky, Michigan, the District of Columbia, and Washington, and this ranking was stable under reasonable shifts of weights. These findings supported the hypothesis in this study that rewarding higher exposure to artificial intelligence with gentle penalty on extremes generated a center-clustered, yet innovation-oriented portfolio. Given limitations in this study, it is recommended for future studies to focus on updated exposure with more recent data, while adding simple controls with education, wages, industry mix, and adoption rates, to test alternative weights. In addition, it is also suggested to delve more into metros for finer targeting, while using causal or quasi-experimental designs to estimate the influence of artificial intelligence innovation on employment, wages, and productivity.

CONFLICT OF INTEREST

The author declares no conflicts of interest related to this work.

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APPENDIX

State	Exposure	Policy Index	Policy Focus	State	Exposure	Policy Index	Policy Focus
Indiana	0.065	0.030	Innovation-max	North Dakota	-0.004	-0.002	Balanced
Kentucky	0.064	0.029	Innovation-max	Arkansas	-0.008	-0.004	Balanced
Michigan	0.053	0.025	Innovation-max	Arizona	-0.011	-0.005	Balanced
District of Columbia	0.049	0.023	Innovation-max	Pennsylvania	-0.011	-0.006	Balanced
Washington	0.049	0.023	Innovation-max	Vermont	-0.014	-0.007	Balanced
Wisconsin	0.045	0.021	Innovation-max	Oregon	-0.015	-0.008	Balanced
South Carolina	0.043	0.020	Innovation-max	Idaho	-0.015	-0.008	Balanced
Tennessee	0.041	0.019	Innovation-max	Missouri	-0.016	-0.008	Balanced
Alabama	0.040	0.019	Innovation-max	Wyoming	-0.016	-0.008	Balanced
Georgia	0.037	0.018	Innovation-max	Oklahoma	-0.019	-0.010	Balanced
Illinois	0.033	0.016	Balanced	Rhode Island	-0.028	-0.014	Balanced
Utah	0.030	0.014	Balanced	West Virginia	-0.033	-0.017	Balanced
Iowa	0.023	0.011	Balanced	Delaware	-0.035	-0.018	Balanced
Maryland	0.021	0.010	Balanced	Texas	-0.036	-0.019	Balanced
Ohio	0.020	0.009	Balanced	New Hampshire	-0.040	-0.021	Balanced
Kansas	0.019	0.009	Balanced	Alaska	-0.044	-0.023	Balanced
Nebraska	0.019	0.009	Balanced	Louisiana	-0.045	-0.023	Balanced
North Carolina	0.010	0.005	Balanced	Florida	-0.054	-0.028	Job-preservation support
Connecticut	0.007	0.003	Balanced	South Dakota	-0.063	-0.033	Job-preservation support
New Jersey	0.006	0.003	Balanced	New York	-0.069	-0.036	Job-preservation support
Minnesota	0.005	0.002	Balanced	Maine	-0.072	-0.038	Job-preservation support
Virginia	0.004	0.002	Balanced	New Mexico	-0.082	-0.044	Job-preservation support
California	0.004	0.002	Balanced	Montana	-0.087	-0.047	Job-preservation support
Mississippi	0.003	0.001	Balanced	Nevada	-0.114	-0.063	Job-preservation support
Massachusetts	0.003	0.001	Balanced	Hawaii	-0.115	-0.064	Job-preservation support
Colorado	-0.001	-0.000	Balanced				

Appendix. Full ranking of all 50 U.S states and the District of Columbia by policy index (a = 0.5). All values were based on standardized artificial intelligence exposure scores in Brookings. Higher values show stronger suitability for the support of innovation. Lower values show higher need for the support of job-preservation.