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The Smarter State? Artificial Intelligence and Modern State and Local Public Finance

David R. Agrawal and William F. Fox[1]
May 11, 2026

Abstract

This paper examines how artificial intelligence (AI) reshapes subnational public finance, largely through familiar channels observed from prior technological change. Although some effects are novel, many issues surrounding the taxation of AI-related income and consumption parallel earlier challenges from e-commerce, digitalization, and remote work. AI shifts income from labor toward capital and reallocates tax bases toward consumption and market-based activity, raising questions such as the sales tax treatment of digital services. For governments, AI relaxes long-standing informational and administrative constraints in taxation, enforcement, budgeting, and service delivery, while strengthening scale economies. Cost reductions depend critically on labor-intensive sectors like K–12 education. However, government AI use may advantage larger jurisdictions with greater data access, raising equity and transparency concerns and increasing the value of interstate cooperation to harness scale economies from more data. Overall, AI reinforces—rather than overturns—the classic trade-offs emphasized in the fiscal federalism literature.

Keywords: artificial intelligence, state and local public finance, digital services, economies of scale, federalism
JEL: C55, H71, H72, H77, J45

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1. Introduction

The magnitude of productivity gains from Artificial Intelligence (AI), and their implications for economic outcomes such as employment and GDP, have been widely debated in both the media and academic literature. Less attention, however, has been paid to the potential effects on state and local governments and their constituents. AI could yield gains through lower service delivery costs or improved governance quality, for example via enhanced tax enforcement, more accurate property valuation, more flexible budgetary models, and faster, more precise data collection on service needs. While these applications are important, they account for only a modest share of state and local government functions and expenditures.

As in the private sector, the potential for substantial productivity gains depends on whether AI can effectively complement labor in the provision of labor-intensive public services—such as education, policing, and fire protection—which comprise a large portion of state and local spending. The extent to which technologies such as drones, online education, and AI-enhanced classroom instruction can improve productivity and reduce costs in these areas remains an open empirical question, contingent on the pace of innovation, adoption, and rigorous evaluation of outcomes. Lessons from the COVID-19 pandemic also suggest that there are important equity concerns related to technological adoption, as the ability to effectively use the technologies at home and in the classroom depends on many household characteristics. Moreover, institutional rigidities in government—including unionization and procurement and bidding practices—may slow productivity gains relative to the private sector, underscoring the need for careful empirical research on AI's actual benefits in the public sector distinct from private sector counterparts.

AI may also affect each of the major state and local revenue sources, although similar challenges have arisen from other economic developments and technologies. New products, such as generative AI services, may fall outside existing sales tax base definitions, thereby constraining revenue growth and impacting equity. At the same time, AI-related investment is often concentrated in intangible assets that are generally excluded from property tax bases. More broadly, AI and digital technologies facilitate the geographic separation of where income is earned from where individuals and firms are located, further complicating the situsing of income for tax purposes.

Offsetting these pressures, AI has the potential to improve tax administration and compliance, thereby reducing administrative and deadweight costs. AI cannot be thought of simply as a tool for improving the public sector, but also as a tool for individuals to design better tax avoidance strategies. Whether AI ultimately strengthens tax planning strategies by private individuals or firms or tax enforcement capacity by the public sector remains an open question.

This paper examines both the expenditure and revenue implications of AI for state and local governments. While some of these are novel, others parallel challenges created by earlier technological and economic changes, such as the growth of e-commerce, digitalization, and remote work, which provide a useful framework for the analysis. We begin by considering spending-side issues, focusing on public service delivery, tax administration, the emerging "auditing arms race" between taxpayers and tax authorities, and AI's influence on the degree of fiscal decentralization. Finally, we analyze the implications of AI for major state and local revenue sources, including sales, property, and corporate and personal income taxes.

2. Economic effects of AI

2.1 What is AI?

We start with a working definition of what we mean by AI. The OECD defines AI as "a term used to describe machines performing human-like cognitive functions" (OECD 2017). We use a broad variant of this definition that refers to digital tools and technologies that can assist in performing an economic activity by automating tasks, analyzing information, and supporting decision-making that would traditionally require human cognitive effort. This could include large language models (LLMs), machine learning technologies, chatbots, or data assistants. On the hardware side, this could include robots, drones, or autonomous cars. Key us is that AI extends well beyond the recent often-talked about LLMs.

2.2. AI and the private sector

A large literature has developed studying how labor markets have evolved in the presence of artificial intelligence. Our purpose is not to survey this literature extensively other than to note interesting parallels between the public and private sector. Indeed, as will become clear in our discussions below, AI may

affect public sector employees in many of the same ways that private workers are affected. But there will be some caveats. We begin by surveying some key points concerning private sector effects.

A large literature has studied the effects of other types of technological change on labor markets, including the adoption of IT, broadband technology, and even robots. Broadly speaking, this literature has shown that IT adoption mostly benefits highly educated workers (Bresnahan, Brynjolfsson, and Hitt 2002; Akerman, Gaarder, and Mogstad 2015). With respect to the adoption of robots, any negative effects are mostly concentrated among workers with less than a college education (Acemoglu and Restrepo 2020).

With respect to AI in particular, the literature is mixed on the productivity effects. Acemoglu et al. (2022) find no effect of AI on firm outcomes, but Babina et al. (2024) find positive effects on firm growth. Brynjolfsson, Li, and Raymond (2025) show positive effects of generative AI on worker productivity. Interestingly, less experienced workers see the largest gains in quantity and quality of output, while the most experienced workers see small gains. Thus, generative AI's effects appear to differ from the distributional effects of IT adoption. In his transparent discussion of the potential risks from AI, Jones (2026) concludes "It would be prudent to spend the intervening time making preparations for the potentially large consequences for labor markets, inequality, and catastrophic risk."

But while productivity of public sector workers is important, so too may be the decision-making capacity of policymakers or bureaucrats. Again, some studies find that AI helps workers in the private sector make better decisions (Kanazawa, Kawaguchi, Shigeoka, and Watanabe 2025), while others find that AI assisted individuals make worse decisions (Angelova, Dobbie, and Yang 2025). And Hoffmann et al. (2025) show that AI affects task allocation, allowing workers to shift away from non-core management activities toward more core work. Interestingly, the first study finding positive effects on decision-making focuses on taxi drivers and shows that AI helps drivers pick better routes.

3. Government use versus taxpayer use of AI

Hirsch (1959) divides state and local services into centrally integrated services (e.g., city hall), vertically integrated services that produce services at multiple levels of the supply chain (e.g., collecting, cleaning, and distributing water), and horizontally integrated services (e.g., schools, police, and parks) that are

provided close to the people. He observes that centrally integrated services, which are most likely to have economies of scale, represent only a small share of city government expenditures. While vertically integrated services can have economies of scale, many of these services can be contracted to private providers. In this case, much of what we know of the effect of AI on private firms may apply. Even in vertically integrated services, the economies of scale may only exist in part of the supply chain, such as the cleaning of water or sewer, but not the distribution which is generally to individual users. Finally, horizontally integrated services represent most of city government costs, which are generally not subject to economies of scale. We first focus on how governments might use AI to improve service delivery or tax enforcement, which are centrally integrated services. Education and policing represent the largest sources of expenditure for many localities; whether AI revolutionizes municipal finances and expenditures likely depends on whether or how AI complements labor in schools or police departments.

3.1 Public service delivery

AI has the potential to transform public service delivery by reducing administrative costs, accelerating information flows, and enabling more targeted interventions, but comes with some risks.[2] Consider the three stages in production of service delivery: information collection (who needs what and when), service production (use of labor and capital to produce a service), and targeting and allocation (delivery of the services or benefits to particular people).[3] The relative role of these three differs widely across public services but affects the potential for gains from AI. With respect to information collection, AI potentially shifts collection from street-level bureaucrats to digital feedback. Governments increasingly rely on smartphone apps, digital portals, and chatbots to collect information on service needs and citizen complaints. For example, the city of Lexington has the "LexCall App" which allows residents to provide feedback on garbage collection, potholes, street signs, or park repairs. In addition, the

[2] See the literature in public administration: Young, Bullock, and Lecy (2019), Zou (2023), Tang, Hou, Fay and Annis (2021), Young (2022), and Chen and Gasco-Hernandez (2025).

[3] Several papers study the effectiveness of algorithms versus regulators on targeting: Johnson, Levine, and Toffel (2023) and Andini, Ciani, de Blasio , D'Ignzio, and Salvestrini (2018).

LexComm app allows the city to send alerts, communicate road closures, and provide other information.[4] AI algorithms can use natural language processing to classify complaints and use image recognition to identify structures with problems. The predictive nature of AI allows government officials to prioritize cases for service needs. AI thus substitutes for city employees collecting information through observation, allowing faster response times, lower reporting costs, and less reliance on discretion.

However, this comes with risks. AI driven data collection may rely on smartphone access, digital access by citizens, and trust in platforms. Digital take up and usage are less common among the elderly, rural, and low-income households. The homeless population may be a vulnerable population without access to smartphones and to which the city may wish to provide services. The replacement of human service delivery with AI potentially makes local governments seem more distant from their constituents.

AI can also act as a substitute for public employees in eligibility screening for benefits, case routing, and compliance checks. Reduced staffing in clerical roles may result in faster processing times and cost savings but may come with equity and privacy concerns. Lipsky (2010) emphasizes that street-level bureaucrats can provide discretion, human judgement, and case-by-case adaptation. Shifting toward AI results in less individualized judgements and more uniform but potentially rigid service provision.

With respect to service delivery, especially with respect to social insurance programs, AI can improve fraud detection, income verification, and eligibility reassessment. AI may also reduce individuals inappropriately falling off of programs and allow faster enrollment. But there are risks of algorithmic denials resulting from automated benefit termination or erroneous fraud flags. Appealing these algorithmic denials may be challenging and increase burdens for beneficiaries.

We summarize the effect of AI on service delivery highlighting the potential tradeoffs:

[4] Currier, Glaeser and Kreindler (2023) provide an academic example of using smartphone vibration data.

Channel	Potential Benefit	Potential Harm
Information collection	Faster, cheaper feedback	Digital exclusion
Labor substitution	Cost savings, speed	Loss of discretion
Social assistance	Better targeting	Erroneous exclusion
Equity	Uniform standards	Unequal access
Governance	Scalable delivery	Reduced accountability

3.1.1 Education

The budgetary impact of AI will significantly manifest if it influences horizontally integrated services like education, where AI can be used either by students or teachers. AI is substituting for private school teachers in some limited cases and a Pew Research Center study (McClain, Kennedy, Gottfried, Anderson and Pasquini 2025) found that 31 percent of AI experts thought that AI would lead to fewer teacher jobs. This could be particularly helpful in public education where a shortage of teachers exists.

AI could reduce the time spent on grading, lesson planning or compliance with administrative requirements. Once the AI tools are developed and adopted, the marginal cost of adding another student is negligible. But, while this may result in cost savings, the labor share of teachers in school budgets remains high due to class size constraints. On the administrative side, AI can help with scheduling, transportation or staffing issues. But there may be fixed costs related to its adoption.

There are also political economy reasons to believe that AI replacement of teachers may be more limited for public than private schools. For example, in many states, public school teacher unions remain powerful and could advocate restrictions on AI to limit job losses for current members, without considering future members.[5] And, of course, how parents think about the use of technology in the classroom remains an open question, especially for younger children.

[5] Indeed, during the COVID-19 pandemic, DeAngelis and Makridis (2021) argue that places where teacher unions were strongest were least likely to reopen.

From an equity perspective, wealthier districts are better positioned to adopt AI in the classroom and to have home environments where children can effectively use AI (e.g., internet services), potentially widening achievement gaps. AI trained on historical data can also reinforce existing inequities.

Obviously, AI can have advantages and disadvantages in the classroom when used by students. It potentially offers the opportunity for personalized instruction or a supplement for specialized expertise in complex math or language classes that may have teacher shortages. But its use may depend critically on student discipline, the ability to access the internet at home, and family demographics.[6]

We conclude that AI is more likely to reshape how schooling is delivered than to dramatically reduce its cost and could raise the cost of producing education relative to goods (Baumol, 1967). While it may raise productivity and improve targeting, most fiscal savings are constrained by labor intensity and equity considerations, potentially increasing disparities across school districts.

3.2 Property tax assessments

Good property valuation is an essential characteristic of good property tax administration. AI and machine learning hold promise for property tax assessment by improving predictive accuracy, especially in nonlinear and tail behaviors, automating the choice of comparables, and integrating high-resolution data, reducing routine labor and standardizing valuations, but they raise some issues. Historically, many jurisdictions have used linear regression models to help assessors value properties that have not sold recently but some are now experimenting with machine learning approaches (Bø, Nygård and Thoresen 2025). Linear regression models are complements to site assessments and these linear models generally perform best at the mean property valuation, but can result in poor assessment ratios in the tails of the distribution (low-value or luxury properties). McMillen and Singh (2023) show that linear regression models are biased toward creating regressivity.

[6] We do not get into the large literature estimating the effects of technology on student outcomes but simply note that there are parallels to the digitalization and virtual learning issues that arose during the COVID-19 pandemic, including large inequities created across communities. For a survey of this literature, see Agrawal and Bütikofer (2022).

Machine Learning models (ML) such as random forests may be better at capturing nonlinearities and heterogeneous effects across the price distribution. AI can reduce bias and inequities, especially in the extreme tails of the price distribution. At the same time, ML models can pull real time data, potentially reducing assessment lags, though assessment lags may exist in statutes that require legislative changes.

Traditional regression-based models of property tax assessment require assessors to specify the variables that enter the model (square footage, age, etc.), the functional form of the regression (linear, log-linear, etc.) and whether variables in the model interact. ML models on the other hand can handle and curate thousands of variables and infer nonlinear patterns from the data. As a result, AI can reduce the number of human decisions in the process. Whether this is good or bad depends on the value added of a human assessor with institutional knowledge. Assessors may have specific neighborhood insight, the ability to know about future changes, and institutional memory. Of course, ML models' capacity to replicate or exceed these insights could grow over time.

AI also potentially opens the door to assessors using new information such as satellite imagery or street-level images, while also merging assessment databases with those from other agencies (building permit data, etc.). These types of data can provide information on quality upgrades that existing regression models will miss in the absence of physically inspecting the house. Further, AI models create transparency risks. Opaque ML models might be viewed as a "black box" that is harder for assessors to justify during the property tax appeals process and ultimately could erode public trust in the property tax. Furthermore, AI uses a data driven process that can reinforce any biases in historical data.

Smaller jurisdictions may not have expertise in AI modelling and thus may be more reliant on third-party models or private vendors that may train the models using data from other jurisdictions that are not necessarily good comparisons. Access to taxpayer data by private vendors is one possible concern.[7] However, private vendors may be able to scale the amount of data they use if they work in

[7] Glaeser, Hilli, Kominers, and Luca (2016) discuss this in the context of using algorithms for service delivery and sketch a model where crowdsourcing dominates the consultants.

multiple localities or states. Indeed, private vendors may be a mechanism by which local governments implicitly achieve data cooperation or harmonization to limit any disadvantages of smaller size.

We summarize these issues in the table below:

Mechanism	**Potential Benefit**	**Potential Risk**
Nonlinear prediction	Better tail accuracy	Black box
Automated comparables	Consistency	Opaqueness
New data sources	Richer valuation	Data quality issues
Continuous retraining	Temporal relevance	Overfitting
Labor substitution	Lower routine cost	Skill displacement
Vendor dependence	Access to tech	Loss of control

3.3 The Use of AI in Tax Enforcement

The IRS has long used various algorithms to better target auditing. For example, the Discriminant Function System (DIF) score is used to select returns for audit. The DIF rates the potential for a return to change based on past experience with similar returns. And the Unreported Income DIF (UIDIF) assigns tax returns a score on the basis of unreported income. Auditors then select the highest scoring returns for audit. While how the DIF and UIDIF are calculated is not public knowledge, some factors are widely speculated as contributing to a higher score. Nonetheless, because of its confidentiality, academic research on use of the formulae is limited.

Descriptive evidence suggests that the DIF may have improved audit efficiency. In 1968, prior to DIF introduction in 1969, 43 percent of audits resulted in no tax change. The share declined to 23 percent by 1975 and to 11 percent by 1990 (Hunter and Nelson 1995), though this may not be causal. Ultimately, the question is whether algorithms or bureaucratic discretion produce better outcomes, especially in contexts where subnational governments face constraints in staffing and technological expertise while the federal government remains responsible for most income tax audits.

Many low-income countries have been at the forefront of using algorithms to attempt to curb tax evasion, meaning much of the existing evidence comes from international settings. Under a Value Added

Tax (VAT), the detection of bogus firms is critical to prevent fraudulent tax credits. Barwahwala, Mahajan, Mittal, and Reich (2024) use administrative data in India to develop a ML method that detects bogus firms.[8] Physical field inspections indicate that 53 percent of the firms that were identified as bogus by the ML tool actually appeared to be non-existent. This is better than the 4 percent rate from randomly auditing firms or the 38 percent success rate from traditional rule-of-thumb approaches used by the tax authority. The authors provide the tax authority with half of the firms that were identified as bogus by ML and keep the remaining half confidential. They show that the ML method does not appear to have any differential effects on the tax authority's removal of bogus firms from the registration list. This highlights the possibility that bureaucratic procedures face institutional frictions that may make them hard to change or bureaucrats may be unwilling to rely on ML selection. There are reasons to doubt the applicability of evidence from low-income countries because of the lack of digital records in low-income countries and the fact that many low-income countries cannot devote resources to random audits, potentially limiting the ability to train ML algorithms.

Against this backdrop, some studies have shown more optimistic results for use of algorithms. For example, Battaglini et al. (2025) use ML algorithms in Italy. The authors show that replacing the worst performing audits with ML selected audits can increase detected evasion by 38 percent and increase the taxes recovered by 29 percent. Black et al. (2022) provide some evidence on how more flexible ML can influence the audit process in the U.S. But the authors provide caution from an equity perspective: relative to the discriminant approach, random forest approaches shift the audit burden away from high income households to lower income households. In other words, ML algorithms can shift the distribution of audits, creating trade-offs between efficiency and equity and raising issues discussed extensively in the literature (Pagano et al 2022).[9]

[8] Bachas, Brockmeyer, Ferreira, and Sarr (2025) and Shah (2025) are other examples of research on machine learning in the literature.
[9] See Kleinberg, Ludwig, and Mullainathan (2018) for a discussion of how algorithms may make detecting discrimination easier.

Residency audits are a critically important issue for state and local governments. Increasing globalization and declining mobility costs mean that high-income taxpayers may migrate in response to state tax increases (Moretti and Wilson 2017). Agrawal, Foremny and Martínez-Toledano (2025) note that second homes are one way the wealthy can avoid state income taxes. Some states base residency on the number of days spent in the state, with taxes due in the state if the individual maintains a residence and spends more than 183 days in the state.[10] High income taxpayers with multiple residences may manipulate the number of days spent in the state for tax purposes in the absence of enforcement. Similarly, in the presence of remote work, tracking the location of employment is important, especially for hybrid workers that work in cross-state metropolitan areas. For example, assume the states in question do not have reciprocity agreements or convenience-of-the-employer rules in place. A remote worker who lives in state A and works for an employer in state B needs to apportion workdays based on where the work physically occurs. In particular, state B will tax in-office days spent working in the state and state A will tax any work-from-home days.

Record keeping of the days is complicated and fine-grained hourly cell phone data can help the state tax authorities and taxpayers apportion at modest compliance/administrative costs. Historically, state residency audits have hinged on flight records and credit card data, though credit card information may not provide an accurate count of days when paying cash. Noonan, Wright, and Bly (2019) highlight how cell phone tower pings can instead be used by state auditors to count the number of days in a state though the cell phone data can be misleading for various reasons. AI has the potential to reduce substantially the effort auditors put into curating high frequency databases like cell phone data, and integrating them with credit card data or other sources of information, to construct more accurate residency data.

Taxpayers can also use these data to their advantage in counting the number of days spent residing in each state. For example, AI can readily be used to remove weekend trips to other states or

[10] In other states, such as California, the question of residency is much more complicated than a simple test based on the number of days. See Kirk Stark's article "California's Proposed Billionaire Wealth Tax and the Question of State Residency."

trips outside of business hours, so that a remote worker can best estimate the days spent working in the state, potentially reducing the compliance costs of multistate work substantially.

3.3.1. The Taxpayer-Tax Authority Arms Race

Joint use of AI raises the possibility of an "arms race" where taxpayers use AI to declare information on their returns, and the tax authority also uses AI to audit that information. While our focus is generally on the personal and corporate income taxes, these arguments also apply to sales and property taxes.[11] In our opinion, there are reasons to believe that the AI arms race favors the federal IRS over taxpayers and over subnational governments.[12] The IRS observes the universe of cross-section and time series administrative data, including both tax returns and third-party reporting and has the potential to link data across agencies. AI does best with large datasets and datasets that provide updated information, such as prior audit results. Taxpayers on the other hand only observe their own data and rarely observe the enforcement outcomes of others. Firms have substantial intra-firm data that are not included in administrative reporting though as discussed below, the tax authorities can expand reporting requirements over time. But firm data likely contain a smaller sample of the population than administrative data.

In general, large private firms can pay higher wages than state and local governments, which allows them to obtain the best talent, placing state workers in a less favorable position. But consistent with AI helping the productivity of workers in the private sector, AI may enable state workers to compete better with highly skilled labor in the best tax advising firms. This is especially the case if AI has a larger marginal benefit for slightly lower productivity workers than for highly skilled superstars that the large accounting firms may attract.

In addition, even if taxpayers invent new avoidance strategies, the tax authority does not need to understand *every* scheme ex ante. Instead, they only need to detect statistical irregularities correlated with

[11] Slemrod (2015) highlights "zappers" as a new technology that help with sales tax avoidance. These devices delete transactions after being installed into the retailer's point of sale system. The key is that the zappers, unlike a human, make these deletions relatively randomly such that a tax auditor may not detect the hidden transactions. AI can perhaps even improve on how the transactions are deleted, but also potentially how the tax authority can find them.

[12] Of course, there are also reasons working against this. Large private companies, such as national accounting firms, arguably may enhance their value by using the data they have on multiple companies or states. Even if not explicit, these firms may use data from multiple sources to help design tax strategies.

underpayment of taxes and can redefine information reporting requirements, change their audit focuses dynamically, or update the tax laws. While taxpayers can use AI to *react* to rules, the tax authority can use AI to *reshape* the rules though taxpayers may use political influence to reshape the rules as well.

Taxpayer usage of AI will be most powerful at searching for legal forms, helping understand the interpretation of tax rules, and helping optimize across multi-dimensional decisions, which can lower compliance and avoidance costs. In addition, AI—like a paid preparer—can help individualize avoidance strategies. Heterogeneity across taxpayers can make it hard to catch these avoidance strategies, at least initially. But the tax authority can learn from audits and retrain models over time. And given that AI can dramatically benefit from third-party information, AI may actually trigger additional information reporting requirements, as their added value increases with AI usage.

But there is less reason to believe that AI will advantage state/local tax authorities relative to taxpayers. First, states generally observe less information than the federal government: only observing in-state activity means that states only observe partial information on income for multi-state firms or remote workers. Models that train based on a subset of partial information will be less effective; yet taxpayer used AI can train on the tax rules across all states if tax accounting firms have access to multistate databases. Second, many states have much smaller samples (e.g., Wyoming, etc.). As a result, these states have fewer returns and may not have conducted random audits in the past (due to lower state resources that institutionally constrain the states). Thus, states may have some of the limitations discussed above that are commonly found in low-income countries with less frequent random auditing. Third, AI can be used to increase taxpayer mobility by identifying gray areas in nexus, residence location, or work location. Multistate companies can more easily compare across states and tailor strategies to each. While taxpayers can learn across state rules, in the absence of coordination, state databases cannot.

States may also be disadvantaged relative to the federal government because AI scales in the amount of accessible information. This can be formally modeled in a standard tax evasion model by allowing the detection probability in jurisdiction i to be a function $p_i = p(e_i, n_i)$ that depends on enforcement intensity e_i and the number of taxpayers n_i. Allowing the probability of detection to depend

on the number of taxpayers is a reduced-form approach to modeling how AI affects tax enforcement through increased data availability. As usual $\frac{\partial p}{\partial e_j} > 0$, but AI scaling in the amount of data implies $\frac{\partial p}{\partial n_j} > 0$. AI likely complements enforcement effort, $\frac{\partial^2 p}{\partial e_j \partial n_j} > 0$. Jurisdictions then choose the enforcement effort maximizing a standard objective. In this context, it is easy to show that AI effectiveness scales in size, making the federal government more effective.

The curvature of the probability function is influenced by the scaling of data as one moves from data that is held by Wyoming to California to the nation as a whole. Ultimately, the latter jump probably has little additional value because the number of taxpayers from California's population is quite large even relative to the federal system as a whole. But, the federal government still may be advantaged because the IRS observes more complete data (all multi state income) than the CA tax authority (only CA sourced income). This suggests that AI scales not only with the number of taxpayers, but also with the geographic scope of the data available to the tax authority.

Of course, taxpayer use of AI may also affect the probability of detection. If the effect of taxpayer usage does not depend on the number of people, then it will widen the gap between the federal and state government. And if AI helps taxpayers engage in interstate relocation, then the exit from a state further weakens the amount of information available to the state.

To conclude, AI amplifies existing federal advantages in enforcement. States will likely do best when tax bases are immobile, third-party reporting exists, and cooperation with the federal government or other states exists. Individuals will fare best when they are highly mobile, have multi-state operations, and have some information not collected by the states. We summarize below:

Channel	AI Benefits	AI Risks
Audit & issue selection	Higher audit yield; better targeting	Selection bias; neglect of hard-to-detect margins
Detection & measurement	Scalable anomaly and network detection	False positives; overfitting
Scale & capacity	Large productivity gains	Favors large, centralized authorities
Discretion & consistency	Uniform enforcement decisions	Loss of contextual judgement
Deterrence & behavior	Stronger deterrence on targeted margins	Taxpayer re-optimization elsewhere
Equity & accountability	Less arbitrary conditional on data	Bias, opacity, weaker transparency

Interstate cooperation or information sharing is one potential solution to issues related to scale economies in the amount of data. This has traditionally been the role of the Multistate Tax Commission or the Streamlined Sales and Use Tax Agreement and agreements between the federal and state governments. For example, dating back to the 1950s, states have adopted audit exchange agreements (Troiano 2026) that allow the states and IRS to exchange information on audit plans and techniques (though not necessarily taxpayer information). Public-private partnerships that allow smaller jurisdictions to harness the wealth of information held by many private companies is also encouraged. Given the potential importance of interstate cooperation, we summarize:

Channel	Role of Cooperation	AI-Specific Benefit
Data pooling	Shared enforcement data	Better model accuracy
Joint audits	Coordinated multistate enforcement	Limits arbitrage
Standardization	Harmonized definitions	Lower noise, lower compliance costs
State capacity	Shared expertise	Reduces small-state disadvantage

3.4 Public budgeting

Two dominant theories underly public budgeting: incremental budgeting and zero-based budgeting (Rubin 2019). Incremental budgeting is a process where policymakers adjust last year's budget for the new fiscal year. Zero-based budgeting (ZBB) requires each expense to be justified from scratch in each

budget cycle, which is extremely resource and time intensive to implement. AI has the potential to relax long-standing informational constraints that have historically favored incremental budgeting, particularly by improving revenue forecasting, program evaluation, and scenario analysis.

AI lowers the costs of program evaluation and cost-benefit or cost-effectiveness calculations. As examples, AI allows for continuous performance monitoring and automated flagging of low-value programs. AI also allows for easy usage of big datasets discussed in Einav and Levin (2014). Because AI weakens the informational rational and cost rational for incrementalism, it makes partial or rotating zero-based budgeting reviews more feasible, which may especially important when a city or state government changes political control after several years. Zero-based budgeting allows a new administration to implement promised changes more effectively but may create volatility or uncertainty over the stability of government programs. AI could be used as a tool to detect spending overruns, fraud, or waste.

Forecasting, which often relies on linear models with stable elasticities, is an important part of the budgetary process. ML models are well suited for non-linear relationships, identifying early signals of structural breaks and potentially determining deviations from historical trends. At the same time, these new methods may perform poorly out of sample and may underweight tail risk. AI may improve the statistical accuracy of revenue forecasts while simultaneously worsening fiscal outcomes if its outputs are used without appropriate institutional safeguards.

AI may mask forecast uncertainty and thus create risks of failing to create budget reserves if there is a perception that AI operates without forecast errors. Perhaps more worrisome, AI may entrench the status quo and make zero-based budgeting problematic because AI relies on data dependence. Most AI or ML algorithms are trained on historical data which may reinforce past decisions and undervalue new programs for which there is less evidence (Mullainathan and Spiess 2017). Thus, AI may strengthen not weaken incrementalism.

A literature in public budgeting discusses the importance of transparency in the budget process. Relegating budgetary decisions or analysis may reduce transparency. Further, with respect to fiscal rules,

AI has the potential to improve compliance with fiscal rules, but may also enable creative reclassifications that are harmful for the budget process. We summarize:

Channel	AI Benefits	AI Risks
Incremental vs. zero-based budgeting	Lowers costs of program evaluation; enables partial or rotating ZBB	Data dependence may entrench status quo; program instability
Forecasting	Captures nonlinearities; detects structural breaks	Poor out-of-sample performance; masked uncertainty
Monitoring & control	Flags overruns, fraud, and low-value programs	False precision; overreaction to noise
Governance & transparency	Improves compliance with fiscal rules	Opaqueness; creative reclassification

4. Decentralization vs. centralization

Artificial intelligence alters the traditional trade-off between centralization and decentralization not by uniformly favoring one level of government, but by reshaping the underlying cost structures. In canonical models of fiscal federalism, decentralization has both advantages and disadvantages relative to centralization. For example, Oates (1972) argues that more decentralization enables better matching of citizen preferences to the public goods provided, but comes at the cost of not internalizing spillovers on other jurisdictions. In Alesina and Spolare (2005), the tradeoff is between preference matching and economies of scale in public good provision. Under the latter, decentralization may result in duplicated administrative costs across jurisdictions, but fragmentation can also raise compliance costs as firms (and people) may need to comply with 50 different state tax codes as well as thousands of local regulations.

AI may reduce these classic decentralization costs, weakening one argument for centralization, by relaxing the need for individuals and firms to rely on scarce (and possibly expensive) paid tax preparers, accountants, lawyers, and tax software. For example, AI could potentially automate multistate filing, search and curate databases of tax rates and laws across jurisdictions, assist in nexus determination, and provide real-time classification of the tax treatment of transactions across states.

Similarly, AI could reduce the scale of administration necessary to achieve low costs and allow smaller localities to adopt better enforcement technologies or lower cost service provision as it partially substitutes for human expertise and software enforcement technologies. For example, jurisdictions could use AI to audit taxpayers or employ AI to exploit smartphone app data to better provide public services.

Beyond these scale issues, a traditional argument for decentralization is the ability of state and local governments to serve as laboratories. Policy heterogeneity or experimentation potentially allows the best policy issues to be adopted by other states. But experimentation is costly and evaluating the efficacy of public policy also takes time. AI has the potential to accelerate policy evaluation or enable the simulation of counterfactual policy analysis.

While these forces favor decentralization, AI exhibits increasing returns to scale in the amount of data used to train it, which potentially advantages the federal government in auditing, policy analysis, or service delivery. Relatedly, the scale of data advantages larger states, which can lead to inequality in state capacity and resulting differences in enforcement quality, service quality and policy analysis across states. Centralization or cross state cooperation could level the playing field.

Finally, AI has the potential to influence interjurisdictional fiscal competition (Agrawal, Hoyt, and Wilson 2022) by expanding available data to taxpayers. Whether AI advantages or disadvantages jurisdictions via competition depends on whether the beneficial forces of Tiebout competition dominate the parasitic forces of tax competition. AI can help overcome information asymmetries about communities, potentially enhancing the beneficial Tiebout forces resulting from competition.

On the other hand, AI lowers the cost of cross-state tax planning, potentially enhancing parasitic tax competition as firms or individuals shift income or locations to lower tax jurisdictions, thereby increasing tax base elasticities and heightening tax competition. Further, it is well known that smaller jurisdictions often seek to lure taxpayers (Kanbur and Keen 1993) and become tax havens. But, because AI scales in the amount of data, smaller jurisdictions will be less able to enforce their taxes relative to larger jurisdictions that can exploit the scale economies of AI, causing small and low-tax states to become enforcement havens as well as featuring low statutory tax rates. At the same time, AI may result in

further competition on non-rate margins. In this context, AI has the potential to reinforce the need for interjurisdictional cooperation across many areas (Agrawal, Poterba, and Zidar 2025), and AI makes cooperation more important both because taxpayers may become more mobile, but also because the ability to reduce parasitic effects of tax competition may depend on the amount of information available to jurisdictions. We summarize:

Channel	Decentralization	Centralization
Compliance & administration	Lowers compliance and admin costs	Data scale favors large governments
Enforcement & services	Lowers minimum efficient scale	Superior federal / large-state capacity
Policy experimentation	Faster evaluation and learning	Central data advantages
Fiscal competition & inequality	Stronger Tiebout forces	More tax competition; wider capacity gaps

5. AI and State/Local Tax Policy

AI affects revenues from the major state/local tax sources, income, property, and sales taxes, by altering overall economic activity and by changing taxability. The property tax raises the largest share (36.7 percent) of state/local taxes followed by the sales (29.2 percent) and personal income taxes (25.5 percent). Of course, the property tax dominates *local* taxation, as local governments in only about 10 states use the personal income tax and in 36 states use the sales tax. After a brief review of how AI impacts aggregate economic activity and national tax revenues, we focus on how the interaction between AI and tax institutions alters tax revenues and the steps governments can take to enhance policy.

5.1 Aggregate Economic Activity

AI's overall economic impact remains uncertain. In Acemoglu and Restrepo's (2019) framework, automation can either complement or substitute for labor, implying that employment may rise or fall, particularly in the long run. Generative AI may substitute for labor by automating routine tasks, potentially reducing labor demand and income, or may enhance worker productivity. Conversely, labor demand may increase if new tasks emerge in which workers have a comparative advantage or if firms

reorganize to exploit recent technologies. Empirically, Acemoglu and Restrepo document increased AI-related job postings alongside declines in non-AI positions, with no aggregate effects on employment or wages. Historically, general-purpose technologies have often displaced labor in the short run but increased labor demand over time.

Bastani and Waldenström (2024) examine three channels through which AI may affect national taxation. First, AI may raise capital's share of income relative to labor's, though as noted, task creation can offset automation's labor-displacing effects. Second, AI may alter returns within the labor market and income inequality, with recent evidence suggesting reduced inequality. Third, AI may change capital returns across sectors. Bastani and Waldenström (2024) conclude that relative increases in capital income could reduce total tax revenue and warrant greater reliance on capital taxation, while with equity concerns more progressive labor taxation may be appropriate; however, they argue that policy changes should not be made yet in response to AI. While AI may ultimately reshape labor markets and tax bases, its fiscal consequences depend less on technology than on how institutions accommodate the evolving economy and adapt to new uncertainties.

5.2 AI and State/Local Tax Structures

The state and local tax policy issues arising with respect to AI are generally not novel but may be substantial. Tax privacy likely grows as a concern as data availability and processing expand rapidly. Slemrod (2025) emphasizes that an equitable and efficient tax system requires that governments have access to data on households' wellbeing, but the demand for privacy offers an important countervailing social cost. He notes that privacy has two elements, the ability to keep government from knowing certain information about taxpayers and the government's ability to protect taxpayer information from being leaked by the tax authorities. Nuanced privacy concerns lie outside this paper's scope but will become ever more important as AI and LLMs increasingly rely on accessing data.

With respect to the income tax, AI policy issues relate to timing and location of the base and shifts in the type of income generated. A relative reduction in the personal income tax because of changes in labor income means the sales tax and corporate income tax shares could rise either from simple

mechanical effects or from policy decisions. The sales tax in the U.S. is generally structured narrowly so the policy issues surround the standard concerns for the need/potential for base expansions. The sales tax base could be expanded to more AI related consumption, as has happened in some states with taxes on digital goods. A return to rising sales tax rates (as occurred through the 1990s and 2000s) is also possible if states seek to replace lost general revenue from declining income taxes. This suggests that sales taxes could rise as a share of state/local tax revenues, even if total taxes fall.[13] Property taxes depend on the overall AI investment and how much is included in the taxable base, since intangible investments are likely to remain untaxed.

5.3 Sales Tax

The next two sections provide guidance for design of new statutes to appropriately sales tax services provided through various types of AI. The guidelines are relatively straightforward but are very complex in practice. For example, how sales are monetized, who purchases AI services and which firms use AI in production can affect appropriate taxability. Further, decisions must be made on how theoretically correct tax on AI should be given the shortcomings of the existing sales tax. Thus, ability to administer tax and distortionary consequences of leaving base definitions short of ideal must be elements of any decisions on how to tax AI related services.

5.3.1 Tax Consumption Broadly

Neutrality and horizontal equity argue for imposition of sales tax broadly on consumption, which presumably includes AI.[14] For example, the use of AI to make vacation plans or investigate attributes of various consumer products belongs in the tax base. We begin by considering sales taxation of AI in the context of recent policy action on taxation of digital services (Agrawal and Fox 2021).[15] Frieden and

[13] This would reverse the general pattern since the mid-1990s of personal income taxes rising as a share of tax revenues (particularly state revenues) and sales taxes declining as a share.

[14] Sales tax bases vary widely across states (Beem and Bruce 2021), from Hawaii, which imposes the tax on almost all transactions, to New York and Illinois, which have narrowly defined bases. The breadth of sales tax on services, such as health care, education, and transportation, is the key area where states differ.

[15] AI is any technology that enables machines to mimic human intelligence while digital products are ones that are delivered in binary or digital format. These are related but AI is technologies while digital products are built with technologies; indeed, a case can be made that AI is a subset of digital services. AI and digital products are closely related in some cases, but can differ significantly, as when AI is imbedded into business processes as opposed to being delivered as a service.

Wethekam (2026) observe that about one-third of states tax a narrow range of digital products (or do not tax them) and about one-third tax a little to a medium range of digital products. Recent expansions include Washington, which broadened the base to include information technology services, website development, and access to custom software; Iowa which included digital audio-visual works and digital books; and Connecticut which taxed audio works, audio-visual works, and prewritten software. Nonetheless, considerable opportunity remains to tax consumption of digital services broadly.[16]

Caisse and Eisenstein (2026) state that no state has imposed sales tax on AI, perhaps because any tax is levied on what customers are purchasing, such as information services. They indicated that 21 states, just under one-half of sales taxing states, tax Software as a Service, (SaaS) for example, but determining whether large language models (LLM) services are in the taxable set also requires determinations on what is involved in delivery of the service.[17] They conclude that LLMs are likely to be categorized as software, but the service provided to the user could still be defined as non-taxable depending on what is actually being purchased, which likely depends on facts and circumstances of the specific situations. Many states rely on a true object text, which questions whether the purchase is of the software or responses to questions. Revenue departments in Tennessee and Rhode Island have reached mixed advisory opinions on what is the true object of such purchases.

The sales tax should be due at destination to spread the cost of local public services according to where consumption takes place and because imposing the tax where production occurs is more likely to distort behavior, assuming that production is more mobile than consumption. Of course, distortions can occur with destination-based taxes, such as from cross border shopping, because states assume that consumption occurs where consumers take possession of goods (Bruce, Fox, and Shute, 2025). Taxation at destination raises many challenges in practice, such as where tax is due when family members located

[16] Caissie and Eisenstein (2026) note that four states expanded their sales tax base to more digital transactions in 2025, two of which identified a narrow set of service and two of which levied more comprehensive expansions.
[17] Most states have not provided direct guidance on these issues yet. Two states issued opinions on the taxability of AI chatbots, but neither taxes SaaS. Caisse and Eisenstein (2026) observe that Illinois concluded that an AI chatbot is SaaS, but the sales are not taxable in the state. Indiana concluded that AI chatbot services are not taxable in the state, but it also does not tax SaaS.

in multiple jurisdictions benefit from the same service, which likely means the tax is paid in only one jurisdiction even though consumption occurs in multiple places.

Sales taxation of AI, like other digital technologies such as social media, is complicated by the multisided platforms through which these services are monetized (Agrawal and Fox, 2021). For example, ChatGPT reported approximately $13 billion in user-fee revenue in 2025, though this figure does not distinguish between payments for final consumption and those for intermediate inputs. In addition to direct user fees, digital firms frequently monetize their services through alternative channels such as advertising and data sales. This raises a central concern: if these different revenue streams are taxed inconsistently, production and consumption decisions may become distorted. The existence of multiple monetization channels, however, does not preclude the taxation of AI consumption. One approach would be to levy a sales tax on all firm revenues attributable to AI services. At the subnational level, taxing revenues generated through non-consumer platforms would likely require apportionment, since identifying the location of consumption is more difficult without direct transactions. The economic incidence of such a tax remains uncertain. It could be passed forward to consumers (eg, through increased advertising), shifted to advertisers via higher prices, or absorbed by AI firms in the form of lower profits.

AI consumption fits squarely within a neutral sales tax base, but heterogeneous monetization, bundling, sourcing ambiguity, and enforcement constraints make subnational taxation highly complex under existing, and likely under any retail sales tax structure. We summarize as:

Channel	Neutrality Case for Taxing AI	Key Complications
Consumption base	AI can be consumption like other digital services	Statutes often exclude or narrowly define digital goods
Final vs. intermediate use	Final AI consumption belongs in base	Risk of pyramiding if intermediate use taxed
Monetization models	User fees, ads, and data can be taxed in principle	Indirect monetization complicates sourcing
Bundling & classification	AI comparable to taxable software/services	True-object ambiguity; embedded AI
Subnational administration	Broad base supports neutrality	Apportionment and enforcement challenges

5.3.2 Exempt Intermediate Transactions

Good policy levies sales tax on all final consumption, while exempting intermediate inputs to avoid cascading and production distortions. The VAT's credit invoice system reduces cascading, but intermediate inputs must be exempted with the sales tax. Companies may use embedded AI to provide services directly to final consumers in areas such as education, health, personal finance, home repair, and legal services. The final service, health care or legal services, belongs in the tax base if delivered to consumers, but payments for AI, such as LLMs, should not be taxed. Similarly, tax should not be imposed on AI used by businesses to investigate the lowest input prices, to find the lowest airfares for business travel or to improve call centers, even if not used directly in production of the final product.

However, sales tax on intermediate inputs may be appropriate in cases where the final consumption is not included in the base, as a second best, indirect/incomplete means of taxing the final product. This suggests that AI services provided to firms producing taxable goods should be exempt and the same services should be taxable when sold for production of non-taxed services.

These principles indicate that payments for AI services should be taxable when sold to final consumers and exempt when sold to businesses, assuming the final consumption produced with the inputs is taxable. The challenge in practice, which arises with many sales taxable transactions, exists because exemption depends on the purchaser and use and not the product alone, which requires a means to

determine who the buyer is and how the buyer will use the AI. The problem is further complicated when the transaction is not monetized to the consumer because revenues associated with business use of the AI should not be included in an apportioned base since this would implicitly tax intermediate inputs.

Efforts to limit sales tax cascading are not unique to digital products and AI. States often allow two broad input exemptions. Manufacturing inputs are generally exempt when they become a component part of a manufactured good or are directly used in production of the good, depending on the state statutes. Inputs are often taxable when used in production of services because many of the services themselves are not taxable at the consumer level. Second, sales for resale are generally exempt. Overall, about 42 percent of sales and gross receipts taxes are imposed on business purchases, evidencing a strong propensity to tax many business inputs that do not fit under the above exemptions.[18]

In this context, states are left with the challenge of whether broad exemption of inputs should be granted for digital products and AI, while continuing to tax many intermediate products used in production of goods and other services. Already, all 38 states offering specific tax exemptions for data centers grant sales tax exemptions for essential equipment. Different degrees of cascading between AI, digital products and other goods and services could distort relative prices and consumption and the extent of innovation for emerging industries and products. We are unaware of specific analysis of tax on digital intermediate transactions and AI, but overall, a significant share of revenues comes from tax on intermediate transactions.

Appropriate exemptions for digital products have received considerable discussion over the past decade or two, though in many cases exemptions have not been enacted, even as some expansions of the base to digital products has occurred.[19] Frieden and Nicely (2024) argue that Connecticut and Massachusetts enacted manufacturing-like input exemptions for digital products when they expanded the

[18] Authors' calculations based on COST (2024) estimates that businesses paid $240.6 billion sales and gross receipts taxes in FY 2023 and Census reporting that General Sales and Gross Receipts Taxes were $577.3 billion for the four quarters ending with the second quarter of 2023. Using data from the U.S. Census Time Series and Trend Charts.
[19] See Kearns, Chien, and Ahmadi (2025) Frieden and Nicely (2024).for discussion of approaches to exemptions.

sales tax base to specified digital products, though they observe that relatively few states exempt tangible and digital business inputs in production of digital products.

Iowa provides a relatively broad attempt to follow the two sales tax principles described above. The state taxes a set of specified digital products (such as digital books) if electronically transferred, other digital products (such as greeting cards and electronic games), information services, and SaaS. Services involved in producing digital products may also be taxed.[20] The state exempts intermediate digital sales if sold to a commercial enterprise and used exclusively by the enterprise. Businesses and manufacturers operating for profit, insurance and financial institutions, professions and occupations, and public utilities are included as commercial enterprises, but the exemption is not inclusive since construction, health, and non-profit firms are not classified as exempt commercial enterprises. Thus, digital products used as inputs are exempt for some producers but not for others. The final product may not be taxable for the second set of industries, suggesting their input purchases should be taxable.

Bundling further complicates the challenge of exempting intermediate inputs because state laws often impose the tax on the entire transaction if taxable and exempt sales are bundled together without separately stated prices. Embedded AI, such as in automobile technology and software, may be bundled with other purchases that results in uneven taxation for the same input purchases, depending on the bundle being sold. Thus, an otherwise exempt input may be taxable if one component of the bundled transaction is taxable.

Considerable progress is necessary to bring the sales tax base in line with the two guiding principles: tax consumption broadly and exempt intermediate sales when the final output is taxed, as the sales tax base falls well short of taxing consumption of AI and digital products, even when monetized to consumers. Even less taxation of social media and related consumption occurs when not monetized to consumers, leaving the base farther from consumption.

[20] The list does not appear to include AI specifically, but in this discussion, we assume that Iowa will tax AI as a digital product when it falls within the legal description.

We summarize AI and sales tax exemption policy issues as:

Issue	Policy Principle	AI-Specific Complication
Intermediate inputs	Exempt to avoid cascading	AI often improves productivity rather than directly producing output
Final vs. business use	Tax final consumption only	Same AI service used by consumers and firms
Second-best taxation	Inputs may be taxed if final output untaxed	Many personal services remain outside the base
Apportionment	Exclude business inputs from base	Indirect monetization obscures use and location
Bundling	Taxability depends on transaction structure	Bundled AI services may override exemptions

5.4 Property Tax

AI's effect on the property tax focuses on the type and level of investment.[21] Gartner estimates that worldwide AI spending was $1.76 trillion in 2025 and will rise to $2.52 trillion in 2026 and $3.34 trillion in 2027.[22] Infrastructure represents about 55 percent of the AI spending, so real and personal property tax bases can rise significantly as data center and other investments occur. The investments are lumpy, benefiting a subset of local jurisdictions, though at least 4000 data center investments have been announced across the country.[23] Further, five states and some local governments offer property tax incentives for data centers, which is somewhat surprising given the modest employment gains and even the possibility of negative local externalities.

The property tax base concentrates on real and personal property to the near exclusion of intangible property, though exceptions exist. For example, the full value of firms in Oregon including intangibles is measured in cases where appraisal is done by the state rather than local assessors. Gartner expects software to be 1/6th and AI services nearly 1/4th of AI expenditures, and these are more likely to

[21] See Fox and Zodrow (2026) for some parallel discussion.
[22] See the article "Gartner Says Worldwide AI Spending Will Total $2.5 Trillion in 2026" from January 15, 2026.
[23] NCSL, "Policy Snapshot: Data Center Incentives," April 9. 2026.

be reflected in intangibles and fall outside the real and personal property tax base. Further, assessors may understate the true value of capital in AI intensive firms that look property light relative to capital intensive firms. The result can be a much smaller share of business investment reflected in local property tax bases than might occur with other large investment expenditures.

We summarize AI and property tax issues as:

Channel	Property Tax Implication
Data centers & hardware	Expands real/personal property base, sometimes offset by abatements
Software & AI services	Largely excluded as intangibles
Assessment & incentives	Base growth varies widely across states and localities

5.5 Personal and Corporate Income Taxes

Institutional features governing the taxation of in-state and cross-state income will be especially important in determining overall revenue effects. As in Bastani and Waldenström (2024), we expect capital income to grow relative to labor income, reducing the share of tax revenue derived from labor. We briefly examine differences between the taxation of capital and labor income, including the potential for capital income to be taxed at multiple levels. Our aim is to outline the broad issues rather than provide a detailed discussion of the underlying complexities.

5.5.1 Form of Income

The timing and rates of taxation often differ between labor and capital income. Personal taxes are imposed on labor income in 41 states and by local governments in about 10 states. Forty-three states have a corporate income tax while others, such as Ohio and Washington, rely on gross receipts taxes. The shift from labor income to capital income may lower effective personal tax rates and delay when income is taxed. Labor income is typically realized and taxed in the year it is earned, except in cases such as bonuses or equity compensation that may be received in a later tax year. Income from pass-through entities is also generally realized and taxed annually at the individual level, similar to labor income, although firms may choose between individual and corporate tax structures.

In contrast, capital income at the individual level is often not taxed until it is realized, allowing taxation to be deferred for many years. For example, increases in a business's value are not taxed until they are realized through an event such as the sale of an ownership stake, which may not occur during the owner's lifetime. When realized as long-term capital gains, this income is often taxed at preferential rates.

Capital income may also be taxed at both the firm and individual levels, depending on the business structure and state tax system. Corporate earnings are generally subject to state corporate income taxes on an annual basis, with rates that may differ from personal income tax rates. When these earnings are distributed to shareholders as dividends, they are taxed again under the personal income tax. However, gains remain untaxed until realization and then are often taxed at preferential capital gains rates. While the deferral of unrealized income is not unique to AI, the growing importance of intangible assets, data, and platform-based business models may increase its significance.

A shift toward capital income could increase the share of income subject to both corporate and personal taxation, depending on the prevalence of businesses choosing corporate structures. However, it also presents challenges for state and local governments. Because capital income may go unrealized, taxable income could decline even as overall economic income rises. In addition, corporate tax revenues tend to be more volatile than other revenue sources, increasing fiscal risk. Capital income is also generally more mobile, although the increasing use of market-based apportionment limits firms' ability to shift income by relocating production. Finally, the distributional effects are uncertain: while ownership of capital is concentrated among higher-income households, productivity gains from AI may also benefit smaller businesses and may not accrue exclusively to top earners.

We summarize as:

Dimension	Labor Income	Capital Income
Timing	Taxed when earned	Taxed upon realization
Rates	Ordinary PIT rates	Often preferential
Withholding	Strong	Quarterly payments
Entity effects	Limited	Sensitive to business form
State challenge	Stable, source-based	mobile, deferrable

5.5.2 Cross State Distribution of Income

The cross-state distribution of the corporate base frequently differs from the personal income base. Labor income is taxed in the state of residence for workers who live and work in the same state. For those who live in one state and work in another state(s), different approaches are employed for situsing the base for labor income, with it being due in state of work in some cases and state of residence in others.[24] Capital income on interest and investment returns is taxed in the residence state. AI does not alter the rules for where tax is due, but may help taxpayers arbitrage in the context of multi-state income.

Similarly, state corporate income is taxable in the state where earned for firms that produce and sell in a single state. State corporate apportionment formulas situs the base for multi-state businesses. At least 32 states apportion profits using a single-factor sales formula and another six at least double-weight sales in a three-factor formula.[25] Thus, tax on any shift from labor income to capital income is more likely to be distributed across states according to the location of firms' markets as opposed to firms' workers. Thus, the apportionment formula moves the distribution somewhat towards a consumption tax.

6. Conclusion

As in earlier periods of dramatic technological change and digitalization, AI raises many of the core issues of what should be taxable and where it should be taxable but these technological advances will not dissolve the fundamental tensions of federalism. Fiscal policy may become increasingly algorithmic, with dynamic tax bases, adaptive rates, and constant evaluation of programs. Both taxpayers and

[24] See Agrawal and Stark (2022) for a detailed discussion of tax on cross state labor income.
[25] See "State apportionment of corporate income" from the Tax Foundation.

governments will utilize AI, creating a tension over whether its use will give a larger advantage to governments or taxpayers. On the government production side, scale advantages, distributional conflict, democratic accountability, and interjurisdictional competition will remain central, and perhaps intensified, as governments decide not whether AI can govern fiscal systems, but how much authority to delegate to it and to what extent coordination across governments may harness some of its advantages. Local public finance may appear more automated and less reliant on the institutional knowledge of specific government workers. Artificial intelligence will likely be used in many routine functions: tax compliance, property assessment, enforcement, budgeting, and even elements of service delivery. The next several years will ultimately provide empirical evidence on whether AI remakes local governments as (artificially) smarter states or not.

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