The Local Effects of Artificial Intelligence Labor Investments: Evidence from the Municipal Bond Market

Lefteris Andreadis, Eleni Kalotychou, Manolis Chatzikonstantinou,

Christodoulos Louca, and Christos A. Makridis *

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Abstract

We investigate the economic impact of artificial intelligence (AI) technologies on local economies by leveraging spatial variation in county-level labor investments in AI and the municipal bond market. Our identification strategy exploits a Bartik-type instrument based on the exposure of a county to AI-related jobs, and controls for a wide array of local characteristics and both county and state × year fixed effects. We find that increases in AI investments are associated with reductions in bond yields, particularly for longer-maturity and lower-rated bonds. Robustness checks, including an event study around the introduction of ChatGPT, further support a causal interpretation. The yield declines are driven by improvements in local productivity and government revenues, consistent with an economic revitalization channel.

Keywords: Artificial intelligence, Data analytics, Productivity, Municipal bonds, Public finance.

JEL Codes: O33, G12, G18, H74

*Lefteris: Bank of Greece and Cyprus University of Technology, lefandreadis@gmail.com; Manolis: Georgetown University Qatar ec1269@georgetown.edu; Elena: Cyprus University of Technology eleni.kalotychou@cut.ac.cy; Christodoulos: Cyprus University of Technology christodoulos.louca@cut.ac.cy; Christos: University of Nicosia and Stanford University, cmakridi@stanford.edu. Christos thanks the Institute for Humane Studies for their support (grant no. IHS018282 and IHS018661). These views are our own and not those of any affiliated institutions.

1 Introduction

"*The future is already here - it's just not evenly distributed yet.*"

- *William Gibson, Author*

Over the past decade, we have witnessed a profound technological shift marked by the rapid proliferation and widespread adoption of artificial intelligence (AI). AI-related job postings surged from 0.5% in 2014 to an impressive 2.05% in 2022 (Maslej et al., 2024), with projections suggesting that as many as 80% of the workforce could have at least 10% of their tasks affected by AI and large language models (LLMs) (Eloundou et al., 2024). Fueled by advances in computing power and storage, machine learning (ML) models and AI systems hold the potential to deliver substantial economic gains, akin to the impact of general purpose technologies (GPTs) (Romer, 1990; Aghion and Howitt, 1992; Bresnahan and Trajtenberg, 1995). However, lackluster aggregate productivity growth, and the resulting pass-through to workers, has led to skepticism about the benefits of AI, as they may be over-hyped with unintended consequences (Acemoglu, 2024) or simply require more time to materialize (Mihet and Philippon, 2019; Brynjolfsson et al., 2021).

While much attention has been given to AI's impact on aggregate productivity, we instead explore its effects on local economies, by leveraging spatial variation in county-level AI labor investments and the municipal bond market. This approach offers two key advantages. First, by using spatial variation in AI labor investments at the local level, we can capture both within-region dynamics and broader effects across different areas. Importantly, AI investments could yield not only localized economic effects, but also spillover effects (positive or negative) that affect neighboring areas (Greenstone et al., 2010; Moretti, 2021), necessitating a granular investigation to understand

the overall impact of AI technologies on the economy. Second, given the well-documented relationship between local economic conditions and municipal finance (Cornaggia et al., 2022; Hund et al., 2024), the municipal bond market is ideal to evaluate how local investments in AI are capitalized and reflected in different bond maturities. Differential effects depending on bond maturities provide information about short-term and long-term implications of AI investments, thus facilitating a more comprehensive understanding of the economic consequences of AI investments.

Identifying the causal impact of AI investments on local economies presents several empirical challenges, primarily due to the widespread demand for AI and its potential correlation with other factors influencing local government outcomes. Our identification strategy incorporates multiple controls, including local characteristics such as per capita income and population, along with county and state-by-year fixed effects to account for broader regional effects. Furthermore, recognizing the possibility of unobserved, time-varying shocks, as well as reverse causality, we employ a Bartik-type instrument to measure county-level exposure to AI. This instrument leverages the historical presence of AI-related jobs within a county, under the assumption that pre-sample AI shares of jobs are uncorrelated with long-run local economic outcomes. This assumption is supported by evidence showing that counties with higher shares of AI-related jobs historically did not outperform others in traditional economic metrics like population growth, household income, or unemployment rates. In addition, we provide further supporting evidence using diagnostics for Bartik-type instruments following Goldsmith-Pinkham et al. (2020).[1]

Our results reveal that more AI job posting, relative to county establishments lead to significant

[1]First, in our baseline specification, we interact our pre-existing measure of exposure of a county to AI-related jobs with year fixed effects, The results yield a statistically indistinguishable effect on the coefficient on local AI investments. Second, we compute Rotemberg weights. While computer occupations receive a large weight, we replicate our main results without this occupation and show that the resulting Rotemberg weights are all below 0.20 except for one at 0.37.

municipal bond yield reductions. These reductions are economically important. An additional AI job posting, relative to county establishments, leads to a 0.118 basis point (bps) decline in bond yields. When we evaluate this coefficient estimate at the average number of job postings (2,227), establishments (29,293), and AI growth (51.1%), our coefficient implies a 44.84bps decrease in bond yields. Given an aggregate face value amount of $478 billion in the bond sample, this reduction in yield translates to a saving of $2.15 billion.

Next, we perform several additional tests aimed at further addressing endogeneity concerns. First, by analyzing within-county clusters with similar per capita income and by exploiting variation within adjacent counties, which likely share similar economic environment, we still find a consistent significant negative effect of AI labor investments on bond yields. This suggests that the effect is causal and not an artifact of economic conditions coinciding with local AI labor investments. Second, we exploit the release and proliferation of ChatGPT by OpenAI as a plausibly exogenous shock to investor attention around the potential value of AI. The introduction of ChatGPT and particularly its corresponding success were arguably unanticipated by the bulk of the market, providing exogenous variation to assess the impact of local AI labor investments on secondary market bond yields. In particular, we use a difference-in-differences approach that compares yields within a narrow event window, before and after the introduction of ChatGPT in areas with greater versus less exposure to AI. On average, we find a decline in bond yields after the introduction of ChatGPT, but the larger decline is observed for bonds of municipalities located in counties with higher cumulative AI labor investments. Economically, the introduction of ChatGPT led to a decrease in yields in the secondary market with a magnitude of 3.7 bps (2.1 bps) when analyzing cross-sectional (within-bond) variation.

Then, we explore heterogeneity in the treatment effects on different types of bonds. If, for ex-

ample, AI investments lead to efficiency gains and innovation, then they could lead to an uptick in the local economy and consequently a decrease in default risk. Given that default risk significantly influences bond yields, we investigate its role in the relationship between AI labor investments and offering yields by focusing on two bond characteristics: maturity and credit rating. Longer-term and lower credit rating bonds are inherently riskier, as they are more susceptible to economic shifts. We find that the effect of local AI labor investments on bond offering yields concentrates among riskier bonds—specifically, longer maturity and lower credit rating bonds—whose cash flows are more sensitive to the implications of local AI labor investments. These results are consistent with microeconomic literature that most of the benefits of AI are over the long-run (Brynjolfsson et al., 2021) and concentrate among lower productivity workers (Brynjolfsson et al., 2023).

Furthermore, we investigate the impact of local AI labor investments on municipal finance, considering both the quantity and the maturity structure of bonds issued. Despite the expectation that local AI labor investments, due to lower bond offering yields, would facilitate easier capital raising, our findings suggest otherwise. Local AI labor investments show no significant effect on the quantity of bond issuance, possibly due to counties with increased local AI investments also experiencing additional revenue influx, which reduces the need for external financing. However, our analysis reveals a notable influence of local AI labor investments on the composition of bond issuances. Municipalities exhibit a preference for longer-term bonds, likely driven by the desire to capitalize on the decrease in bond offering yields. In summary, while local AI labor investments may not impact the volume of bonds issued, they do influence the maturity structure of the bonds, particularly based on expectations of future local economic development.

What mechanism can explain these effects? We focus on the potential spillover effects of an AI workforce on the local economy. We posit that the bond market prices AI investments based

on an expectation of improved local economic prospects and the resulting municipal cash flows. Our identification strategy exploits the entropy balancing approach of Hainmueller (2012) that matches the first moment of covariate distributions across treated and control counties. Treated counties comprise the top tercile of the annual labor investments in AI, while the rest counties are the control group. Covariates include per capita income, county population level and changes, and one-year employment growth. The results show that treated counties exhibit a significant and consistent improvement in real productivity over one to three years after matching, compared to the control counties. Interestingly, this improvement is driven by growth in GDP rather than employee displacement. Additionally, treated counties exhibit a steady rise in total revenues over one to three years after matching, relative to the control counties. This increase reflects upticks in total taxes and property taxes, rather than sales taxes. Overall, these findings are consistent with an expanding economic activity and a thriving real estate market and underscore the positive contribution of local AI labor investments to local economic revitalization.

This study is related to several strands of the literature. First, it is related to a growing literature examining economic effects of AI. Many studies take a macro perspective to explore implications of AI investments: from how governments should regulate AI (Beraja and Zorzi, 2022), to how it affects competition (Eeckhout and Veldkamp, 2024), and economic growth (Aghion et al., 2017; Farboodi and Veldkamp, 2021). Most relevant to our work are the studies that take a micro perspective to investigate implications of investments in AI in various settings: for instance, Babina et al. (2024) focus on firm growth, innovation and market value, Gofman and Jin (2024) on entrepreneurship, Grennan and Michaely (2020) and Abis and Veldkamp (2024) on financial analysts, and Chen et al. (2019) on fintech innovation. None of these studies, however, focus on local government and economy effects. We contribute to this literature by providing a nationwide

evaluation of labor investments in AI benefits at the county level and by evaluating municipal capital market consequences of AI technologies. Our result that AI technology lead to significant and highly variable economic benefits for municipalities contributes to a large question posed by Autor (2015) and Acemoglu and Restrepo (2019) regarding the potentially unequal distribution of technology's economic benefits. Importantly, growth in GDP rather than labor replacement appears to be the mechanism driving county-level effects, unlike the task-based model of automation that has been applied to previous technologies (Acemoglu and Restrepo, 2018). Exploiting the maturity structure of municipal bonds, we also find that investors anticipate more AI technology benefits in the long-term (Mihet and Philippon, 2019; Brynjolfsson et al., 2021). Finally, the observed shift in bond issuance structure towards longer-term bonds in AI-intensive counties introduces a novel dimension to our understanding of how local governments strategize their financing in response to technological advancements. This finding suggests that local governments anticipate long-term economic benefits from AI labor investments, a perspective that has not been previously documented in the literature on public finance and technology adoption.

Second, we add to a broader question about the economics of place-based policy and technological spillovers for general-purpose technologies (GPTs) (Romer, 1990; Aghion and Howitt, 1992). For example, place-based policies, as discussed by Moretti (2011) and Kline and Moretti (2013), aim to address the stark regional variations in income, unemployment rates, and living conditions within countries, which are persistent across decades (Barro and Sala-i Martin, 1991; Blanchard and Katz, 1992) and even generations (Chetty et al., 2014).[2] By demonstrating that AI labor investments are associated with significant decreases in bond yields, we provide empirical support for the notion that AI, as a GPT, can enhance local economic development through

[2]See Kline and Moretti (2014) for a survey of the literature.

improved productivity and innovation. These results on the democratizing effects of AI are especially timely given the debate about whether the productivity benefits of AI will be broadly distributed or concentrated. On one hand, there is growing evidence that most of the variation in earnings inequality is across firms, rather than within (Song et al., 2019), suggesting that superstar firms could leverage AI to further consolidate their positions, especially for larger firms (Begenau et al., 2018; Mihet and Philippon, 2019; Babina et al., 2024). On the other hand, if recent AI advances, especially those from LLMs, are general purpose technologies that have at least some open-source components, then the benefits may be broadly distributed, potentially even serving as complements to worker productivity. Already, there is some evidence that LLMs may benefit productivity at the task-level, especially for lower productivity workers (Brynjolfsson et al., 2023).

Finally, we directly add to the literature examining factors such as economic conditions, demographics and policies to understand the dynamics of municipal bond markers and their implications for local governments. Prior studies focus on market transparency (Schultz, 2012), credit ratings (Cornaggia et al., 2018), local government policy (Gao et al., 2019), opioid crisis (Cornaggia et al., 2022), and climate change (Painter, 2020; Goldsmith-Pinkham et al., 2023). A notable gap remains in understanding the influence of recent technological advancements on municipal finance.[3]

Most closely related is the study by Makridis and Mishra (2022). Using similar job posting data on the AI share over time, they find a positive association between the expansion of AI jobs on subjective well-being and both GDP per capita and income per capita. Our paper differs in several capacities. First, we produce a time series of county-level data so that we can link to municipal bond yields to infer the economic effects of AI investments. The municipal bond market has the

[3]An exception is Andreadis et al. (2022) who study the effects of data breaches on the municipal bond market, showing an increase in the cost of raising additional funds for municipalities.

advantage of capitalizing local amenities, allowing us to infer how AI investments are priced by investments. Second, our Bartik-like instrument and difference-in-difference strategies allow us to make causal statements about the effects of AI investments on local economies, whereas their work was still subject to potential time-varying identification threats.

2 Data and Measurement

To construct our sample, we gather data from various databases. We use the Lightcast (formerly Burning Glass Technologies) for job postings data, the Census Bureau's American Community Survey (ACS) for occupational employment composition by county, the FTSE Russell (known as Mergent Municipal Bond Securities database) and the Thomson Reuters for municipal bond data, the U.S. Bureau of Economic Analysis (BEA) and the U.S. Bureau of Labor and Statistics (BLS) for county-level demographics and economic data. In addition, we use the U.S. Census of Government Surveys to get county-level data on finances and the U.S. Department of the Treasury to get the risk free rate. Tables A1, A2, and A3 in the Online Appendix provide a list of the variables we used with their corresponding data sources, information about sample construction for various analyses of the study, and descriptive statistics for each sample, respectively.

2.1 Job Postings Data

Motivated by the growing body of empirical literature utilizing job posting data, we proxy for AI labor investments using data from Lightcast, a leading source with a vast repository of millions of job postings. Their technology extracts information from more than 40,000 online job boards, newspapers and employer websites. Lightcast employs advanced machine learning techniques to

streamline the data, eliminating duplicate job postings, whether they are posted multiple times on the same site or across multiple sites, and enriching profiles using standardized information on job titles, company names, skills, and educational requirements.[4,5] Additionally, Lightcast supplements the data with relevant indicators from the BLS and other published sources.

Lightcast data offer two main advantages: First, they contain a comprehensive occupational taxonomy built hierarchically, with over 1,900+ specialized occupations that are mapped to the Standardized Occupation Classification (SOC) used in the official publications by the BLS.[6] Using this occupation taxonomy and the local occupational composition we construct our bartik-type instrument. Second, they have precise location data for job postings allowing us to link labor demand at a granular level (i.e., county-level). Because the dispersion in AI labor investments can be large over time and space, this granularity is essential for capturing the heterogeneous effects of AI on municipal bond yields and the local economy.

We measure AI labor investments using the skills associated with each vacancy and keywords relating to AI.[7] Specifically, we define AI related jobs by parsing text from job postings and by linking them with a list of skills that have been associated with the use and development of AI (Table A4 in the Online Appendix provides a list of all the skills). Following Acemoglu et al. (2022), we classify vacancies into three categories: A narrow category which includes a selection of skills relating to AI (*AI jobs*). A broad category of AI that includes skill relating with Data Analytics (DA) but not explicitly listing as a requirement one of the AI keywords (*DA jobs*),

[4]For more detail, see their methodology: `https://kb.lightcast.io/en/articles/6957446-job-posting-analytics-jpa-methodology`

[5]Our description follows that of related papers that have increasingly used Lightcast data to measure demand for AI related skills, including Makridis and Mishra (2022), Babina et al. (2024), and Makridis and Alterovitz (2024).

[6]More than 95% of vacancies are assigned a six-digit SOC occupation code.

[7]Note that the classification of skills in job postings comes from the Lightcast Open Skills Taxonomy (containing over 15,000 skills for the period 2014-2021).

and a combination of the narrow and broad categories which encompass job postings with AI or DA keywords or both (*AI/DA jobs*). A concern with broader categories of AI is that they may capture various information technology (IT) functions that are not closely linked with AI activities. Accordingly, we mainly discuss the narrow measure of AI, and we present the other measures for robustness. Our results are stronger when focusing just on AI.

Having classified each vacancy, we then count the number of vacancies that contain at least one particular skill in the AI or DA skills group for each county-occupation pair on a yearly basis. This generates for every skill group (e.g., AI jobs, DA jobs, AI/DA jobs) and each pair (county-occupation) a corresponding measure of intensity. We also get the intensity of the vacancies for a particular occupation at a national or county-level by aggregating over 2014-2021.[8,9]

Prior research highlights a sharp increase in AI-related job postings over the past decade. According to data from the Stanford AI Index (Maslej et al., 2024), the share of AI jobs in the U.S. rose from under 0.5% in 2014 to 1.62% in 2023, with the U.S. showing the largest growth compared to other developed countries. This makes the U.S. an especially interesting focus, given its significant geographic variation in AI exposure. Figure 2 illustrates this variation at the county level. Panel A presents the share of AI jobs relative to total jobs, while Panel B shows data analytics jobs for comparison. There is a strong correlation between the two (0.66). Although the median share of AI jobs is modest at 0.17% (average 0.36%), some counties have over five times that amount, with upwards of 1.4% of jobs classified as AI. Panels C and D show the percentage-point increase in AI and data analytics jobs between 2014-15 and 2020-21. The average county saw a 0.32 percentage-point increase in AI jobs, but some experienced more than a full percentage-

[8]While the Lightcast data include 2007 and then 2010 onward, it is recommended to use the data starting in 2014 as the quality is substantially lower in years 2007 and 2013 (Cammeraat and Squicciarini, 2021).

[9]Table A5 in the Online Appendix presents top and bottom occupation by the number of AI-related postings. As expected, computer-related occupation job vacancies exhibit more skill requirements related to AI and DA.

point rise, highlighting the concentration of AI jobs in the West (e.g., California) and Northeast (e.g., Massachusetts). Notably, there is substantial variation even within states, reinforcing the importance of county-level analysis to capture the granularity of AI job growth.

While this variability suggests that different regions could experience diverse economic benefits from AI, it also raises concerns about selection bias. Counties with higher AI job growth might inherently differ from those with less growth, potentially skewing results. Our identification strategy will mitigate these exercises through the inclusion of controls, county and state × year fixed effects, a Bartik instrument, and other diagnostics to establish a causal estimate.

2.2 Occupational Composition by County

Our instrumental variable requires information on the importance of each occupation in the local market, by county. Thus, we augment our analysis with data from IPUMS that provides an accessible interface for the Census Bureau's ACS (Ruggles et al., 2021). We use the ACS data from the 5-year sample in 2005-2009 to create our weights for the shift-share design used in our econometric analysis. Specifically, to examine the occupational composition across various U.S. counties we leverage data on employed workers by county.[10] We access detailed information on employment statuses, occupation types, and county of work from the 5-year sample. We use this information to create a consistent set of occupation codes over time. After we have a consistent set of occupations, we use the 5-year sample, to create the occupation composition of each county by estimating the number of full-time workers for each county-occupation pair. This allows us to understand the exposure of each county to US-wide increases in AI by occupation, through

[10]The sample includes full-time workers, aged 16 to 75 with information on the occupation classification and the place of work.

a shift-share instrument. This instrument uses as weights the occupation shares for each county based on the 2005-2009 5-year American Community Survey (ACS) sample.

2.3 Municipal Bond Data

We use the Municipal Bonds dataset by FTSE Russell to compile primary market issuance data and municipal bond characteristics. This initial dataset encompasses 4,465,887 issued by 67,408 municipal issuers across different local government units such as counties, cities, school districts, etc. We restrict the sample to bonds issued between January 2015 and December 2021, to mark the AI growth rates we observe in the job vacancy data and the end date for our access to FTSE Russell. We focus exclusively on new borrowing, thus we exclude bonds issued for refunding purposes. Finally, we exclude all bonds issued through unconventional channels such as the U.S. government or under certain schemes, such as the tobacco and tuition agreements, Build America bonds, notes, certificates, and taxable bonds. We then retrieve key bond characteristics such as 9- and 6-digit issuance and issuer CUSIP, respectively, settlement date, amount issued, state of the issuing authority, name of the issuer, yield to maturity, tax status, insurance status, call status, credit ratings, coupon rate and maturity date.[11] We further refine the sample by excluding bonds with missing information and bonds with less than a year of maturity since they are considered out of scope for the ensuing analyses. Finally, using the issuer's 6-digit CUSIP and information from Thomson Reuters we locate each bond to the county of issuance and obtain the Federal

[11] The individual bond-level credit ratings are derived from FTSE Russell database or, replaced by issuer ratings if issuance-level ratings are unavailable. In the case of multiple ratings from S&P, Fitch and Moody's we opt for the lowest. We encode reported ratings into numerically equivalent values ranging from 1 for the lowest to 21 for the highest quality. In the bond-level analysis, we use insured ratings for the insured bonds and underlying ratings for the uninsured bonds. Furthermore, we follow prior literature, namely Cornaggia et al. (2022), in our exclusion of bonds that are the pre-funded portion of an original new borrowing bond, which accounts for the decline in sample size.

Information Processing Standard (FIPS) codes.

Using this sample we perform two types of analyses: a bond-level analysis and a county-level analysis. After matching with the job postings data and control variables, the final sample for the bond-level analysis include 239,024 bond issues. Concerning the county-level analysis, we aggregate all the bonds at the county-year level; the final sample consists of 5,547 observations.

We complement our primary market analysis with secondary market trades from the Municipal Securities Rulemaking Board (MSRB) to examine implications due to the release of ChatGPT by OpenAI. This extensive database comprises 87,710,279 municipal bond trades involving 46,213 municipal issuers. For this sample, we extract key bond characteristics such as issuance details, trade date, traded amount, and yield of trade. We restrict the sample to trades around the (-2,+2) months time window around the introduction of ChatGPT, which was on November 30, 2022. Like before, we utilize the issuer's 6-digit CUSIP and information from Thomson Reuters to link each bond to its respective county and obtain the corresponding FIPS codes. Subsequently, we match the bonds with the job postings data and control data to create a final sample of 383,815 trades.

2.4 County Finances

We also compile a database of county finances (total revenues, total taxes, sales, and property taxes) using the U.S. Census of Governments surveys from legacy files provided by the U.S. Census from 1972-2021. Note that the quinquennial Census surveys include all local government units (e.g., cities, states, counties, etc.) whereas the intercensal years include only the larger municipalities. To avoid sampling and selection biases, we linearly interpolate values for all cities, townships, and counties between the 5-year census survey years, preserving the data when intercensal years

data exist. Our final dataset ranges from 2,040 to 3,070 counties based on the available information from the U.S. Census during the period 2014-2021, resulting in 19,630 county-year observations with non-missing job-postings data and economic control variables.

2.5 Local Economy and Demographic Data

As a proxy for the local economy, we use real productivity, defined as the real gross domestic product (deflated with 2012 prices) from BEA scaled by the number of employees from BLS. To distinguish among the drivers of real productivity, we also employ its components, namely, real gross domestic product growth and employee growth. In addition, we gather other county-level control variables. We obtain per capita personal income from U.S. BEA, population as well as demographic characteristics such as the percentages of individuals that live under poverty, elderly, female and white population from the U.S. Census Bureau and the share of religious residents from the U.S. Association of Religion Data Archives (ARDA).

3 Empirical Strategy

Identifying the causal effects of AI investments on the local economy is challenging for at least two reasons. First, there could be omitted variables: differences in AI investments might reflect unobserved heterogeneity in local resources, attractiveness to business, and access to human capital. Second, there could be reverse causality: increases in local economic performance could lead to increases in AI investments after basic requirements for operations are met.

We address these challenges in a couple of ways and provide further robustness later. Following Makridis and Mishra (2022), we leverage panel data on AI job postings, allowing us to exploit

within-county variation for nearly a decade. As a result, we can purge time-invariant heterogeneity that could be correlated with the propensity to make AI labor investments. We also control for time-varying demographic and economic factors, isolating variation in AI labor investments independent of broader local forces, like population growth. However, these controls may still be insufficient to deal with both unobserved heterogeneity and reverse causality, so we construct a Bartik-like estimator that exploits counties' heterogeneous exposure to national trends in AI investments. In particular, we construct the following Bartik-like measure:

$$BARTIK_{ct} = \sum_{j} (Emp_{c,j,t_0}/Emp_{c,t_0}) \times \Delta AI_{jt} \tag{1}$$

where the term $Emp_{c,j,t_0}/Emp_{c,t_0}$ denotes the share of employment in county c for occupation j, and year $t_0 = 2009$ (following the best practices from Goldsmith-Pinkham et al. (2020) who recommend fixing the exposure variable prior to the start of the sample) and $\Delta AI_{j,t}$ denotes the year-by-year (national) growth in AI job postings by occupation.[12]

We use our Bartik-like measure as an instrument for the normalized share of AI job postings in the following two-stage least squares regression:

$$AI_{ict} = \zeta BARTIK_{ct} + \alpha X_{it} + \beta D_{ct} + \phi_c + \Lambda_{st} + \varepsilon_{ict} \tag{2}$$

$$Y_{ict} = \gamma \widehat{AI_{ct}} + \alpha X_{it} + \beta D_{ct} + \phi_c + \Lambda_{st} + \xi_{ict} \tag{3}$$

where Y_{ict} denotes the yield for bond i, issued in county c, and year t, $BARTIK$ denotes

[12] We use the ACS 5-year sample 2005-2009 and the place of work and occupations variables to count the number of full-time workers in each occupation and each county for year 2009.

our Bartik instrument, X denotes a vector of bond characteristics, D denotes a vector of local demographic characteristics, and ϕ and Λ denote fixed effects on county and state $\times$ year. We use the predicted values from Equation 2 to generate a causal effect of the local AI jobs on our bond yields. The identifying assumption is that unobserved shocks to a county's yields are uncorrelated with the pre-existing share of AI job postings, conditional on controls and after purging all shocks that are common within the same state and year (we discuss this assumption in Section 4.1.1). In particular, we exploit plausibly exogenous shocks to national AI demand over the past decade, which should affect counties with a larger share of AI-related occupations prior to the start of the sample more than their counterparts. We cluster standard errors at the county-level.

The outcome of interest γ, reflects the average difference in bond yields due to AI-related employment opportunities. Like prior municipal finance literature (Gao et al., 2020; Cornaggia et al., 2022), we control for bond characteristics, such as credit rating, coupon rate, bond maturity and its inverse, log bond size, indicator variables for whether the bond is callable or insured and risk-free rate using the corresponding maturity-matched treasury yield. We also include county demographic factors, such as per capita income, county population level and changes, and one-year employment growth. Our baseline specifications also contain county and state $\times$ year fixed effects, exploiting pre-existing exposure in a county to national-level AI shocks after controlling for all shocks that are common within a state-year. This is important given time-varying changes in the municipal bond markets, and across states that are related to tax policy and risk.[13]

[13]Incorporating fixed effects alongside Treasury yields as an additional control variable not only enhances the robustness of our analysis but also aligns our estimates closely with those obtained from models utilizing tax-adjusted yield spreads as the dependent variable (see, for instance, Schwert (2017)).

4 Capital Market Implications: Bond Yields

4.1 Instrumental Variable Results

Before presenting our two-stage least squares results, we begin by assessing the relevance of the instrument. In particular, we examine the partial R-squared, i.e. the proportion of the variation in local AI intensity that is explained by the instrument, rather than the control variables (Jiang, 2017).[14] Table 1 presents the results of the first stage regression of our 2SLS analysis. The partial R-squared suggests that the Bartik-type AI instrument accounts between 11% (in column (2)) and 19% (in column (1)) of the variance in AI job postings. Additionally, the F-test rejects the hypothesis of instrument weakness. Collectively, these tests confirm that our instrument meets the relevance criterion as an instrumental variable for AI job postings.

We construct the Bartik-type instrument to be orthogonal to the error term in our main specification to ensure that it does not capture factors directly influencing bond yields, thereby violating the exclusion restriction. We provide various supporting evidence following the best practices suggested by Goldsmith-Pinkham et al. (2020): First, Figure A.1 in the Online Appendix shows the correlation between historical growth rates in population, household income, and unemployment rate and the initial share of AI job postings in a county in 2011-12.[15] The correlations are zero for unemployment rate and median household income growth, and 0.06 for population growth. This

[14] Unlike the commonly used first-stage F-statistic, the partial R-squared remains unaffected by changes in sample size, ensuring a more stable measure of instrument relevance. Larcker and Rusticus (2010) demonstrate that the two-stage regression estimator exhibits less absolute bias than the OLS estimator under certain conditions, underscoring the importance of the partial R-squared in approximating the true relationship.

[15] We choose to use historical growth rates between 2000 and 2008-2011 (5 year ACS), but our results are robust to using 2005-2009 as an alternative too given that 2009 is our starting year. Our rationale for 2008-2011 is that we want our data to be as minimally affected by the financial crisis as possible.

suggests that areas with higher shares of AI job postings were not areas that had historically been over-performing in traditional capacities. Figure A.2 replicates these results for data analytics.

Second, to ensure that our 2009 employment shares are exogenous and not correlated with time trends that also affect municipal bond yields, we interact these employment shares with year fixed effects. As we will present shortly, our baseline estimate is -0.118 on AI jobs per establishments, whereas the coefficient from this exercise with interactions is -0.099. In particular, they are not statistically different from one another. Through our controls and fixed effects, we are empirically demanding that our coefficients do not contain any time-varying local and observable heterogeneity that could be correlated with local composition effects that could affect bond yields.

Finally, we provide a decomposition of the identifying variation in the Bartik-type instrument. Goldsmith-Pinkham et al. (2020) find that IV regressions using shift-share instruments can be written as an over-identified GMM estimator where the local shares are treated as a set of individual instruments under a given weighting matrix. These weights, also known as Rotemberg weights (Rotemberg, 1983), are a combination of information provided by the local occupational shares and time-varying national changes in AI job postings. The IV estimator, therefore, can be decomposed into a set of individual estimators, each of which is associated with a Rotemberg weight. While we initially found that the Rotemberg weights were concentrated among computer occupations (SOC 15-10), we replicate our main 2SLS results without that occupation (Table A6) and report the corresponding Rotemberg weights without those occupations (Table A7). These new weights are much smaller: the eight largest occupations have weights ranging from 0.03 (business operations) to 0.37 (other managerial occupations).

Table 2 presents the main results associated with our IV regressions, as in Equation 3. Our preferred specification is in column 1, suggesting that an additional AI job posting as a share of

establishments is associated with a 0.118 percentage point decline in offering yields. This result also holds when focusing on data analysis job postings in column 2, although the estimate is about half in magnitude. Furthermore, when pooling both AI and data analysis job postings together in column 3, the coefficient is slightly smaller, which could result from attenuation bias. Put together, these results suggest a causal link between AI job postings and decreased municipal yields, implying that the cost of financing debt declines following additional local AI investments.

To put our results in perspective and give an economic interpretation, consider a 50% increase in AI job postings, holding the number of establishments constant, which corresponds with the average year-to-year growth rate across counties over 2014-21. The mean number of AI job postings and establishments are 2,227 and 29,293, respectively, meaning that the ratio is 76 AI jobs per 1,000 establishments. A 50% increase in AI job postings raises the number to 3,340.5, resulting in a new AI job-posting ratio of 114 AI jobs per 1,000 establishments. This represents an increase of 38 AI jobs per 1,000 establishments, or a 3.8 percentage point increase in the AI job-to-establishment ratio. Given the coefficient of -0.118, this increase leads to a reduction in bond yields of 3.8 percentage points multiplied by -0.118, which equals a 44.84 basis point decrease in bond yields. In economic terms, this substantial reduction in yields would significantly lower the cost of borrowing for municipalities, especially in large bond markets.

Our other features used as controls also generate coefficient estimates that are generally consistent with prior literature (e.g., Cornaggia et al. (2022)). For instance, bonds with higher credit ratings, with a greater maturity inverse and with a greater issuance amount exhibit lower yields. In contrast, bonds with a longer maturity, with a call provision, insured bonds, and bonds issued in counties with greater per capita income and employment growth exhibit higher yields. The results are consistent with the view that the AI job postings affect municipal investors who in

turn demand less compensation for investing in municipal bonds.

4.2 Alternative Explanations

While our findings suggest a negative relationship between the AI job postings and bond yields, we nonetheless consider the influence of unobserved variables that could confound our results. If our empirical strategy overlooks factors that may generate an association between AI job postings and bond yields, the observed relationship may be spurious. One such factor that needs further attention is the local economic conditions. If AI job postings concentrate in counties experiencing economic upturns, then our findings could be an artefact of the underlying economic condition.

To address this concern, we undertake two approaches: First, we replicate our main analysis after including deciles of per capita income as additional controls. This more semi-parametric refinement enable us to isolate variation in the effect of AI job postings by utilizing across-county cluster variation derived from per capita income deciles, which sets a high standard for identifying the impact of AI job postings on bond yields. The results, presented in Panel A of Table 4, demonstrate that the AI effect remains largely consistent in magnitude and continues to exhibit a negative and statistically significant association.

Second, we employ adjacent counties to identify the effect by leveraging variation within neighboring counties. This approach is grounded in the notion that economically similar counties are often situated in close proximity to each other. In this respect, there is a plethora of evidence about the importance of geography on knowledge spillovers (Ellison et al., 2010) and more broadly on the economic environment (Almeida and Kogut, 1999; Belenzon and Schankerman, 2013). Methodologically, we combine county-specific datasets comprising a treated county (each county in our

sample) and all its adjacent counties, which serve as a control group. Bonds of municipalities belonging in both treated and control group counties share similar exposure to economic conditions but differ in terms of AI job postings and offering yields. Accordingly, the inclusion of adjacent county fixed effects in the IV regression analysis ensures that the coefficient estimates rely on within-adjacent county variation in AI job postings and offering yields. The results, presented in Panel B of Table 4, again reveal a negative and statistically significant relationship between the AI job postings and bond yields, consistent with our previous findings.

Overall, these results support the view that the local economic environment is unlikely to fully account for the observed negative relationship between AI job postings and bond yields.

4.3 Difference-in-Differences Results

Thus far, using a Bartik-type instrument we provide evidence that AI employment opportunities lead to lower bond offering yields. In this section, we leverage an event to offer additional support for a causal interpretation of the AI employment opportunity effects on bond yields. Specifically, OpenAI introduced ChatGPT on November, 30, 2022, which quickly gained traction among users (currently boasting more than 180 million users) and revolutionized the way that individuals view AI and its role for technology and the society. The introduction of ChatGPT likely introduces exogenous variation in the effect of AI employment opportunities on bond yields because OpenAI's aim was not to directly influence bond yields, but rather to advance AI capabilities and enhance interactions between humans and machines.

If the introduction of ChatGPT enables investors to appreciate more the value of AI employment opportunities, then we should observe a negative impact on bond yields. Consistent with

this view, a simple search of the term "Artificial Intelligence" in Google Trends reveals a considerable surge in the interest of individuals about AI after the introduction of ChatGPT. To identify the effect of the introduction of ChatGPT on bond yields, we use secondary market trades and employ a difference-in-differences approach, which exploits the interaction between two sources of variation. The first source is variation before and after the introduction of ChatGPT, denoted by the variable *Post*. However, this variation alone may not suffice to identify the effects of ChatGPT on bond yields, as other structural changes may occur during the same period for unrelated reasons. Therefore, we introduce a second source of variation across counties based on the cumulative number of AI job postings since the beginning of our sample period (2014-2021). We create a binary variable indicating counties in the top quartile of cumulative AI job postings, deflated by the number of establishments as of 2013; we refer to this variation using the variable *High(AI)Rank*.

Because municipal bonds in the secondary market are thinly traded, we run the regression analysis using bonds that trade during the [-2,+2] month window period around the event.[16] Table 3 presents the results. Models (1) and (3) rely only on *Post* variation whereas models (2) and (4) consider also variation in *High(AI)Rank*. Models (1) and (2) capture a cross-sectional effect before and after the introduction of ChatGPT. In models (3) and (4), however, we include bond fixed effects, therefore they capture within the same bond effect before and after the introduction of ChatGPT. This approach provides an even higher hurdle for identifying the impact of the introduction of ChatGPT on bond yields. Regardless of whether we capture a cross-sectional effect or a within bond effect, the results show a decline in bond yields after the introduction of ChatGPT with larger declines observed for bonds of municipalities located in counties with higher AI job postings. In economic terms, the introduction of ChatGPT leads to a decrease in yields

[16]Using alternative event windows such as [-3,+3] months around the event does not alter our main results.

in the secondary market, with a magnitude of 3.7 basis points (1.4 basis points) when analyzing cross-sectional (within-bond) variation, consistent with our main primary market analysis.

4.4 Which Bonds Benefit More?

In this section, we investigate the impact of AI on bond yields, focusing on default risk as a key determinant, which we proxy for in two ways. AI could stimulate local economies through improved efficiency, innovation, and job creation, thereby fostering economic growth and lowering default risk at the community level. However, we know little about what areas might benefit more than others. Existing evidence suggests a substantial talent gap between the public and private sectors (Makridis and Alterovitz, 2024), so the expansion of AI in an area could spillover into, or at least be viewed as a signal of, potential future benefits for the local public sector.

First, we examine the bond's time to maturity. Bonds with longer-term maturities are expected to be more sensitive to economic shocks arising from labor investments in AI, leading to a more pronounced impact on their yields. Second, we assess the bond's credit rating status. Bonds with more vulnerable cash flows face higher default risk and exhibit lower credit ratings. Consequently, labor investments in AI are likely to exert a greater influence on bonds with lower credit ratings, reflecting their increased susceptibility to economic changes.

We explore these concepts using variants of the baseline analysis. Table 5 displays the results after considering each bond characteristic independently. Panel A scrutinizes the impact on bond maturity by incorporating an interaction term of instrumented AI with the variable *Long Maturity*, denoting bonds with a maturity exceeding 10 years.[17] The results highlight a notable negative and

[17]To run this analysis, it is important to recalibrate the first-stage results. In addition to Equation (1), it is crucial to estimate the interaction term of labor investments in AI with our moderating variable (i.e., *Long Maturity*). This is necessary because interactions involving an endogenous variable, such as labor investments in AI, are inherently

significant effect of AI job postings on yields for bonds with longer maturities. Likewise, Panel B explores the effect on bonds with different credit ratings using an interaction term of instrumented AI with the variable *Low rating*, indicating bonds with a rating below 19. The results reveal a negative and significant effect of AI job postings with bond yields which concentrates among low rated bonds. These results suggest that default risk is a channel through which labor investments in AI affect bond yields, suggesting democratizing effects by helping more at-risk areas.

4.5 Quantity and the Maturity Structure of Bond Issuances

Municipalities often issue bonds to finance large capital projects such as infrastructure improvements, public services, or educational facilities. The quantity of bond issuances reflects both the financing needs of the municipality and its ability to access capital markets at favorable rates. Classical municipal finance theory suggests that governments will issue debt when the marginal cost of borrowing is less than the expected marginal benefit of the project being financed, under the assumption that financing constraints are binding. In a frictionless market, labor investments in advanced technologies like AI could be expected to reduce the cost of financing, facilitating an increase in the volume of bond issuances as municipalities capitalize on lower borrowing costs.

Given labor investments in AI decrease the cost of financing, especially for longer-term bonds, municipalities in regions with large labor investments in AI are expected to easier tap external market for capital raising. To scrutinize this hypothesis, we adopt an IV framework, similar to Equations (2) and (3). The main dependent variables of interest are two: (i) the aggregate amount of issuance (logged) and (ii) the ratio of aggregate amount of issuance of bonds with short

endogenous themselves (Murnane and Willett, 2011). To satisfy the rank condition, as outlined by Wooldridge (2002), we introduce a new instrument comprising the interaction between the original instrument (i.e., Bartik-type AI) and the moderating variable (i.e., *Long Maturity*).

maturity (<10 year) to the aggregate amount of issuance of bonds with long maturity. The main variable of interest is the instrumented labor investment in AI. Control variables include county-level characteristics. Notably, we also include county fixed effects, to account for unobserved variation within counties, and year fixed effects to control for time trends and macroeconomic characteristics that might affect municipal bond issuance.

Table 6 presents the results. Panel A reveals an unexpected result: labor investments in AI appear to have no discernible impact on the quantity of bond issuance. One potential explanation for this observation could be that counties experiencing heightened investments in AI also witness an influx of additional revenues, thus reducing the necessity for additional financing. Panel B, however shows a different result: labor investments in AI do influence the composition of bond issuances. Municipalities seem inclined to issue longer-term bonds, aligning with the notion that they seek to capitalize on the decline in bond offering yields. In economic terms, the short-term bond issuance declines by 8.1% compared to the long -term bond issuance.

Theoretically, the absence of volume effects can be interpreted in several ways. First, municipal governments may prioritize managing long-term fiscal sustainability over increasing short-term borrowing. If investments in AI lead to an influx of additional tax revenues—either through increased property values, higher business activity, or higher wages—local governments may face less pressure to raise additional capital through bond issuances. This aligns with traditional fiscal smoothing theories (Barro, 1979), where governments choose to borrow only when necessary to avoid significant fluctuations in tax rates over time. If AI investments improve local economic conditions, municipalities might anticipate future revenue gains, reducing their immediate need to issue more debt. Second, the results may reflect the so-called "flypaper effect" (Hines and Thaler, 1995), wherein local governments are cautious about increasing debt levels despite lower borrowing

costs, choosing instead to earmark AI-driven revenue gains for future spending or reserves rather than immediate capital projects. In this sense, municipalities may avoid issuing additional bonds and instead strategically use new revenues to minimize debt accumulation or fund existing projects without resorting to external borrowing.

Empirical studies of municipal bond markets generally find that factors such as interest rates, fiscal capacity, and economic conditions drive the volume of debt issuances (Gao et al., 2019). Typically, favorable borrowing conditions, such as lower interest rates, correlate with higher issuance volumes, as municipalities seek to lock in capital for needed projects. Our findings add to this body of work, suggesting that labor investments in AI, while reducing borrowing costs, do not spur an increase in bond issuance quantity. Our results may reflect unique (and sometimes difficult to observe) characteristics of AI investments, such as their long-term nature and uncertain fiscal impact, which may not immediately necessitate new infrastructure or public spending (Glaeser and Ponzetto, 2018). The results could also imply a potential fiscal conservatism among municipalities where the benefits of AI are internalized through future expected revenues rather than through an expansion of public borrowing. Municipalities may also be cautious about overleveraging in the short term, even in the face of lower borrowing costs, consistent with studies of local government debt aversion (Alesina and Perotti, 1995), where municipalities prefer to mitigate future fiscal risks by avoiding over-reliance on debt markets.

5 Local Economic Mechanisms

If these effects on bond yields are causal, they could be a result of two potentially overlapping forces. First, increases in AI investments at a local level could function as a positive signal that an

area is turning around. For instance, Babina et al. (2024) show that firms investing in AI exhibit higher sales and employment growth. Second, increases in AI investments could also produce local benefits that directly feed into local economic development, including positive spillovers into the public sector. For example, Makridis and Mishra (2022) show that increases in AI investments are associated with improvements in per capita GDP and subjective well-being.

We begin by providing evidence assessing the relationship between real productivity and municipal government revenues to ascertain whether labor investments in AI contribute to local economy revitalization and bolster municipal cash flows, thereby identifying a potential mechanism through which AI job postings may affect bond offering yields. Acknowledging that labor investments in AI may not be random, it is crucial to account for potential demographic and economic disparities between counties with high and low labor investments in AI. As a result, we take an entropy balancing approach, which matches our sample by re-weighting or balancing the first moment of covariate distributions across the treated and control counties (Hainmueller, 2012). Treated counties, comprising the top third of AI employment opportunities, are identified annually, while the remaining counties are the control group. Our covariates include per capita income, county population level and changes, and one-year employment growth. We then assess the treatment effect on real productivity and municipal government revenues over a three-year period after the matching.

Table 7 examines the impact of labor investments in AI on local economy. Panel A presents results using real productivity, measured as GDP per employee, as the dependent variable. We observe a significant and consistent improvement in real productivity across treated counties during the subsequent one to three years. In terms of economic importance, the real productivity increases from 0.3% in the first year to 1% in the third year. Panels B-C employ GDP growth and employee

growth as dependent variables, respectively. The results show that GDP growth is higher for treated counties. This pattern is persistent during the subsequent one to three years. Interestingly, no such effect exists for employee growth. Accordingly, the growth in GDP rather than employee displacement seems to drive the improvement in real productivity.

These results have important implications for the ongoing debate about the displacement effects of AI. Crucially, Acemoglu and Restrepo (2018) show how the net effect of AI and automation on the labor share depends on whether new tasks are created faster than old tasks are displaced. Our empirical results suggest that, at least so far, counties with greater growth in AI also show greater productivity and GDP growth, although we cautiously interpret these results since more analysis is needed to understand the longer-term, causal effects.

If local productivity rises, then there are positive spillovers into local public finance. Table 8 evaluates the effects of investments in AI on local government revenues. Panel A presents the results using total revenues as the dependent variable. We find that treated counties experience a monotonic increase in total revenues over the subsequent one and three years. In economic terms, the total revenue increases from 8.8% in the first year to 17.2% in the third year for the treated counties. Panels B-D disaggregate total revenues into its major components: total taxes, sales taxes and property taxes. The results show that the rise in total revenues is primarily driven by increases in total taxes and property taxes rather than sales taxes.

Overall, these findings suggest that labor investments in AI contribute to the revitalization of the local economy, resulting in a revenue influx for municipalities.

6 Conclusion

There is now a voluminous literature examining the effects of technological change and automation on firms, but there remains uncertainty about the unique effects of AI. Unlike automation, AI has the potential to augment, rather than displace, worker inputs. Motivated by the emerging debate about the local effects of AI investments, we gather data on job postings and exploit variation in the municipal bond market. Leveraging within-county variation over time, we find a significant decrease in municipal bond yields following increased AI labor investments, indicating reduced borrowing costs for municipalities. Additionally, our study highlights a strategic shift towards longer-term bond issuances in AI-intensive areas, reflecting anticipation of long-term economic benefits. These findings contribute to the broader understanding of AI as a GPT driving local economic development through enhanced productivity and innovation. By quantifying the fiscal benefits of AI adoption at the local level, our research provides valuable insights for policymakers and stakeholders navigating the evolving technological landscape.

There are several important avenues for future research. First, while our study primarily focuses on bond market reactions to AI labor investments, future research could explore how these investments affect local economic outcomes beyond financing, including employment patterns, wage growth, and income inequality. This would provide a more holistic view of the economic consequences of AI adoption at the local level. Second, further exploration is needed into the the complementarities of both public and private sector AI investments, whereas we focus just on total local AI investments. There could be even greater economic effects and positive externalities. Finally, studies could also examine the interplay between AI investments and other forms of infras-

tructure development, such as transportation or energy, to determine whether these technologies complement traditional public projects or create new forms of competition for municipal resources. Understanding these dynamics could help local governments make more informed investment and financing decisions in the face of technological disruption.

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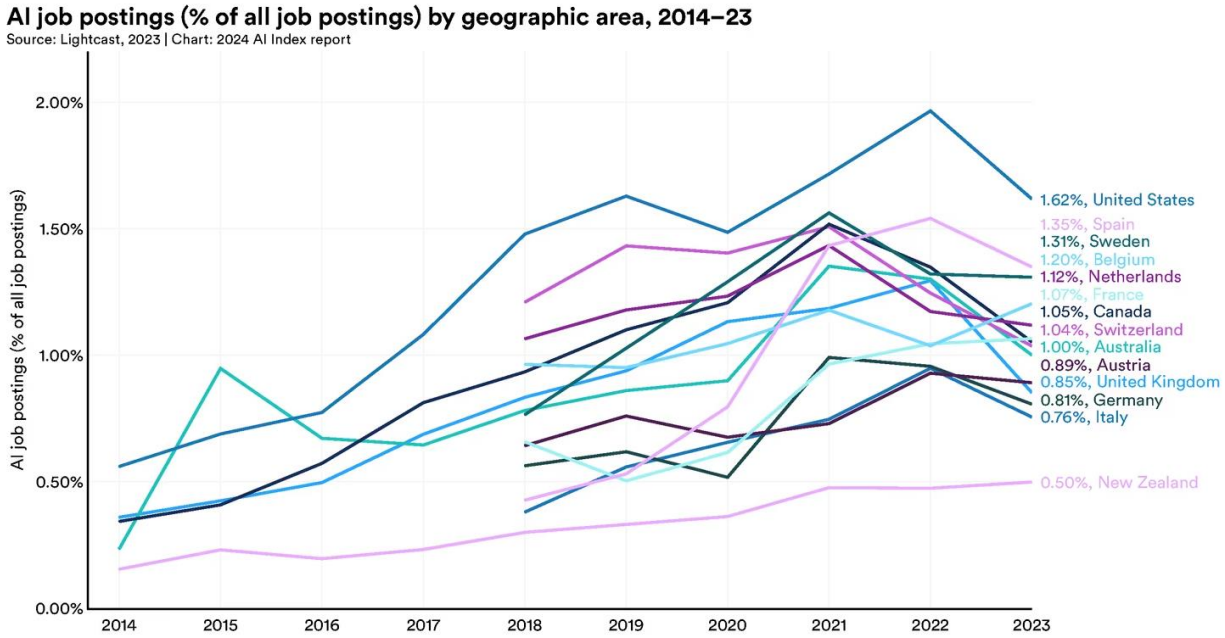


Figure 1: AI jobs, by country and time
This graph displays the percentage of AI job postings across countries between 2014 and 2023 from the Stanford AI Index (2024), drawing on the Lightcast data. https://lightcast.io/resources/blog/on-the-job-ai-postings

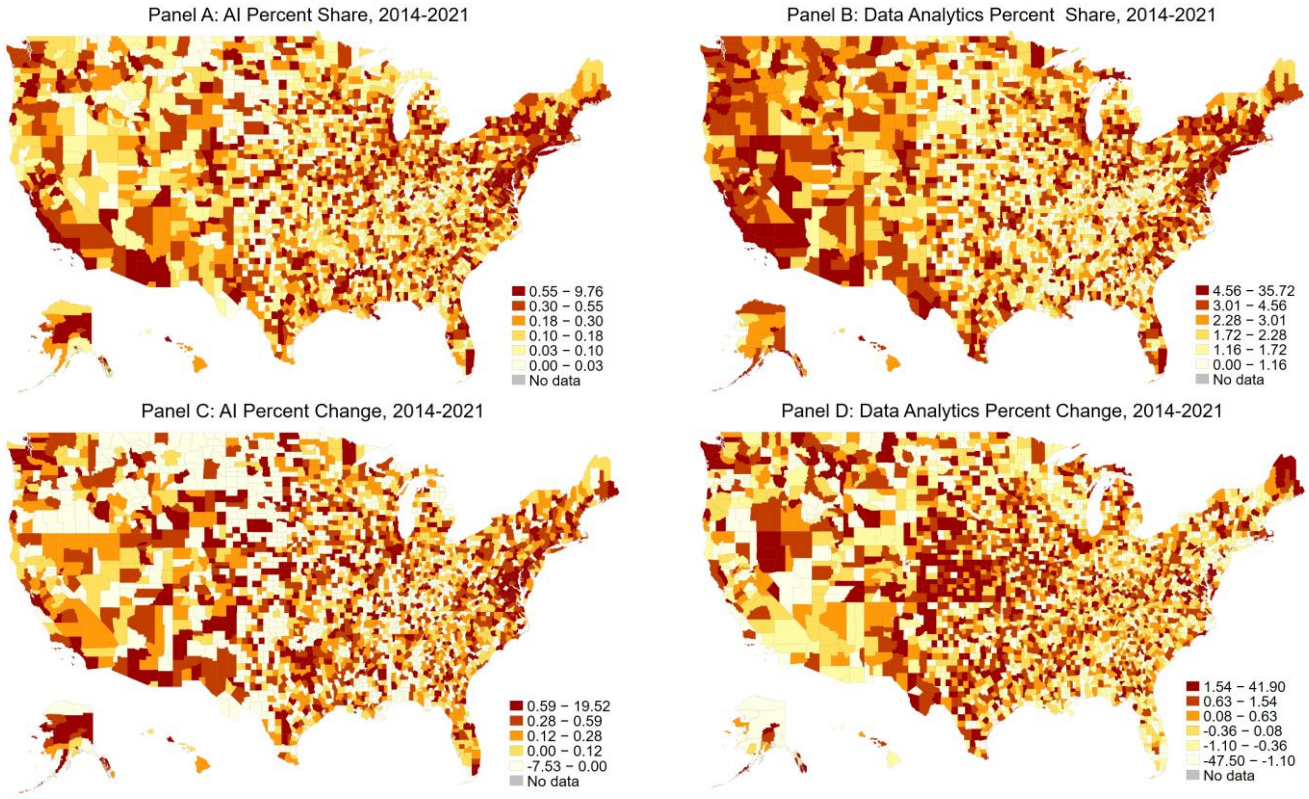
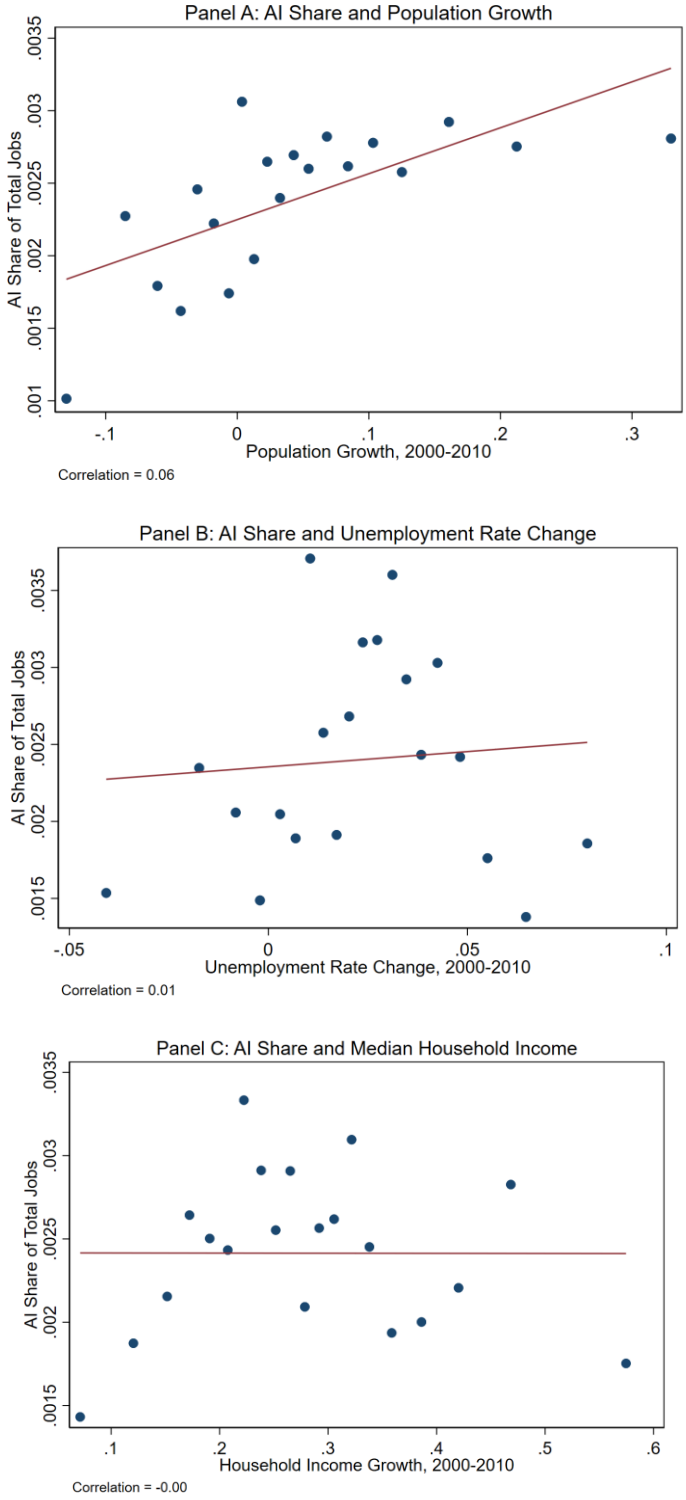


Figure 2: Cumulative AI job postings intensity, by county
This heat map presents the artificial intelligence (AI) share of jobs by county (Panel A) with the data analytics (DA) share of jobs by county (Panel B) for reference. The heat map also presents the percentage point growth in AI and DA job shares between 2014-15 and 2020-21 averages within the same county. The redder the county, the higher the share and percentage point growth.

Figure 3 – AI Share of Job Postings in 2011-12 and Historical Growth



Source: Census Bureau and Lightcast. The figures show a binscatter between the proportion of AI job postings (as a share of the total) in 2011-12 and the growth rate of population and median household income, and percentage point change in unemployment rate between 2000 and 2008-2011.

Table 1. Instrument Validation

This table presents results concerning instrument validation and more specifically it reports results about the relevance of the instrument. The results are based on the first stage regression of a two-stage instrumental variable analysis (2SLS) for the effect of the AI job postings on offering yields of municipal bonds in the primary market. Columns (1), (3), (5) report the results without control variables and column (2), (4), (6) report the results including control variables. Detailed definitions of variables are in Table A1 in the Appendix. All models include county, state x year and time fixed effects. Standard errors are clustered by county and p-values are reported in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

	AI jobs		**DA jobs**		**AI -DA jobs**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Bartik_AI	0.010***	0.007***				
	(0.000)	(0.000)				
Bartik_DA			0.006***	0.005***		
			(0.000)	(0.000)		
Bartik_AI-DA					0.007***	0.005***
					(0.000)	(0.000)
Control Variables	No	Yes	No	Yes	No	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State X Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	County	County	County	County	County	County
R^2	0.901	0.915	0.950	0.957	0.94	0.921
Partial R^2	0.190	0.110	0.066	0.046	0.093	0,059
F-test p-value	0,000	0.000	0.000	0.000	0.000	0,000
Observations	237,528	236,870	237,528	236,870	237,528	236,870

Table 2. AI Job Postings and Bond Yields: Instrumental Variable Results

This table presents second-stage results of an instrumental variable (IV) regression of AI job postings measured at the county level on municipal bond yields in the primary market, controlling for standard bond and county-level variables. Detailed definitions of variables are in Table A1 in the Appendix. Standard errors are clustered by county and p-values are reported in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

	Offering yields (%)		
	(1)	**(2)**	**(3)**
Instrumented AI jobs (x100)	-0.118**		
	(0.022)		
Instrumented DA jobs (x100)		-0.058**	
		(0.017)	
Instrumented AI – DA jobs (x100)			-0.040**
			(0.017)
Rating	-0.060***	-0.060***	-0.060***
	(0.000)	(0.000)	(0.000)
Coupon Rate	-0.006	-0.006	-0.006
	(0.626)	(0.633)	(0.629)
Maturity	0.074***	0.074***	0.074***
	(0.000)	(0.000)	(0.000)
Maturity Inverse	-0.706***	-0.707***	-0.707***
	(0.000)	(0.000)	(0.000)
Amount (ln)	-0.016***	-0.016***	-0.016***
	(0.000)	(0.000)	(0.000)
Call or Insured	0.168***	0.168***	0.168***
	(0.000)	(0.000)	(0.000)
Risk Free	0.025***	0.025***	0.025***
	(0.000)	(0.000)	(0.000)
Employment Growth	0.546**	0.558**	0.557**
	(0.030)	(0.026)	(0.026)
Population (x1000)	0.000	0.000	0.000
	(0.998)	(0.723)	(0.793)
Per capita Income (x1000)	0.000**	0.000**	0.000**
	(0.020)	(0.015)	(0.013)
Population Growth	-1.018	-0.737	-0.924
	(0.234)	(0.380)	(0.277)
Time fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
State X Year fixed effects	Yes	Yes	Yes
Clustered SE	County	County	County
Observations	236,870	236,870	236,870
R^2	0.729	0.728	0.729

Table 3. AI Job Postings and Bond Yields: Difference-in-Differences Results

This table reports difference-in-differences results utilizing the introduction of ChatGPT by OpenAI as an event. The dependent variable is the secondary market yields. The main independent variables are the Post and Post X High AI Rank. Post takes the value of 1 (0) if the trade conducted after (before) the introduction of ChatGPT. High AI Rank refers to counties which belong in the top tercile of cumulative labor investments in AI as of 2021. The event window is (-2, +2) months. Detailed definitions of variables are in Table A1 in the Appendix. Standard errors are clustered by county and p-values are reported in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

	Yields (%)			
	(1)	**(2)**	**(3)**	**(4)**
Post	-0.540***	-0.510***	-0.560**	-0.512***
	(0.000)	(0.000)	(0.000)	(0.000)
Post x High AI Rank		-0.037***		-0.014**
		(0.000)		(0.047)
Bond fixed effects	No	No	Yes	Yes
Clustered SE	County	County	County	County
Observations	383,815	383,815	293,264	293,264
R^2	0.041	0.041	0.833	0.833

Table 4. AI Job Postings and Bond Yields: Alternative Explanation

This table presents the second-stage results of an instrumental variable (IV) regression of AI job postings measured at the county level on municipal bond yields in the primary market, controlling for standard bond and county-level variables. Panel A presents results by relying on AI job postings variation within counties with similar per capita income. Panel B shows results by relying on AI job postings variation with adjacent counties. Detailed definitions of variables are in Table A1 in the Appendix. Standard errors are clustered by county and p-values are reported in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Panel A: AI job postings variation within similar per capita income counties

	Offering Yields (%)		
	(1)	**(2)**	**(3)**
Instrumented AI jobs (x100)	-0.127**		
	(0.025)		
Instrumented DA jobs (x100)		-0.059**	
		(0.019)	
Instrumented AI – DA jobs (x100)			-0.041**
			(0.019)
Control Variables	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
State X Year fixed effects	Yes	Yes	Yes
Decile fixed effects	Yes	Yes	Yes
Adjacent county fixed effects	No	No	No
Clustered SE	County	County	County
Observations	236,870	236,870	236,870
R^2	0.729	0.728	0.728

Panel B: AI job postings variation within adjacent counties

	Offering Yields (%)		
	(1)	**(2)**	**(3)**
Instrumented AI jobs (x100)	-0.118**		
	(0.020)		
Instrumented DA jobs (x100)		-0.060**	
		(0.015)	
Instrumented AI – DA jobs (x100)			-0.041**
			(0.015)
Control Variables	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
State X Year fixed effects	Yes	Yes	Yes
Decile fixed effects	No	No	No
Adjacent county fixed effects	Yes	Yes	Yes
Clustered SE	County	County	County
Observations	1,639,535	1,639,535	1,639,535
R^2	0.730	0.729	0.729

Table 5. AI Job Postings and Bond Yields: Bond Risk Characteristics

This table presents the second-stage results of an instrumental variable (IV) regression of AI job postings measured at the county level on municipal bond yields in the primary market, controlling for standard bond and county-level variables. Panel A reports results based on the duration of a bond. The variable Long (Short) is a dummy variable that takes the value of 1 if the bond has a maturity greater (less) than 10 years. Panel B reports results based on the credit rating of a bond. The variable High (Low) Rating is a dummy variable that takes the value of 1 (0) if a bond has a credit rating larger (smaller) than 18 (High Grade). Detailed definitions of variables are in Table A1 in the Appendix. Standard errors are clustered by county and p-values are reported in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Panel A: Short vs Long duration bonds

	Offering Yields (%)		
	(1)	**(2)**	**(3)**
Instrumented AI jobs (x100)	-0.058		
	(0.279)		
Instrumented AI jobs X Long Maturity (x100)	-0.136***		
	(0.000)		
Instrumented DA jobs (x100)		-0.037	
		(0.145)	
Instrumented DA jobs X Long Maturity (x100)		-0.045***	
		(0.000)	
Instrumented AI – DA jobs (x100)			-0.025
			(0.154)
Instrumented AI – DA jobs X Long Maturity (x100)			-0.033***
			(0.000)
Control Variables	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
State X Year fixed effects	Yes	Yes	Yes
Clustered SE	County	County	County
Observations	236,870	236,870	236,870
R^2	0.588	0.585	0.586

Panel B: High vs Low credit rating bonds

	Offering Yields (%)		
	(1)	**(2)**	**(3)**
Instrumented AI jobs (x100)	-0.082		
	(0.125)		
Instrumented AI jobs X Low Rating (x100)	-0.043***		
	(0.005)		
Instrumented DA jobs (x100)		-0.040*	
		(0.078)	
Instrumented DA jobs X Low Rating (x100)		-0.026***	
		(0.001)	
Instrumented AI – DA jobs (x100)			-0.028*
			(0.082)
Instrumented AI – DA jobs X Low Rating (x100)			-0.016***
			(0.001)
Control Variables	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
State X Year fixed effects	Yes	Yes	Yes
Clustered SE	County	County	County
Observations	236,870	236,870	236,870
R^2	0.713	0.711	0.712

Table 6. AI and Bond Issuances

This table presents the second-stage results of an instrumental variable (IV) regression of AI job postings measured at the county level on municipal bond issuances in the primary market, controlling for standard county-level variables. In Panel A, the dependent variable is the amount of municipal bond issuances in a county per year. In Panel B, the dependent variable is the amount of municipal bond issuances with short maturity deflated by the amount of municipal bond issuances with long maturity, measured at the county-year level. This ratio is calculated conditional of at least one bond in a county-year. Bonds with long (short) maturity have a time to maturity greater (less or equal) than 10 years. Standard errors are clustered by county and t-statistics are reported in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Panel A: Amount of financing			
	Total Issuance (ln)		
	(1)	**(2)**	**(3)**
Instrumented AI jobs (x100)	1.564		
	(0.366)		
Instrumented DA jobs (x100)		0.7777	
		(0.320)	
Instrumented AI – DA jobs (x100)			0.525
			(0.334)
Control Variables	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Clustered SE	County	County	County
Observations	10,962	10,962	10,962
R^2	-	-	-

Panel B: Maturity structure			
	Short to Long Issuances		
	(1)	**(2)**	**(3)**
Instrumented AI jobs (x100)	-0.108**		
	(0.029)		
Instrumented DA jobs (x100)		-0.051**	
		(0.053)	
Instrumented AI – DA jobs (x100)			-0.035**
			(0.043)
Control Variables	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Clustered SE	County	County	County
Observations	4,492	4,492	4,492
R^2	-	-	-

Table 7. AI Job Postings and Local Economy

This table presents regression results about the impact of AI labor investments on the local economy, using an entropy balancing approach. Treated counties comprise the top tercile of AI employment opportunities in each year. Covariates include per capita income, county population level and changes, and one-year employment growth. In Panel A the dependent variable is the annualized growth of real productivity per county. In Panel B the dependent variable is the annualized growth of real GDP per county. In Panel C the dependent variable is the annualized growth of employment per county. Detailed definitions of variables are in Table A1 in the Appendix. Standard errors are clustered by county and p-values are reported in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Panel A: Annualized growth of real productivity

	Productivity Growth $_{t+1}$	**Productivity Growth $_{t+2}$**	**Productivity Growth $_{t+3}$**
	(1)	**(2)**	**(3)**
Treat	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)
Time Fixed Effects	Yes	Yes	Yes
Observations	21,555	18,475	15,396
R^2	0.012	0.008	0.011

Panel B: Annualized growth of real GDP

	GDP Growth $_{t+1}$	**GDP Growth $_{t+2}$**	**GDP Growth $_{t+3}$**
	(1)	**(2)**	**(3)**
Treat	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)
Time Fixed Effects	Yes	Yes	Yes
Observations	21,555	18,475	15,396
R^2	0.075	0.023	0.016

Panel C: Annualized growth of employment

	Employment Growth $_{t+1}$	**Employment Growth $_{t+2}$**	**Employment Growth $_{t+3}$**
	(1)	**(2)**	**(3)**
Treat	0.001	0.000	0.001
	(0.268)	(0.555)	(0.241)
Time Fixed Effects	Yes	Yes	Yes
Observations	21,555	18,475	15,396
R^2	0.196	0.110	0.062

Table 8. AI Job Postings and Local Finances

This table presents regression results about the impact of AI labor investments on local finances, using an entropy balancing approach. Treated counties comprise the top tercile of AI employment opportunities in each year. Covariates include per capita income, county population level and changes, and one-year employment growth. In Panel A the dependent variable is the annualized total revenues growth of the municipalities aggregated at the county-level. In Panel B the dependent variable is the annualized total taxes income growth of the municipalities aggregated at the county-level. In Panel C the dependent variable is the annualized sales taxes income growth of the municipalities aggregated at the county-level. In Panel D the dependent variable is the annualized property taxes income growth of the municipalities aggregated at the county- level. Detailed definitions of variables are in Table A1 in the Appendix. Standard errors are clustered by county and p-values are reported in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Panel A: Annualized total revenues growth

	Total Revenues Growth $_{t+1}$	Total Revenues Growth $_{t+2}$	Total Revenues Growth $_{t+3}$
	(1)	(2)	(3)
Treat	0.034***	0.030***	0.030***
	(0.000)	(0.000)	(0.000)
Time Fixed Effects	Yes	Yes	Yes
Observations	13,570	11,576	9,326
R^2	0.214	0.198	0.179

Panel B: Annualized total taxes growth

	Total Taxes Growth $_{t+1}$	Total Taxes Growth $_{t+2}$	Total Taxes Growth $_{t+3}$
	(1)	(2)	(3)
Treat	0.029	0.025***	0.026***
	(0.112)	(0.000)	(0.000)
Time Fixed Effects	Yes	Yes	Yes
Observations	12,090	10,308	8,283
R^2	0.191	0.162	0.151

Panel C: Annualized sales taxes growth

	Sales Taxes Growth $_{t+1}$	Sales Taxes Growth $_{t+2}$	Sales Taxes Growth $_{t+3}$
	(1)	(2)	(3)
Treat	0.000	0.003	0.011
	(0.959)	(0.810)	(0269)
Time Fixed Effects	Yes	Yes	Yes
Observations	12,637	10,767	8,651
R^2	0.096	0.091	0.076

Panel D: Annualized property taxes growth

	Property Taxes Growth $_{t+1}$	Property Taxes Growth $_{t+2}$	Property Taxes Growth $_{t+3}$
	(1)	(2)	(3)
Treat	0.030	0.044***	0.044***
	(0.251)	(0.031)	(0.015)
Time Fixed Effects	Yes	Yes	Yes
Observations	12,259	10,450	8,402
R^2	0.157	0.116	0.107

Online Appendix

Table A1: List of Dependent and Independent Variables

Dependent variables

Offering Yield (Primary market): Yield to maturity at the time of issuance of Municipal Bonds, based on the coupon and any discount or premium to par value at the time of sale. This variable is created using FTSE Russell Database Mergent Municipal Bond Securities Database.

Offering Yield (Secondary market): The effective interest rates or returns that investors can expect to earn when buying and holding bonds that are already issued and traded in the secondary market. We calculate secondary market yields at the bond-month level using the size-weighted average yield across all transactions for each bond in every month.

Real Productivity: The ratio of real Gross Domestic Product (GDP) to the number of employees in a given county on an annual basis.

Real GDP: The value of the goods and services produced by an economy in a given county on an annual basis, adjusted for price changes.

Total Revenues: The natural logarithm of the total revenues in a given county on a year basis. This variable is created using Census Bureau Database.

Total Taxes: The natural logarithm of the total taxes in a given county on a year basis. This variable is created using Census Bureau Database.

Sales Taxes: The natural logarithm of the total taxes derived from sales in a given county on a year basis. This variable is created using Census Bureau Database.

Property Taxes: The natural logarithm of the total taxes derived from properties in a given county on a year basis. This variable is created using Census Bureau Database.

Total Issuance (Ln): The natural logarithm of the total amount of municipal bonds' issuance in a given county on an year basis. This variable is created using Mergent Municipal Bond Securities Database.

Structure of the issuances: The ratio of the total issuance amount of short maturity bonds (greater than 10 years) to the total issuance amount of long maturity bonds (less than 10 years) in a given county on a year basis. We include only the counties that have at least one issuance every year during the period 2015-2021.

Main independent variables

AI workers per 1,000 firms: The number of Artificial intelligence-related job postings normalized per 1,000 firms of the year 2013 in a given county.

DA workers per 1,000 firms: The number of Data Analytics-related job postings normalized per 1,000 firms of the year 2013 in a given county.

AI - DA workers per 1,000 firms: The number of Artificial intelligence and Data Analytics-related job postings normalized per 1,000 firms of the year 2013 in a given county.

Instruments

Bartik AI: The Bartik instrument for Artificial intelligence-related job postings as introduced by Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020).

Bartik DA: The Bartik instrument for Data Analytics-related job postings as introduced by Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020).

Bartik AI - DA: The Bartik instrument for Data Analytics and Artificial Intelligence-related job postings as introduced by Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020).

Bond – level control variables

Coupon Rate: The current applicable annual interest rate of a bond. This variable is created using Mergent Municipal Bond Securities Database.

Maturity: The time period in years before the bond issuer must repay the original bond value to the bond holder. The variable is created by deducting the maturity date from the settlement date and divided by 360 days, using Mergent Municipal Bond Securities Database.

Maturity Inverse: The arithmetical inverse of the Maturity.

Rating: The long-term rating assigned to each individual bond (or the issuer if the bond rating is missing) by the three main credit rating agencies. We convert character ratings into numeric ratings with 21 corresponding to the highest credit quality and 1 the lowest. When rating information is available from multiple rating agencies, we employ the harshest rating. In analysis of bond yields, we use the insured rating for insured bonds and the underlying rating for uninsured bonds.

Amount: The principal amount of the maturity's original offering that the issuer has to pay back to the bond holder at the maturity date. This variable is created using Mergent Municipal Bond Securities Database.

Insured: A dummy variable that takes the value of one if the bond is insured and zero otherwise. This variable is created using Mergent Municipal Bond Securities Database.

Call: A dummy variable that takes the value of one if the bond is callable and zero otherwise. This variable is created using Mergent Municipal Bond Securities Database.

Risk Free: The interest rate of the corresponding Treasury bond at the settlement date. This variable is created using U.S. Department of the Treasury.

County – level control variables

Population: The number of civilians in a given county on a year basis. This variable is created using data from the Census Bureau.

Population Growth (%): The growth rate of the total population in a given county. This variable is created using data from the U.S. Census Bureau.

Per capita Personal Income: The average income earned by individuals in a given county on a year basis. This measure of income is calculated as the personal income of the residents of a given area divided by the resident population of the area. This variable is created using data from the U.S. Bureau of Economic Analysis (BEA).

Employment Growth (%): The percentage change of employed persons in a given county on a year basis. The variable is created using data from the U.S. Bureau of Labor Statistics (LBS).

Poverty rate (%): The ratio of the estimated total number of people in poverty divided by the total population in a given county. This variable is created using data from the U.S. Census Bureau.

Religion: The number of a county's population whose residents adhere to any religion in a given county on a year basis. This variable is created using the "Churches and Church Membership" files from the U.S. Association of Religion Data Archives (ARDA).

Seniors (%): The portion of residents of a county's population who are aged 65 or older. This variable is created using data from the U.S. Census Bureau.

Female: The number of female population in a given county. This variable is created using data from the U.S. Census Bureau

White (%): The number of white population divided by the number of total population in a given county. This variable is created using data from the U.S. Census Bureau

Table A2. Information about Sample Construction

This table provides information about the sample construction. Panel A provides information about the bond-level sample. Panel B provides information about the county-level volume sample. Panel C provides information about the county-level finances sample. Finally, panel D provides information about the local economy sample.

Panel A: Bond-level sample

Steps	Data Filter	Observations
1	All bonds in Mergent FISD (2000-2021)	4,465,887
2	Bonds issued for new borrowing (i.e., excluding refunding)	1,810,262
3	Bonds issued through conventional channels only (i.e., excluding bonds issued by the U.S. government or under tobacco agreement and tuition agreement, Build America bonds, notes, certificates, and taxable bonds)	1,527,483
4	Bonds with non-missing offering yield, rating at issuance, coupon rate, or maturity date	1,178,902
5	Bonds with non-missing county FIPS code	830,351
6	Bonds issued between Jan 2015 to Dec 2021	245,360
7	Bonds issued matched economic control variables and job postings data	245,345
8	Bonds with maturity greater than one year	239,024

Panel B: County-level volume sample

Steps	Data Filter	Observations
1	County – year observations for the counties that issue bonds during 2015-2021	15,830
2	County – year observations with non-missing and job postings data	11,081
3	County – year observations with issuance every year during 2015-2021	5,547

Panel C: County-level finances sample

Steps	Data Filter	Observations
1	County – year observations with available information during 2014-2021	20,083
2	County -year observations with non-missing economic control variables and job postings data	19,630

Panel D: Local economy sample

Steps	Data Filter	Observations
1	County – year observations for the 3,142 counties during 2014-2021	34,562
2	County with non-missing economic control variables and job postings data	24,637

Table A3. Summary Statistics

This table reports summary statistics for the variables used in each type of analysis. Panel A reports summary statistics of the bond-level sample. Panel B reports summary statistics for the county-level volume sample. Panel C reports summary statistics for the county-level finances sample. Finally, panel D reports summary statistics for the local economy sample.

Panel A: Bond-level sample

	No Observations	Mean	Std. Dev	P50
Dependent Variable				
Yield (%)	239,024	2.139	0.949	2.100
Main Variables of Interest				
AI job postings per 1,000 firms	239,024	57.281	96.856	19.587
DA job postings per 1,000 firms	239,024	351.959	411.568	197.961
AI - DA job postings per 1,000 firms	239,024	368.922	443.250	934.081
Control Variables				
Bond Characteristics				
Rating	239,024	16.971	2.323	17.000
Coupon rate (%)	239,024	3.388	1.182	3.125
Maturity	239,024	10.900	6.733	9.939
Maturity inverse	239,024	0.215	1.241	0.107
Amount (ln)	238,596	13.318	1.420	13.209
Callable or insured	239,024	0.636	0.481	1.000
Risk free rate (%)	238,808	1.892	0.789	1.969
County Characteristics				
Population	239,024	1,049,396	1,738,766	451,716
Per capita income ($)	237,536	56,848	17,262	53,242
Employment growth (%)	229,628	0.800	3.200	1.200
Population growth (%)	237.536	0.7	1.200	0.500
Poverty rate (%)	239,024	11.93	4.476	11.4
Religion	238,319	742,778	1,089,036	372,600
Seniors (%)	239,024	15.200	3.700	14.900
Female	239,024	531,425	880,164	230,308
White (%)	239,024	79.600	12.700	81.300
Productivity (Real GPD/Employes) _	237,536	91.879	45.173	85.485

Panel B: County-level volume sample

	No Observations	Mean	Std. Dev	P50
Dependent Variable				
Total issuance ($)	11,081	44,181,712	179,108,365	110,000
Total issuance long ($)	11,081	30,393,258	135,934,250	0.000
Total issuance short ($)	11,081	13,788,455	53,141,054	0.000
Main Variables of Interest				
AI job postings per 1,000 firms	11,081	43.508	104.979	8.617
DA job postings per 1,000 firms	11,081	326.234	580.929	123.864
AI - DA job postings per 1,000 firms	11,081	371.426	687.172	20.272
Control Variables				
Population	11,081	180,430	445,841	57,542
Per capita income ($)	11,081	47,415	13,313	44,912
Employment growth (%)	11,081	0.400	3.200	0.200

Population growth (%)	11,081	0.400	1.200	0.200

Panel C: County-level finances sample

	No Observations	Mean	Std. Dev	P50
Dependent Variable				
Total revenues (th. $)	19,630	497,744	15,200,000	89,811
Total taxes (th. $)	19,630	276,925	3,870,192	34,812
Sales taxes (th. $)	19,630	58,771	1,034,106	3,481
Property taxes (th. $)	19,630	168,693	5,083,276	20,365
Main Variables of Interest				
AI job postings per 1,000 firms	19,630	12.438	33.414	1.584
DA job postings per 1,000 firms	19,630	101.401	192.011	37.117
AI - DA job postings per 1,000 firms	19,630	114.094	223.483	40.188

Panel D: Local economy sample

	No Observations	Mean	Std. Dev	P50
Dependent Variable				
Real Productivity	24,637	102.93	825.99	71.329
Main Variables of Interest				
AI job postings per 1,000 firms	24,637	10.867	30.105	0.782
AI job postings per 1,000 firms	24,637	89.055	175.829	31.925
AI - DA job postings per 1,000 firms	24,637	100.085	203.296	34.483
Control Variables				
Population	24,637	104,900	334,875	25,804
Per capita income ($)	24,637	44,652	13,296	42,183
Employment growth (%)	24,637	0.243	0.368	0.608
Population growth (%)	24,637	0.066	1.364	0.030

Table A4. List of AI skills

This table contains a list of keywords relating to either AI or DA. We define AI related job postings by parsing text from job postings and by linking them with the list of keywords.

AI Keywords	DA Keywords
Apache Ant	Apache Hadoop
Apache Spark	Apache Hive
Artificial Intelligence	Apache Kafka
Automated Testing	Bayesian Inference
Automation Consulting	Bayesian Modeling
Automation Systems	Bayesian Networks
Automation Techniques	Big Data
Automation Tools	Big Data Analytics
AWS Elastic MapReduce (EMR)	Data Analysis
BigQuery	Data Analytics
Boosting (Machine Learning)	Data Conversion
Caffe Deep Learning Framework	Data Engineering
Cluster Analysis	Data Management
Clustering	Data Modeling
Clustering Algorithms	Data Science
Computer Vision	Data Visualization
Convolutional Neural Network (CNN)	Extraction Transformation and Loading (ETL)
Decision Trees	Microsoft Power BI
Deep Learning	Microsoft SQL
Deeplearning4j	MongoDB
Machine Learning	MySQL
Machine Vision	NoSQL
MapReduce	Oracle PL/SQL
Kubernetes	PostgreSQL
Natural Language Processing	Predictive Analytics
Natural Language Toolkit (NLTK)	Predictive Models
Neural Networks	Prepare Spreadsheets
Splunk	Spreadsheets
Supervised Learning (Machine Learning)	SQL
Support Vector Machines (SVM)	SQL Injection
TensorFlow	SQL Plus
Torch (Machine Learning)	SQL Server
	SQL Server Analysis Services (SSAS)
	SQL Server Reporting Services (SSRS)
	SQL*Loader
	SQLAlchemy
	SQLite
	Tableau
	Transact-SQL

Table A5. Top/Bottom Occupations, by the number of AI job postings

This table provides information about the top 4 and bottom 4 occupations by the number of AI-related job postings during the year 2021.

Occupation	AI job postings
Software Developers, Applications	334,698
Computer Occupations, All Other	224,961
Computer and Information Research Scientists	125,174
Database Administrators	50,291
. . .	. . .
Food Cooking Machine Operators and Tenders	0
Environmental Science Teachers, Postsecondary	0
Forging Machine Setters, Operators, and Tenders	0
Funeral Service Managers	0

Table A6. AI Job Postings and Bond Yields: Alternative Measures

This table presents the second-stage results of an instrumental variable (IV) regression of AI job postings measured at the county level on municipal bond yields in the primary market, controlling for standard bond and county-level variables. Panel A presents results when we do not winsorize the Instrumental variable to be consistent with the estimated Rotemberg weights. Panel A presents results when we exclude from the data the variation coming from occupation 1510: "Computer Occupations" to be consistent with the Rotemberg weights presented in table B2. Detailed definitions of variables are in Table A1 in the Appendix. Standard errors are clustered by county and p-values are reported in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Panel A: AI job postings variation within similar per capita income counties

	Offering Yields (%)		
	(1)	**(2)**	**(3)**
Instrumented AI jobs (x100)	-0.119**		
	(0.031)		
Instrumented DA jobs (x100)		-0.055**	
		(0.040)	
Instrumented AI – DA jobs (x100)			-0.038**
			(0.036)
Control Variables	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
State X Year fixed effects	Yes	Yes	Yes
Decile fixed effects	Yes	Yes	Yes
Adjacent county fixed effects	No	No	No
Clustered SE	County	County	County
Observations	236,870	236,870	236,870
R^2	0.729	0.728	0.728

Panel B: AI job postings variation within adjacent counties

	Offering Yields (%)		
	(1)	**(2)**	**(3)**
Instrumented AI jobs (x100)	-0.391**		
	(0.047)		
Instrumented DA jobs (x100)		-0.079**	
		(0.039)	
Instrumented AI – DA jobs (x100)			-0.066**
			(0.039)
Control Variables	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
State X Year fixed effects	Yes	Yes	Yes
Decile fixed effects	No	No	No
Adjacent county fixed effects	Yes	Yes	Yes
Clustered SE	County	County	County
Observations	1,639,535	1,639,535	1,639,535
R^2	0.730	0.729	0.729

Table A7. Largest Rotemberg Weights (Excluding SOC Computer Occupations 15-10) :

Occupation Group	4-d SOC	Weight
Business Operations	13-10	0.03
Mathematical and Science Occupations	15-20	0.03
Management Analysts	13-11	0.07
Advertising and Sales Managers	11-20	0.13
Other Management Occupations	17-21	0.14
Operations Specialists Managers	11-30	0.15
Financial Specialists	13-20	0.20
Other Management Occupations	11-91	0.37

Figure A.1: AI Share of Job Postings in 2011-12 and Historical Growth

The figures show a binscatter between the proportion of AI job postings in 2011-12 and the growth rate of population and median household income, and change in unemployment rate between 2000 and 2008-11.

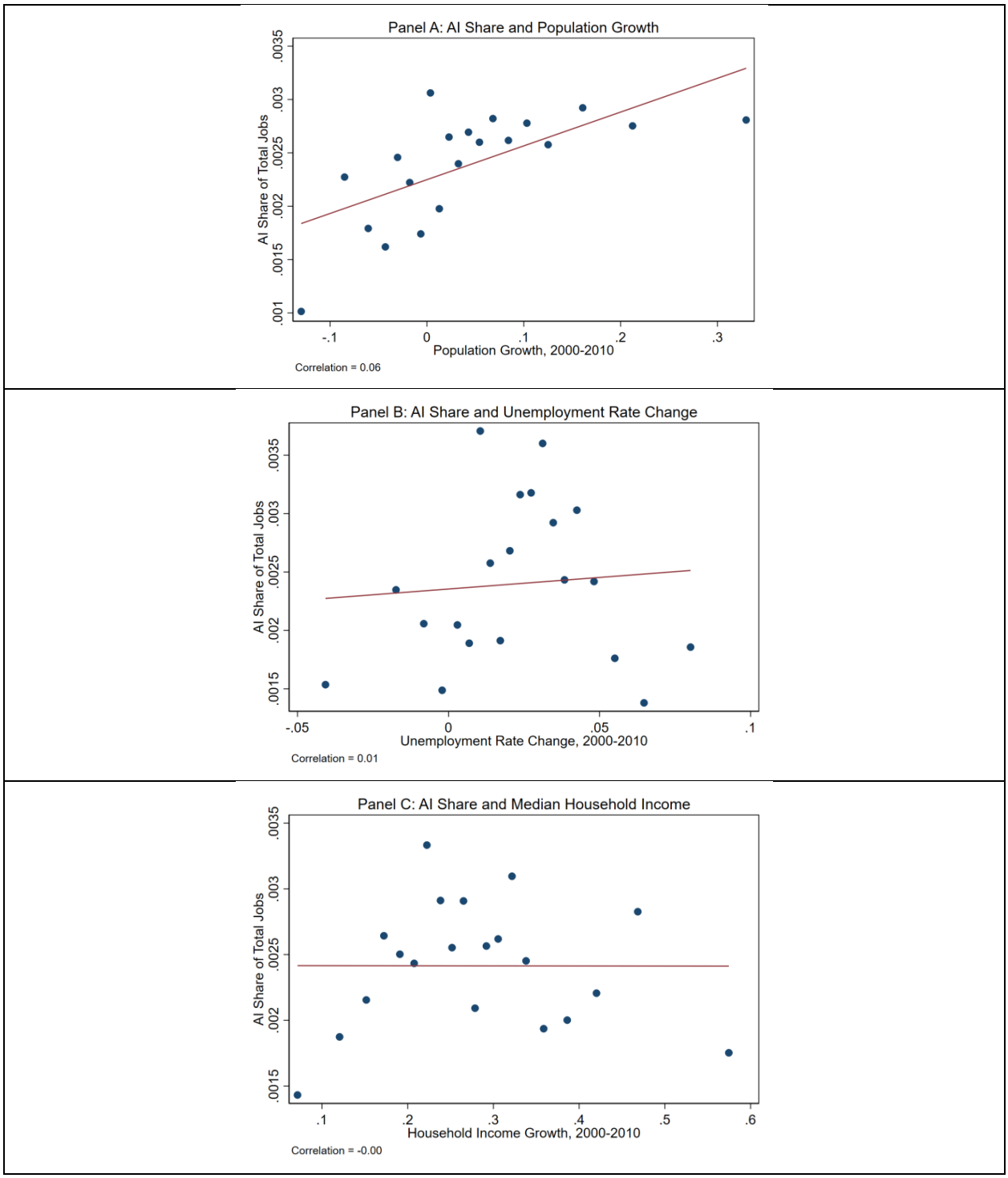


Figure A.2: Data Analytics Share of Job Postings in 2011-12 and Historical Growth

The figures show a binscatter between the proportion of data analytics job postings in 2011-12 and the growth rate of population and median household income, and change in unemployment rate between 2000 and 2008-11.

