AI Exposure and Household Financial Fragility

Abstract

We study how the emergence of generative artificial intelligence (AI) affects household financial fragility in the United States. We construct a county-level measure of AI exposure and use the launch of ChatGPT in November 2022 as an exogenous technological shock. We find that counties with higher AI exposure experience greater financial fragility following ChatGPT's release. Households in these counties exhibit slower bank deposit growth, lower equity investment growth in AI-exposed industries, reduced borrowing, and higher student loan and credit card delinquencies. At the aggregate level, high-AI-exposure counties experience weaker employment and wage growth and slower GDP growth. Overall, the results suggest that the diffusion of generative AI may increase household financial vulnerability during periods of rapid technological change.

JEL classification:

Keywords: Generative AI, ChatGPT, household financial fragility, bank deposit, equity investment, debt delinquency

I. Introduction

The introduction of General Purpose Technologies (GPT) in November 2022 represents a shock to the workplace with the potential to transform the workplace and alter how white-collar labor is organized. What makes generative AI particularly striking is not only its potential application but also the speed of adoption. According to Swiss investment bank UBS research, ChatGPT reached 100 million monthly active users within just two months of its launch. This pace of adoption even surpasses earlier transformative technologies such as the internet, search engines, and personal computers. For example, personal computers took nearly 20–25 years to reach 100 million users. The unprecedented diffusion of generative AI suggests that its economic effects may materialize much more rapidly than those of prior technologies, in worker productivity, job opportunities, and ultimately household economic well-being. Therefore, it is important to understand and assess how this technological shift influences household financial fragility.

While a rapidly expanding research has documented AI's impact on firms and labor demand (Eisfeldt, Schubert and Zhang, 2023; Babina, Fedyk, He and Hodson, 2024, 2023a,b; Hui, Reshef and Zhou, 2024), much less is known about its impact on household financial behavior. Prior studies show that the introduction of LLMs could affect nearly 80% of the U.S. workforce across all wage levels, especially for high-income jobs (Eloundou, Manning, Mishkin and Rock, 2024). At the firm level, adoption of AI leads to shifts in workforce composition (Babina et al., 2023b). At the labor market level, evidence suggests that generative AI reduces demand for online freelancers (Hui et al., 2024). Similarly, Demirci, Hannane and Zhu (2025) document a 21% reduction in automation-prone jobs in eight months after the introduction of ChatGPT. Unlike industrial robots, which disproportionately displaced routine manual workers (Acemoglu and Restrepo, 2018, 2020), generative AI appears to directly affect white-collar, knowledge-intensive, and relatively high-wage occupations. This shift raises new questions about how households, particularly those specialized in knowledge work respond to rapid technological adoption.

Yet, despite this growing body of evidence on firms and workers, little is known about the household financial behaviors response to generative AI. On the one hand, AI could enhance productivity and earnings for some workers (Brynjolfsson, Li and Raymond, 2025; Noy and Zhang, 2023), which may strengthen household finance. On the other hand, AI may displace human workers in certain roles, resulting in job losses and fewer new hires, which may lead households to adopt more conservative financial behaviors. The net effect is ambiguous and may emerge more quickly than households can adjust.

This paper fills the gap by examining how the emergence of ChatGPT affects household financial decisions, including bank deposits, equity investments, and debt management. The first challenge of the empirical analysis is to measure local AI exposure. We use a multi-step methodology that builds from task-level AI exposure to county-level AI exposure. First, following Eloundou et al. (2024) and Eisfeldt et al. (2023), we employ GPT-4 model to evaluate the potential of 19,281 occupational tasks for total 924 occupations in the O*NET database, classifying each task into four exposure categories based on whether generative AI can reduce task completion time. We develop a novel county-level measure of AI exposure that captures the share of local employment in tasks susceptible to automation by large language models. This approach creates a granular measure of how each county's employment exposed to generative AI disruption. The high AI exposure counties concentrate in finance and information sectors, while low-exposure counties rely heavily on physical labor-intensive industries like construction and manufacturing.

Our empirical strategy exploiting the ChatGPT's release in November 2022 as a quasi-experimental shock. We employ a difference-in-differences framework that compares changes in local household financial behaviors before and after ChatGPT's release across counties with varying levels of AI exposure. This approach allows us to isolate the impact of AI exposure from other macroeconomic trends that affect all counties simultaneously.

Our findings reveal substantial and economically meaningful effects of AI exposure on household financial fragility. First, households in high AI exposure counties experience slower

growth in bank deposits. Counties in the top quartile of exposure see 1.8 percentage points lower deposit growth relative to others. Retail deposit growth decreases, while institutional deposits rise, indicating that individual households have reduced savings while institutions experience increased deposit growth.

Second, we find that household investment behavior changes. Equity investment growth in top AI-exposed industries declines by more than 5 percentage points in high AI-exposure counties. This pattern may reflect both reduced household willingness to take risk and weakened expectations about future returns in AI-intensive sectors.

Third, debt outcomes provide further evidence of fragility. We find significant increases in student loan and credit card delinquencies, while mortgage and auto loan delinquencies remain unaffected. Households appear to prioritize repayment of secured obligations while defaulting on unsecured debt. At the same time, mortgage borrowing itself contracts: home purchase applications decline by more than 2 percentage points in high-exposure counties, and home improvement applications fall nearly 10 percentage points. These magnitudes highlight households' reluctance to make large or discretionary financial commitments amid AI-driven uncertainty.

Finally, through our channel tests, we find that high AI-exposure counties exhibit weaker employment growth, lower wages, and slower GDP growth following the ChatGPT's release. For example, counties in the top quartile of AI exposure experience a 0.45 percentage points decrease in employment growth and 1.3 percentage points decline in GDP growth relative to less-exposed counties. These labor market and macroeconomic channels provide support for the fragility observed in household financial behaviors, which is consistent with Eisfeldt et al. (2023) that suggest that

Taken together, these findings highlight a novel channel through which generative AI adoption shapes household financial fragility. They underscore the importance of considering household-level outcomes in ongoing debates about the economic and distributional consequences of AI adoption. More broadly, our results suggest that while generative AI

may improve productivity, it also introduces risks for household financial stability.

This paper makes several contributions to the burgeoning literature on the impact of generative AI. First, while existing studies focus primarily on firm-level impacts of AI adoption (Eisfeldt et al., 2023; Babina et al., 2023a,b, 2024), we shift the focus to households and provide novel evidence that the emergence of generative AI has immediate consequences for household financial fragility across U.S. counties. Our study documents changes in bank deposits, equity investments, debt delinquency, and credit demand after the ChatGPT shock. Additionally, we find that AI exposure increases defaults on unsecured debt (student loans and credit cards) but leaves secured debt (mortgages and auto loans) unaffected, which suggest important distinctions in how households adjust their financial strategies amid AI-driven economic uncertainty.

Our study complements the broader literature on the impact of technological shocks (Acemoglu and Restrepo, 2018, 2020, 2022). Past automation shocks disproportionally affect lower-skilled and routine workers, e.g., Acemoglu and Restrepo (2020). In contrast, Generative AI represents a different pattern: rather than primarily targeting routine manual jobs, recent research suggests it may disproportionately affect highly educated workers and high-income occupations (Eloundou et al., 2024). While prior studies emphasize employment and wage outcomes, they have not examined how these technological shocks affect financial behaviors of households. Our paper fills this gap by linking generative AI exposure directly to measures of household financial fragility. Moreover, the adoption of generative AI is occurring at unprecedented pace, leaving households limited time to adjust precautionarily. We show that the financial fragility effects emerge almost immediately after ChatGPT's release, as households reduce deposits, cut equity investments, and default selectively on unsecured debt. This rapid response underscores another key difference between generative AI and prior technological shocks: while past disruptions unfolded gradually, giving households some time to adapt, the generative AI shock has rapidly produced stress on local household finance.

Third, the existing studies examine the impact of AI on workforce within a single platform or sector. For example, Demirci et al. (2025) studies the impact of Generative AI on the demand for online freelancers. Hui et al. (2024) investigate the impact of AI on employment outcomes on Upwork, a online freelancing platform. By contrast, our study shifts the focus to the broader household level, analyzing how AI adoption affects the financial decisions of all local households. This approach allows us to capture comprehensive adjustments in savings, investment, borrowing, and delinquency across counties, thereby providing a more complete picture of the economic consequences of rapid AI diffusion.

Our study differs from Acemoglu, Autor, Hazell and Restrepo (2022), who show that AI adoption alters hiring practices at the establishment level but find aggregate labor market effects too small to detect during 2010–2018. In contrast, we document that the rapid adoption of generative AI since 2022 generates immediate and substantial impacts on household financial fragility and local economic outcomes.

More broadly, our findings underscore that the diffusion of generative AI is not merely a productivity story but also a financial stability story. Households in high-exposure regions face heightened fragility, and local economies show early signs of stress. These results suggest that policymakers, regulators, and financial institutions should consider the household balance sheet as a central margin of adjustment in the era of AI. While generative AI promises long-run gains, its short-run consequences may create vulnerabilities and weaken economic resilience.

The rest of the paper proceeds as follows. Section II discuss the related literature. Section III describes the data and the construction of the key measures. Section IV reports empirical evidence. Section VII concludes.

II. Literature Review and Background

The rapid adoption of generative AI has attracted significant attention from researchers, with early studies focusing primarily on the implication of AI adoption on labor demand and firm-level outcomes. A burgeoning literature has investigated how AI adoption affects firm-level workforce composition and organizational structure. Babina et al. (2023a) examine firm-level AI investment, using employee resumes to measure firm-level AI investment. They find a spark increase in AI investments across sectors. The research reveals that AI-investing firms experience higher growth in sales, employment, market valuation, and product innovation. However, the same authors also find that AI-investing firms face higher systematic risks (Babina et al., 2023a).

Eisfeldt et al. (2023) examine how generative AI affects firm-level productivity and market valuations. They document significant positive effects on firm performance for companies with high AI exposure, suggesting that early adopters may gain competitive advantages. More directly addressing workforce restructure, Babina et al. (2023b) show that firms investing in AI tend to hire more educated workers, increase junior-level positions and decrease the share of workers in middle-management and senior roles. This research suggests that the investment of AI at workplace has profound organizational changes beyond simply job displacement, which could have significant impact on labor market dynamics.

Recent empirical evidence has begun to document the realized effects of AI adoption on employment outcomes. Using online freelancing platform, Demirci et al. (2025) document a 21% reduction in automation-prone jobs within eight months of ChatGPT's introduction, suggesting that AI's labor market effects materialize more rapidly than previous technological shocks. Similarly, Hui et al. (2024) also focus on online freelancers labor market and find that generative AI introduction has adverse effects on freelancers' employment opportunities, particularly in tasks involving writing, translation, and basic programming. Acemoglu et al. (2022) study the effect of artificial intelligence on labor markets using establishment-level data on online job vacancies. They observe the growth of AI-related job postings but find

that AI-adopted establishments reduce hiring in non-AI positions.

While the research on AI's firm-level and labor market impacts has grown rapidly, evidence on household and local economy effects remains limited. Previous literature has studied how international trade shock affect labor market and local economy. For example, Autor, Dorn and Hanson (2013) examine local exposure to international trade and find the exposure leads to employment decline and the persistent effects on employment and wages extended from directly-affected workers to local communities. This research demonstrates that economic shocks in labor market can have far-reaching effects on household and local communities. Other studies examine how automation technological shock affect labor market. For instance, Acemoglu and Restrepo (2020) investigate the impact of industrial robot on local labor market. They find negative automation effects on local employment and wages. Importantly, they find that automation effects are concentrated among workers without college education and in routine manual occupations. The same authors find that automation decreases wage (Acemoglu and Restrepo, 2018) and increases income inequality in the U.S. (Acemoglu and Restrepo, 2022).

The rapid adoption of generative AI in the workplace may influence employment and household finances through two competing channels. On the one hand, displacement effects can reduce earnings, increase income volatility, and heighten financial stress. On the other hand, productivity effects may enhance job performance and strengthen household balance sheets. The net impact remains an open question. While despite the growing literature on AI's economic impacts, existing research focuses primarily on firm-level outcomes and labor market, with limited attention to household and region effects. This represents an overlook in the literature, given that household financial stability is crucial for economic stability and policy design. Therefore, this paper aims to fill the gap by focusing on local households. We examine how generative AI adoption affects household financial behaviors using the ChatGPT's release as a quasi-experimental shock.

III. Data and Methodology

We measure a county's exposure to Generative AI in the following four steps. First, we measure the task-level Generative AI exposure using the Occupational Information Network (O*NET 28.1 database), following Eisfeldt et al. (2023). We employ GPT-4 model to evaluate the potential of 19,281 occupational tasks for total 924 occupations in the O*NET database, classifying each task into four exposure categories based on whether generative AI can reduce task completion time. Then we aggregate these task-level AI exposure to occupation-level exposure, using equally weighted task exposures. Next, we create an industry-level AI exposure measure using industry employment patterns from the Bureau of Labor Statistics (BLS). Specifically, we aggregate the occupational-level Generative AI exposure to the industry-level using the 2022 BLS Industry-occupation matrix data. Lastly, we aggregate the industry-level Generative AI exposure to the county-level using the 2022 county-level industry[1] employment data from the Bureau of Economic Analysis. Figure 1 illustrates how we construct the county-level AI exposure step by step from O*NET occupation-task database.

A. Evaluating Tasks' AI Exposure

Occupational tasks We first assess the task-level Generative AI exposure for an occupation and then aggregate the tasks' AI exposure to the occupation level. We obtain the tasks of each occupation from the Occupational Information Network (O*NET 28.1 database), which covers 924 occupations and 19,281 tasks. Each occupation has a list of tasks involved. We evaluate whether these tasks can be done more efficiently with the assistance of ChatGPT and other large language models (LLMs) or the applications that can be developed by the LLMs. The methodology notes are presented in the appendix section C.

Specifically, we use Open AI's GPT 4.0 Preview model[2] to evaluate the task's AI exposure.

[1]Here, industry is defined by NAICS 2-digit.

[2]We performed the task in OpenAI during March 30, 2024 to April 2, 2024.

Following Eloundou et al. (2024); Eisfeldt et al. (2023), we classify the exposure level into four categories. The classification of the categories are based on whether ChatGPT or other LLMs can shorten the time to complete the task by at least half for the same quality as human work. Specifically, *E0* indicates no exposure as the tool is either insufficiently useful for this task, or cannot be brought to bear as a result of the intrinsic nature of the task. *E1* implies that half reduction in time to compete is feasible with the existing LLM interfaces. *E2* indicates that such a productivity gain is feasible but only when the current capabilities of the model can be deployed through applications with further inputs (e.g., access to internet or proprietary databases), or if it is trained on domain-specific issues or data. *E3* requires the access to both the LLM and a system that could view, caption, and create images as well as any systems powered by the LLM (those in E2 above) that would reduce the time it takes to complete the task by half. It is important to note that among the four categories, *E1* indicates the highest Generative AI exposure as half of time can be reduced to complete the task with the existing LLM interfaces.

Evaluating tasks' AI exposure using OpenAI We submit the task description and the occupation title to Open AI. Importantly, we do not only require it returns a category of AI exposure but also provide explanations, which allows us to manually audit whether GPT is interpreting the task description correctly and check the creditworthiness of the job. After evaluating task-level AI exposure, we aggregate tasks' AI exposure to the occupation level. Specifically, we calculate the share of tasks for each occupation that can be completed in a shortened time with the help of Generative AI. Following Eloundou et al. (2024); Eisfeldt et al. (2023), we focus on the tasks that affected by Generative AI, which are tasks labeled as E1, E2, or E3. We calculate the AI exposure score of an occupation as in the following equation:

$$\omega_j = \frac{N_{1,j} + 0.5 \times (N_{2,j} + N_{3,j})}{N_j}, \tag{1}$$

j represents occupation, ω_j is the AI exposure of occupation j, $N_{0,j}$ is the number of tasks

that are labeled as *E0*, $N_{1,j}$ is the number of tasks that are labeled as *E1*, $N_{2,j}$ is the number of tasks that are labeled as *E2*, $N_{3,j}$ is the number of tasks that are labeled as *E3*, N_j equals $N_{0,j} + N_{1,j} + N_{2,j} + N_{3,j}$, is the total number of tasks for occupation j.

Occupations' AI exposure We aggregate the task-level exposure to the occupation level (6-digit SOC code) to match the industry-occupation matrix data from the Bureau of Labor Statistics. Table A1 reports the top and bottom 20 AI exposure occupations. Occupations among the top AI exposure are clerks, proofreaders, computer programmers, interpreters and translators. Occupations that have lowest AI exposures include roofers, construction laborers, tire repairers and changers, maids and housekeeping cleaners.

B. Measuring County's AI Exposure

Industry-level AI exposure To measure county-level AI exposure, we start with the industry-level first. We measure the industry-level AI exposure using value-weighted occupational exposure as in Equation 2. The weight is calculated using the 2022 industry-occupation matrix from the Bureau of Labor Statistics.

$$AI_exposure_n = \sum_{j=1}^{J} \omega_j \times \frac{Emp_{j,n,2022}}{Emp_{n,2022}}, \tag{2}$$

where j represents occupation, ω_j is the AI exposure of occupation j, n represents industry (NAICS 2-digit), $Emp_{j,n,2022}$ is for occupation j's employment in industry n in 2022, $Emp_{n,2022}$ is industry n's total employment across all occupations in 2022. Table A2 presents the industry-level AI exposure. The top AI exposure industries include finance and insurance, management of companies, and information, and professional, scientific, and technical services. The bottom AI exposure industries are those industries that require more physical works, for example, manufacturing, mining, oil and gas extraction, construction, and accommodation and food services.

County-level AI exposure We proxy county-level AI exposure using the value-weighted

industry exposure. The weight is determined by industry employment in a county in 2022, which is obtained from the Bureau of Economic Analysis. Equation 3 illustrates how we aggregate the industry-level AI exposure to the county-level using the weight of employment of industries in a county.

$$AI_exposure_i = \sum_{n=1}^{N} AI_exposure_n \times \frac{Emp_{n,i,2022}}{Emp_{i,2022}}, \tag{3}$$

where i represents county, n represents industry (NAICS 2-digit), $Emp_{n,i,2022}$ is for industry n's employment in county i in 2022, $Emp_{i,2022}$ is county i's total employment across all industries in 2022.[3] Table A3 presents the list of top and bottom 20 AI exposure counties in the U.S. Figure 2 provides the heatmap of the county-level AI exposure. From the figure, we can infer that the high AI exposure counties widely spread across the country instead of clustering in certain areas.

C. Identify Local Financial Advisers

To obtain data on county-level equity investments, we first follow Pan, Pikulina, Siegel and Wang (2024) to identify local financial advisers. We collect all U.S. advisers data using Form ADV filings from the SEC between 2021 and 2023. We identify advisers that primarily serve individual investors by requiring the percentage of individual clients to be no less than 50% of the adviser's client base or AUM by individual client to be no less than 50% of total AUM in a given year. To focus on advisers who serve locally, we exclude advisers who report office locations in more than one county. Next, we manually matched the local adviser data with asset managers from Thomson Reuters 13F filings database for 2021-2023, which covers advisers with more than $100 million in Section 13F securities, such as domestic stocks and exchange-traded funds (ETFs). Following Pan et al. (2024), we require our sample advisers

[3]For robustness, we also construct county-level AI exposure using the value-weighted NAICS 3-digit industry AI exposure. The weight is determined by the personal income of an industry in a county, which is obtained from the Bureau of Economic Analysis "Personal Income by Major Component and Earnings by NAICS Industry."

to those whose 13F holdings are at least 50% but no more than 110% of their total AUM reported in Form ADV to exclude advisers with large short positions in their portfolio. We identify holding records for about 27% local advisers in our sample. Among 3,057 counties in our original sample, there are 374 counties with identified local advisers and matched 13F equity holding data.

D. Empirical Strategy

We employ a difference-in-differences framework to examine how exposure to generative AI affects household financial decisions, using the release of ChatGPT in November 2022 as the event.

$$Y_{i,t} = \beta GenAIexposure_i \times PostChatGPT_t + \alpha_i + \lambda_t + \epsilon_{i,t}, \tag{4}$$

where indices i and t denote county and year, respectively. The dependent variable $Y_{i,t}$ represents household financial outcomes, such as deposit growth. County fixed effects α_i absorb time-invariant heterogeneity across counties. Year fixed effects λ_t capture aggregate macroeconomic shocks. Our main explanatory variable is the interaction between county-level generative AI exposure and an indicator for the post-ChatGPT period. We measure county-level AI exposure using both the raw value of generative AI exposure, and the indicator variables for whether a county falls into the top quartile, top tercile, or above-median group. To account for serial correlation of errors within counties over time, we cluster standard errors at the county level.

E. Summary Statistics

Our sample spans from 2021 to 2023, covering two years before and one year after the ChatGPT shock in December 2022. The final sample combines multiple comprehensive data sources on household financial behaviors at the county level. First, for deposit activity, we

utilize detailed bank branch-level data (Summary of Deposits) from The Federal Deposit Insurance Corporation (FDIC). The branch-level deposit growth data are aggregated to the county-level, using a value-weighted method. Second, to measure local household investment activity, we first follow Pan et al. (2024) to identify financial advisors working primarily within individual counties using SEC Form ADV filings and track their equity holdings in top AI exposure industries through Thomson Reuters 13F data. This approach allows us to capture how local financial advisors, whose portfolio choices likely reflect the preferences of their local clients, adjust their portfolio allocation following the introduction of ChatGPT. We supplement these financial data with the county-level mortgage application data from the Home Mortgage Disclosure Act (HMDA). Next, the state-level debt delinquency rates by loan type is obtained from New York Fed. Lastly, we explore other county-level economy data, including employment, wages, and GDP growth that are from the Bureau of Economic Analysis and Bureau of Labor Statistics.

The sample includes 3,057 counties in the U.S. Table 1 shows the summary statistics of the main variables in the regressions. County-level AI exposure has a mean of 0.24. While not reported, the county-level generative AI exposure has a min value of 0.21 and a max value of 0.27 in the sample. Table A3 reports how AI exposure relates to other county-level characteristics, for example, total population, education level, age, income, GDP, etc. In one of the robustness checks, we extend the sample of county-level deposit growth to include the 2024 data.

IV. Household Financial Fragility

A. Local deposit growth

We begin our empirical analysis by examining county-level deposit growth, which reveals household saving behavior and liquidity preference. Reduced deposit growth may reflect either constrained liquidity or strategic reallocation of financial assets in response to the

uncertainty induced by the introduction of ChatGPT. Following Lin (2020), we aggregate the branch-level deposit growth to the value-weighted county-level growth, using the Summary of Deposits data from the FDIC. The results in Table 2 consistently suggest that counties with higher AI exposure experience significantly reduced deposit growth after 2022Q4. Columns (1) to (4) report the regressions with county-level controls and year fixed effects but no county fixed effects. Specifically, we control for the 2022 average education, median age, and total population and household income and lagged GDP growth in a county. Using the continuous AI exposure measure interacted with the post-ChatGPT dummy in Column (1), we find that a 1 p.p increase in AI exposure is associated with a 0.52 p.p decrease in deposit growth. The coefficient of the interaction term is statistically significant at a 5% level. When examining AI exposure using dummy measures, counties in the top quartile of AI exposure experienced 1.8 p.p. lower deposit growth compared to other counties. The coefficient is significant at a 1% level. While, counties in the top tercile and above median AI exposure experienced 1.5 and 1.3 p.p. lower deposit growth, respectively.

These effects remain robust across specifications with different fixed effect. The inclusion of county fixed effects in columns (5)-(8) helps control for time-invariant county characteristics, and the results are statistical and economic significant. The magnitudes are economically meaningful, representing immediate substantial reductions in deposit activity for households in high AI exposure areas. In the following empirical analysis, we mainly focus on the estimation with time and county fixed effects.

B. Retail v.s. institutional deposit growth

To better understand the mechanisms leading to the overall deposit decline documented in our main results, we examine whether AI exposure affects retail and institutional deposits growth differently. This decomposition provides important insights into which types of depositors are most responsive to AI disruption. While the Summary of Deposit branch-level deposit data from the FDIC does not differentiate depositor types, we measure the weight

of retail and institutional deposit at the bank level from Call Report of June in the same year and then apply the weight of retail and institutional deposit to the branch-level.

The assumption we make is that the ratio of retail and institutional deposit is identical across branch. We acknowledge that this assumption carries limitation. Banks may operate branches in different markets that serve distinct customer bases, and the retail-institutional mix could vary across branch locations. However, despite the limitation, this approach provides the optimal available approximation for examining deposit growth across different depositor types. Importantly, retail deposits constitute the majority of local deposits, accounting for 87.7% of total branch-level deposits.

The results in Table 3 show a significant divergence on how AI exposure affects different types of bank deposits. Panel A suggests that retail deposit growth experiences significant negative effects from AI exposure. Counties of high AI exposure show substantially reduced retail deposit growth following ChatGPT's release. A 1 p.p. increase in AI exposure is associated with 0.83 p.p. decrease in retail deposit growth, which is statistically significant at a 1% level. The results in Columns (2) to (4) based on categorical measures confirm this pattern. Counties in the top quartile, top tercile, and above median AI exposure experience 2.4, 2.0, and 1.7 p.p. decreases in retail deposit growth, respectively. The coefficients of the interaction terms are all significant at a 1% level.

In contrast, Panel B shows that institutional deposit growth increases in high AI exposure counties. A 1 p.p. increase in AI exposure is associated with a 5.6% increase in institutional deposit growth, which is statistically significant at a 5% level. Counties in the top quartile and top tercile of AI exposure experience 0.18 and 0.15 p.p. increase in institutional deposit growth, respectively and the coefficients are significant at the 1% level.

This divergence of retail and institutional deposits suggests that while individual households in high AI-exposed counties reduce their bank savings due to financial fragility and employment concerns, institutional depositors increase their deposits.

C. *Level of deposits*

We document the negative effects of AI exposure on deposit growth rates. We next examine whether these negative effects translate into absolute changes in the level of total deposits. Table 4 reports the regression results examining the natural logarithm of county-level total deposits as the dependent variable.

The results provide significant evidence that AI exposure leads to substantial reduction in total deposits. Using the continuous AI exposure measure in Column (1), we find the coefficient on the interaction term is -1.024. To translate the magnitude of the coefficient in economic terms, it is important to scale it by the actual range of AI exposure observed in the data. County-level exposure varies only between 0.21 and 0.27, a range of 0.06. Multiplying the log-transformed coefficient (exp(-1.024)-1) by this range gives a decline of about 0.061 log points, which corresponds to a 6% lower in the level of total deposits between the least and most exposed counties.

The categorical specifications in Columns (2)–(4) yield consistent results. Counties in the top quartile of AI exposure experience 2.3% lower deposits, those in the top tercile experience 2.1% lower deposits, and those above the median experience 1.6% lower deposits, relative to less exposed counties. All estimates are statistically significant at the 1% level.

Taken together, these results show that the effects of AI exposure extend beyond slowing deposit growth: they are also associated with persistently lower deposit levels. This suggests that households in highly exposed areas are drawing down liquid savings in response to AI-driven disruptions.

D. *Local equity investment*

Next, we examine whether household adjust their portfolio allocations following ChatGPT's release. Specifically, we examine whether AI exposure affects county-level equity

investment in the top three AI-exposed industries.[4] Table 5 reports the results. Panel A reports the baseline results of difference-in-differences analysis. Using the continuous AI exposure measure in Column (1), we find that a 1 p.p. increase in county-level AI exposure is associated with a 3.26 p.p. decrease in quarterly equity investment growth in top AI exposure industries. The coefficient of the interaction term *GenAI exposure* × *Post-ChatGPT* is statistically significant at a 1% level. The categorical measures of AI exposure tell a consistent story: counties in the top quartile of AI exposure experienced 5.6 p.p. lower quarterly equity investment growth in AI-intensive industries compared to other counties, while counties in the top tercile and above median experienced 7.6 and 7.2 p.p. lower growth, respectively (all significant at the 1% level).

Panel B presents the dynamic difference-in-differences results. Columns (1) to (4) use four measures of AI exposure, i.e., GenAI exposure raw value, top quartile, top tercile, and above median dummies. Using alternative measures of AI, the results consistently indicate no significant pre-trend differences, supporting the parallel trends assumption. However, it reveals a clear and immediate decline in the quarter following the release. Specifically, high AI-exposure counties experience significantly slower equity investment growth. A 1 p.p. increase in the county GenAI exposure leads to 7.23 p.p. decrease in equity investment growth in the top 3 AI-exposed industries in the first quarter following the shock. The coefficient is significant at a 1% level. In the second quarter after the shock, the equity investment growth decreases by 3.68 p.p. and the coefficient is significant at a 10% level. It exhibits a similar trend using the alternative measures in Columns (2) to (3). Taken together, the dynamic patterns suggest that local households, through their financial advisors, quickly adjusted their portfolios by reducing allocations to top AI-exposed industries once ChatGPT was released.

These substantial reductions in equity investment growth in top AI-exposed industries

[4]Top AI-exposed industries are defined by 3-digit NAICS code: Computing infrastructure providers, data processing, web hosting, and related services (NAICS 518), web search portals, libraries, archives, and other information services (NAICS 519), and publishing industries (NAICS 511). There are 243 firms invested by local advisers in the top 3 AI exposed industries.

suggest that local financial advisors, who likely reflect the preferences of their geographically proximate clients, experience a slower equity investment growth in top AI-exposure industries in counties with higher AI-exposure.

E. Local debt balance

While the delinquency results in the previous section suggest household's strategic default decision during economic hardship, a natural question arises: whether AI exposure affects debt balance. In this section, we examine the impact of AI exposure on local household debt balance growth of different types of loan at the state level. The data is obtained from the Fed New York. The results are reported in Table 6. For student loan balance growth (in Panel A), we observe modest increase in high AI exposure states, though the effects are generally not significant except for states in top quartile of AI exposure, which experience a 1 p.p. increase in student loan balance growth. This suggests limited new student loan borrowing amid higher delinquency rates in these states.

Credit card balance growth results in Panel B show negative but insignificant coefficients across all specifications, suggesting no significant change in credit card borrowing pattern despite the increased delinquency rate in Table 8. This may indicate that the higher credit card delinquency rates observed in the previous section reflect difficulties repaying existing debt rather than increased borrowing.

Mortgage balance growth in Panel C reveals consistent significant negative effects. Using the continuous AI exposure measure, a 1 p.p. increase in state-level AI exposure is associated with an 0.8 p.p. decrease in mortgage balance growth. The coefficient of the interaction term is significant at a 5% level. States in the top tercile and above median AI exposure experienced 1.4 p.p. decreases in mortgage balance growth, which are both significant at a 5% level.

Auto loan balance growth (Panel D) reflects no significant effects, suggesting that auto loan financing remain relatively unaffected across different levels of AI exposure. Overall,

these results indicate that while households in high AI exposure states struggle to services existing unsecured debt, they are simultaneously reducing major borrowing, particularly for house mortgage.

F. Mortgage applications

We observe the decreased mortgage balance growth rate in the previous section. Next, employing mortgage data from the HMDA, we examine the mortgage applications activity at the county-level (growth rate of number of applications). The results are reported in Table 7. we find significant reductions in both home purchase and home improvement mortgage application growth rate following ChatGPT's release. For home purchase mortgage applications in Panel A, counties with higher AI exposure experienced substantial reduction in application growth. Using the continuous AI exposure measure, a 1 p.p. increase in county-level AI exposure is associated with 0.81 p.p. decrease in home purchase mortgage application growth, which is significant at a 1% level. The categorical measures suggest a consistent patterns: counties in the top quartile and top tercile AI exposure experienced 2.1 and 1.8 p.p. lower growth in home purchase applications that are significant at a 1% level, while counties with above median AI exposure experienced a 1.2 p.p. lower growth that is significant at a 10% level.

The effects are more pronounced in Panel B for home improvement mortgage applications. Counties with higher AI exposure show dramatically reduced home improvement financing activity, with a 1 p.p. increase in AI exposure associated with a 3.96 p.p. decrease in home improvement application growth. The coefficient of the interaction term is significant at the 1% level. Counties in the top quartile, top tercile, and above median of AI exposure experience 9.7, 8.1, and 5.3 p.p. lower growth in home improvement applications, respectively and all three coefficients are significant at the 1% level.

This substantial reduction in home purchase and improvement mortgage applications aligns with the decreased mortgage borrowing documented in subsection IV.E, indicating

that households in high AI exposure areas are adopting significantly more conservative approaches to housing-related investments, likely reflecting concerns about future income and employment stability amid AI-driven labor market disruptions. The larger magnitude of effects for home improvement applications indicates that households are more reluctant to engage in optional housing investments amid AI-induced economic uncertainty.

G. Local debt delinquency

In this section, we examine the impact of AI exposure on debt delinquency rates across different loan types (Table 8). We obtain the debt delinquency rate data from the Fed New York, which is at the state-level. We therefore aggregate the county-level AI exposure to the state-level using the value-weighted method based on the counties' population. The results reveal a pattern of increasing debt delinquency in high AI exposed states, though the effects vary by loan type. Panel A presents the results on student loan. We observe a significant increase in delinquency rates following ChatGPT's release in high AI exposed states. A 1 p.p. increases in state-level AI exposure is associated with 33.56 p.p. increase in student loan delinquency rates, which is significant at a 1% level. States in the top quartile and tercile of AI exposure experienced 0.57 and 0.56 p.p. increase in student loan delinquency rates, respectively, and the coefficients of the interaction terms are statistically significant at a 1% level. States above median AI exposure saw a 0.28 p.p increase, which is statistically significant at a 10% level.

Credit card delinquencies (Panel B) also increased significantly in high AI exposure states, with a one p.p. increase in AI exposure associated with a 12.2 p.p. rise in delinquency rates (significant at the 10% level). States in the top quartile and top tercile of AI exposure experienced 0.22 and 0.24 p.p.increases in credit card delinquency rates, respectively (significant at the 10% and 5% levels).

The delinquency effects emerge rapidly following the release of ChatGPT. Household default strategically on unsecured debt. In contrast, mortgage and auto loan delinquencies

(Panels C and D) show no statistically significant relationship with AI exposure, suggesting that household prioritize repayment of secured debt while defaulting on unsecured debt obligations. The selective nature of these delinquency patterns indicates that financial stress from AI exposure manifests most in unsecured debt, reflecting the strategic household financial decisions about which obligations to optimize during hard times. The significant effects on unsecured debt implies that traditional measures of household financial distress focused primarily on mortgage default may underestimate the actual impact, as households prioritize their secured obligations while sacrificing obligations that carry no immediate collateral consequences during economic hardship.

V. Channel Test

A. Employment growth

We begin the estimation of labor market outcomes by investigating county-level employment growth following the release of ChatGPT. As shown in Table 9, high AI exposure counties exhibit weaker employment growth, though this effect varies across specifications. Using the continuous AI exposure measure, we find a negative but statistically insignificant coefficient of -4.26 p.p., suggesting a general tendency toward slower employment growth in high AI exposure areas.

The categorical measures of AI exposure provide more robust evidence of employment effects. Counties in the top quartile of AI exposure have significantly lower employment growth, with a 0.45 p.p. reduction compared to other counties that is significant at the 5% level. Similarly, counties in the top tercile of AI exposure experience a 0.36 p.p. decrease in employment growth, which is significant at the 5% level. While, the effects becomes statistically insignificant for counties above the median AI exposure.

These employment effects are economically meaningful along with the evidence of financial fragility documented in previous sections. The most pronounced effects are observed in

the highest AI exposure counties, where labor market disruption is more apparent in areas with the greatest concentration of AI-exposed industries. The slower employment growth in these counties likely contributes to the observed patterns observed in the previous sections, such as reduced deposit growth, lower equity investment growth, and increased debt delinquencies, as local households fact deteriorating labor market conditions amid the massive adoption of generative AI.

B. Establishments employee wage

To further examine the labor market consequences of AI disruption, Table 10 investigates its impact of AI exposure on county-level wages. The dependent variable is the natural logarithm of the average wage in the establishments in a county. We document significant declines in average compensation in high-exposure counties following the release of ChatGPT. Using a continuous measure, we find that a one p.p. increase in AI exposure is associated with a 31.2 p.p. reduction in average wages (significant at the 1% level). This effect represents substantial earnings decline in affected counties.

Examining categorical measures, we find counties in the top quartile of AI exposure experience a 0.7 p.p. decline in wages relative to others, while those in the top tercile and above-median groups show declines of 0.5 p.p., which are significant at the 1% level. Although these estimates appear modest, they are economically significant given the stability of wage adjustments.

Along with the findings of slower employment growth in Table 9, the results likely reflect deteriorating labor market conditions in high AI exposure counties: lower employment growth rate and decreased compensation. These effects help explain the documented household financial distress, including weaker deposit growth, lower equity investment growth, increased debt delinquencies, and declined mortgage application growth.

C. *Local GDP growth*

Lastly, we examine the broader economic impact of AI exposure on county-level GDP growth. The empirical evidence is reported in Table 11. It suggests negative effects on labor economic performance following ChatGPT's release. Specifically, counties with higher AI exposure experienced signficantly slower GDP growth following the release of ChatGPT in November 2022. Column (1) shows that a 1 p.p. in county-level AI exposure is associated with a 66.39 p.p. decrease in GDP growth (significant at the 1% level). The categorical measures of AI exposure in Columns (2) to (4) confirm these negative effects across different AI exposure thresholds. Counties in top quartile of AI exposure experience 1.27 p.p. lower GDP growth, while counties in the top tercile and above median experienced 0.98 and 1.03 p.p. lower growth (all significant at a 1% level). These magnitudes are economically significant, indicating reductions in local economic activity.

The results on GDP underscore the broad economic disruption that AI exposure has brought to local economies. The negative GDP growth results might be a result from reduced consumer spending due to financial fragility, decreased local business investment and activity, and potential productivity disruptions. This economic slowdown provides important evidence for understanding why households in high AI exposure areas exhibit more conservative financial behavior and increased loan delinquencies.

VI. Robustness Checks

A. *Alternative AI exposure measures*

To check whether our findings are robust to the alternative construction of the AI exposure measure, we construct an alternative measure that based solely on core tasks from the O*NET occupation-tasks data to calculate the first-step occupation-level AI exposure. Table A4 presents the results using this alternative measure of AI exposure. The results

remain consistent with our main findings, confirming that counties with higher AI exposure experience significantly decrease deposit growth following ChatGPT's release. Using the continuous core-task-only AI exposure measure, a 1 p.p. increase in AI exposure is associated with a 0.43 p.p. decrease in deposit growth, which is significant at the 10% level. The categorical measures shows that counties in the top quartile, top tercile, and above median of core-tasks-only AI exposure experienced 1.3, 1.7, and 0.9 p.p. decreases in deposit growth, and the coefficients are significant at the 5%, 1%, and 10% levels, respectively. These results demonstrate that our findings are robust to alternative specifications of AI exposure measurement.

B. Local deposit growth 2021-2024

To examine the robustness of our main deposit growth results, we extend the sample period to include 2024. This extended sample period allows us to assess whether the negative effects of AI exposure on household deposits persist beyond the 1-year post-ChatGPT period. The results in Table A5 continue to show significant negative effects of AI exposure on county-level deposit growth. Counties in the top quartile, top tercile, and above median AI exposure experience 1.5, 1.3, and 1.0 p.p. decreases in deposit growth, respectively. The coefficients are significant at the 1% level for top quartile and top tercile and 5% level for above median measures.

These results indicate that the household financial fragility effects documented in our main analysis are not merely temporary responses to the initial ChatGPT shock, but represent a persistent behavioral changes as generative AI adoption becomes more widespread.

C. Robustness of the estimation model

Table A6 presents additional robustness checks that controls for potential confounding factors by including interactions between county-level characteristics and the post-ChatGPT dummy variable. To address concerns that our results might be drive by underlying county

characteristics that correlates with both AI exposure and the outcome variables, we include interaction terms between our AI exposure measures and key county demographics such as eduction, population, median age, household income, and GDP growth. Among these control variables, eduction, population, median age, household income are measured using the 2022 annual data, and GDP growth data is lagged 1-year.

The results remain robust across all specifications. Counties in higher AI exposure categories continues to show significantly reduced deposit growth following ChatGPT's release. Counties in the top quartile, top tercile, and above median AI exposure experience 1.2, 1.2, and 0.9 p.p. decrease in deposit growth, respectively. The coefficients are statistically significant at the 10% level for top quartile and top tercile measures. These empirical evidence suggest that our main results are robust and not confounded by observable county characteristics.

VII. Conclusion

The introduction of ChatGPT and other LLMs represents a significant shock across various industries, influencing not only workplace dynamics but also household financial stability. To study the impact of the disruption of generative AI on household financial fragility, we construct a novel measure of county-level AI exposure. We document that households in high exposure areas exhibit heightened financial fragility following the introduction of ChatGPT. These households have slower deposit and equity investment growth, higher student loan and credit card delinquencies, and declined home purchase and improvement mortgage activity. The broader local economies in these regions also face slower employment and wage growth and weaker GDP growth.

These findings highlight the need to consider household-level channels when evaluating the economic impact of AI. The results are particularly relevant for institutions, regulators, and policymakers seeking to understand the consequences of rapid adoption of generative

AI on local economy. Future research may investigate survey-based evidence on household expectations and psychological responses to AI, which may shed light on the mechanisms driving these behavior and provide insights on how AI adoption shapes household financial decision-making.

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Figure 1: The Construction of County-level Generative AI Exposure

This figure shows the steps to construct the county-level Generative AI exposure.

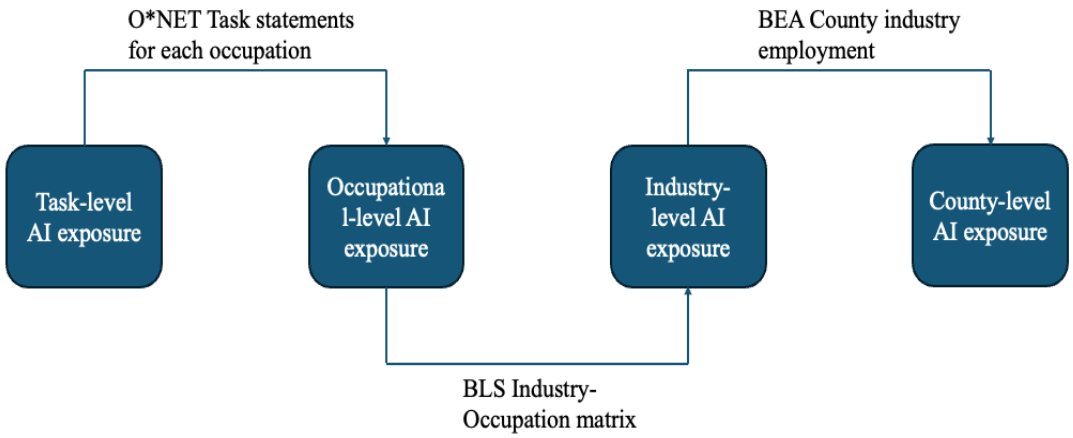


Figure 2: The county-level AI Exposure

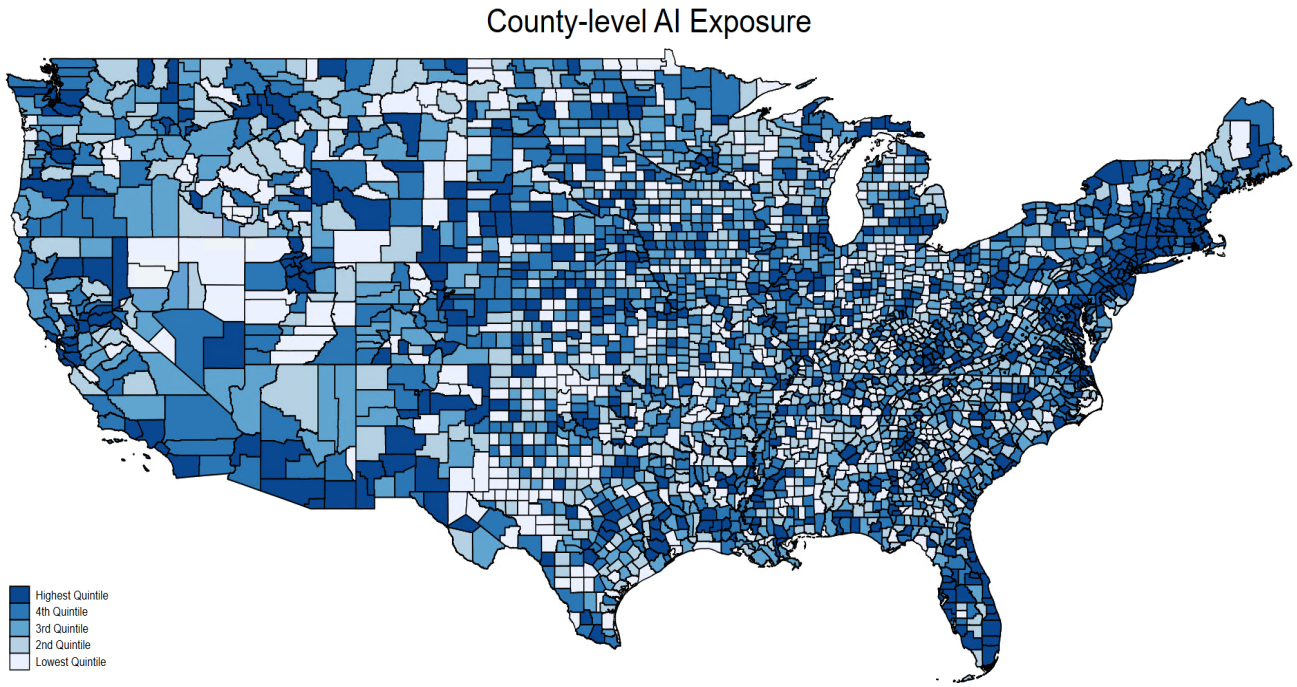


Figure 3: **Event Study Dynamic Model Estimation Coefficients**

This figure is based on the dynamic difference-in-difference results using GenAI exposure in Panel B Column (1) of Table 5.

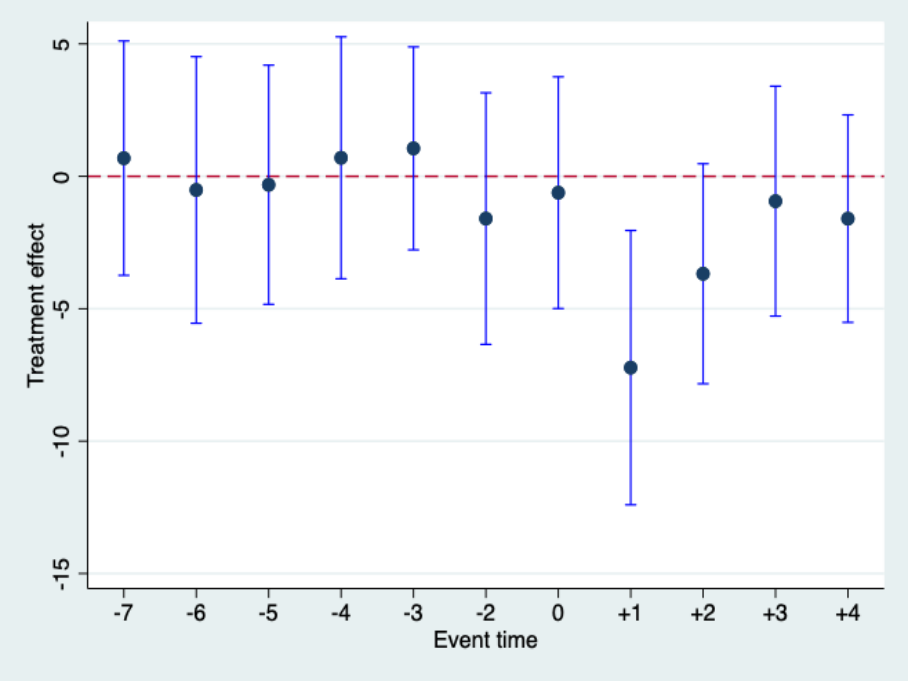


Figure 4: **Event Study Dynamic Model Estimation Coefficients**

This figure is based on the dynamic difference-in-difference results using GenAI exposure (top quartile) in Panel B Column (2) of Table 5.

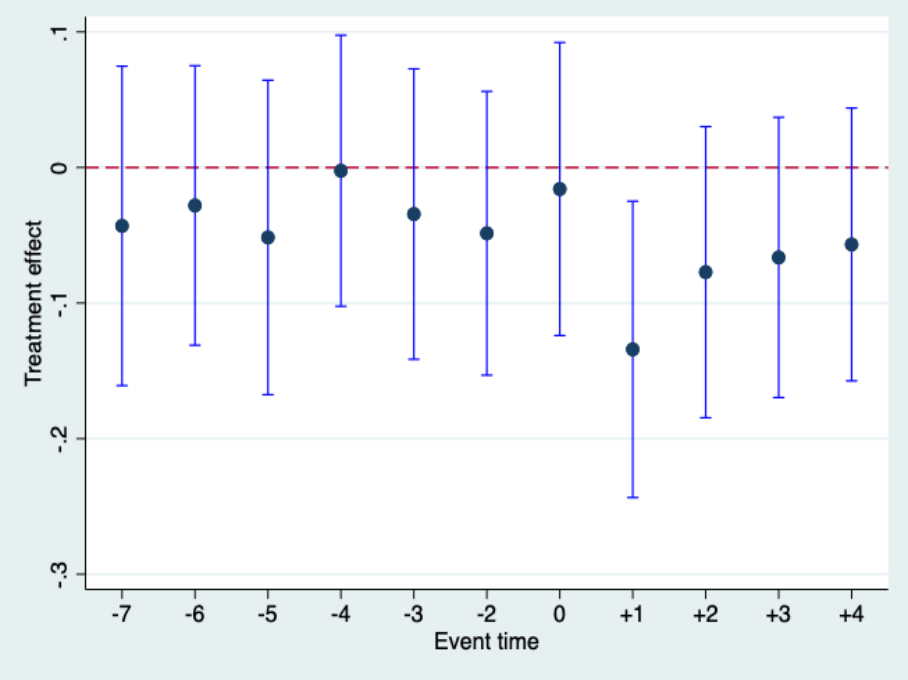


Figure 5: **Event Study Dynamic Model Estimation Coefficients**

This figure is based on the dynamic difference-in-difference results using GenAI exposure (top tercile) in Panel B Column (3) of Table 5.

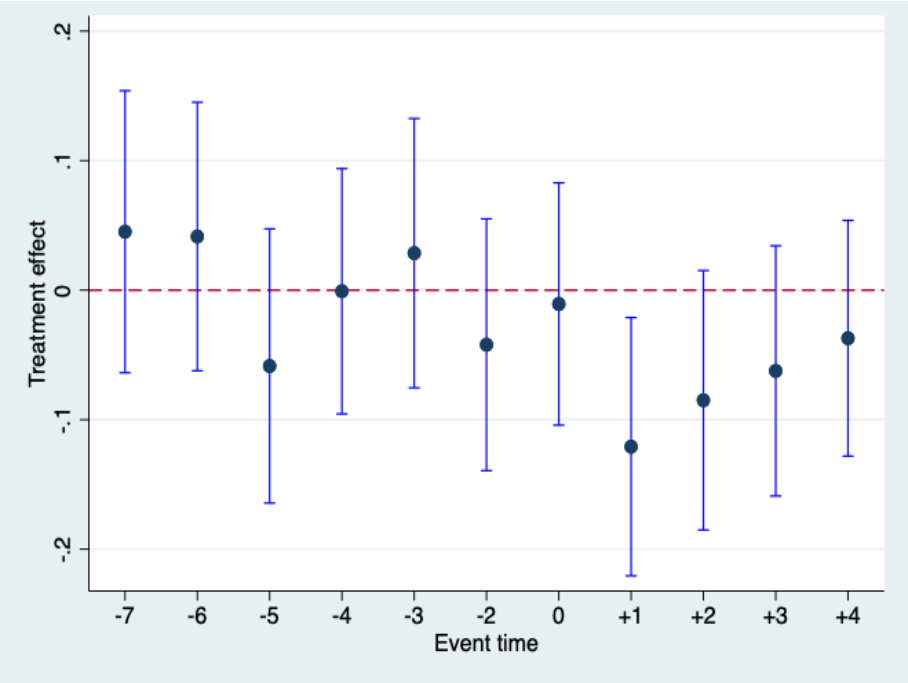


Figure 6: **Event Study Dynamic Model Estimation Coefficients**

This figure is based on the dynamic difference-in-difference results using GenAI exposure (above median) in Panel B Column (4) of Table 5.

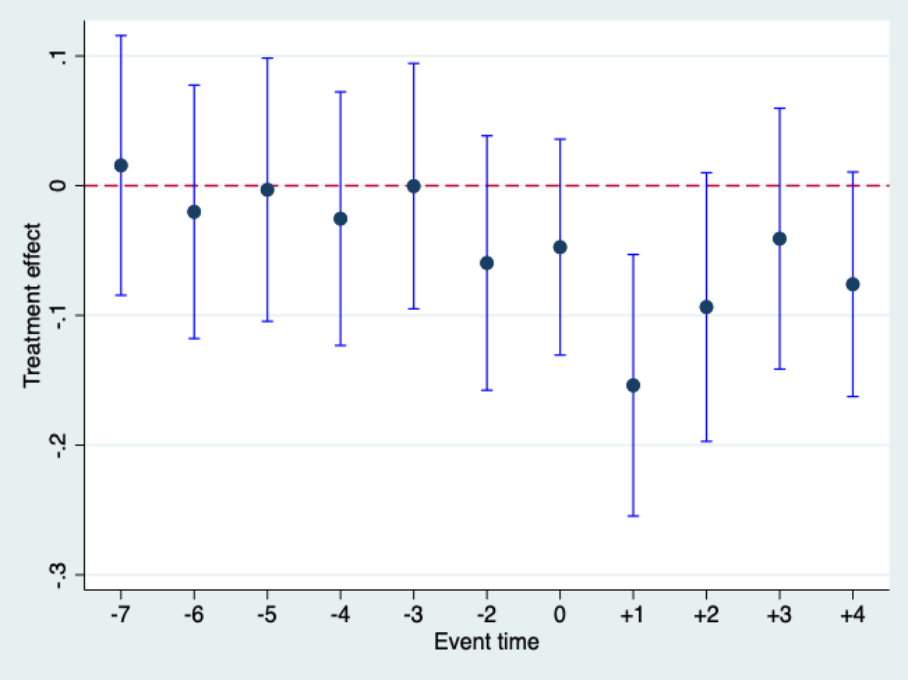


Table 1: Summary Statistics

VARIABLES	N	Mean	STD	p25	p50	p75
County-level variables						
GenAI exposure	9,157	0.24	0.01	0.23	0.24	0.25
GenAI exposure (core tasks only)	9,157	0.25	0.01	0.24	0.25	0.25
GenAI exposure (using NAICS3)	9,157	0.24	0.02	0.23	0.24	0.25
GenAI exposure (using NAICS3 and core tasks only)	9,157	0.25	0.02	0.23	0.24	0.26
Deposit growth	9,157	0.03	0.13	-0.03	0.04	0.11
Retail deposit growth	9,157	0.03	0.15	-0.08	0.05	0.13
Institutional deposit growth	8,708	0.29	1.12	-0.29	-0.01	0.50
Equity growth[5] (quarterly)						
Equity growth (annual)						
home purchase mortgage applications growth	9,152	-0.04	0.20	-0.18	-0.07	0.08
home improve mortgage applications growth	8,842	0.21	0.41	-0.09	0.14	0.42
ln(wage)	9,156	10.79	0.19	10.66	10.77	10.89
GPD growth (in %)	9,157	3.30	7.24	-0.30	2.80	6.20
Annual employee growth (in %)	7,776	2.14	3.88	0.03	1.98	4.15
Quarterly mployee growth (in %)	31,100	2.04	4.29	-0.25	2.04	4.26
Education	9,133	23.32	13.40	16.50	20.80	27.70
Population	9,133	10.30	8.56	9.32	10.17	11.13
Median age	9,133	3.72	3.57	3.65	3.72	3.80
Household income	9,133	11.02	10.72	10.87	11.02	11.16
GDP growth	9,157	3.30	-4.10	-0.30	2.80	6.20
State-level variables						
GenAI exposure	153	0.25	0.01	0.25	0.25	0.26
credit card debt growth	153	0.10	0.05	0.03	0.12	0.14
auto loan growth	153	0.04	0.02	0.03	0.04	0.05
mortgage growth	153	0.05	0.03	0.03	0.06	0.07
student loan growth	153	0.003	0.02	-0.01	0.00	0.01
total loan growth	153	0.05	0.03	0.03	0.05	0.06
mortgage delinquency rate (in %)	153	0.51	0.21	0.36	0.47	0.66
auto delinquency rate (in %)	153	3.77	1.54	2.53	3.69	4.65
credit card delinquency rate (in %)	153	7.89	1.56	6.67	7.67	8.94
student loan delinquency rate (in %)	153	2.20	2.15	0.67	0.88	4.19

Table 2: AI Exposure and Local Deposit Growth (County-level)

This table reports the county-level OLS regression results. The dependent variable is the county-level deposit growth, which is defined as value-weighted deposit growth of all bank branches in a county. The sample period is 2021-2023. Columns (1) to (4) present the results of the regressions with year fixed effects and control variables, i.e., county-level education (percentage of population that over 25 years old with a bachelor degree or higher), ln(total population), ln(Household median income), GDP growth. Columns (5) to (8) report the regression results with county and year fixed effects. The variable definition is in the Appendix section D. T-statistics are in parentheses. Standard errors are clustered at the county level. Coefficients statistically significant at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GenAI exposure×Post-ChatGPT	-0.521**				-0.477**			
	(-2.34)				(-2.15)			
GenAI exposure(top quartile)×Post-ChatGPT		-0.018***				-0.017***		
		(-3.11)				(-2.92)		
GenAI exposure(top tercile)×Post-ChatGPT			-0.015***				-0.014***	
			(-2.84)				(-2.67)	
GenAI exposure(above median)×Post-ChatGPT				-0.013**				-0.012**
				(-2.48)				(-2.36)
GenAI exposure	-0.054							
	(-0.35)							
GenAI exposure(top quartile)		0.003						
		(0.87)						
GenAI exposure(top tercile)			0.005					
			(1.37)					
GenAI exposure(above median)				0.003				
				(0.95)				
Education	0.000	0.000	0.000	0.000				
	(1.05)	(0.63)	(0.40)	(0.48)				
Population	-0.001	-0.001	-0.001	-0.001				
	(-0.50)	(-0.85)	(-0.95)	(-0.91)				
Median age	-0.003	-0.003	-0.003	-0.003				
	(-0.26)	(-0.26)	(-0.22)	(-0.23)				
Household income	-0.009	-0.008	-0.007	-0.007				
	(-1.39)	(-1.18)	(-1.09)	(-1.13)				
GDP growth	0.001***	0.001***	0.001***	0.001**				
	(2.60)	(2.60)	(2.58)	(2.56)				
Constant	0.197**	0.135*	0.128	0.130*	0.069***	0.032***	0.032***	0.033***
	(2.35)	(1.74)	(1.64)	(1.67)	(3.87)	(67.60)	(55.04)	(38.61)
Observations	9,133	9,133	9,133	9,133	9,152	9,152	9,152	9,152
R-squared	0.187	0.187	0.187	0.187	0.456	0.456	0.456	0.456
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
County FE	N	N	N	N	Y	Y	Y	Y

Table 3: AI Exposure and Local Retail v.s. Institutional Deposit Growth (County-level)

This table reports the county-level OLS regression results. The dependent variable is the county-level retail or institutional deposit growth. The local branch retail to institutional deposit ratio is assigned by the bank-level ratio from call reports in June each year. The sample period spans from 2021 to 2024. The variable definition is in the Appendix section D. T-statistics are in parentheses. Standard errors are clustered at the county level. Coefficients statistically significant at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Panel A: Retail deposit growth rate

VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	-0.833***			
	(-3.91)			
GenAI exposure(top quartile) ×Post-ChatGPT		-0.024***		
		(-4.34)		
GenAI exposure(top tercile)×Post-ChatGPT			-0.020***	
			(-3.94)	
GenAI exposure(above median) ×Post-ChatGPT				-0.017***
				(-3.34)
Constant	0.096***	0.031***	0.031***	0.032***
	(5.59)	(67.42)	(54.30)	(38.06)
Observations	9,152	9,152	9,152	9,152
R-squared	0.605	0.605	0.605	0.605
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y

Panel B: Institutional deposit growth rate

VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	5.613**			
	(2.29)			
GenAI exposure(top quartile)×Post-ChatGPT		0.184***		
		(2.93)		
GenAI exposure(top tercile)×Post-ChatGPT			0.151***	
			(2.60)	
GenAI exposure(above median)×Post-ChatGPT				0.089
				(1.53)
Constant	-0.153	0.282***	0.280***	0.282***
	(-0.78)	(53.20)	(42.90)	(28.50)
Observations	8,662	8,662	8,662	8,662
R-squared	0.430	0.431	0.431	0.430
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y

Table 4: AI Exposure and Local Deposit (County-level)

This table reports the county-level OLS regression results. The dependent variable is the natural logarithm of total deposits. The sample period spans from 2021 to 2024. The variable definition is in the Appendix section D. T-statistics are in parentheses. Standard errors are clustered at the county level. Coefficients statistically significant at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	ln(total deposits)			
VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	-1.024***			
	(-4.05)			
GenAI exposure(top quartile)×Post-ChatGPT		-0.023***		
		(-4.26)		
GenAI exposure(top tercile)×Post-ChatGPT			-0.021***	
			(-4.48)	
GenAI exposure(above median)×Post-ChatGPT				-0.016***
				(-3.91)
Constant	13.565***	13.485***	13.486***	13.486***
	(669.60)	(29,969.52)	(26,368.55)	(19,700.81)
Observations	9,152	9,152	9,152	9,152
R-squared	0.998	0.998	0.998	0.998
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
S.E. clustered by county	Y	Y	Y	Y

Table 5: AI Exposure and Local Equity Investment in the Top AI Exposure Industries (County-level)

This table reports the OLS regression results of the county-level quarterly growth rate of equity investment in top 3 AI exposure industries. The dependent variable is the value-weighted growth rate of the equity investment in the top 3 AI exposure industries by the local advisors (quarterly or annually). The equity holding data comes from Thomson Reuters 13F. The sample contains 374 counties with identified local investment advisors. We follow Pan et al. (2024) to identify local investment advisors using the SDC form ADV filings. The sample period is 2021-2023. The variable definition is in the Appendix section D. The fixed effects of the regressions are reported at the bottom of the table. T-statistics are in parentheses. Standard errors are clustered at the county level. Coefficients statistically significant at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Panel A: The difference-in-differences model estimation

VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	-3.255***			
	(-3.74)			
GenAI exposure(top quartile)×Post-ChatGPT		-0.056***		
		(-2.97)		
GenAI exposure(top tercile)×Post-ChatGPT			-0.076***	
			(-4.12)	
GenAI exposure(above median)×Post-ChatGPT				-0.072***
				(-3.67)
Constant	0.334***	0.042***	0.046***	0.050***
	(4.21)	(22.80)	(19.48)	(13.52)
Observations	3,713	3,713	3,713	3,713
R-squared	0.092	0.090	0.092	0.092
County FE	Yes	Yes	Yes	Yes
Quarter-Year FE	Yes	Yes	Yes	Yes
S.E. Clustered by county	Yes	Yes	Yes	Yes

Panel B: The dynamic model estimation

VARIABLES	(1) AI exp (raw value)	(2) (top quartile)	(3) (top tercile)	(4) (above median)
ChatGPT(t-7)×GenAI exposure	0.685	-0.043	0.045	0.016
	(0.30)	(-0.72)	(0.81)	(0.31)
ChatGPT(t-6)×GenAI exposure	-0.516	-0.028	0.041	-0.020
	(-0.20)	(-0.53)	(0.79)	(-0.41)
ChatGPT(t-5)×GenAI exposure	-0.319	-0.052	-0.059	-0.003
	(-0.14)	(-0.87)	(-1.09)	(-0.06)
ChatGPT(t-4)×GenAI exposure	0.700	-0.002	-0.001	-0.025
	(0.30)	(-0.05)	(-0.02)	(-0.51)
ChatGPT(t-3)×GenAI exposure	1.055	-0.034	0.029	-0.000
	(0.54)	(-0.63)	(0.54)	(-0.01)
ChatGPT(t-2)×GenAI exposure	-1.597	-0.049	-0.042	-0.060
	(-0.66)	(-0.91)	(-0.85)	(-1.20)
ChatGPT(t)×GenAI exposure	-0.618	-0.016	-0.011	-0.047
	(-0.28)	(-0.29)	(-0.22)	(-1.12)
ChatGPT(t+1)×GenAI exposure	-7.226***	-0.134**	-0.121**	-0.154***
	(-2.74)	(-2.41)	(-2.38)	(-3.00)
ChatGPT(t+2)×GenAI exposure	-3.680*	-0.077	-0.085*	-0.094*
	(-1.74)	(-1.41)	(-1.67)	(-1.78)
ChatGPT(t+3)×GenAI exposure	-0.938	-0.066	-0.062	-0.041
	(-0.43)	(-1.26)	(-1.27)	(-0.80)
ChatGPT(t+4)×GenAI exposure	-1.599	-0.057	-0.037	-0.076*
	(-0.80)	(-1.11)	(-0.80)	(-1.73)
Constant	0.356	0.050***	0.047***	0.060***
	(0.84)	(4.21)	(3.31)	(3.16)
Observations	3,713	3,713	3,713	3,713
R-squared	0.096	0.092	0.095	0.095
County FE	Y	Y	Y	Y
Quarter-Year FE	Y	Y	Y	Y
S.E. Clustered by county	Y	Y	Y	Y

Table 6: AI Exposure and Local Debt Balance (State-level)

This table reports the state-level OLS regression results. The dependent variables are the balance growth rate (in fraction) of student loan (Panel A), credit card (Panel B), mortgage (Panel C), and auto loan (Panel D). The sample period is 2021 to 2023. The variable definition is in the Appendix section D. The fixed effects of the regressions are reported at the bottom of the table. T-statistics are in parentheses. Standard errors are clustered at the state level. Coefficients statistically significant at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Panel A: Student loan balance growth

VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	0.505			
	(1.28)			
GenAI exposure(top quartile)×Post-ChatGPT		0.010*		
		(1.73)		
GenAI exposure(top tercile)×Post-ChatGPT			0.008	
			(1.26)	
GenAI exposure(above median)×Post-ChatGPT				0.002
				(0.25)
Constant	-0.040	0.002***	0.002***	0.002**
	(-1.19)	(4.37)	(2.91)	(2.03)
Observations	153	153	153	153
R-squared	0.310	0.312	0.309	0.303
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Panel B: Credit card balance growth

VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	-1.397			
	(-1.29)			
GenAI exposure(top quartile)×Post-ChatGPT		-0.011		
		(-0.87)		
GenAI exposure(top tercile)×Post-ChatGPT			-0.006	
			(-0.62)	
GenAI exposure(above median)×Post-ChatGPT				-0.002
				(-0.31)
Constant	0.213**	0.096***	0.096***	0.096***
	(2.34)	(93.58)	(87.27)	(74.73)
Observations	153	153	153	153
R-squared	0.913	0.913	0.913	0.913
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Panel C: Mortgage balance growth

VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	-0.876**			
	(-2.16)			
GenAI exposure(top quartile)×Post-ChatGPT		-0.008		
		(-1.21)		
GenAI exposure(top tercile)×Post-ChatGPT			-0.014**	
			(-2.04)	
GenAI exposure(above median)×Post-ChatGPT				-0.014**
				(-2.14)
Constant	0.128***	0.055***	0.056***	0.056***
	(3.74)	(100.60)	(72.45)	(51.71)
Observations	153	153	153	153
R-squared	0.763	0.763	0.763	0.763
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Panel D: Auto loan balance growth

VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	0.108			
	(0.34)			
GenAI exposure(top quartile)×Post-ChatGPT		0.004		
		(0.77)		
GenAI exposure(top tercile)×Post-ChatGPT			0.001	
			(0.30)	
GenAI exposure(above median)×Post-ChatGPT				-0.004
				(-0.75)
Constant	0.029	0.038***	0.038***	0.039***
	(1.07)	(96.94)	(69.70)	(43.56)
Observations	153	153	153	153
R-squared	0.467	0.467	0.467	0.467
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 7: AI Exposure and Mortgage Applications (County-level)

This table reports the county-level OLS regression results. The dependent variables are county-level home purchase mortgage growth rate (in fraction) in Panel A and home improvement mortgage growth rate (in fraction) in Panel B. The growth rate is based on number of applications. The data is obtained from Consumer Financial Protection Bureau (CFPB), Home Mortgage Disclosure Act (HMDA) data. The sample period is 2021 to 2023. The variable definition is in the Appendix section D. The fixed effects of the regressions are reported at the bottom of the table. Home purchase mortgage growth rate is winsorized at 1% and 99% level. Home improvement mortgage growth rate is winsorized at 5% and 95% level. T-statistics are in parentheses. Standard errors are clustered at the county level. Coefficients statistically significant at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Panel A: Home purchase mortgage growth rate

VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	-0.807***			
	(-2.68)			
GenAI exposure(top quartile)×Post-ChatGPT		-0.021***		
		(-2.87)		
GenAI exposure(top tercile)×Post-ChatGPT			-0.018***	
			(-2.67)	
GenAI exposure(above median)×Post-ChatGPT				-0.012*
				(-1.75)
Constant	0.029	-0.034***	-0.034***	-0.034***
	(1.20)	(-56.58)	(-44.79)	(-29.73)
Observations	9,147	9,147	9,147	9,147
R-squared	0.531	0.531	0.531	0.531
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Panel B: Home improvement mortgage growth rate

VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	-3.955***			
	(-5.39)			
GenAI exposure(top quartile)×Post-ChatGPT		-0.097***		
		(-5.10)		
GenAI exposure(top tercile)×Post-ChatGPT			-0.081***	
			(-4.56)	
GenAI exposure(above median)×Post-ChatGPT				-0.053***
				(-3.02)
Constant	0.527***	0.217***	0.218***	0.218***
	(8.95)	(136.33)	(109.24)	(73.47)
Observations	8,783	8,783	8,783	8,783
R-squared	0.312	0.312	0.311	0.310
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 8: AI Exposure and Local Debt Delinquency (State-level)

This table reports the state-level OLS regression results. The dependent variables are the delinquency rate (in percentage) of student loan (Panel A), credit card (Panel B), mortgage (Panel C), and auto loan (Panel D). The sample period is 2021 to 2023. The variable definition is in the Appendix section D. The fixed effects of the regressions are reported at the bottom of the table. T-statistics are in parentheses. Standard errors are clustered at the state level. Coefficients statistically significant at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Panel A: Student loan delinquency rate (in %)

VARIABLES	(9)	(10)	(11)	(12)
GenAI exposure×Post-ChatGPT	33.562***			
	(3.29)			
GenAI exposure(top quartile)×Post-ChatGPT		0.572***		
		(3.62)		
GenAI exposure(top tercile)×Post-ChatGPT			0.564***	
			(4.00)	
GenAI exposure(above median)×Post-ChatGPT				0.283*
				(1.73)
Constant	-0.630	2.156***	2.138***	2.153***
	(-0.73)	(173.95)	(136.46)	(77.49)
Observations	153	153	153	153
R-squared	0.932	0.932	0.932	0.932
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Panel B: Credit card delinquency rate (in %)

VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	12.172*			
	(1.72)			
GenAI exposure(top quartile)×Post-ChatGPT		0.222*		
		(1.74)		
GenAI exposure(top tercile)×Post-ChatGPT			0.236**	
			(2.08)	
GenAI exposure(above median)×Post-ChatGPT				0.104
				(0.84)
Constant	6.867***	7.876***	7.868***	7.876***
	(11.47)	(788.80)	(623.84)	(374.60)
Observations	153	153	153	153
R-squared	0.974	0.974	0.974	0.974
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Panel C: Mortgage delinquency rate (in %)

VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	0.461			
	(0.20)			
GenAI exposure(top quartile)×Post-ChatGPT		-0.011		
		(-0.33)		
GenAI exposure(top tercile)×Post-ChatGPT			-0.016	
			(-0.55)	
GenAI exposure(above median)×Post-ChatGPT				0.008
				(0.26)
Constant	0.469**	0.509***	0.510***	0.506***
	(2.38)	(198.86)	(157.73)	(102.10)
Observations	153	153	153	153
R-squared	0.932	0.932	0.932	0.932
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Panel D: Auto loan delinquency rate (in %)

VARIABLES	(5)	(6)	(7)	(8)
GenAI exposure×Post-ChatGPT	3.597			
	(1.06)			
GenAI exposure(top quartile)×Post-ChatGPT		0.030		
		(0.38)		
GenAI exposure(top tercile)×Post-ChatGPT			-0.020	
			(-0.25)	
GenAI exposure(above median)×Post-ChatGPT				0.180*
				(1.95)
Constant	3.462***	3.763***	3.768***	3.735***
	(12.06)	(619.65)	(412.42)	(237.26)
Observations	153	153	153	153
R-squared	0.984	0.984	0.984	0.984
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 9: AI Exposure and Establishments Employment Growth (County-level)

This table reports the county-level OLS regression results. The dependent variable is county-level annual employment growth rate (in percentage) in county establishments of all size. The sample period is 2021 to 2023. The employment data is obtained from Quarterly Census of Employment and Wages (QCEW) of the U.S. Bureau of Labor Statistics (BLS). The variable definition is in the Appendix section D. The fixed effects of the regressions are reported at the bottom of the table. T-statistics are in parentheses. Standard errors are clustered at the county level. Coefficients statistically significant at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	-4.257			
	(-0.50)			
GenAI exposure(top quartile)×Post-ChatGPT		-0.452**		
		(-2.37)		
GenAI exposure(top tercile)×Post-ChatGPT			-0.359**	
			(-2.00)	
GenAI exposure(above median)×Post-ChatGPT				-0.129
				(-0.70)
Constant	2.481***	2.176***	2.178***	2.161***
	(3.66)	(143.66)	(113.92)	(71.93)
Observations	7,776	7,776	7,776	7,776
R-squared	0.354	0.351	0.351	0.351
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 10: AI Exposure and Establishments Employee Wage (County-level)

This table reports the county-level OLS regression results. The dependent variable is the natural logarithm of county-level average annual wage (lnwage). The sample period is 2021 to 2023. The variable definition is in the Appendix section D. The fixed effects of the regressions are reported at the bottom of the table. T-statistics are in parentheses. Standard errors are clustered at the county level. Coefficients statistically significant at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	-0.312***			
	(-5.26)			
GenAI exposure(top quartile)×Post-ChatGPT		-0.007***		
		(-5.43)		
GenAI exposure(top tercile)×Post-ChatGPT			-0.005***	
			(-4.13)	
GenAI exposure(above median)×Post-ChatGPT				-0.005***
				(-3.85)
Constant	10.814***	10.790***	10.790***	10.790***
	(2,275.97)	(102,978.95)	(81,054.35)	(51,826.06)
Observations	9,161	9,161	9,161	9,161
R-squared	0.987	0.987	0.987	0.987
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 11: AI Exposure and Local GDP Growth (County-level)

This table reports the county-level OLS regression results. The dependent variable is county-level GDP growth rate (in %). The sample period is 2021 to 2023. The variable definition is in the Appendix section D. The fixed effects of the regressions are reported at the bottom of the table. T-statistics are in parentheses. Standard errors are clustered at the county level. Coefficients statistically significant at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	-66.392***			
	(-3.96)			
GenAI exposure(top quartile)×Post-ChatGPT		-1.266***		
		(-3.60)		
GenAI exposure(top tercile)×Post-ChatGPT			-0.977***	
			(-2.82)	
GenAI exposure(above median)×Post-ChatGPT				-1.027***
				(-2.76)
Constant	8.632***	3.410***	3.413***	3.476***
	(6.42)	(117.66)	(89.48)	(56.15)
Observations	9,162	9,162	9,162	9,162
R-squared	0.253	0.252	0.252	0.252
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Appendix A.

Table A1: Top and Bottom 20 AI Exposure Occupations

Panel A: Top 20 AI exposure occupations

ONET_SOC6	Occupation	number of tasks	AI_exp	AI_exp_rank
43-4021	Correspondence Clerks	20	0.825	1
43-9081	Proofreaders and Copy Markers	11	0.818	2
15-1251	Computer Programmers	17	0.765	3
27-3091	Interpreters and Translators	17	0.765	3
13-2071	Credit Counselors	23	0.739	5
43-3011	Bill and Account Collectors	15	0.733	6
13-1131	Fundraisers	28	0.714	7
27-3043	Writers and Authors	36	0.708	8
27-3043	Poets, Lyricists and Creative Writers	36	0.708	8
15-1242	Database Administrators	18	0.694	10
19-3022	Survey Researchers	16	0.688	11
15-1243	Data Warehousing Specialists	43	0.686	12
15-1243	Database Architects	43	0.686	12
43-6011	Executive Secretaries and Executive Administrative Assis	22	0.682	14
43-9111	Statistical Assistants	14	0.679	15
15-2051	Business Intelligence Analysts	54	0.667	17
15-2051	Data Scientists	54	0.667	17
15-2051	Clinical Data Managers	54	0.667	17
15-1254	Web Developers	29	0.655	19
13-1151	Training and Development Specialists	20	0.650	20
25-9031	Instructional Coordinators	30	0.650	20

Panel B: Bottom 20 AI exposure occupations

ONET_SOC6	Occupation	number of tasks	AI_exp	AI_exp_rank
37-2012	Maids and Housekeeping Cleaners	25	0	924
47-2044	Tile and Stone Setters	25	0	924
47-3013	Helpers–Electricians	25	0	924
49-3021	Automotive Body and Related Repairers	25	0	924
47-2051	Cement Masons and Concrete Finishers	26	0	924
47-2053	Terrazzo Workers and Finishers	26	0	924
47-2081	Drywall and Ceiling Tile Installers	26	0	924
47-4061	Rail-Track Laying and Maintenance Equipment Operators	26	0	924
49-3031	Bus and Truck Mechanics and Diesel Engine Specialists	26	0	924
49-3093	Tire Repairers and Changers	26	0	924
51-7042	Woodworking Machine Setters, Operators, and Tenders, Exc	26	0	924
47-2121	Glaziers	27	0	924
51-6041	Shoe and Leather Workers and Repairers	27	0	924
29-9093	Surgical Assistants	28	0	924
47-2181	Roofers	28	0	924
51-6021	Pressers, Textile, Garment, and Related Materials	28	0	924
51-2011	Aircraft Structure, Surfaces, Rigging, and Systems Assem	30	0	924
47-2061	Construction Laborers	32	0	924
51-4031	Cutting, Punching, and Press Machine Setters, Operators,	32	0	924
49-9063	Musical Instrument Repairers and Tuners	37	0	924

Table A2: Industry (NAICS-2 digit) AI Exposure

This table reports the industry-level AI exposure.

NAICS-2	Description	AI_exp	AI_exp(core tasks only)
52	Finance and Insurance	0.404	0.408
55	Management of Companies and Enterprises	0.389	0.398
51	Information	0.383	0.387
54	Professional, Scientific, and Technical Services	0.382	0.391
61	Educational Services	0.324	0.321
42	Wholesale Trade	0.282	0.297
92	Public Administration	0.271	0.282
53	Real Estate and Rental and Leasing	0.266	0.271
62	Health Care and Social Assistance	0.261	0.255
44-45	Retail Trade	0.254	0.256
81	Other Services (except Public Administration)	0.243	0.239
48-49	Transportation and Warehousing	0.230	0.238
71	Arts, Entertainment, and Recreation	0.227	0.226
22	Utilities	0.225	0.246
56	Administrative and Support and Waste Management and Remediation Services	0.220	0.228
11	Agriculture, Forestry, Fishing and Hunting	0.199	0.215
31-33	Manufacturing	0.187	0.191
21	Mining, Quarrying, and Oil and Gas Extraction	0.160	0.174
23	Construction	0.144	0.149
72	Accommodation and Food Services	0.124	0.114

Table A3: Top and Bottom 20 AI Exposure Counties

This table reports the top and bottom 20 AI exposure counties in the U.S.

Panel A: Top 20 AI exposure counties

FIPS	County	AI_exp
36061	New York, NY	0.304
6075	San Francisco, CA	0.293
51013	Arlington, VA	0.293
32017	Lincoln, NV	0.291
19049	Dallas, IA	0.290
51919	Fairfax, VA	0.290
8014	Broomfield, CO	0.290
25025	Suffolk, MA	0.289
47187	Williamson, TN	0.285
6081	San Mateo, CA	0.284
48085	Collin, TX	0.283
13121	Fulton, GA	0.282
51099	King George, VA	0.281
25017	Middlesex, MA	0.280
11001	District of Columbia	0.280
34035	Somerset, NJ	0.280
34027	Morris, NJ	0.280
29510	St. Louis, MO	0.280
8035	Douglas, CO	0.280
42029	Chester, PA	0.279

Panel B: Bottom 20 AI exposure counties

FIPS	County	GenAI exposure
2068	Denali Borough, AK	0.177
22023	Cameron, LA	0.184
48301	Loving, TX	0.193
2060	Bristol Bay Borough, AK	0.199
30057	Madison, MT	0.200
32029	Storey, NV	0.201
6051	Mono, CA	0.201
2013	Aleutians East Borough, AK	0.201
48237	Jack, TX	0.203
18117	Orange, IN	0.204
8047	Gilpin, CO	0.205
48235	Irion, TX	0.207
51036	Charles City,	0.207
48283	La Salle, TX	0.208
13319	Wilkinson, GA	0.208
18165	Vermillion, IN	0.209
40007	Beaver, OK	0.209
48383	Reagan, TX	0.209
18051	Gibson, IN	0.210
48311	McMullen, TX	0.210

Table A4: AI Exposure (core tasks only) and Local Deposit Growth (County-level)

This table reports the county-level OLS regression results. The dependent variable is the county-level deposit growth, which is defined as value-weighted deposit growth of all bank branches in a county. The sample period spans from 2021 to 2024. The independent variable of interest is GenAI exposure based on core tasks only in the SOC O*NET occupation-task data as well as the indicator variables based on this GenAI exposure measure. The variable definition is in the Appendix section D. T-statistics are in parentheses. Standard errors are clustered at the county level. Coefficients statistically significant at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	-0.430*			
	(-1.88)			
GenAI exposure(top quartile)×Post-ChatGPT		-0.013**		
		(-2.14)		
GenAI exposure(top tercile)×Post-ChatGPT			-0.017***	
			(-3.13)	
GenAI exposure(above median)×Post-ChatGPT				-0.009*
				(-1.74)
Constant	0.066***	0.032***	0.032***	0.032***
	(3.51)	(65.09)	(55.45)	(38.12)
Observations	9,152	9,152	9,152	9,152
R-squared	0.455	0.456	0.456	0.455
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y

Table A5: AI Exposure and County-level Deposit Growth (2021-2024)

This table reports the county-level OLS regression results. The dependent variable is the county-level deposit growth, which is defined as value-weighted deposit growth of all bank branches in a county. The sample period spans from 2021 to 2024. The variable definition is in the Appendix section D. T-statistics are in parentheses. Standard errors are clustered at the county level. Coefficients statistically significant at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	-0.387**			
	(-2.15)			
GenAI exposure(top quartile)×Post-ChatGPT		-0.015***		
		(-3.22)		
GenAI exposure(top tercile)×Post-ChatGPT			-0.013***	
			(-3.01)	
GenAI exposure(above median)×Post-ChatGPT				-0.010**
				(-2.38)
Constant	0.071***	0.026***	0.026***	0.026***
	(3.26)	(45.75)	(37.14)	(25.72)
Observations	12,199	12,199	12,199	12,199
R-squared	0.379	0.379	0.379	0.379
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y

Table A6: AI Exposure and County-level Deposit Growth

This table reports the county-level OLS regression results. The dependent variable is the county-level deposit growth, which is defined as value-weighted deposit growth of all bank branches in a county. The regressions control for the interactions of county-level GenAI exposure with education (percentage of population that over 25 years old with a bachelor degree or higher), ln(total population), ln(Household median income), GDP growth, respectively. The sample period spans from 2021 to 2023. The variable definition is in the Appendix section D. T-statistics are in parentheses. Standard errors are clustered at the county level. Coefficients statistically significant at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

VARIABLES	(1)	(2)	(3)	(4)
GenAI exposure×Post-ChatGPT	-0.235			
	(-0.93)			
GenAI exposure(top quartile)×Post-ChatGPT		-0.012*		
		(-1.86)		
GenAI exposure(top tercile)×Post-ChatGPT			-0.010*	
			(-1.68)	
GenAI exposure(above median)×Post-ChatGPT				-0.009
				(-1.62)
GenAI exposure	-0.057			
	(-0.36)			
GenAI exposure(top quartile)		0.003		
		(0.72)		
GenAI exposure(top tercile)			0.004	
			(1.06)	
GenAI exposure(above median)				0.002
				(0.71)
Education(residual)	0.001***	0.001***	0.001***	0.001***
	(3.28)	(2.86)	(2.70)	(2.70)
Education (residual)×Post-ChatGPT	-0.002***	-0.002***	-0.002***	-0.002***
	(-3.89)	(-3.68)	(-3.67)	(-3.65)
ln(total population)	-0.001	-0.002	-0.002	-0.002
	(-0.74)	(-1.30)	(-1.35)	(-1.33)
ln(total population)×Post-ChatGPT	0.001	0.003	0.002	0.003
	(0.64)	(1.11)	(1.06)	(1.12)
ln(median age)	-0.014	-0.014	-0.014	-0.014
	(-0.89)	(-0.90)	(-0.86)	(-0.86)
ln(median age)×Post-ChatGPT	0.033	0.033	0.033	0.032
	(1.36)	(1.36)	(1.35)	(1.34)
GDP growth	0.001***	0.001***	0.001***	0.001***
	(3.83)	(3.78)	(3.78)	(3.79)
GDP growth ×Post-ChatGPT	-0.001***	-0.001***	-0.001***	-0.001***
	(-3.73)	(-3.70)	(-3.69)	(-3.69)
ln(Household median income)	0.005	0.007	0.007	0.007
	(0.58)	(0.76)	(0.83)	(0.84)
ln(Household median income)×Post-ChatGPT	-0.046***	-0.048***	-0.048***	-0.048***
	(-3.01)	(-3.18)	(-3.16)	(-3.18)
Constant	0.194**	0.157**	0.148*	0.148*
	(2.53)	(1.98)	(1.86)	(1.86)
Observations	9,128	9,128	9,128	9,128
R-squared	0.198	0.197	0.197	0.197
FIPS FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
Cluster at FIPS	Yes	Yes	Yes	Yes

Table A7: Occupation and Tasks Examples

Panel A: Computer programmers

Tasks	GPT_label
Write, analyze, review, and rewrite programs, using workflow chart and diagram, and applying knowledge of computer capabilities, subject matter, and symbolic logic.	E1
Correct errors by making appropriate changes and rechecking the program to ensure that the desired results are produced.	E1
Perform or direct revision, repair, or expansion of existing programs to increase operating efficiency or adapt to new requirements.	E1
Write, update, and maintain computer programs or software packages to handle specific jobs such as tracking inventory, storing or retrieving data, or controlling other equipment.	E1
Consult with managerial, engineering, and technical personnel to clarify program intent, identify problems, and suggest changes.	E0
Conduct trial runs of programs and software applications to be sure they will produce the desired information and that the instructions are correct.	E1
Prepare detailed workflow charts and diagrams that describe input, output, and logical operation, and convert them into a series of instructions coded in a computer language.	E1
Compile and write documentation of program development and subsequent revisions, inserting comments in the coded instructions so others can understand the program.	E1
Consult with and assist computer operators or system analysts to define and resolve problems in running computer programs.	E1
Perform systems analysis and programming tasks to maintain and control the use of computer systems software as a systems programmer.	E1
Write or contribute to instructions or manuals to guide end users.	E1
Investigate whether networks, workstations, the central processing unit of the system, or peripheral equipment are responding to a program's instructions.	E0
Assign, coordinate, and review work and activities of programming personnel.	E0
Train subordinates in programming and program coding.	E1
Develop Websites.	E1
Train users on the use and function of computer programs.	E1
Collaborate with computer manufacturers and other users to develop new programming methods.	E0

Panel B: Software developers

Tasks	GPT_label
Analyze information to determine, recommend, and plan installation of a new system or modification of an existing system.	E2
Analyze user needs and software requirements to determine feasibility of design within time and cost constraints.	E2
Confer with data processing or project managers to obtain information on limitations or capabilities for data processing projects.	E0
Confer with systems analysts, engineers, programmers and others to design systems and to obtain information on project limitations and capabilities	E0
Consult with customers or other departments on project status, proposals, or technical issues, such as software system design or maintenance.	E0
Coordinate installation of software system.	E0
Design, develop and modify software systems, using scientific analysis and mathematical models to predict and measure outcomes and consequences of design.	E1
Determine system performance standards.	E2
Develop or direct software system testing or validation procedures, programming, or documentation.	E1
Modify existing software to correct errors, adapt it to new hardware, or upgrade interfaces and improve performance.	E1
Monitor functioning of equipment to ensure system operates in conformance with specifications.	E0
Obtain and evaluate information on factors such as reporting formats required, costs, or security needs to determine hardware configuration.	E2
Prepare reports or correspondence concerning project specifications, activities, or status.	E1
Recommend purchase of equipment to control dust, temperature, or humidity in area of system installation.	E2
Specify power supply requirements and configuration.	E2
Store, retrieve, and manipulate data for analysis of system capabilities and requirements.	E1
Supervise and assign work to programmers, designers, technologists, technicians, or other engineering or scientific personnel.	E0
Supervise the work of programmers, technologists and technicians and other engineering and scientific personnel.	E0
Train users to use new or modified equipment.	E1

Appendix B. Selected GPT explanations for some tasks

Computer programmers

Task 1: Write, analyze, review, and rewrite programs, using workflow chart and diagram, and applying knowledge of computer capabilities, subject matter, and symbolic logic.

Label: E1

Explanation: The task falls under the E1 category. The task involves writing, analyzing, reviewing, and rewriting programs, which directly aligns with the capabilities of the LLM as described in the E1 category. Specifically, the LLM can assist in writing and transforming text and code according to complex instructions, providing edits to existing text or code following specifications, and writing code that can help perform a task that used to be done by hand. Additionally, the task of applying knowledge of computer capabilities, subject matter, and symbolic logic can be supported by the LLM's ability to generate explanations and provide feedback on documents or code. The use of workflow charts and diagrams might not be directly supported in terms of visual creation, but the LLM can help in planning and describing the logic that would go into such charts and diagrams, thus reducing the time it takes to complete the task with equivalent quality by at least half.

Task 2: Consult with managerial, engineering, and technical personnel to clarify program intent, identify problems, and suggest changes.

Label: E0

Explanation: The task falls under the E0 category. The primary reason for this classification is that the task involves a high degree of human interaction, specifically consulting with managerial, engineering, and technical personnel to clarify program intent, identify problems, and suggest changes. This process requires nuanced communication, understanding of complex technical and organizational contexts, and often real-time problem-solving and negotiation skills that are beyond the current capabilities of an LLM. While an LLM could assist in preparing documents, summarizing discussions, or even drafting potential solutions or changes to code based on specifications, the core of the task—effective communication and consultation with a variety of stakeholders to solve problems—relies heavily on human skills and intuition. Therefore, even though an LLM could support some aspects of the task, it would not significantly reduce the time it takes to complete the core components of the task with high quality by at least half.

Software developers

Task 1: Consult with customers or other departments on project status, proposals, or technical issues, such as software system design or maintenance.

Label: E0

Explanation: The task falls under the E0 category. Consulting with customers or other departments on project status, proposals, or technical issues, such as software system design or maintenance, involves a high degree of human interaction and understanding of specific, potentially up-to-date contexts that an LLM alone cannot provide. While an LLM can assist in generating reports, summarizing documents, or even drafting responses to

technical queries, the nuanced understanding required for effective consultation, especially in dynamic and complex fields like software development, goes beyond text generation. This task requires understanding the specific needs, concerns, and contexts of the project or issue at hand, which can vary greatly and may involve up-to-date information not available to the LLM. Additionally, the task involves decision-making based on these consultations, which is explicitly mentioned as a limitation in the E0 category. Therefore, despite the LLM's capabilities in assisting with certain aspects of the task, the core requirement for human interaction and decision-making based on up-to-date, specific contexts means that the LLM would not significantly reduce the time it takes to complete the task with high quality by at least half.

Task 2: Determine system performance standards.

Label: E2

Explanation: The task of determining system performance standards falls under the E2 category. This task involves analyzing data, understanding the specific requirements of a system, and making recommendations based on that analysis. While the LLM can assist in providing general knowledge about system performance and possibly help in drafting documents or guidelines based on general principles, the task requires a deeper understanding of specific system requirements, data analysis, and the ability to make tailored recommendations. These aspects may not be fully addressed by the LLM alone but could be significantly aided by additional software developed on top of the LLM that specializes in analyzing system performance data and making recommendations. Such software could leverage the LLM's capabilities to process and summarize information, but it would need to integrate more specialized knowledge and data analysis tools to effectively determine system performance standards.

Painters, Construction and Maintenance

Task 1: remove old finishes by stripping, sanding, wire brushing, burning, or using water or abrasive blasting.

Label: E0

Explanation: The task involves physical labor and manual skills such as stripping, sanding, wire brushing, burning, or using water or abrasive blasting to remove old finishes, which are tasks that cannot be performed by a language model or any software tool. These tasks require hands-on work, precise measurements, and often a degree of human judgment based on the condition of the material being worked on. Therefore, this task falls under the E0 category, as the LLM and systems built on top of it cannot perform physical tasks, make decisions that impact human livelihood, or replace the need for human labor in tasks that require physical interaction with materials.

Fashion designer

Task 1: Research the styles and periods of clothing needed for film or theatrical productions.

Label: E1

Explanation: The task of researching styles and periods of clothing needed for film or theatrical productions can be significantly expedited by using a large language model (LLM) like ChatGPT. The LLM can provide detailed information on historical clothing styles, the cultural context of different periods, and even suggest sources for further research. This task involves writing and transforming text according to complex instructions, summarizing documents, and providing feedback on documents, all of which are capabilities listed under the E1 category. The LLM can help fashion designers by quickly generating comprehensive overviews of fashion trends from different periods, which would otherwise require extensive manual research. This use of the LLM can reduce the time it takes to complete the research with equivalent quality by at least half, as it streamlines the information gathering and synthesis process.

Appendix C. OpenAI Methodology Notes

GPT prompt for exposure scoring

The following prompt structure was based on the rubric language by Eloundou et al. (2024) and Eisfeldt et al. (2023). Below is the instruction prompts submitted before asking GPT-4.0 Preview to classify each task statement (using the version as of March 30th to April 2nd, 2024). The GPT temperature is set to 0.

systemprompt="Consider the most powerful OpenAI large language model (LLM). This model can complete many tasks that can be formulated as having text input and text output where the context for the input can be captured in 2000 words. The model also cannot draw up-to-date facts (those from $<$ 1 year ago) unless they are captured in the input. Assume you are a worker with an average level of expertise in your role trying to complete the given task. You have access to the LLM as well as any other existing software or computer hardware tools mentioned in the task. You also have access to any commonly available technical tools accessible via a laptop (e.g. a microphone, speakers, etc.). You do not have access to any other physical tools or materials. You are a helpful research assistant who wants to label the given tasks according to the rubric below. Equivalent quality means someone reviewing the work would not be able to tell whether a human completed it on their own or with assistance from the LLM. If you aren't sure how to judge the amount of time a task takes, consider whether the tools described exposed the majority of subtasks associated with the task.

rubric:

E1 - Direct exposure: Label tasks E1 if direct access to the LLM through an interface like ChatGPT or the OpenAI playground alone can reduce the time it takes to complete the task with equivalent quality by at least half. This includes tasks that can be reduced to: - Writing and transforming text and code according to complex instructions, - Providing edits to existing text or code following specifications, - Writing code that can help perform a task that used to be done by hand, - Translating text between languages, - Summarizing medium-length documents, - Providing feedback on documents, - Answering questions about a document, - Generating questions a user might want to ask about a document, - Writing questions for an interview or assessment, - Writing and responding to emails, including ones that involve refuting information or engaging in a negotiation (but only if the negotiation is via written correspondence), - Maintain records of written data, - Prepare training materials based on general knowledge, or - Inform anyone of any information via any written or spoken medium.

E2 - Exposure by LLM-powered applications: Label tasks E2 if having access to the LLM alone may not reduce the time it takes to complete the task by at least half, but it is easy to imagine additional software that could be developed on top of the LLM that would reduce the time it takes to complete the task by half. This software may include capabilities such as: - Summarizing documents longer than 2000 words and answering questions about those documents, - Retrieving up-to-date facts from the Internet and using those facts in combination with the LLM capabilities, - Searching over an organization's existing knowledge, data, or documents and retrieving information, - Retrieving highly specialized domain knowledge, - Make recommendations given data or written input, - Analyze written information to inform decisions, - Prepare training materials based on highly specialized knowledge, - Provide counsel on issues, and - Maintain complex databases.

E3 - Exposure given image capabilities: Suppose you had access to both the LLM and a system that could view, caption, and create images as well as any systems powered by the LLM (those in E2 above). This system cannot take video as an input and it cannot produce video as an output. This system cannot accurately retrieve very detailed information from image inputs, such as measurements of dimensions within an image. Label tasks as E3 if there is a significant reduction in the time it takes to complete the task given access to a LLM and these image capabilities: - Reading text from PDFs, - Scanning images, or - Creating or editing digital images according to instructions. The images can be realistic but they should not be detailed. The model can identify objects in the image but not relationships between those options.

E0 - No exposure: Label tasks E0 if none of the above clearly decrease the time it takes for an experienced worker to complete the task with high quality by at least half. Some examples: - If a task requires a high degree of human interaction (for example, in-person demonstrations) then it should be classified as E0. - If a task requires precise measurements then it should be classified as E0. - If a task requires reviewing visuals in detail then it should be classified as E0. - If a task requires any use of a hand or walking then it should be classified as E0. - Tools built on top of the LLM cannot make any decisions that might impact human livelihood (e.g.hiring, grading, etc.). If any part of the task involves collecting inputs to make a final decision (as opposed to analyzing data to inform a decision or make a recommendation) then it should be classified as E0. The LLM can make recommendations. - Even if tools built on top of the LLM can do a task, if using those tools would not save an experienced worker significant time completing the task, then it should be classified as E0. - The LLM and systems built on top of it cannot do anything that legally requires a human to perform the task. - If there is existing technology not powered by an LLM that is commonly used and can complete the task then you should mark the task E0 if using an LLM or LLM-powered tool will not further reduce the time to complete the task. When in doubt, you should default to E0.

Appendix D. Variable definitions

Variables	Definitions	Sources
GenAI exposure (task-level)	The Generative AI exposure of tasks determined by GPT-4-0125 Preview Model on OpenAI April 2, 2024.	OpenAI
GenAI exposure (occupation-level)	The weighted average task-level Generative AI exposure aggregated to the occupation-level Generative AI exposure.	O*NET
GenAI exposure (industry-level)	The weighted average occupation-level AI exposure aggregated to industry -level. The weight is determined by number of jobs of each occupation in an industry using the 2022 BLS Occupation-industry matrix data.	Bureau of Labor Statistics (BLS)
GenAI exposure (county-level)	The weighted average industry-level Generative AI exposure aggregated to county-level. The weight is determined by the number of jobs of each NAICS-2 industry in a county. The county-industry jobs data is from the BEA 2022 employment by NAICS industries.	Bureau of Economic Analysis (BEA)
GenAI exposure (state-level)	The weighted average county-level Generative AI exposure aggregated to the state-level using the 2022 county population data.	As above
GenAI exposure (top quartile)	A binary variable that equals 1 if a county's AI exposure is in top quartile.	
GenAI exposure (top tercile)	A binary variable that equals 1 if a county's AI exposure is in top tercile.	
GenAI exposure (above median)	A binary variable that equals 1 if a county's AI exposure is above the sample median.	
post-ChatGPT	A dummy variable that equals 1 for 2023 and 0 for 2021 and 2022.	
Deposit growth	The value-weighted deposit growth of all bank branches in a county.	FDIC Summary of Deposits
Retail deposit_growth	The value-weighted of retail deposit growth of all bank branches in a county. The percentage of retail deposits is determined by the data from banks' call reports in June each year.	FDIC Summary of Deposits and Call Reports

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Variables	Definition	
Institutional deposit_growth	The value-weighted of institutional deposit growth of all bank branches in a county. The percentage of institutional deposits is determined by the data from banks' call reports in June each year.	As above
Equity growth (quarterly)	The value-weighted quarterly equity growth of all local advisors in a county. Local advisor is defined as investment managers whose offices are located in no more than one county.	Thomas Reuters 13F data
Equity growth (annual)	The value-weighted annual equity growth of all local advisors in a county.	As above
Student loan delinquency rate	Percent of student loan debt balance with 90+ days delinquent (and in default).	New York Fed Consumer Credit
Credit card delinquency rate	Percent of credit card debt balance with 90+ days delinquent.	As above
Mortgage delinquency rate	Percent of mortgage debt balance with 90+ days delinquent.	As above
Auto loan delinquency rate	Percent of auto debt debt balance with 90+ days delinquent.	As above
Student loan balance growth	The growth rate of student loan debt balance per capita.	As above
Credit card delinquency rate	The growth rate of credit card debt balance per capita.	
Mortgage delinquency rate	The growth rate of mortgage debt balance per capita.	
Auto loan delinquency rate	The growth rate of auto debt balance per capita.	
Home purchase mortgage applications growth	The number of home purchase mortgage applications growth rate in a county.	Home Mortgage Disclosure Act
Home improvement mortgage applications growth	The number of home improvement mortgage applications growth rate in a county.	As above
Employee growth rate	The number of employee growth rate of establishments (all size and industries) in a county.	U.S. Bureau of Labor Statistics

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Variables	Definition	
ln(wage)	The natural logarithm of county-level wage of all industries including government (all establishment size).	As above
GDP growth	The county GDP growth rate of real Gross Domestic Product (Percent change from last year same month)	BEA
Education	The percentage of population over 25 years old holding bachelor degree or higher in 2022.	U.S. Census
Polulation	The natural logarithm of county total population in 2022.	As above
Median age	The natural logarithm of county median age in 2022.	As above
Household income	The natural logarithm of household median income in a county in 2022.	As above