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

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Abstract

We investigate the economic impact of artificial intelligence (AI) technologies on municipalities by leveraging spatial variation in labor investments in AI. Employing an instrumental variable analysis, difference-in-differences regressions and an entropy balancing approach, we identify causal effects while controlling for economic conditions and demographics. We find that increases in labor investments in AI within a county lead to lower yields, which prompts municipalities to issue more longer-term bonds. Qualitatively similar results that exploit the introduction of ChatGPT, further support causality. Differential effects due to labor investments in Al within a region on economic activity and government revenues suggest an economic revitalization channel.

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

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1 Introduction

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

- *William Gibson, Author*

The last decade has undergone a profound technological shift, characterized by the rapid proliferation and deep-seated adoption of artificial intelligence (AI). AI-related job postings surged from 0.5% in 2014 to an impressive 2.05% in 2022 (Beckett, 2023), 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., 2023). Driven by improvements 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 scepticism 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).

To address this tension, our paper explores the quantitative effects of AI technology on local economies by leveraging spatial variation in labor investments in AI and the municipal bond market. This setting provides at least two main 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, because AI investments often yield localized economic effects, positive impacts in one region may be offset by negative spillovers elsewhere, 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, 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, facilitating thus, a more comprehensive understanding of the economic consequences of AI investments.

Estimating causal effects of labor investments in AI for local economy and municipalities is empirically challenging. The demand for AI investments tends to be ubiquitous and correlate with observed and unobserved factors, such as financial constraints and human capital, that may drive local economy and government finances. Our identification strategy controls for not only local characteristics, such as per capita income and population, but also for county and state × year fixed effects. In addition, recognizing the potential for omitted time-varying shocks, we also instrument for AI exposure using a Bartik-like instrument that exploits the pre-existing exposure of a county to AI-related jobs. Bartik-like instruments rely on the assumption that the pre-existing exposure of a county to AI-related jobs is not correlated with the outcomes of our study. This assumption likely hold as the correlation between the initial share of AI job postings in a county and historical growth rates in population, household income, and unemployment rate is closed to zero, attesting that areas with higher shares of AI job postings were not areas that had historically been over-performing in traditional capacities. In addition, we provide further supporting evidence using diagnostics for Bartik-type instruments following Goldsmith-Pinkham et al. (2020).

Our results reveal that more AI-related job postings by entities operating within a county lead to significant municipal bond yield reductions. These reductions are economically important. For instance, a one standard deviation increase in local AI labor investments leads to approximately 21.93 bps decrease in the offering yields. Given an aggregate face value amount of $478 billion in the bond sample, this reduction in yield translates to a saving of $1.5 billion.

We next perform several additional tests aimed at further addressing endogeneity concerns. First, we test the robustness of our results by exploiting the release of ChatGPT by OpenAI as a plausibly exogenous shock that enables investors to understand and most importantly appreciate more the 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. This approach allows us to isolate the impact of AI from other concurrent technological or economic developments, providing robust evidence of AI's influence on local governments' cost of finance. The results show a decline in bond yields after the introduction of ChatGPT, with larger decline observed for bonds of municipalities located in counties with higher cumulative AI labor investments. In economic terms, the introduction of ChatGPT led to a decrease in yields in the secondary market, with a magnitude of 3.7 basis points (2.1 basis points) when analyzing cross-sectional (within-bond) variation.

Second, we acknowledge concerns about the potential influence of local economic conditions on both local AI labor investments and bond offering yields. If local AI labor investments are more likely in counties experiencing economic upturns, then our findings might be biased, reflecting merely favorable economic conditions. However, 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 artefact of economic conditions coinciding with local AI labor investments.

Next, we explore the bonds that are most affected by local AI labor investments. AI initiatives can drive efficiency gains and innovation, thereby fostering local development and enhancing public services. As AI represents an investment opportunity with potential fiscal benefits, it may lead to an upturn 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 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).

What 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 of 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.

Finally, 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.

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 (**?**), 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 (e.g., Acemoglu and Restrepo (2018a)). Exploiting the maturity structure of municipal bonds we also find that investors anticipate more AI technology benefits in the long-term, consistent with Mihet and Philippon (2019) and 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).[1] By demonstrating that AI labor

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

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 improved productivity and innovation. This aligns with the theoretical expectations about GPTs' role in facilitating broader-based economic growth.

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., 2022a), 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. Although Andreadis et al. (2022) examine implications from cybersecurity risk, our study marks a significant departure by offering the first empirical evidence on the effects of AI technology specifically on local government financing.

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 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 (formally 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 Treasure to get the risk free rate. Tables A1 and A2 in the Internet Appendix provide a list of the variables used in the study in conjunction with their corresponding data sources, and information about sample construction for various analyses of the study. Table A3 in the Internet Appendix presents descriptive statistics for each sample.

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.[2,3] 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 build hierarchically, with over 1,900+ specialized occupations that are mapped to the Standardized Occupation Classification (SOC) used in the official publications by the BLS.[4] 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, 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.[5] 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 Internet 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*), 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

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

[3]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 et al. (2024).

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

[5]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).

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 purposes.

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 our sample period 2014-2021.[6,7]

Figure 1 present the frequency of AI jobs over the years. Consistent with (Beckett, 2023), a notable trend emerges, with a significant surge in job postings related to AI, beginning in 2016. Particularly striking is also the nearly four-fold increase in AI postings observed between 2014 and 2021. Note that this increase is also significant when considered relative to other job postings. Figure 2 shows the percentage of AI jobs relative to total job postings, by year. As shown, although AI jobs constitute a relatively modest share of total job postings, there is a discernible upward trend, with AI jobs comprising 1% of total postings in 2021 compared to negligible levels in 2014. This signifies a growing demand for these skills in the labor market.

Figure 3 presents a heat map of the cumulative labor demand throughout our study period, by county. Areas with yellow color exhibit a greater AI-related labor demand. The map highlights considerable variation in the prevalence of AI jobs. For example, AI jobs tend to concentrate in parts of the West (e.g., California) and Northeast (e.g., Massachusetts). Interestingly, there

[6] 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).

[7] Table A5 in the Internet 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.

is substantial heterogeneity, even within states, underscoring the importance of conducting our analysis at a county-level to preserve the granularity of AI job locations. Across counties, the concentration of AI jobs varies significantly, ranging from less than 1% to nearly 10%. On the one hand, such variability could imply different economic benefits across counties. On the other hand, it may raise concerns about potential selection bias, as counties with higher levels of AI jobs may exhibit different characteristics compared to those with fewer jobs. To address this concern, we conduct rigorous robustness tests, accounting for variations in economic conditions and demographics. Encouragingly, these tests demonstrate that our results remain consistent, bolstering confidence about the reliability of our findings.

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.[8] 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.[9] After we have a consistent set of occupations, we use the 5-year sample, to create the occupation composition of each county

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

[9]According to Acemoglu and Restrepo (2018b), this approach allows us to increase the set of counties with accurate measures of occupational composition.

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 a shift-share instrument. This instrument use as weights the occupation shares for each county based on the 2005-2009 5-year American Community Survey (ACS) sample.[10]

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 encompass 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, excluding thus, 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

[10] In the construction of the occupation shares, we follow Rossi-Hansberg et al(2023) to include as many counties as possible (even counties with population less than 100,000 that are not reported in the IPUMS ACS sample), by inferring the county shares using a consistent PUMA-county apportionment matrix.

[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.

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 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 areas 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 [12] 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.

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:

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

[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.

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

where Y_{ict} denotes the yield for bond i, issued in county c, and year t, $BARTIK$ denotes 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 to match the measurement level of the main outcome.

The outcome of interest γ, reflects the average difference in bond yields attributable to AI employment opportunities. Like prior literature (Gao et al., 2020; Cornaggia et al., 2022b), 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 proxied by the corresponding maturity-matched treasury yield. We also include county demographic factors: per capita income, county population level and changes, and one-year employment growth.

Our most stringent specification layers county, and state $\times$ year fixed effects, purging variation in counties and state-level policies and labor market flows over these years. That is important given time-varying changes in the municipal bond markets, and across states that are related to tax policy and risk.[13]

4 Capital Market Implications: Bond Yields

In this section, we analyze implications of AI labor investments on municipal bond yields. Specifically, we ask whether municipal investors incorporate local labor investments in AI into offer yields. We begin our analysis by plotting in Figure 4 the average yield across terciles of AI job postings. The results show a steady decline from the low to high AI job postings tercile groups. More specifically, for the AI job postings the average bond yield in the lowest group is 2.13% and declines to 2.07% in the highest group. Importantly, a Chi-square test indicates that the difference between low and high groups is statistically significant. Overall, this monotonic reduction underscores a potentially impactful association between AI job postings and municipal bond yields. To substantiate these findings in a multivariate setting, we next perform a two-stage instrumental variable (IV) approach.

4.1 Instrumental Variable Results

4.1.1 Instrument Validation

When considering the use of an instrumental variable approach, it is crucial to evaluate whether the instrument satisfies two criteria: (i) relevance, and (ii) exclusion. We assess the instrument's relevance by examining the partial R-squared, which is a measure of the proportion of variation

[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).

in the response variable explained solely by the included instrument, independent of the excluded ones (Jiang, 2017). 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. Panel A of 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 13% (in column (2)) and 21.93% (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.

The Bartik-like instrument is also designed to be orthogonal to the error term in the regression model, ensuring that it does not capture factors directly influencing bond yields. We provide various supporting evidence following the best practices suggested by Goldsmith-Pinkham et al. (2020): First, Figure 5 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.[14] The correlations are zero for unemployment rate and median household income growth, and 0.06 for population growth. This suggests that areas with higher shares of AI job postings were not areas that had historically been over-performing in traditional capacities. Second, we also present results containing interactions between year fixed effects and demographic characteristics taken at the beginning of the sample in 2010 (using the 2008-2011 ACS). These characteristics include:

[14]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.

median household income, population, the share of college graduates, and the share of professional services workers. Because of the large number of controls, we are empirically demanding that our coefficients do not contain any variation that could be correlated with local composition effects that could affect bond yields.

Lefteris - YET TO DO...

Finally, we provide a decomposition of the identifying variation in the Bartik-like 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. We find that the identifying variation in our instrument is concentrated in...

4.1.2 Second-stage Regression Results

Table 2 presents the main results associated with our IV regressions, as in Equation 3. The results indicate a negative relation between the instrumented AI job postings and offering yields, suggesting a causal link between AI job postings and decreased municipal yields. Economically, the impact of AI job postings on municipal yields is significant. For instance, in Model (1), the coefficient estimate of the instrumented AI job postings is -0.051, implying that a one standard deviation increase in the instrumented AI job postings leads to approximately 21.9 bps decrease in the offering yields (that is estimated as the product of -0.079 x 277). Given an aggregate face value amount of $478 billion in the bond sample, this reduction in yield translates to a saving of approximately $1.5 billion.

Our controls generate coefficient estimates that are generally consistent with prior literature. 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.

Overall, the results support the view that the AI job postings affect municipal investors who in turn demand less compensation for investing in municipal bonds.

4.2 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 revolutionalized 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). Specifically, 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 bond that trade during the [-2,+2] month window period around the event.[15] 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 on 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

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

higher AI job postings. In economic terms, the introduction of ChatGPT lead to a decrease in yields in the secondary market, with a magnitude of 3.7 basis points (2.1 basis points) when analyzing cross-sectional (within-bond) variation. Overall, these results complement our main primary market analysis.

4.3 Alternative Explanations

Although our findings suggest a strong negative relationship between the AI job postings and bond yields, we nonetheless consider the potential influence of unobserved variables that could confound our results. If our regression model 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 refinement enable us to isolate the effect of AI job postings in our IV framework, 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, 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.

4.4 Which Bonds Benefit More?

In this section, we investigate the impact of AI on bond yields, focusing on a key determinant: default risk. AI has the potential to stimulate local economies through improved efficiency, innovation, and job creation, thereby fostering economic growth and lowering default risk at the community level. Leveraging on this framework, we utilize two bond characteristics to refine our analysis and explore the link between AI and bond yields, particularly in relation to default risk.

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.[16] The results highlight a notable negative and 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. Overall, these results suggest that default risk is an important channel through which labor investments in AI affect bond yields.

5 Local Economic Mechanisms

We examine 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

[16] 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 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*).

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 tercile of AI employment opportunities, are identified annually, while the rest 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 treated effect on real productivity and municipal government revenues over a three-year period after the matching.

Table 6 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 greater 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.

Table 7 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 rise in total revenues is primarily driven by increases in total taxes and property taxes rather than sales taxes.

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

6 Quantity and the Maturity Structure of Bond Issuances

In this section, we look into the multifaced impact of labor investments in AI on municipal finance, exploring both the quantity and the maturity structure of bonds issued. 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 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 8 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.

In summary, these results indicate that while labor investments in AI may not alter the quantity of bonds issued, they do shape the maturity of the bonds issued.

7 Conclusion

There is now a voluminous literature examining the effects of technological change and automation on firms, but much uncertainty remains about the unique effects of AI. Unlike automation, AI has the potential to augment worker inputs, rather than displace them. 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, indicative of 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 elucidating the fiscal benefits of AI adoption at the local level, our research provides valuable insights for policymakers and stakeholders navigating the evolving technological landscape.

Overall, our research extends the analysis of AI's economic effects to the domain of public finance, highlighting the role of AI in shaping local government strategies and financing decisions.

As AI continues to permeate various sectors, understanding its implications for local economies becomes increasingly crucial, and our study contributes to this ongoing discourse, offering valuable insights for shaping future policy and investment decisions.

References

Abis, S. and Veldkamp, L. (2024). The changing economics of knowledge production. *The Review of Financial Studies*, 37(1):89–118.

Acemoglu, D. (2024). The simple macroeconomics of ai. *Working paper*.

Acemoglu, D., Autor, D., Hazell, J., and Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, 40:S293–S340.

Acemoglu, D. and Restrepo, P. (2018a). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American economic review*, 108(6):1488–1542.

Acemoglu, D. and Restrepo, P. (2018b). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6):1488–1542.

Acemoglu, D. and Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2):3–30.

Aghion, P. and Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60(2):323–351.

Aghion, P., Jones, B. F., and Jones, C. I. (2017). Artificial intelligence and economic growth. *NBER Working paper*, (w23928).

Almeida, P. and Kogut, B. (1999). Localization of knowledge and the mobility of engineers in regional networks. *Management Science*, 45(7):905–1024.

Andreadis, L., Kalotychou, E., Louca, C., Lundblad, C. T., and Makridis, C. (2022). Cyberattacks, media coverage and municipal finance. *Media Coverage and Municipal Finance (October 14, 2022)*.

Autor, D. H. (2015). Why are there still so many jobs? the history and future of workplace automation. *Journal of Economic Perspecitves*, 29(3):3–30.

Babina, T., Fedyk, A., He, A., and Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, 151(103745).

Barro, R. J. and Sala-i Martin, X. (1991). Convergence across states and regions. *Brookings Papers on Economic Activity*, pages 107–182.

Beckett, E. (2023). Demand for ai skills continues climbing. *Stanford AI Index*.

Belenzon, S. and Schankerman, M. (2013). Spreading the word: Geography, policy, and knowledge spillovers. *Review of Economics and Statistics*, 95(3):884–903.

Beraja, M. and Zorzi, N. (2022). Inefficient automation. Technical report, National Bureau of Economic Research.

Blanchard, O. and Katz, L. F. (1992). Regional evolutions. *Brookings Papers on Economic Activity*, pages 1–75.

Bresnahan, T. and Trajtenberg, M. (1995). General purpose technologies 'engines of growth'? *Journal of Econometrics*, 61(1):83–108.

Brynjolfsson, E., Li, D., and Raymond, L. R. (2023). Generative ai at work. *NBER working paper 31161*.

Brynjolfsson, E., Rock, D., and Syverson, C. (2021). The productivity j-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics*, 13(1):333–72.

Cammeraat, E. and Squicciarini, M. (2021). Burning glass technologies' data use in policy-relevant analysis: An occupation-level assessment.

Chen, M. A., Wu, Q., and Yang, B. (2019). How valuable is fintech innovation? *The Review of Financial Studies*, 32(5):2062–2106.

Chetty, R., Hendren, N., Kline, P., and Saez, E. (2014). Where is the land of opportunity? the geography of intergenerational mobility in the united states. *The Quarterly Journal of Economics*, 129(4):1553–1623.

Cornaggia, J., Cornaggia, K. J., and Israelsen, R. D. (2018). Credit ratings and the cost of municipal financing. *The Review of Financial Studies*, 31(6):2038–2079.

Cornaggia, K., Hund, J., Nguyen, G., and Ye, Z. (2022a). Opioid crisis effects on municipal finance. *The Review of Financial Studies*, 35(4):2019–2066.

Cornaggia, K., Hund, J., Nguyen, G., and Ye, Z. (2022b). Opioid crisis effects on municipal finance. *Review of Financial Studies*, 35(4):2019–2066.

Ellison, G., Glaeser, E. L., and Kerr, W. R. (2010). What causes industry agglomeration? evidence from coagglomeration patterns. *American Economic Review*, 100(3):1195–1213.

Eloundou, T., Manning, S., Mishkin, P., and Rock, D. (2023). Gpts are gpts: An early look at the labor market impact potential of large language models. *arXiv*.

Farboodi, M. and Veldkamp, L. (2021). A model of the data economy. Technical report, National Bureau of Economic Research Cambridge, MA, USA.

Gao, P., Lee, C., and Murphy, D. (2019). Municipal borrowing costs and state policies for distressed municipalities. *Journal of Financial Economics*, 132(2):404–426.

Gao, P., Lee, C., and Murphy, D. (2020). Financing dies in darkness? the impact of newspaper closures on public finance. *Journal of Financial Economics*, 135(2):445–467.

Gofman, M. and Jin, Z. (2024). Artificial intelligence, education, and entrepreneurship. *The Journal of Finance*, 79(1):631–667.

Goldsmith-Pinkham, P., Gustafson, M. T., Lewis, R. C., and Schwert, M. (2023). Sea-level rise exposure and municipal bond yields. *The Review of Financial Studies*, 36(11):4588–4635.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624.

Grennan, J. and Michaely, R. (2020). Artificial intelligence and high-skilled work: Evidence from analysts. *Swiss Finance Institute Research Paper*, (20-84).

Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis*, 20:2546.

Jiang, W. (2017). Have instrumental variables brought us closer to the truth. *Review of Corporate Finance Studies*, 6(2):127–140.

Kline, P. and Moretti, E. (2013). People, places, and public policy: Some simple welfare economics of local economic development programs. *Annual Review of Economics*, 5:629–662.

Kline, P. and Moretti, E. (2014). People, places, and public policy: Some simple welfare economics of local economic development programs. *Annual Review of Economics*, 6:629–662.

Larcker, D. F. and Rusticus, T. O. (2010). On the use of instrumental variables in accounting research. *Journal of Accounting and Economics*, 49(3):186–205.

Makridis, C. A., Hakakian, J., Strebel, T., and Alterovitz, G. (2024). Measuring and understanding differences in private and public sector technology jobs: Evidence from artificial intelligence job posting data. *SSRN working paper*.

Makridis, C. A. and Mishra, S. (2022). Artificial intelligence as a service, economic growth, and well-being. *Journal of Services Research*, 25(4).

Mihet, R. and Philippon, T. (2019). The economics of big data and artificial intelligence. *International Finance Review*, 20.

Moretti, E. (2011). The new geography of jobs.

Murnane, R. J. and Willett, J. B. (2011). Methods matter: Improving causal inference in educational and social science research. *Oxford University Press*.

Painter, M. (2020). An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics*, 135(2):468–482.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, 98(5, Part 2):S71–S102.

Rotemberg, J. (1983). Instrument variable estimation of misspecified models. *Sloan School of Management Working Paper 1508-83*.

Ruggles, S., Flood, S., Foster, S., Goeken, R., Pacas, J., Schouweiler, M., and Sobek, M. (2021). IPUMS USA: Version 11.0 [dataset]. *Minneapolis, MN: IPUMS*.

Schultz, P. (2012). The market for new issues of municipal bonds: The roles of transparency and limited access to retail investors. *Journal of Financial Economics*, 106(3):492–512.

Schwert, M. (2017). Municipal bond liquidity and default risk. *Journal of Finance*, 72(4):1683–1722.

Wooldridge, J. (2002). Econometric analysis of cross section and panel data. *MIT Press*.

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Tables and Figures

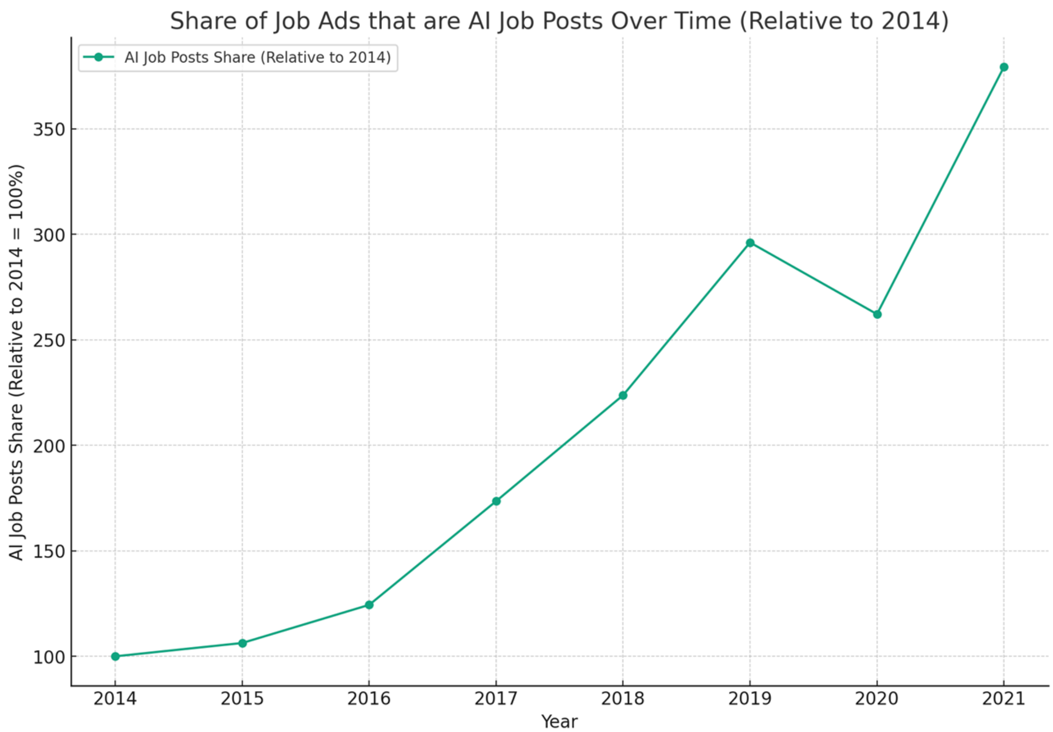

Figure 1: Growth of AI Job Market: This line graph illustrates the trend in the share of job advertisements for AI-related positions from 2014 to 2021. The y-axis represents the relative percentage change compared to the base year 2014, indicating a substantial increase in AI job market share over the years. Notably, there's a sharp rise from 2016 onward.

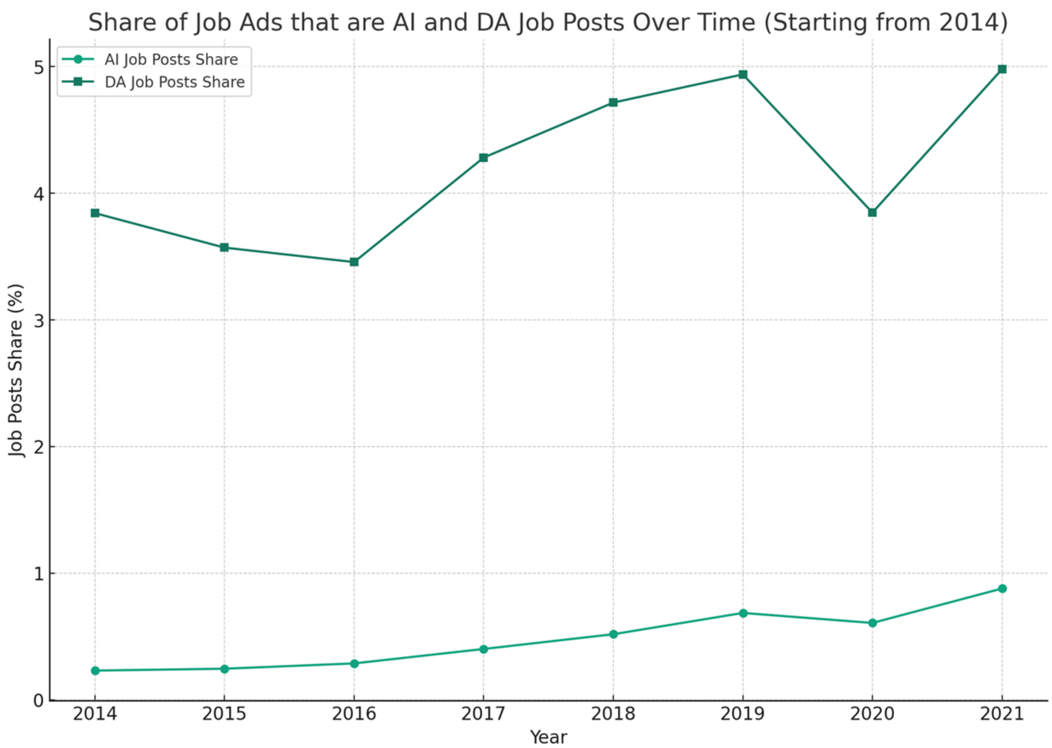

Figure 2: Comparison of AI and DA Job Market Trends: The graph displays the percentage of job postings in AI (Artificial Intelligence) and DA (Data Analytics) from 2014 to 2021. The percentages represent the share of total job advertisements that are categorized within these skill groups. Both fields show growth over time, with AI positions experiencing a more notable increase, indicating a significant surge in demand for AI skills in the job market.

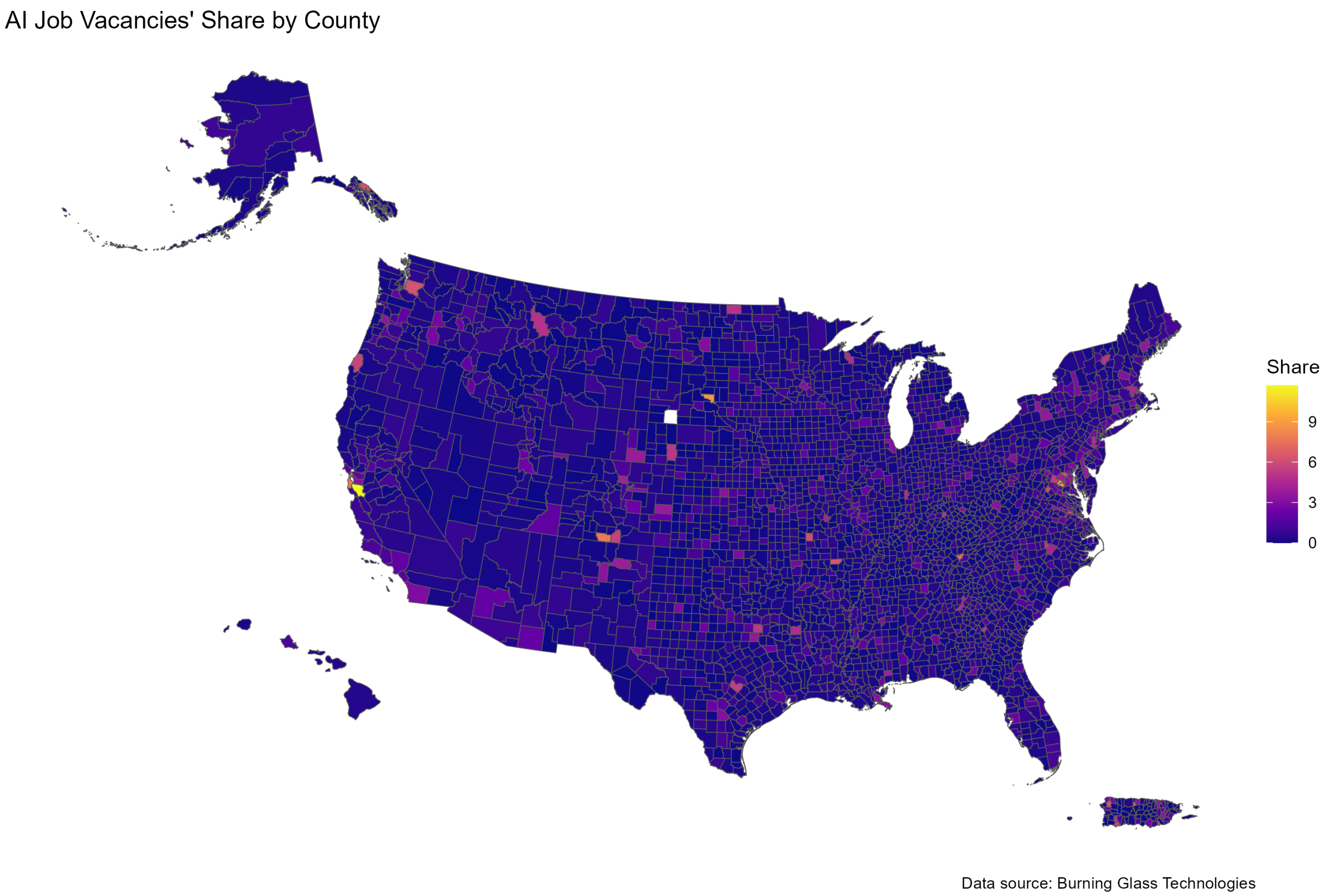

Figure 3: The map provides a county-level analysis of the Artificial Intelligence Intensity of each county. Artificial Intelligence shares are calculated as the ration of the cumulative number of job ads classified as AI ads to cumulative number of job ads posted online for the period 2014-2021.The Artificial Intelligence job ads as a share of all ads is represented through a color gradient. Areas with higher concentrations of the statistic are indicated in brighter colors. The shares are expressed in percentage points.

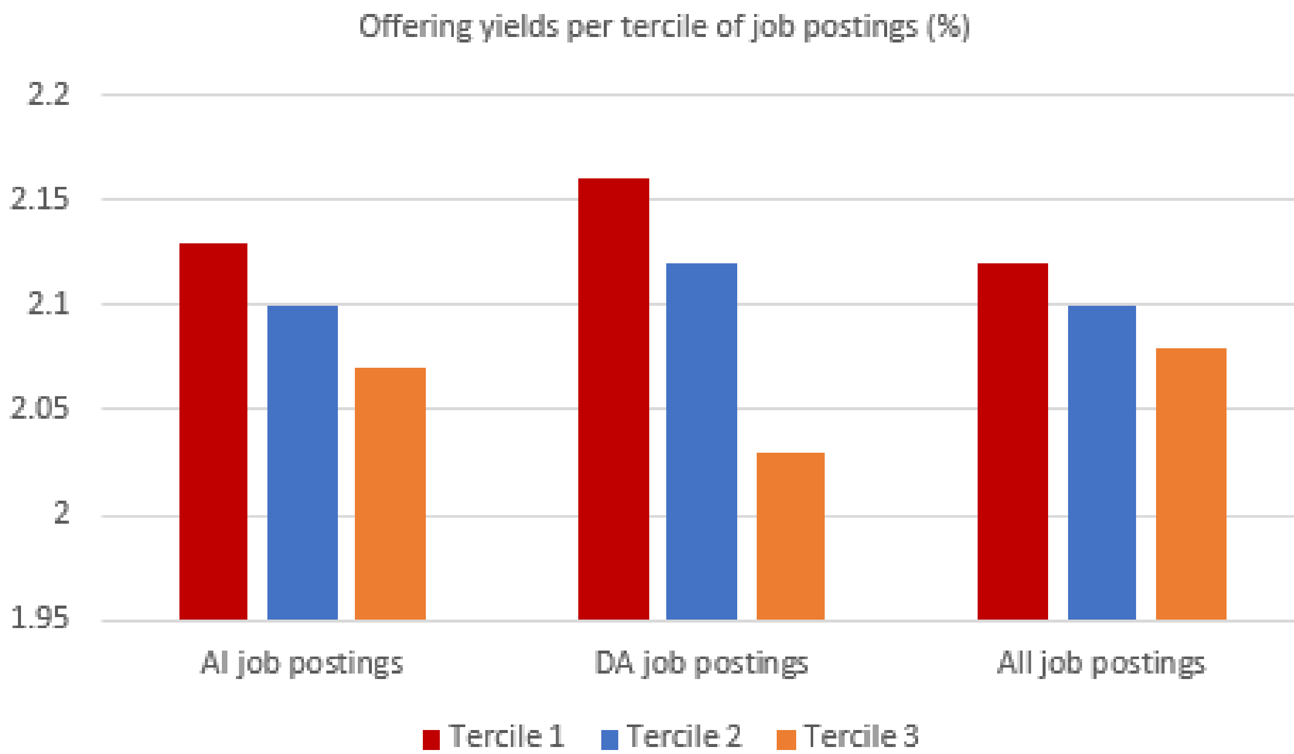

Figure 4: AI - DA job postings and offering yields: The graph displays the evolution of offering yields of municipal bonds during the period 2014-2021 per tercile of AI (Artificial Intelligence) and DA (Data Analytics) job postings per county.

Table 1. Information about Sample Construction

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

Panel A: Sample for Bond-level Analysis

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: Sample for Local Economy Analysis

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

Panel C: Sample for County Finances Analysis

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: Sample for County -Volume level Analysis

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

Table 2. 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 local economy sample. Panel C reports summary statistics for the county finances sample. Panel D reports summary statistics for the county-level volume sample. All the variables are defined in the Internet Appendix.

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: 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

Panel C: County 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: County -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

Table 3. Artificial Intelligence – Data Analytics Job Postings and Bond Yields: Main Results

This table presents results for the effect of the county - level labor investments in artificial intelligence and data analytics on municipal bond market. Panel A presents the estimates of the second stage of the 2SLS instrumental variables (IV) regressions for the effect of AI – DA job postings on municipal bond offering yields controlling for the standard bond and county level variables. The dependent variable is the offering yield of municipal bonds in the primary market. The main independent variables are the instrumented number of AI (in column (1)), DA (in column (2)) and AI – DA (in column (3)) employees per 1,000 firms, measured at the county level. All the remaining bond-specific and county-specific variables are defined in the Internet Appendix. Standard errors are clustered by county and p-values are reported in parentheses. ∗p < 0.1, ∗∗p < 0.05, ∗∗∗p < 0.01.

Second – Stage Regressions

	Offering yields (%)		
	(1)	**(2)**	**(3)**
Instrumented AI workers (x100)	-0.051**		
	(0.042)		
Instrumented DA workers (x100)		-0.028**	
		(0.025)	
Instrumented AI – DA workers (x100)			-0.019**
			(0.026)
Rating	-0.060***	-0.060***	- 0.060***
	(0.000)	(0.000)	(0.000)
Coupon Rate	-0.005	-0.005	-0.005
	(0.625)	(0.627)	(0.625)
Maturity	0.074***	0.074***	0.074***
	(0.000)	(0.000)	(0.000)
Maturity Inverse	-0.705***	-0.706***	-0.706***
	(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)
Per capita Income (x1000)	0.006***	0.008***	0.008***
	(0.009)	(0.006)	(0.009)
Population (x1000)	-0.001	-0.001	-0.001
	(0.588)	(0.792)	(0.961)
Employment Growth	0.552**	0.525**	0.540**
	(0.027)	(0.036)	(0.030)
Population Growth	-0.778	-1.200	-1.100
	(0.323)	(0.192)	(0.204)
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 4. Artificial Intelligence – Data Analytics Job Postings and Bond Yields: Validity and Excludability

This table presents the results for the validation and the excludability of the instrument used in our analysis. Panel A presents the estimates of the first stage regressions of a two-stage instrumental variable analysis (2SLS) for the effect of the AI and DA 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. Panel B presents the estimates of the second stage of the 2SLS instrumental variables (IV) regressions for the effect of AI – DA job postings on municipal bond offering yields controlling for the standard bond and county variables, expanding them to account for the excludability restriction The variable AI (DA) (AI-DA) workers is the number of AI (DA) (AI-DA) related job postings per 1,000 firms, measured at the county level. Panel C presents the results of a placebo test, wherein the AI-DA labor investments and the corresponding Bartik measures assigned to a bond are applied to another bond of the same issuer and with the same characteristics (coupon, duration, rating. callable, insured) of a different period out of the sample (2000-2013). Panel D displays the outcomes of a placebo test, wherein the AI-DA labor investments and the corresponding Bartik measures of one county are applied to another county with similar characteristics (population, population growth, per capita income, and employment growth), but differing in terms of AI-DA labor investments. The variable Bartik_AI (DA) (AI-DA) is the respective bartik measure for the AI (DA) (AI-DA) related employees. Appendix A provides detailed definitions of all variables. 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.

Panel A: Relevance of the Instrument

	AI workers		**DA workers**		**AI -DA workers**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Bartik_AI	0.078^{***}	0.057^{***}				
	(0.000)	(0.000)				
Bartik_DA			0.049^{***}	0.036^{***}		
			(0.000)	(0.000)		
Bartik_AI-DA					0.059^{***}	0.042^{***}
					(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	0.869	0.889	0.912	0.926	0.903	0.921
Partial R^2	0.2193	0.130	0.064	0.041	0.096	0,058
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

Panel B: Exclusion Restriction

	Offering yields (%)		
	(1)	**(2)**	**(3)**
Instrumented AI workers (x100)	0.055*		
	(0.053)		
Instrumented DA workers (x100)		0.029**	
		(0.035)	
Instrumented AI – DA workers (x100)			0.020**
			(0.036)
Rating	-0.060***	-0.060***	- 0.060***
	(0.000)	(0.000)	(0.000)
Coupon Rate	-0.006	-0.006	-0.006
	(0.590)	(0.591)	(0.589)
Maturity	0.074***	0.074***	0.074***
	(0.000)	(0.000)	(0.000)
Maturity Inverse	-0.708***	-0.709***	-0.709***
	(0.000)	(0.000)	(0.000)
Amount (ln)	-0.016***	-0.016***	-0.016***
	(0.000)	(0.000)	(0.000)
Call or Insured	0.169***	0.169***	0.169***
	(0.000)	(0.000)	(0.000)
Risk Free	0.024***	0.024***	0.024***
	(0.000)	(0.000)	(0.000)
Per capita Income (x1000)	0.006**	0.008**	0.008**
	(0.045)	(0.026)	(0.026)
Population (x1000)	0.002	0.004	0.003
	(0.266)	(0.153)	(0.177)
Employment Growth	0.482*	0.422	0.448*
	(0.068)	(0.127)	(0.096)
Population Growth	-0.475	-0.681	-0.683
	(0.541)	(0.438)	(0.420)
Poverty Rate (%)	0.001	-0.001	-0.001
	(0.833)	(0.771)	(0.869)
Religion (x1000)	-0.000	-0.000	-0.000
	(0.464)	(0.259)	(0.332)
Seniors (%)	-1.933	-2.157	-2.169
	(0.152)	(0.124)	(0.119)
Female (x1000)	-0.004	-0.007	-0.006
	(0.246)	(0.147)	(0.169)
White (%)	0.243	0.039	0.099
	(0.759)	(0.964)	(0.906)
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	236,198	236,198	236,198
R^2	0.730	0.728	0.729

Panel C: Time Placebo Test

	Offering Yields (%)		
	(1)	**(2)**	**(3)**
Instrumented AI workers (x100)	-0.000		
	(0.976)		
Instrumented DA workers (x100)		-0.002	
		(0.861)	
Instrumented AI – DA workers (x100)			-0.001
			(0.869)
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	39,929	39,929	39,929
R^2	0.773	0.773	0.773

Panel D: Geographic Placebo Test

	Offering Yields (%)		
	(1)	**(2)**	**(3)**
Instrumented AI workers (x100)	0.018		
	(0.406)		
Instrumented DA workers (x100)		0.006	
		(0.397)	
Instrumented AI – DA workers (x100)			0.004
			(0.400)
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	108,463	108,463	108,463
R^2	0.747	0.743	0.745

Table 5. Artificial Intelligence – Data Analytics Job Postings and Bond Yields: Robustness Check

This table presents a test to check for the robustness of the results. The table reports results of the secondary market yields using a difference – in – differences approach utilizing the launch of the ChartGPT as an exogenous shock in a time window of (-2, +2) months. The variable Post takes the value of 1 (0) if the trade conducted after (before) the introduction of ChatGPT. The counties are classified as having high rank if their total labor investments in AI – DA belongs to the top tercile of the sample in a year, and zero otherwise. All the remaining bond-specific and county-specific variables are defined in the Internet Appendix. Standard errors are clustered by county and p-values are reported in parentheses. ∗p < 0.1, ∗∗p < 0.05, ∗∗∗p < 0.01.

Secondary Market

	Yields (%)			
	(1)	**(2)**	**(3)**	**(4)**
Post	-0.540***	-0.510***	-0.560***	-0.544***
	(0.000)	(0.000)	(0.000)	(0.000)
Post x High (AI – DA) Rank		-0.037***		-0.021***
		(0.000)		(0.008)
Instrument 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 6. Alternative Explanation: Deteriorating Economic Conditions

This table presents two-stage instrumental variable (IV) regression results on the effect of county - level labor investments in artificial intelligence and data analytics on municipal bond market. For brevity, the table reports only the second-stage regression results. Panel A presents results by utilizing variation of the AI – DA labor investments within counties with similar per capita income. Panel B presents results by utilizing variation of the AI – DA labor investments within adjacent counties. All the remaining bond-specific and county-specific variables are defined in the Internet 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: Within county characteristics variation

	Offering Yields (%)		
	(1)	**(2)**	**(3)**
Instrumented AI workers (x100)	-0.055**		
	(0.038)		
Instrumented DA workers (x100)		-0.030**	
		(0.023)	
Instrumented AI – DA workers (x100)			-0.020**
			(0.024)
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	0.728	0.728	0.728

Panel B: Within adjacent county variation

	Offering Yields (%)		
	(1)	**(2)**	**(3)**
Instrumented AI workers (x100)	-0.048*		
	(0.060)		
Instrumented DA workers (x100)		-0.028**	
		(0.026)	
Instrumented AI – DA workers (x100)			-0.020**
			(0.028)
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 7. Artificial Intelligence – Data Analytics Job Postings and Bond Yields: Bond Risk Characteristics

This table presents two-stage instrumental variable (IV) regression results on the effect of county - level labor investments in artificial intelligence and data analytics on municipal bond market. For brevity, the table reports only the second-stage regression results. The table reports results based on individual bond characteristics. 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). The county-level independent variables are lagged by a period. 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 workers (x100)	-0.004		
	(0.885)		
Instrumented AI workers X Long Maturity (x100)	-0.106***		
	(0.000)		
Instrumented DA workers (x100)		-0.012	
		(0.352)	
Instrumented DA workers X Long Maturity (x100)		-0.035***	
		(0.000)	
Instrumented AI – DA workers (x100)			-0.009
			(0.392)
Instrumented AI – DA workers X Long Maturity (x100)			-0.026***
			(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	0.589	0.584	0.586

Panel B: High vs Low Credit Rating Bonds

	Offering Yields (%)		
	(1)	**(2)**	**(3)**
Instrumented AI workers (x100)	-0.031		
	(0.293)		
Instrumented AI workers X Low Rating (x100)	-0.035**		
	(0.013)		
Instrumented DA workers (x100)		-0.028	
		(0.181)	
Instrumented DA workers X Low Rating (x100)		-0.015***	
		(0.000)	
Instrumented AI – DA workers (x100)			-0.012
			(0.191)
Instrumented AI – DA workers X Low Rating (x100)			-0.010***
			(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	0.713	0.711	0.712

Table 8. Artificial Intelligence – Data Analytics Job Postings and Bond Yields: Cross – Sectional Analysis

This table presents two-stage instrumental variable (IV) regression results on the effect of county - level labor investments in artificial intelligence and data analytics on municipal bond market. For brevity, the table reports only the second-stage regression results. The table presents results based on the number of small firms (less than 49 employees) in each county.The counties are classified as having low number of small firms if their number of small firms belongs to bottom tercile of the sample in the year 2013, and zero otherwise. Standard errors are clustered by county and p-values are reported in parentheses. ∗p < 0.1, ∗∗p < 0.05, ∗∗∗p < 0.01.

Small vs Large Firms within counties

	Offering Yields (%)		
	(1)	**(2)**	**(3)**
Instrumented AI workers (x100)	-0.118*		
	(0.077)		
Instrumented AI workers X Low small firms (x100)	0.071		
	(0.178)		
Instrumented DA workers (x100)		-0.075**	
		(0.016)	
Instrumented DA workers X Low small firms (x100)		0.048**	
		(0.029)	
Instrumented AI - DA workers (x100)			-0.049**
			(0.020)
Instrumented AI – DA workers X Low small firms (x100)			0.031**
			(0.041)
Control Variables	Yes	Yes	Yes
Year 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	0.727	0.728

Table 9. Artificial Intelligence – Data Analytics Job Postings and Local Economy

This table presents the effects of the AI – DA labor investments on the local finances using an entropy matching procedure based on the county characteristics but different in their level of exposure to AI -DA labor investments. Panel A reports results based on the real productivity. Panel B reports results based on the real productivity of a county's economy comparing counties with similar characteristics but different level of labor investments in AI- DA. The variable Treat takes the value of 1 (0) if the county belongs to the highest (lowest) quartile of each year's labor investments in AI-DA. Panel B reports results based on the number of small firm (<49 employes) in each county. The counties are classified as having low number of small firms if their number of small firms belongs to bottom tercile of the sample in the year 2013, and zero otherwise. The county-level independent variables are lagged by a period. Standard errors are clustered by county and p-values are reported in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Panel A: Effects on real productivity

	Productivity$_{t+1}$	**Productivity$_{t+2}$**	**Productivity$_{t+3}$**
	(1)	**(2)**	**(3)**
Real Productivity $_t$	0.994***	0.994***	0.986***
	(0.000)	(0.000)	(0.000)
Treat	0.003***	0.008***	0.010***
	(0.000)	(0.000)	(0.000)
Observations	21,555	18,475	15,396
R^2	0.979	0.963	0.945

Panel B: Effects on real productivity based on the number of small firms within the county

	Productivity$_{t+1}$	**Productivity$_{t+2}$**	**Productivity$_{t+3}$**
	(1)	**(2)**	**(3)**
Real Productivity $_t$	0.996***	0.992***	0.987***
	(0.000)	(0.006)	(0.000)
Treat	0.005***	0.011***	0.017***
	(0.002)	(0.000)	(0.000)
Treat X Low Small firms	-0.010	-0.004	-0.009**
	(0.599)	(0.135)	(0.030)
Observations	21,555	18,475	15,396
R^2	0.979	0.961	0.942

Table 10. Artificial Intelligence – Data Analytics: Local Finances

This table presents the effects of the AI – DA labor investments on the local finances using an entropy matching procedure based on the county characteristics but different in their level of exposure to AI -DA labor investments. Panel A reports results based on the total revenues of the municipalities aggregated at the county- level. Panel B reports results based on the total taxes of the municipalities aggregated at the county- level. Panel C reports results based on the sales taxes of the municipalities aggregated at the county- level. Panel D reports results based on the property taxes of the municipalities aggregated at the county- level. The variable Treat takes the value of 1 (0) if the county belongs to the highest (lowest) quartile of each year's labor investments in AI-DA.The county-level independent variables are lagged by a period. Standard errors are clustered by county and p-values are reported in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Panel A: Total Revenues

	Total Revenues$_{t+1}$	**Total Revenues$_{t+2}$**	**Total Revenues$_{t+3}$**
	(1)	**(2)**	**(3)**
Total Revenues $_t$	0.910***	0.901***	0.860***
	(0.000)	(0.000)	(0.000)
Treat	0.088***	0.118***	0.172***
	(0.000)	(0.000)	(0.000)
Time Fixed Effects	Yes	Yes	Yes
Observations	13,570	11,576	9,326
R^2	0.827	0.796	0.732

Panel B: Total Taxes

	Total Taxes$_{+1}$	**Total Taxes$_{+2}$**	**Total Taxes$_{+3}$**
	(1)	**(2)**	**(3)**
Total Taxes $_t$	0.928***	0.901***	0.891***
	(0.000)	(0.000)	(0.000)
Treat	0.080***	0.115***	0.178***
	(0.000)	(0.000)	(0.000)
Time Fixed Effects	Yes	Yes	Yes
Observations	12,090	10,308	8,283
R^2	0.827	0.796	0.775

Panel C: Sales Taxes

	Total Sales$_{+1}$	**Total Sales$_{+2}$**	**Total Sales$_{+3}$**
	(1)	**(2)**	**(3)**
Sales Taxes $_t$	0.967***	0.962***	0.945***
	(0.000)	(0.000)	(0.000)
Treat	0.022	0.026	0.178*
	(0.273)	(0.302)	(0.071)
Time Fixed Effects	Yes	Yes	Yes
Observations	12,637	10,767	8,651
R^2	0.926	0.908	0.876

Panel D: Property Taxes

	Property Taxes$_{+1}$	**Property Taxes$_{+2}$**	**Property Taxes$_{+3}$**
	(1)	**(2)**	**(3)**
Property Taxes $_t$	0.783***	0.901***	0.772***
	(0.000)	(0.000)	(0.000)
Treat	0.323***	0.378***	0.423***
	(0.000)	(0.000)	(0.000)
Time Fixed Effects	Yes	Yes	Yes
Observations	12,484	10,677	8,642
R^2	0.5548	0.531	0.775

Table 11. Artificial Intelligence – Data Analytics and Municipal Bonds: Volume Analysis

This table presents two-stage instrumental variable (IV) regression results on the effect of county - level labor investments in artificial intelligence and data analytics on municipal bond market. For brevity, the table reports only the second-stage regression results. Panel A reports results about the amount of bond issuance in a county per year. Panel B reports results about the structure of issuance. The dependent variable is a ratio of the long duration bonds compare to short duration bonds conditional of at least one bond issuance in the county during the year. All the remaining bond-specific and county-specific variables are defined in the Internet Appendix. 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 workers (x100)	0.602		
	(0.502)		
Instrumented DA workers (x100)		0.407	
		(0.297)	
Instrumented AI – DA workers (x100)			0.318
			(0.267)
Control Variables	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Clustered SE	County	County	County
Observations	11,081	11,081	11,081
R^2	-	-	-

Panel B: Short to Long issuances

	Structure of Issuances		
	(1)	**(2)**	**(3)**
Instrumented AI workers (x100)	-0.043*		
	(0.066)		
Instrumented DA workers (x100)		-0.019*	
		(0.090)	
Instrumented AI – DA workers (x100)			-0.014*
			(0.080)
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	4,992	4,992
R^2	-	-	-

A Internet Appendix

A.1 Variables definition

A.1.1 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.

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.

A.1.2 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.

ALL 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.

A.1.3 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 DA: The Bartik instrument for Data Analytics-related job postings as introduced by

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020).

A.1.4 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.

A.1.5 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.

A.2 Measuring Artificial Intelligence Job Postings

Table A.1: Top 4 and Bottom 4 Occupations by Artificial Intelligence Skills Engagement in 2021

Occupation	Data Analytics	Artificial Intelligence
Software Developers, Applications	1,189,203	334,698
Computer Occupations, All Other	981,458	224,961
Computer and Information Research Scientists	200,076	125,174
Database Administrators	412,318	50,291
...	...	...
Food Cooking Machine Operators and Tenders	7	0
Environmental Science Teachers, Postsecondary	10	0
Forging Machine Setters, Operators, and Tenders	1	0
Funeral Service Managers	5	0

A.3 Keywords for AI - DA job postings

DA Keywords	AI Keywords
Apache Hadoop	Apache Ant
Apache Hive	Apache Spark
Apache Kafka	Artificial Intelligence
Bayesian Inference	Automated Testing
Bayesian Modeling	Automation Consulting
Bayesian Networks	Automation Systems
Big Data	Automation Techniques
Big Data Analytics	Automation Tools
Data Analysis	AWS Elastic MapReduce (EMR)
Data Analytics	BigQuery
Data Conversion	Boosting (Machine Learning)
Data Engineering	Caffe Deep Learning Framework
Data Management	Cluster Analysis
Data Modeling	Clustering
Data Science	Clustering Algorithms
Data Visualization	Computer Vision
Extraction Transformation and Loading (ETL)	Convolutional Neural Network (CNN)
Microsoft Power BI	Decision Trees
Microsoft SQL	Deep Learning
MongoDB	Deeplearning4j

DA Keywords	AI Keywords
MySQL	Machine Learning
NoSQL	Machine Vision
Oracle PL/SQL	MapReduce
PostgreSQL	Kubernetes
Predictive Analytics	Natural Language Processing
Predictive Models	Natural Language Toolkit (NLTK)
Prepare Spreadsheets	Neural Networks
Spreadsheets	Splunk
SQL	Supervised Learning (Machine Learning)
SQL Injection	Support Vector Machines (SVM)
SQL Plus	TensorFlow
SQL Server	Torch (Machine Learning)
SQL Server Analysis Services (SSAS)	
SQL Server Reporting Services (SSRS)	
SQL*Loader	
SQLAlchemy	
SQLite	
Tableau	
Transact-SQL	

A.4 Goldsmith-Pinkham et al. (2020) Diagnostics

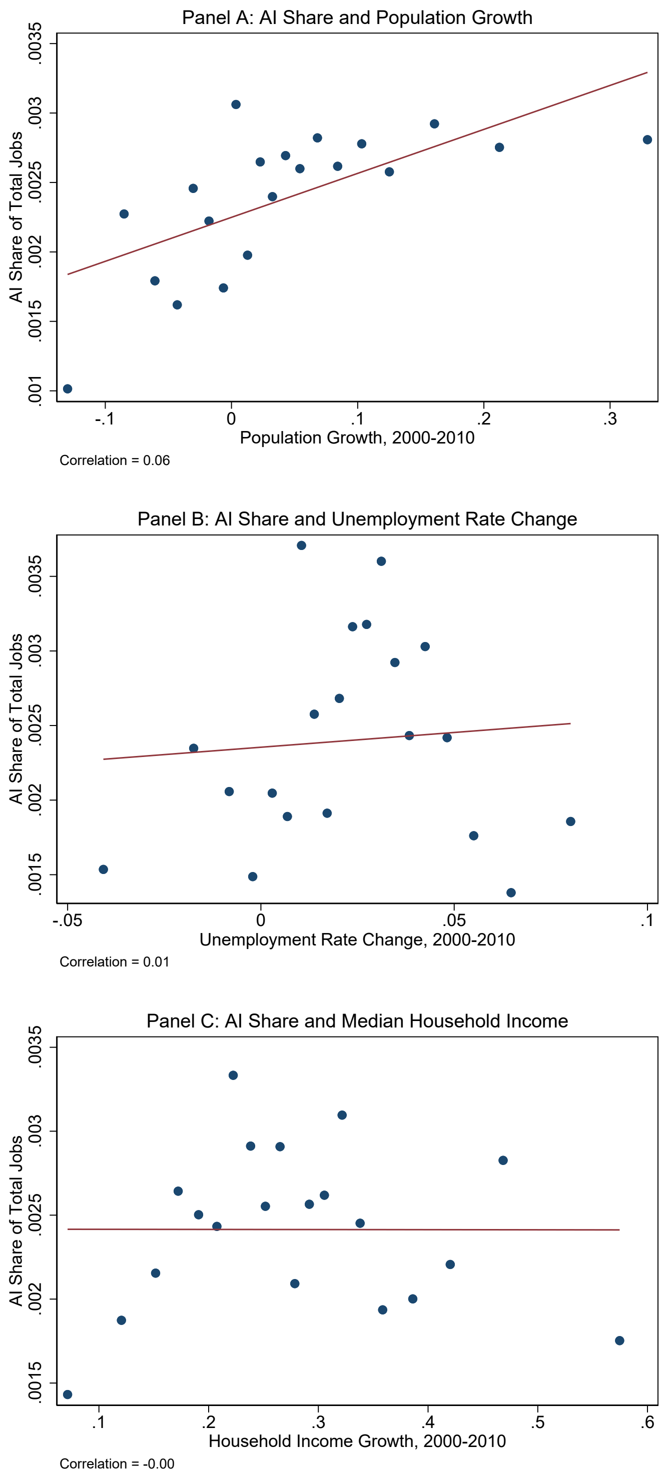

Figure A.1: AI Share of Job Postings in 2011-12 and Historical Growth

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.

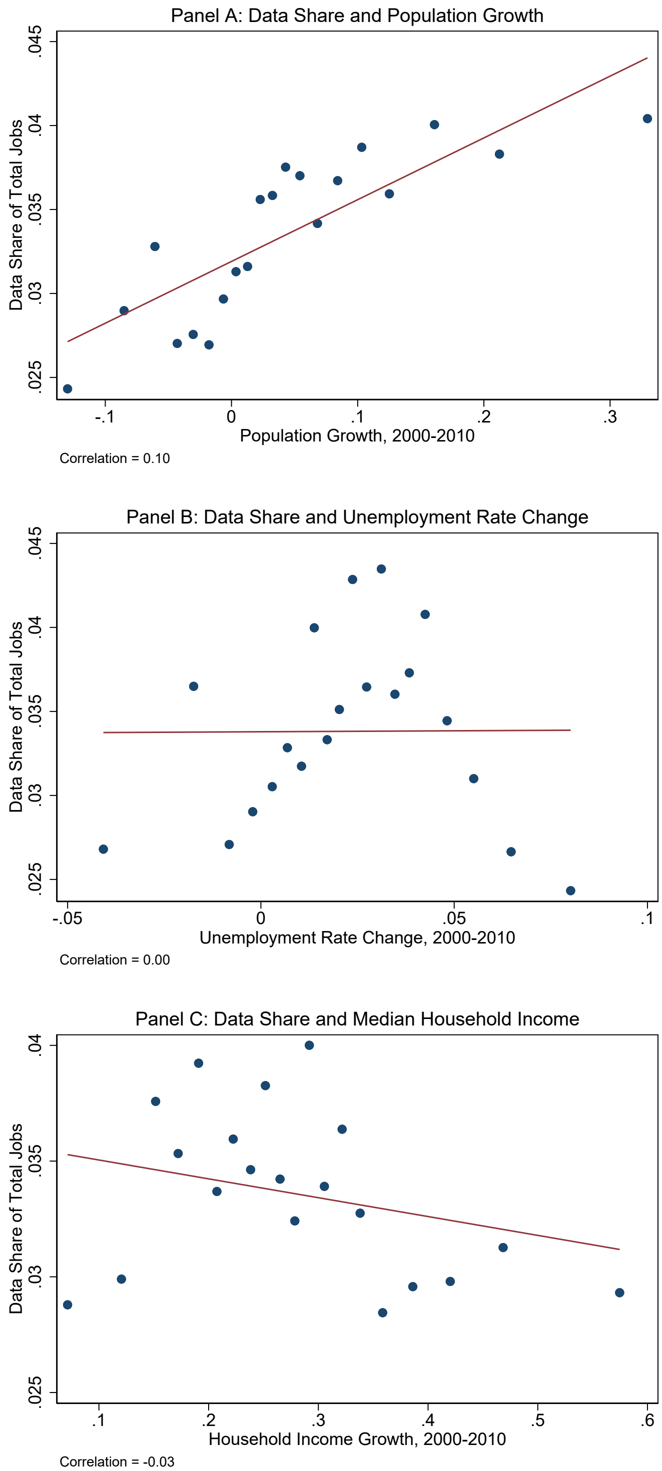

Figure A.2: Data Analytics Share of Job Postings in 2011-12 and Historical Growth

Source: Census Bureau and Lightcast. The figures show a binscatter between the proportion of data analytics 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.