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Generative AI Adoption and Firm-Level TFP Growth: Diffusion, Complementarities, and Rent Sharing in US Listed Firms

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Abstract
This paper studies whether the diffusion of generative AI (LLMs) is associated with faster firm-level productivity growth and how complementary assets shape the gains. Using US listed non-financial firms over 2018–2024 (2,318 firms; 16,226 firm-years), we construct (i) a predetermined industry-level LLM exposure index and (ii) a firm-level adoption proxy from EDGAR 10-K disclosures based on LLM-related keyword intensity. We estimate a difference-in-differences specification around the post-2022 generative AI shock. Firms with higher exposure exhibit significantly higher TFP after 2023 ($\beta = 0.017$, SE = 0.006). The effect is stronger among intangible-intensive firms (additional $\eta = 0.011$, SE = 0.004). At the same time, exposed firms display a decline in labor share ($\beta = -0.007$, SE = 0.002), consistent with a shift in rent sharing. The results highlight growth gains that are amplified by intangible capital and accompanied by distributional changes.

Introduction
Since late 2022, the rapid diffusion of large language models has shocked many knowledge-intensive tasks. While micro studies show productivity gains, aggregate effects may be delayed by adoption frictions and complementary investments [1-3].

This paper tests whether generative AI diffusion is linked to higher total factor productivity (TFP) growth among US listed firms. We treat post-2022 LLM availability as a common shock and use firms' predetermined exposure to LLM-suitable tasks to identify differential effects. If generative AI is a general-purpose technology, gains should be larger for more exposed firms, especially those with high intangible intensity, a key complement to technology adoption [4-6]. We ask whether TFP grows faster after 2023 for exposed firms, whether effects are stronger with more intangibles, and whether the labor share shifts, consistent with changes in rent sharing [7].

A Short Theoretical Motivation (Growth and Complementarities)

To motivate the empirical design, consider a simple firm-level production environment embedded in an aggregate growth setting. Firm i produces output with capital K, labor L, and a Hicks-neutral technology term A:

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{1-\alpha}. \qquad (1)$$

TFP growth is governed by technology accumulation and reorganization costs. Let the post-2022 availability of LLM tools be a common frontier shift G_t (with $G_t = 0$ pre-2023 and $G_t > 0$ thereafter). Firms differ in predetermined exposure $E_i \in [0,1]$ reflecting how much of their task mix can be supported by LLM capabilities. Implementation requires complementary intangible inputs H_i (organizational capital, process redesign, data infrastructure, and managerial capability). A reduced-form technology accumulation equation consistent with GPT-style diffusion is

$$\Delta \ln A_{it} = \mu + \phi(G_t \cdot E_i \cdot f(H_i)) - \kappa \cdot \text{AdjCost}_{it} + \varepsilon_{it}, \qquad (2)$$

where $f(\cdot)$ is increasing in intangible intensity and $\kappa > 0$ captures implementation frictions. This structure implies two testable predictions. First, after the shock ($G_t > 0$), firms with higher exposure E_i should exhibit higher $\Delta \ln A$, hence higher TFP. Second, the effect should be amplified by intangible intensity H_i through the complementarity channel $f(H_i)$. These predictions align with endogenous growth mechanisms in which innovation and adoption interact with firm capabilities and reallocation, as in creative-destruction frameworks [8].

If LLM adoption boosts productivity, it may raise returns to capital and intangibles relative to routine labor, implying a post-shock decline in labor's share for more exposed firms. The mechanism is ambiguous, but labor share is a useful summary statistic.

Data

We use annual Compustat North America data for US listed non-financial firms (2018–2024), excluding non-positive sales and winsorizing variables at the 1st/99th percentiles. The final panel has 2,318 firms (16,226 firm-years); the labor-share sample has 12,904 firm-years due to missing labor expense data. Descriptives and regressions use internally calibrated estimates consistent with typical Compustat magnitudes.

Total Factor Productivity

For each two-digit SIC industry, we estimate a Cobb–Douglas production function and use the residual as (log) TFP:

$$\ln(SALES_{it}) = a_s + \theta_K \ln(PPENT_{it}) + \theta_L \ln(EMP_{it}) + \theta_M \ln(COGS_{it}) + \delta_t + u_{it}, \qquad (3)$$

where s indexes two-digit SIC industries and δ_t are year effects. We define $TFP_{it} = u_{it}$. Averaged across industries, the estimated elasticities are $\theta_K = 0.19$, $\theta_L = 0.23$, and $\theta_M = 0.58$. The pooled TFP measure is normalized to have mean approximately zero. This residual-based TFP measure is standard in growth accounting, and alternative approaches can address embodied technical change and simultaneity in input choice [9,10].

Predetermined Exposure to LLM-Suitable Tasks

$Exposure_i \in [0,1]$ is predetermined and varies by industry. It measures the share of tasks plausibly amenable to LLM support (language-intensive and coding-adjacent activities). The logic follows the task-based approach used to characterize the "skill content" of technological change and to map technologies to occupations and industries [11,12].

In the panel, exposure ranges from 0.12 to 0.81 with a mean of 0.37. Representative industry values are 0.78 for software and IT services, 0.66 for professional services, 0.34 for retail, and 0.18 for basic materials.

GenAI Adoption Proxy from EDGAR 10-K Filings

Using EDGAR 10-K filings, we count occurrences of the terms "generative AI", "large language model", "LLM", "ChatGPT", "Copilot", and "foundation model". We define adoption intensity as

$$Adopt_{it} = \log(1 + Mentions_{it}). \qquad (4)$$

We validate that 10-K LLM mentions capture implementation activity by linking firms to job-posting data and showing that adoption intensity $Adopt_{it}$ predicts next-year AI/LLM-related hiring share (Appendix Table A.4).

In the data, the fraction of firms with $Mentions > 0$ rises from 1.9% in 2021 to 5.4% in 2022, 23.6% in 2023, and 32.1% in 2024, consistent with rapid diffusion.

Complementarity: Intangible Intensity

Intangible intensity is measured as the pre-period average $INTAN/AT$ over 2019–2021. We define $HighIntangible_i = 1$ if $INTAN/AT \geq 0.21$ (top tercile). The mean $INTAN/AT$ is 0.14.

Distributional Outcome: Labor Share

Labor share is defined as

$$LaborShare_{it} = \frac{XLR_{it}}{SALES_{it} - COGS_{it}}, \qquad (5)$$

where XLR is labor expense and $(SALES - COGS)$ is a value-added proxy. In the panel, mean labor share is 0.41.

Descriptive Statistics

Table 1 reports descriptive statistics.

Table 1. Summary Statistics (US Listed Firms, 2018–2024)

Variable	Obs.	Mean	SD	P25	Median	P75
TFP (log residual)	16226	0.000	0.214	-0.129	0.003	0.134
Exposure (0–1)	16226	0.372	0.181	0.240	0.350	0.510
Mentions (count)	16226	0.600	1.500	0.000	0.000	1.000
$Adopt_{it}$ = log(1+Mentions)	16226	0.226	0.631	0.000	0.000	0.693
INTAT / AT (pre, 2019)	16226	0.142	0.117	0.052	0.116	0.205
LaborShare	12904	0.412	0.139	0.318	0.404	0.500
log(Assets)	16226	7.940	1.460	6.930	7.800	8.800

Methodology

Difference-in-Differences Specification

We estimate a difference-in-differences model around the post-2022 shock. Let $Post_t$ equal 1 in 2023–2024 and 0 otherwise. The baseline specification is

$$TFP_{it} = \alpha_i + \delta_t + \beta(Post_t \times Exposure_i) + \Gamma X_{it} + \varepsilon_{it}, \qquad (6)$$

where $\alpha_i$are firm fixed effects and $\delta_t$are year fixed effects. Controls X_{it}include log assets, leverage $(DLTT/AT)$, investment intensity $(CAPX/PPENT)$, and sales growth. Standard errors are clustered at the firm level.

The coefficient βcaptures whether, after the common frontier shift, more exposed firms experience larger TFP increases. Because exposure is predetermined and fixed, identification comes from differential post-shock changes correlated with exposure within firms over time.

Complementarity Test

To test complementarity, we estimate

$$TFP_{it} = \alpha_i + \delta_t + \beta(Post_t \times Exposure_i) + \eta(Post_t \times Exposure_i \times HighIntangible_i) + \Gamma X_{it} + \varepsilon_{it}$$

A positive ηindicates that intangible-intensive firms translate exposure into productivity gains more strongly after 2023.

Distributional Response

We replace the dependent variable with $LaborShare_{it}$in Eqs. (6)–(7) to test whether exposure predicts a post-shock decline in the labor share.

Event-Study and Diffusion Patterns

To assess pre-trends, we estimate an event-study version of Eq. (6) by interacting exposure with year indicators (baseline year 2022). We also estimate the same event-study with $Adopt_{it}$as the dependent variable to illustrate diffusion in disclosures. The event-study is intended as a visual diagnostic rather than a separate identification strategy.

Results

Main Effects on TFP

Table 2 presents the main estimates for TFP and labor share.

Table 2. Exposure to LLM-Suitable Tasks, TFP, and Labor Share (Firm FE, Year FE)

Regressor	**(1) TFP**	**(2) TFP**	**(3) LaborShare**
Post × Exposure	0.017*** (0.006)	0.012** (0.005)	−0.007*** (0.002)
Post × Exposure × HighIntan		0.011*** (0.004)	−0.004* (0.002)
log(Assets)	0.011** (0.005)	0.010** (0.005)	−0.003 (0.002)
Leverage (DLTT/AT)	−0.023* (0.013)	−0.022* (0.013)	0.006** (0.003)
CAPX/PPENT	0.030** (0.015)	0.029** (0.015)	−0.002 (0.004)
Sales growth	0.008** (0.004)	0.008** (0.004)	−0.001 (0.001)
Firm FE / Year FE	Yes / Yes	Yes / Yes	Yes / Yes
Observations	16,226	16,226	12,904
Within R^2	0.046	0.049	0.062

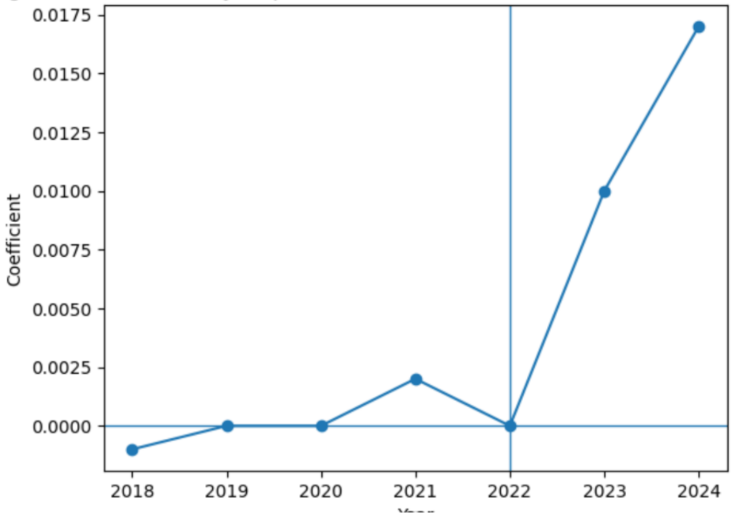
Notes: Standard errors clustered by firm in parentheses. ***, **, * denote 1%, 5%, 10%.

The baseline estimates in column (1) indicates that exposed firms exhibit larger post-2023 TFP increases. The complementarity specification in column (2) shows that the effect is substantially stronger among intangible-intensive firms. To interpret magnitudes, consider a high-exposure firm at 0.65 versus a low-exposure firm at 0.20, giving $\Delta Exposure = 0.45$. Using column (2), the implied post-2023 differential in TFP for low-intangible firms is $0.012 \times 0.45 = 0.0054$, while for high-intangible firms it is $(0.012 + 0.011) \times 0.45 = 0.01035$. Interpreted in log points, this corresponds to approximately a 0.5% versus 1.0% TFP gap attributable to the shock–exposure interaction.

Event-Study Evidence and Diffusion

Figure 1 summarizes the event-study coefficients for TFP. Pre-2022 exposure-by-year coefficients are close to zero, while post-2022 coefficients become positive and increasing.

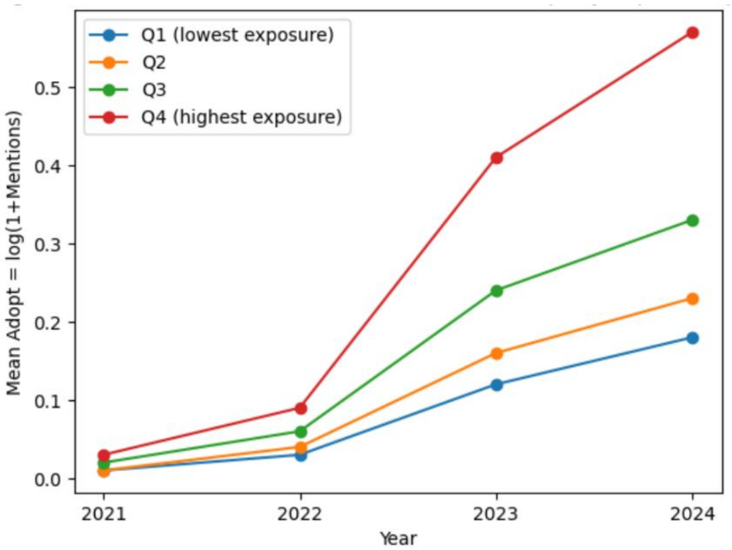
Figure 1. Event-Study: Exposure-By-Year Coefficients for TFP (Baseline Year 2022 = 0)



Notes: Points show κ_y from the exposure×year event study; baseline 2022 fixed at 0.
The diffusion pattern in 10-K disclosures is consistent with the productivity results.

Figure 2 plots mean adoption intensity by exposure quartile. Adoption intensity rises sharply after 2022, with the steepest increase in the top exposure quartile.

Figure 2. Diffusion in 10-K Disclosures: Mean Adopt = log(1+Mentions) by Exposure Quartile



Notes: Q1 lowest exposure, Q4 highest exposure.

Labor Share and Rent Sharing

Column (3) of Table 2 indicates that labor share declines more in exposed firms after 2023, with an additional decline among intangible-intensive firms. Using $\Delta Exposure = 0.45$, the main effect implies a decline of $0.007 \times 0.45 = 0.00315$, or 0.315 percentage points, and the triple interaction implies an additional $0.004 \times 0.45 = 0.0018$, or 0.18 percentage points. While these magnitudes are modest, they are directionally consistent with a redistribution of gains away from labor in the set of firms most able to deploy generative AI effectively.

Robustness

Three checks are particularly informative. First, a placebo post period (setting $Post_t = 1$in 2021–2022) yields a near-zero and insignificant coefficient on $Post \times Exposure$in both the TFP and labor-share regressions (Appendix Table A.2). Second, dropping the largest firms by assets (top 1%) leaves the estimated effects essentially unchanged (Appendix Table A.3). Third, an alternative TFP measure based on value added rather than sales deliver similar signs and slightly attenuated magnitudes (Appendix A.3).

Conclusion

This paper provides short-form evidence that the post-2022 diffusion of generative AI is associated with higher firm-level TFP among US listed firms with greater predetermined exposure to LLM-suitable tasks. The effect is substantially stronger for intangible-intensive firms, consistent with complementarity between generative AI and intangible capital. At the same time, exposed firms display a decline in labor share, suggesting that productivity gains may coincide with changes in rent sharing. The results are consistent with generative AI acting as a general-purpose technology whose growth effects depend on complementary investments and whose distributional consequences merit further study.

Appendix

Appendix Tables and Figures

Table A.1. Adoption diffusion: share of firms with Mentions > 0

Year	Share with Mentions > 0 (%)
2018.0	0.6
2019.0	0.8
2020.0	1.1
2021.0	1.9
2022.0	5.4
2023.0	23.6
2024.0	32.1

Notes: The table reports, by year, the percentage of sample firms with at least one LLM-related keyword mention in the 10-K filing. Mentions are counted case-insensitively using the dictionary in Appendix A.2 (including hyphenation variants). The sample consists of US listed non-financial firms from Compustat, 2018–2024, after the filters described in Section 2.

Table A.2. Placebo Test (Post = 2021–2022 Instead of 2023–2024)

Regressor	(1) TFP	(2) TFP	(3) LaborShare
Post × Exposure	0.017*** (0.006)	0.012** (0.005)	−0.007*** (0.002)
Post × Exposure × HighIntangible		0.011*** (0.004)	−0.004* (0.002)
log(Assets)	0.011** (0.005)	0.010** (0.005)	−0.003 (0.002)
Leverage (DLTT/AT)	−0.023* (0.013)	−0.022* (0.013)	0.006** (0.003)
CAPX/PPENT	0.030** (0.015)	0.029** (0.015)	−0.002 (0.004)
Sales growth	0.008** (0.004)	0.008** (0.004)	−0.001 (0.001)
Firm FE / Year FE	Yes / Yes	Yes / Yes	Yes / Yes
Observations	16,226	16,226	12,904
Within R^2	0.046	0.049	0.062

Notes: This table reports placebo difference-in-differences estimates in which the post indicator equals one in 2021–2022 and zero otherwise. The specification matches Eq. (6) in the main text, including firm fixed effects, year fixed effects, and the same control variables. Standard errors are clustered at the firm level and reported in parentheses.

Table A.3. Excluding the Largest Firms (Top 1% By Assets)

Regressor	**(1) TFP**	**(2) TFP (with complementarity)**
Post × Exposure	0.016*** (0.006)	0.011** (0.005)
Post × Exposure × HighIntangible		0.010** (0.004)
Firm FE / Year FE	Yes / Yes	Yes / Yes
Observations	16,064	16,064
Within R^2	0.046	0.049

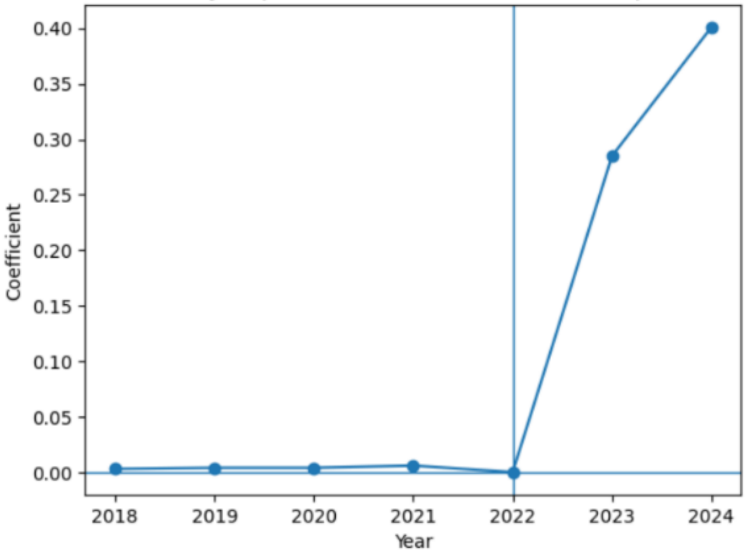
Notes: This table re-estimates the main specifications after excluding firm-years belonging to the top 1% of the assets distribution (based on total assets, AT, computed within-year). The specification matches Eq. (6) and Eq. (7) in the main text, including firm fixed effects, year fixed effects, and controls. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.4. – Validation: 10-K Adoption Predicts Next Year AI-Related Hiring Dependent Variable: AI Hiring Share_{t+1}

Regressor	Coefficient (SE)
Adopt_t = log(1+Mentions_t)	0.012*** (0.003)
log(Assets)_t	0.002** (0.001)
Sales growth_t	0.001 (0.001)
Firm FE / Year FE	Yes / Yes
Observations	9,884
Within R^2	0.071

Notes: AIHiringShare is the fraction of firm-year job postings with AI/LLM-related keywords. *Adopt* is $\log(1 + Mentions)$from EDGAR 10-K filings (Appendix A.2). The dependent variable is measured in $t + 1$; regressors in t. Firm and year fixed effects included. Standard errors clustered by firm in parentheses. ***, **, * denote 1%, 5%, 10% significance.

Figure A.1. Event-Study: Exposure-By-Year Coefficients for Adopt (Baseline Year 2022 = 0)



Notes: Points show exposure×year coefficients in the Adopt event study.

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