Disrupted Spaces: How Automation and Artificial Intelligence Reshape Corporate Real Estate Demand[*]

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Abstract

We study how artificial intelligence (AI) reshapes corporate real estate using three complementary analyses: balance-sheet evidence from Compustat, novel property-level evidence extracted from Item 2 disclosures in 10-K filings using textual analysis, and lease-market evidence from CompStak transactions. Using a panel of U.S. publicly traded firms from 2002 to 2023, we measure firm-level AI exposure by aggregating ability-level AI scores to industries and then to firms using text-based segment weights. In the balance-sheet data, a one-standard-deviation increase in firm-level AI exposure reduces owned corporate real estate by about 0.14 percentage points of assets per year in the IV estimates. The 10-K-based evidence shows that AI-exposed firms report fewer properties, operate in fewer states, and are more likely to sublease space and shift toward leasing. The leasing-market evidence shows that tenants in more AI-exposed industries are more likely to reduce leased square footage and rent commitments. The effect is stronger among firms with highly replaceable tasks, low R&D intensity, weak internal liquidity, and during the post-2015 accelerated AI adoption period, consistent with AI reducing space demand by substituting for routine labor and thereby lowering the value of maintaining underutilized physical assets. Our findings identify corporate real estate as an important margin through which technological change reshapes the firm.

JEL Classifications: G01, G11, G12, G14, R30

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1 Introduction

Corporate real estate is one of the largest and least flexible components of the corporate balance-sheet. For a typical U.S. public firm, owned buildings, land, and construction account for a meaningful share of assets, often representing the vast majority of physical capital (Chaney et al., 2012; Tuzel, 2010). Unlike equipment or financial assets, real assets cannot be easily redeployed, resized, or liquidated in response to changing business conditions. This rigidity has long been recognized as economically important: corporate real estate anchors firms' collateral capacity and borrowing constraints (Chaney et al., 2012; Lian and Ma, 2021), generates a "real estate premium" in the cross-section of stock returns (Tuzel, 2010), shapes investment sensitivity to local property price fluctuations (Cvijanović, 2014), and depresses liquidation recovery rates in secondary markets (Kermani and Ma, 2020; Campello et al., 2022). Yet even as the corporate finance literature has studied real estate as a source of collateral, risk, and financial friction, it has largely treated the quantity of corporate real estate as a slow-moving residual of past capital expenditure decisions rather than as an actively managed margin of adjustment. This perspective raises a natural question: under what conditions do firms actively adjust their demand for physical space?

We argue that the rise of artificial intelligence and automation technologies provides precisely the kind of large-scale, persistent technological shock that can induce firms to fundamentally reconfigure their demand for physical space. AI changes the production function by automating tasks that previously required on-site labor (Acemoglu and Restrepo, 2018, 2022), enabling digital coordination across geographically dispersed teams, and shifting the locus of value creation from physical capital to intangible capital such as software, data, and organizational knowledge (Babina et al., 2024; Eisfeldt et al., 2024; Brynjolfsson et al., 2025).

If AI makes certain forms of labor less location-bound and reduces the complementarity between workers and physical workspace, then firms should rationally adjust their corporate real estate holdings - downsizing offices, consolidating facilities, shifting from ownership to leasing, and contracting their geographic footprint. The economic stakes are substantial: U.S. nonresidential structures represent trillions of dollars in asset value, and persistent shifts in corporate space demand have first-order implications for commercial real estate markets, landlord cash flows, local tax revenues, and urban economic geography.

In this paper, we provide firm-level evidence that exposure to artificial intelligence reduces corporate real estate demand. We begin with a firm-level balance-sheet analysis using Compustat data for U.S. publicly traded firms from 2002 to 2023. Following the corporate real estate literature (Chaney et al., 2012; Cvijanović, 2014; Li et al., 2025), we construct several measures of firms' owned real estate holdings from PP&E subcomponents, including buildings, land and improvements, construction in progress, and leasehold-related assets, scaled by adjusted total assets.

To measure firm-level AI exposure, we start from the broad, task-based framework of Felten et al. (2021), which links AI applications to O*NET occupational abilities and captures the extent to which occupations rely on abilities susceptible to AI technologies. This definition is important because our sample spans a period in which AI evolved from earlier machine-learning, data-science, and automation tools to deep learning and, late in the sample, generative AI. We construct a time-varying firm-year AIE measure by aggregating ability-level AI exposure to occupations using O*NET importance and level scores, to industry-year cells using BLS occupational employment shares, and finally to firms using the time-varying text-based segment weights of Hoberg and Phillips (2025). This approach goes beyond assigning each firm to a single industry by capturing how much of the firm's product-market activity is tied to AI-exposed occupations, especially for diversified firms operating across multiple product markets. The long panel is useful for this question because corporate real estate is a slow-moving stock that adjusts gradually as firms renew leases, consolidate facilities, relocate operations, and revise capital expenditure plans.

To address endogeneity in firm-level AI exposure, we use a shift-share instrumental-variable design that combines predetermined industry shares with time-varying industry-level AI shocks, following the framework of Borusyak et al. (2025). We find that greater AI exposure leads firms to reduce owned real estate. In our baseline IV estimates, a one-standard-deviation increase in AI exposure lowers the ratio of owned real estate to total assets by 0.14 percentage points per year. Although the annual effect is modest, it accumulates to roughly 0.7 percentage points over five years, or about 8.4% of the sample mean. The IV estimates remain negative under shock-level inference, as in Borusyak et al. (2022). The results are also robust to broader corporate real estate definitions, a leave-one-out version of the instrument, alternative model specifications and differencing horizons, and sample restrictions that exclude the post-2019 period and other settings in which accounting changes or unusual macro shocks are most likely to complicate interpretation.

The heterogeneity tests are informative about mechanisms, allowing us to characterize *where*, *when*, and *how* AI reshapes corporate space demand. We document multiple dimensions of heterogeneity in the AI–real-estate relationship. The effect is concentrated among firms with high occupational replaceability, low R&D intensity, high leverage, and low cash flow - precisely the firms where AI is most likely to substitute for labor rather than complement it, and where the opportunity cost of maintaining underutilized real estate is most acute. For example, financially constrained firms (i.e., the bottom half of cash flow) exhibit effects roughly three times as large as the baseline, consistent with AI providing a technology-driven impetus to rationalize costly physical assets. Across time, the effect approximately doubles after 2015, coinciding with the commercial maturation of deep learning and cloud-based AI infrastructure. Across geography, the effect is largest among firms headquartered in high-AI states, where agglomeration externalities in AI adoption lower the adjustment costs of transitioning to asset-light operations.

We complement the balance-sheet evidence using two additional data sources that capture more direct margins of space adjustment. First, using property-level disclosures extracted from 10-K Item 2 filings via large language models, we show that AI-exposed firms reduce their total number of disclosed properties by 5.2 facilities over a five-year horizon, contract their geographic presence by 0.4 states, and are significantly more likely to initiate subleasing and shift from ownership to leasing. These Item 2 results provide direct, non-accounting evidence that AI exposure triggers discrete facility closures and consolidations. Second, using transaction-level lease data from CompStak covering 242,556 commercial tenants, we show that both public and private companies in more AI-exposed industries are 1.24 percentage points more likely to reduce their leased square footage in any given year. This confirms that AI-driven space reductions extend beyond publicly traded firms and beyond owned real estate to the broader commercial leasing market, where companies directly transact the use of physical space.

1.1 Related Literature

Our findings contribute to several literatures. First, we contribute to the corporate real estate literature, which has primarily treated real estate as an explanatory variable that affects borrowing capacity, capital structure, investment, and asset prices through its role as collateral and tangible assets (Chaney et al., 2012; Almeida and Campello, 2007; Gan, 2007; Rampini and Viswanathan, 2013; Cvijanović, 2014; Tuzel, 2010; Brounen and Eichholtz, 2005). We shift the focus from corporate real estate as a determinant of firm outcomes to corporate real estate as an outcome of technological change. Specifically, we study how AI alters firms' demand for physical space and show that corporate real estate is not merely a slow-moving legacy asset, but a margin of adjustment that firms actively restructure in response to new technology.

Second, we contribute to the rapidly growing literature on the economic effects of AI and automation. Prior work has documented that AI investments raise firm productivity and growth (Babina et al., 2024), reshape workforce composition toward STEM-intensive occupations (Acemoglu and Restrepo, 2020), flatten organizational hierarchies (Garicano and Rossi-Hansberg, 2006), and displace routine tasks (Acemoglu and Restrepo, 2022, 2019). Yet this literature has been largely silent on how AI affects firms' *physical* capital and balance-sheets. We fill this gap by documenting a systematic transition: AI-exposed firms reduce owned real estate, contract their physical footprint, and shift toward more flexible space arrangements. This provides a new, asset-side channel through which AI affects financing constraints, the cost of capital, and firm value.

Third, we contribute to the emerging literature on technology and commercial real estate markets. Recent work has examined how remote work affects office valuations (Gupta et al., 2022), and how generative AI disrupts commercial lease markets (Wang et al., 2024). We provide the first evidence that links firm-level AI exposure to firm-level corporate real estate decisions using a causal identification strategy, and we trace the mechanism from balance-sheet adjustments through property-level restructuring to transaction-level lease transaction outcomes. This evidence - from balance-sheet components to 10-K disclosures to CompStak transactions - provides a more complete picture of how AI propagates through the commercial real estate market.

The remainder of the paper proceeds as follows. Section 2 presents balance-sheet evidence from Compustat, including summary statistics, descriptive plots, OLS and IV results, robustness tests, and heterogeneity analyses. Section 3 presents property-level evidence from 10-K disclosures. Section 4 presents lease-market evidence from commercial transactions. Section 5 concludes.

2 Evidence from balance-sheet

2.1 Data, Key Variables, and Sample Construction

2.1.1 Data Sources and Sample Construction

Our analysis draws on several data sources. First, we obtain annual financial statements for U.S. publicly traded firms from Compustat North America, which provide the firm-level variables used to construct our corporate real estate measures as well as the standard firm controls. Second, we use the text-based industry classification data from Hoberg and Phillips (2025), which assigns each firm-year a vector of weights across approximately 300 industries based on textual analysis of 10-K product descriptions. These weights allow us to map industry-level AI exposure to the firm level, accommodating multi-segment firms that operate across multiple industries. Third, we combine the O*NET Abilities database with the ability-level AI exposure scores developed by Felten et al. (2021) and employment data from the Bureau of Labor Statistics Occupational Employment Statistics (OES) program to construct our firm-level AI exposure measure (AIE).

Our initial sample consists of all Compustat North America annual firm-year observations from fiscal years 2002 through 2023. We require non-missing values for total assets and for the PP&E components used to construct our corporate real estate measures (*fatb*, *fatc*, and *fatp*), which yields the summary-statistics sample reported in Table 1. The regression sample is smaller for two reasons. First, because our dependent variables are annual first differences of the CorRE ratios, we require consecutive firm-year observations and non-missing lagged total assets for scaling. Second, we require non-missing values for all firm-level controls (log assets, leverage, cash flow, and Tobin's Q) and for firm AI exposure (AIE). Imposing these requirements leaves 72,426 firm-year observations in the OLS specification for ΔCorRER1 (Table 2, Column 2) and 72,945 for ΔCorRER2 (Column 4). The baseline IV sample is smaller, at about 63,000 firm-years (in Table 3), because constructing the shift-share instrument requires additional non-missing data on segment-based exposure shares and industry-level AI shocks.

2.1.2 Corporate Real Estate Measures

We construct several proxies for the quantity of firms' owned real estate space. The underlying components are drawn from Property, Plant, and Equipment (PP&E), including Buildings, Land and Improvements, and Construction in Progress, as well as lease-related investments that proxy for economically meaningful operating lease commitments. Beginning in fiscal years affected by the adoption of ASC 842 (ASU 2016–02, Leases (Topic 842)), operating leases that were previously off-balance-sheet are capitalized, with firms reporting the estimated present value of operating leases as right-of-use (ROU) assets and corresponding lease liabilities.[1] This shift increases transparency regarding leasing obligations and applies to public companies for fiscal years beginning after December 15, 2018 (i.e., fiscal year 2019 onward). Compustat provides separate balance-sheet line items for lease ROU assets and for the current and long-term portions of lease liabilities. Following Lian and Ma (2021), we reconstruct balance-sheet quantities to maintain comparability with pre-adoption data by netting out lease ROU assets from total assets (and from net PP&E when using fixed assets), and by netting out lease liabilities from short-term and long-term debt when constructing debt and leverage measures. Accordingly, when constructing asset-scaled CorRE ratios for post-adoption firm-years (fiscal year 2019 onward), we scale by total assets net of lease ROU assets.

Our baseline measure, *CorRER1*, captures firms' owned real estate investment on the balance-sheet and serves as a standard proxy for pledgeable collateral in the collateral channel literature (e.g., Tuzel (2010), Li et al. (2025)). *CorRER1* is defined as the sum of three Compustat PP&E components - the same three used in the collateral channel literature—including buildings

[1] ROU assets are accounting assets that represent the lessee's contractual right to use leased property over the lease term; they are paired with lease liabilities of similar magnitude and do not represent newly acquired owned real estate.

($fatb$), construction in progress ($fatc$), and land and improvements ($fatp$). We scale all measures by adjusted total assets to facilitate comparability across firms, where adjusted total assets are defined as total assets net of operating lease right-of-use assets to ensure consistency following the adoption of ASC 842.

We measure corporate real estate using book values at historical cost rather than the market-value approach of Chaney et al. (2012) and Cvijanović (2014), which revalues historical holdings using local real estate price indices. A central reason is sample preservation. Implementing the market-value approach in Compustat requires firms to be present in 1993, when accumulated depreciation for buildings was last broadly available. Imposing that restriction would substantially shrink the sample and create survivorship concerns by excluding many firms that entered the public market after 1993.[2] That loss is especially problematic in our setting because the economic effects of AI are concentrated in the post-2015 period and are likely to be most visible among younger public firms, particularly in technology and professional services. In addition, the market-value approach is designed for settings in which the value of pledgeable real estate is the object of interest, whereas our goal is to study whether AI exposure changes firms' real-estate footprint. For our purposes, book-based measures are better aligned with changes in firms' owned real-estate footprint on the balance-sheet, whereas a market-value series built from a fixed historical stock mainly captures revaluation rather than quantity adjustment. Because firms may also adjust through leasing and other off-balance-sheet margins, we complement the book-value measure evidence with Item 2 disclosures and CompStak evidence.

To isolate firms' exposure to stabilized real estate assets, we define *CorRER2* as the sum of buildings ($fatb$) and land and improvements ($fatp$), scaled by adjusted total assets. By excluding construction in progress, *CorRER2* focuses on completed and operational real estate assets only. Construction in progress represents assets that are not yet contributing to the firm's output and may be subject to different risks (e.g., development risk) compared to stabilized assets; excluding it thus provides a cleaner measure of current productive capacity.

[2] Compustat exhibits substantial attrition over our horizon: the 1993 cohort of 3,303 firms shrinks to 407 with non-missing CorRER1 and controls by 2023. A market-value restriction would further narrow this already-selected sample.

Our main dependent variables are the annual first differences of these ratios, $\Delta\mathit{CorRER1}$ and $\Delta\mathit{CorRER2}$. Using changes in CorRER reduces the influence of time-invariant differences in baseline real estate intensity and focuses the analysis on within-firm adjustment. It also focuses estimation on within-firm changes—the year-to-year adjustments in real estate holdings that are most plausibly responsive to evolving AI exposure—rather than cross-sectional level differences that are difficult to interpret causally. In the alternative specification tests (Appendix Table A4), we also examine three-year and five-year differences to capture longer-horizon adjustments.

We also construct various alternative CorRE measures. First, while ratios control for firm size, they conflate changes in the numerator (real estate) with changes in the denominator (total assets). This distinction is crucial in the context of AI, which is known to drive rapid sales growth and firm expansion (Babina et al., 2024). For example, a decline in real estate ratio (e.g., CorRER1 over assets) may reflect faster growth in non-real-estate assets rather than an absolute reduction in physical space. To distinguish whether AI firms are merely "growing out" of their real estate ratios or actively divesting physical space, we construct level-based measures. Specifically, we take the natural logarithm of one plus the relevant CorRE stock, which both mitigates right skewness and retains firm-year observations with zero reported holdings. These measures allow us to capture extensive-margin adjustments, such as net property acquisitions and dispositions, and interpret changes in CorRE holdings in percentage terms rather than as shifts in asset composition.

In addition to ratio- and level-based CorRE measures, we construct indicator variables that capture discrete adjustments in firms' real estate usage. Because our owned CorRE components are recorded at historical cost, they do not mechanically incorporate contemporaneous real estate price changes. Changes in the gross book value of real estate primarily reflect net acquisitions and dispositions, rather than valuation re-measurement. Moreover, corporate real estate is often managed through lumpy, transaction-based choices rather than smooth marginal changes. For example, firms may retain, sell, or sell and leaseback their properties. Accordingly, we complement continuous CorRE measures with indicator variables for increases in historical cost holdings, which provide a cleaner signal of expansion and net additions than levels or ratios alone. Specifically, for each level-based real estate measure, we define an indicator that equals one if the firm's real estate holdings increase relative to the prior fiscal year and zero otherwise.

2.1.3 AI Exposure

This section describes the construction of the AI Exposure (AIE) variable. AIE captures the extent to which industries and firms are exposed to artificial intelligence technologies based on the AI-related abilities required by occupations within those industries. The construction proceeds in four steps: (i) identifying AI exposure at the ability level using the O*NET Abilities domain; (ii) computing occupation-level AI exposure scores; (iii) aggregating to industry-year exposure using occupational employment shares; and (iv) aggregating to firm-year exposure using text-based measures of product-market scope and segment weights from Hoberg and Phillips (2025).

The construction of AIE begins with the O*NET Abilities database, which provides detailed information on occupational requirements within the Abilities domain. For each occupation (defined at the 6-digit Standard Occupational Classification (SOC) level) - ability pair, O*NET reports two measures: (i) *Importance*, recorded on a 1-5 scale, and (ii) *Level*, recorded on a 1-7 scale. To gauge the extent of AI exposure at the ability level, we follow the classification scheme of Felten et al. (2021), who use survey responses from Amazon Mechanical Turk workers to construct an application-ability relatedness score between 0 and 1 for each application-ability pair and then aggregate these scores to the ability-level AI exposures.

Using these inputs, AIE is constructed in three steps. Let a index abilities, o occupations (6-digit SOC), j industries (4-digit NAICS), i firms, and t years. From Felten et al. (2021), let $AI_a \in [0, 1]$ denote the ability-level AI exposure score for ability a. From O*NET, let $Importance_{oat}$ and $Level_{oat}$ denote the *Importance* and *Level* scores for ability a within occupation o in year t. For each occupation-year, we define the weight on ability a as

$$w_{oat} = Importance_{oat} \times Level_{oat}.$$

We then construct occupation-level AI exposure as the weighted average

$$AIratio_{ot} = \frac{\sum_a AI_a \, w_{oat}}{\sum_a w_{oat}}.$$

To facilitate comparability across occupations, we standardize this measure to a z-score:

$$AIZ_{ot} = \frac{AIratio_{ot} - \mu_t}{\sigma_t},$$

where μ_t and σ_t are the mean and standard deviation of $AIratio_{ot}$ across occupations in year t.

Next, we aggregate occupation-level exposure to the industry-year level using BLS OES employment shares. Let $EmpShare_{ojt}$ denote occupation o's employment share within industry j in year t. The industry-year AI exposure measure is

$$AIIE_{jt} = \sum_{o} AIZ_{ot} \times EmpShare_{ojt}.$$

Finally, we map industry-year exposure to the firm-year level using the Hoberg-Phillips text-based industry weights. Let s_{ijt} denote firm i's share in industry j in year t. Firm-level AI exposure is then

$$AIE_{it} = \sum_{j} s_{ijt} \times AIIE_{jt}.$$

2.1.4 Control Variables

Our firm-level control variables are drawn from Compustat and include the natural logarithm of adjusted total assets (firm size), leverage (adjusted total debt divided by market value of equity), cash flow (net income plus depreciation scaled by lagged adjusted total assets), and Tobin's Q (market value of equity plus adjusted total debt, divided by adjusted total assets). Total assets and total debt are net of ASC 842 capitalized lease amounts to maintain comparability across the adoption period, as described in Section 2.1.2. To mitigate the influence of outliers while preserving within-industry variation, all control variables are winsorized at the 1st and 99th percentiles within three-digit SIC industry by fiscal year cells. Long-difference specifications include the corresponding first differences of these controls.

2.2 Summary Statistics and Descriptive Evidence

Table 1 reports summary statistics for the main variables used in our firm-level analysis, organized into three panels. Panel A presents corporate real estate measures in both levels and first differences. CorRER1, our baseline measure, has a mean of 0.081 and a standard deviation of 0.154, indicating substantial cross-sectional dispersion. The median is close to zero (0.004), reflecting the fact that many firms report little or no owned real estate on their balance-sheets, while the 75th percentile is 0.105, indicating that among more real-estate-intensive firms, owned buildings, land, and construction account for a sizable share of total assets. CorRER2, which excludes construction in progress, exhibits a similar pattern (mean 0.072, median 0.000). The first-differenced measures, ΔCorRER1 and ΔCorRER2, which serve as the main dependent variables in our regressions, have means near zero (0.001), consistent with slow-moving real estate holdings. The standard deviations (0.051 and 0.044) indicate that meaningful year-to-year adjustments do occur, and the interquartile ranges spanning from slightly negative to slightly positive values confirm that both expansions and contractions are common. Overall, these distributional characteristics are highly consistent with the prior literature. Specifically, the heavily right-skewed levels closely match the ownership and concentration patterns observed by Chaney et al. (2012) and Li et al. (2025), while the near-zero means of the first differences reflect the slow-moving, high-adjustment-cost nature of real estate capital (Tuzel, 2010; Bai et al., 2024). Regression results for the broader CorRE measures CorRER3 and CorRER4, which incorporate capital leases and rental commitments, are reported in Appendix Table A2 and discussed in Section 2.3.1.

Panel B reports the key treatment variable, firm-level AI Exposure (AIE). AIE has a mean of 0.319 and a standard deviation of 0.484, with an interquartile range from -0.069 to 0.738. Because the underlying occupation-level scores are standardized, negative values indicate below-average AI exposure. The wide dispersion reflects substantial cross-sectional variation in firms' exposure to AI technologies through their product-market environments.

Panel C reports standard firm controls. The median firm has approximately \$393 million in total assets (median log assets of 5.973). Leverage is positively skewed (median 0.191, mean 0.979), consistent with a subset of highly leveraged firms in the right tail. Cash flow is negatively skewed (median 0.030, mean −0.361), driven by a long left tail of firms with low or negative cash flows. Tobin's Q has a median of 1.143, consistent with distributions documented in the broader corporate finance literature (e.g., Kermani and Ma, 2023; Mao, 2021).

Before turning to formal regression analysis, we present descriptive evidence on the cross-sectional relationship between AI exposure and corporate real estate holdings. Figure 1 plots industry-average CorRER1 against industry-average AIE for each two-digit NAICS sector, revealing a pronounced negative relationship: industries with higher AI exposure maintain substantially lower corporate real estate intensity. Figure 2 replicates the industry-level analysis at the state level using firms' headquarters locations, and again reveals a negative relationship between AI exposure and corporate real estate intensity. Figure 3 complements this evidence by mapping the geographic distribution of average AI exposure across U.S. states. The highest values are concentrated in California and in parts of the Northeast and Mid-Atlantic corridor, including Massachusetts, New York, Maryland, Virginia, and the District of Columbia, suggesting that AI exposure is elevated in several major knowledge-economy hubs. This geographic variation motivates the time-and-geography subsample tests in Section 2.6.3.

In sum, these descriptive patterns suggest a negative relationship between AI exposure and corporate real estate in the cross section. We turn next to firm-level regression analysis to assess whether this relationship remains after controlling for observable firm characteristics, fixed effects, and endogeneity concerns.

2.3 OLS Results

Our baseline specification regresses the year-over-year change in corporate real estate intensity on the level of AI exposure, controlling for firm characteristics and absorbing industry and time fixed effects:

$$\Delta\text{CorRER}_{it} \;=\; \beta\,\text{AIE}_{it} \;+\; \mathbf{X}_{it}'\boldsymbol{\gamma} \;+\; \mu_j \;+\; \delta_t \;+\; \varepsilon_{it}, \tag{1}$$

where ΔCorRER_{it} is the first difference in the corporate real estate ratio for firm i in year t; AIE_{it} is the firm's AI Exposure, segment-weighted across industries; $\mathbf{X}_{it}$ is a vector of time-varying controls (log total assets, leverage, cash flow, and Tobin's Q, all winsorized at the 1st and 99th percentiles); μ_j are industry fixed effects; and δ_t are year fixed effects. Standard errors are clustered at the firm level.[3]

Following Acemoglu et al. (2022); Hampole et al. (2025), we use a changes-on-levels specification because our question is whether firms with greater AI exposure adjust their corporate real estate more rapidly over time. Corporate real estate is a slow-moving capital stock, so modeling its annual change focuses on the relevant adjustment margin. We keep AI exposure in levels because the key identifying variation lies in differences in exposure across firms, rather than in short-run within-firm changes. Differencing AI exposure would discard much of this signal and amplify measurement error, while a levels on levels specification with firm fixed effects would rely too heavily on limited within firm variation. This specification also aligns naturally with our IV design, which instruments the level of firm AI exposure using predetermined shares and common industry-year AI shocks. Appendix Table A4 shows that our results are robust to alternative specifications.

The coefficient β captures the marginal effect of a one-unit increase in AI exposure on the annual change in CorRE intensity. A negative β indicates that firms with higher AI exposure experience faster declines (or slower growth) in their CRE-to-assets ratio. Table 2 presents OLS estimates. The dependent variables are ΔCorRER1 (columns 1–2) and ΔCorRER2 (columns 3–4). All specifications include NAICS two-digit industry and year fixed effects; even-numbered columns additionally control for log assets, leverage, cash flow, and Tobin's Q. Standard errors are clustered at the firm level.

In Table 2, the coefficients on AIE are negative and statistically significant across all four columns. In the specification without controls (column 1), a one-unit increase in AIE is associated with a 0.15 percentage points annual decline in CorRER1, significant at the 1% level. Adding firm-level controls (column 2) strengthens the estimate to -0.18 percentage point.

[3]Results hold when we cluster at industry level in Appendix Table A4.

For CorRER2, the corresponding estimates are -0.08 percentage points and -0.12 percentage points in columns 3 and 4, respectively. The fact that coefficients increase in absolute value after controlling for firm size, leverage, cash flow, and Tobin's Q suggests that omitting these variables introduces an upward bias that attenuates the negative impact of AI.

To gauge economic magnitude, a one-standard-deviation increase in AIE (0.484) is associated with a 0.087 percentage points annual decline in CorRER1 (0.0018×0.484), approximately 1.1% of the sample mean (0.081). For a firm at the median total assets of $393 million, this translates to roughly $342,000 less corporate real estate per year. While this annual flow effect may appear modest, it cumulates over time: over a five-year horizon, the implied reduction is approximately 0.4 percentage points, or about 5.4% of mean CorRER1. For a firm with $10 billion in total assets, this implies approximately $44 million less in owned real estate over five years.

While the OLS estimates are consistent with AI exposure reducing corporate real estate intensity, they may be biased by omitted variables or reverse causality. For instance, firms anticipating a shift toward asset-light operations may simultaneously adopt AI and divest real estate, or unobserved strategic changes may drive both. We address these endogeneity concerns through the instrumental variable analysis in Section 2.4.

2.3.1 Alternative Corporate Real Estate Ratios

Appendix Table A2 extends the OLS analysis to two broader measures: CorRER3, which adds capital leases (*fatl*) to the CorRER2 components, corresponding to the "productive structure" definition in Zhang (2019); and CorRER4, which further includes construction in progress. The coefficient on AIE is negative in all specifications, reaching -0.0020 for ΔCorRER3 and -0.0026 for ΔCorRER4 with controls. These estimates are somewhat larger in absolute value than the baseline CorRER1 and CorRER2 results, suggesting that the baseline pattern is not sensitive to using broader corporate real estate measures that include capital leases and construction in progress.

2.4 Instrumental Variable Results

A natural concern is that firms do not adopt AI randomly. Firms that reorganize production, face changing demand, or anticipate lower space needs may also invest more aggressively in AI. To address this concern, we instrument firm-level AI exposure with a shift-share design in the spirit of Bartik (1991) and Borusyak et al. (2022). The instrument takes the form

$$Z_{it} = \sum_j w_{ij}^{t=0} g_{jt},$$

where $w_{ij}^{t=0}$ measures firm i's predetermined exposure to industry j and g_{jt} is the industry-year AI shock (i.e., the change in industry-level AI exposure, $AIIE_{jt}$ for industry j at time t). In our setting, the shares come from the firm's Hoberg-Phillips product-market assignments, and the shifts are changes in industry-level AI exposure. The identifying assumption is that, conditional on controls and fixed effects, these common industry AI shocks are unrelated to firm-specific shocks to corporate real estate demand. This logic is close in spirit to recent papers that use predetermined exposure to later AI-related supply shifts or adoption costs (Babina et al., 2024; Hampole et al., 2025).

Table 3 reports the second-stage results. The coefficient on AIE is -0.0028 for ΔCorRER1 and -0.0020 for ΔCorRER2, both statistically significant. Both estimates are larger in absolute value than in OLS. That pattern is consistent with attenuation from measurement error: because AIE is constructed by aggregating industry AI scores through text-based segment weights, the firm-level treatment is likely measured with noise, biasing OLS toward zero. It may also reflect non-random adoption if firms with higher latent AI demand differ systematically from other firms. The shift-share IV addresses these concerns by isolating the component of firm-level AI exposure induced by common industry shocks transmitted through predetermined exposure.

The magnitudes are also meaningful. A one-standard-deviation increase in AIE (0.484) implies an annual decline of about 0.14 percentage points in CorRER1 and 0.10 percentage points in CorRER2. For CorRER1, this corresponds to a five-year cumulative decline of roughly 0.7 percentage points, or about 7% of the sample mean. For a slow-moving balance-sheet item such as owned property, this is economically large.

Since many observations share the same underlying industry-year shocks, conventional first-stage statistics can exaggerate the amount of independent variation. To mitigate this concern, we treat the shock-level diagnostics in Section 2.5.4 as the relevant benchmark. We also show below that the results are stable when we replace the IV with a leave-one-out version of the instrument.

2.5 Robustness Tests

We next ask whether the baseline estimate is sensitive to the way we construct the instrument, measure real-estate adjustment, define the sample, or conduct inference. The purpose of these exercises is to examine whether the negative relation between AI exposure and owned corporate real estate survives the natural concerns in this setting.

2.5.1 Alternative Instrumental Variable

Appendix Table A3 replaces the baseline instrument with a leave-one-out variant that excludes firm i's own contribution when constructing the industry-level AI shift. This refinement addresses a standard reflection concern in shift-share settings: if a firm's own AI exposure mechanically enters the industry aggregate used to build the instrument, the exclusion restriction may be weakened. By removing the firm's own contribution, the IV ensures that identification comes from peer-industry exposure rather than from a mechanical feedback between the firm and its instrument. The resulting estimates remain close to the baseline. The coefficient on AIE is -0.0020 for ΔCorRER1 and -0.0015 for ΔCorRER2, both statistically significant. The point estimates are modestly smaller than our main IV discussed in Section 2.4, but the sign, economic magnitude, and inference are unchanged.

2.5.2 Alternative Model Specifications

Appendix Table A4 asks whether the baseline result depends on a particular functional form or horizon. All six columns report 2SLS estimates. This exercise is especially important in our setting for two reasons. First, AI can raise sales, market value, and other assets (Babina et al., 2024), so an asset-scaled real-estate ratio could fall either because firms shed space or because the denominator grows faster. Second, AI exposure is highly persistent, while corporate real estate is costly to adjust. In such environments, annual first differences may understate the medium-run response, and alternative specifications can be informative about the dynamics of adjustment. The broader shift-share literature (e.g., Autor et al., 2013, Bloom et al., 2016, Borusyak et al., 2025) has made similar use of levels, differences, and long differences when treatment is persistent and the underlying capital stock adjusts slowly.

The first three columns of Appendix Table A4 address the denominator issue directly: because AI can also raise sales and other assets, a lower real-estate-to-assets ratio need not imply a smaller physical footprint. In column (1), when the dependent variable is the log level of owned real estate, the estimated effect remains negative. In column (2), when we move to an extensive-margin indicator for whether real estate increased, the effect is again negative, implying that AI-exposed firms are substantially less likely to expand physical space in a given year. In column (3), a levels-on-levels specification for CorRER1 also yields a robust and negative coefficient. Taken together, these columns show that the baseline result is not only a denominator effect.

In columns (4) and (5), the long-difference specifications strengthen that interpretation. The three-year and five-year estimates are both negative and larger in absolute value than the annual baseline coefficient, with the five-year specification delivering the largest effect. This pattern is exactly what one would expect if firms face substantial adjustment frictions in shrinking owned real estate. Space can be repurposed, sold, or allowed to depreciate, but those decisions rarely occur instantaneously. The long-difference results therefore complement the annual specification by showing that the effect of AI on corporate real estate accumulates over time rather than dissipating.

Finally, column (6) shows that when we cluster at the industry level, the baseline coefficient is essentially unchanged. This stability is reassuring because the identifying variation is ultimately induced by industry-level shocks. Overall, Appendix Table A4 suggests that, regardless of whether we look at levels, changes, extensive-margin adjustment, or longer horizons, firms with greater exogenous exposure to AI reduce their corporate real estate.

2.5.3 Alternative Samples

Having established that the negative effect holds across alternative CorRE definitions, instrument constructions, functional forms, and time horizons, we next ask whether specific subsets of the sample drive the findings. Three potential confounds merit direct investigation: the COVID-19 pandemic, which triggered an exogenous shift toward remote work after 2019; the adoption of ASC 842, which mechanically altered balance-sheet composition after 2018; and the outsized presence of technology firms, which are both the primary developers of AI and among the least real-estate-intensive industries. Table A5 examines each in turn.

The COVID-19 pandemic triggered an unprecedented and abrupt shift toward remote work beginning in 2020, which may have independently reduced firms' demand for corporate real estate. If the pandemic is driving our results, the negative effect should disappear or weaken substantially when we restrict the sample to the pre-2020 period. In Panel A, the IV estimates are -0.0025 for ΔCorRER1 and -0.0020 for ΔCorRER2, respectively. These coefficients are nearly identical to the full-sample estimates (-0.0028 and -0.0020), confirming that the AI–real-estate relationship is not an artifact of pandemic-era disruptions. The negative effect of AI exposure on corporate real estate was already present and statistically significant before COVID-19.

The adoption of ASC 842 (effective for public companies with fiscal years beginning after December 15, 2018) required firms to capitalize operating leases on the balance-sheet, adding right-of-use assets and corresponding lease liabilities. Although we adjust for this accounting change by netting out ROU assets from total assets when constructing CorRE ratios, one may be concerned that the mechanical balance-sheet effects of ASC 842 adoption confound our estimates. In Panel B, restricting the sample to pre-2019 yields coefficients of -0.0026 and -0.0021 for CorRER1 and CorRER2, respectively. These estimates are comparable to the full-sample estimates. The results confirm that the ASC 842 accounting change does not drive our findings.

Technology and professional services firms (NAICS 51: Information; NAICS 54: Professional, Scientific, and Technical Services) are the most directly involved in developing and deploying AI technologies. One concern is that these industries drive the overall results, and that the relationship reflects industry-specific trends in real estate usage rather than a generalizable effect of AI exposure. Dropping NAICS 51 and 54 yields coefficients of -0.0029

for CorRER1 and -0.0019 for CorRER2. The CorRER1 estimate is marginally larger than the full-sample estimate, indicating that the negative effect is, if anything, stronger outside the technology sector. This finding reinforces the heterogeneity results in Table 4 (Panel B), which showed that the AI–real-estate relationship is driven by non-technology firms.

Across all three sample restrictions, the coefficients remain negative, statistically significant, and similar in magnitude to the baseline estimates. This stability provides strong evidence that the results are not confounded by pandemic-specific disruptions, accounting rule changes, or technology-sector-specific trends.

2.5.4 BHJ Shock-Level Inference

One concern in a shift-share design is inference rather than point identification. When many firm-year observations load on the same underlying industry-year shock, conventional observation-level standard errors can misstate precision because the effective identifying variation is closer to the number of independent shocks than to the number of firm-year observations (Borusyak et al., 2022). Whereas Goldsmith-Pinkham et al. (2020) emphasize the exogenous-shares view of Bartik designs, Borusyak et al. (2022) show that SSIV designs can also be interpreted through quasi-random shocks and re-expressed at the level of those shocks. That perspective fits our setting closely, because it allows the exposure shares to be endogenous provided the industry-year AI shocks are quasi-random conditional on the included controls. Borusyak et al. (2022) propose a shock-level inference procedure ("BHJ") that estimates the regression at the level of the shocks rather than at the observation level, providing valid inference under weaker assumptions about the correlation structure of the identifying variation. We therefore turn to the equivalent shock-level regression as a more conservative, design-specific inference benchmark.

In Panel A of Appendix Table A6, the firm-level IV estimate for ΔCorRER1 is -0.0028, as reported in Table 3. The BHJ shock-level estimate is -0.0030, slightly larger in absolute value but with a wider standard error (0.0020 versus 0.0010). The BHJ standard error is approximately twice the firm-clustered standard error, which is typical in shift-share designs where the effective number of independent observations is determined by the number of shocks rather than the number of firms. The shock-level first-stage F-statistic is 771.3, far exceeding conventional thresholds for instrument relevance, and is computed over 3,179 shock observations (i.e., industry $\times$ year cells).

The BHJ estimate implies that a one-standard-deviation increase in AIE is associated with about a 0.15 percentage points annual decline in CorRER1, or roughly 0.7 percentage points over five years. The point estimate is very close to the firm-level IV estimate, while the confidence interval widens once inference is based on the number of independent industry-year shocks rather than firm-year observations. We therefore interpret the BHJ results as showing that the baseline effect remains economically similar under exposure-robust inference, albeit with lower precision.

Panel B provides a balance test for the shift-share design by examining whether the industry-year AI shocks, g_{jt}, are related to predetermined observables. The coefficients on lagged CorRER1, lagged CorRER2, and lagged log assets are small and statistically insignificant, suggesting that the shocks are not systematically related to prior real-estate intensity or firm size along these observed dimensions. The only significant predictor is lagged AIE, which is expected given the persistence of industry AI exposure over time. These results do not prove the exclusion restriction, but they are consistent with the view that the identifying variation in the instrument is not driven by obvious pre-existing differences in firms' real-estate positions or scale. Together with the strong shock-level first stage and the similarity of the firm-level and shock-level point estimates, the balance test supports a cautious causal interpretation of the baseline IV results.

2.5.5 Excluding Financial Firms and Utilities

Our baseline sample retains all industries to maximize statistical power and external validity. However, financial firms (SIC 6000–6999) and utilities (SIC 4900–4999) are subject to distinct regulatory and accounting regimes that may affect the relationship between AI exposure and real estate holdings. Banks, insurers, and regulated utilities hold real property for reasons that differ fundamentally from non-financial firms, such as branch networks, trading floors, and regulated rate-base assets. Appendix Table A8 shows that our results are robust to excluding these industries. Dropping approximately 7,200 financial and utility firm-years (about 10% of the OLS sample), the OLS coefficient on ΔCorRER1 moves from −0.0018 to −0.0020, while the IV estimate moves from −0.0028 to −0.0024. Results for ΔCorRER2 are similarly stable. These findings confirm that the baseline results are not driven by the distinctive real estate patterns of financial and utility firms.

2.6 Heterogeneity

We next examine whether the effect of AI exposure on corporate real estate is stronger in settings where AI is more likely to substitute for routine, space-dependent activities or where firms have stronger incentives to economize on fixed real estate commitments. All estimates in this section are 2SLS estimates using the baseline shift-share instrument, with the same controls and fixed effects as in Table 3.

2.6.1 Industry Characteristics

Panel A of Table 4 reveals that AI-driven real estate reductions are concentrated in sectors exposed to competitive product-market pressure, a pattern also visible in Figure 1. Specifically, when we classify industries as tradable or non-tradable following Mian and Sufi (2014), based on employment concentration patterns at the four-digit NAICS level, the negative effect is concentrated among tradable industries (−0.0027 for ΔCorRER1, and −0.0022 for ΔCorRER2), while non-tradable estimates are near zero and insignificant. Both results point to a common mechanism: firms that face international or interregional competition have stronger incentives to optimize costs, including the cost of physical space, when AI creates opportunities to do so.

The task-based framework of Acemoglu and Restrepo (2022) predicts that automation disproportionately displaces *routine* tasks, with the largest labor-market effects in occupations where human work can be codified and substituted by algorithms (Autor, 2015; Goos et al., 2014). Panels B and C of Table 4 provide the firm-level analog of this prediction. Among non-technology firms (outside NAICS 51 and 54), the coefficients are −0.0029 and −0.0019, whereas technology firms show insignificant estimates. This is consistent with AI playing a stronger substitution role outside the technology sector: AI primarily automates routine office-based tasks; technology firms, already organized around digital workflows, experience less marginal disruption from additional AI exposure. Occupational replaceability (R-share) is the employment-weighted share of routine occupations in a firm's workforce, following Zhang (2019); firms with above-median R-shares are classified as having high replaceability. High-replaceability firms show coefficients of -0.0036 and -0.0032, higher than the baseline IV coefficients, while low-replaceability estimates are insignificant. This finding is consistent with (Wang et al., 2024), who show that the AI-induced productivity shock reduces the value of real assets by lowering firms' demand for space via labor substitution effects.

2.6.2 Firm Characteristics

Industry classifications mask meaningful within-industry heterogeneity: even within the same broad sector, firms differ in technological orientation and financing constraints. We therefore split the sample by firm characteristics, such as R&D intensity, leverage, and cash flow. Panel A of Table 5 separates firms by R&D within each industry-year. The results show that low-R&D firms exhibit significant negative coefficients (-0.0044 and -0.0035), while high-R&D firms show insignificant effects. This divergence maps onto the routine-task distinction from a different angle: R&D-intensive firms invest in knowledge production that often requires physical laboratories and specialized facilities - activities that are inherently non-routine and difficult to automate (Autor, 2015). Low-R&D firms, which rely more heavily on routine administrative and operational activities, are more amenable to AI-enabled labor and commercial space optimization.

Panels B and C of Table 5 separate firms by leverage and cash flow within each year. The results reveal that the AI-CorRE relationship is strongest among firms for which these financial frictions are most binding. Highly leveraged firms show significant negative coefficients (-0.0035 and -0.0028), while low-leverage firms show insignificant effects. Similar effects emerge along the cash flow dimension: low-cash-flow firms exhibit coefficients of -0.0080 and -0.0064, while high-cash-flow firms show insignificant effects. These findings suggest that financially constrained firms face a higher opportunity cost of maintaining underutilized real estate, making them more responsive to AI-driven opportunities to shed space.

2.6.3 Time and Geography

Panel A of Table 6 splits the sample at 2015, motivated by the commercial maturation of deep learning, cloud-based AI infrastructure, and, later in the sample, large language models (Adams et al., 2024; Donelson et al., 2025; Acemoglu et al., 2022). Pre-2015, the coefficient on AIE is -0.0021 for CorRER1 and insignificant for CorRER2. Post-2015, the effects approximately double: -0.0049 and -0.0035. A one-standard-deviation increase in post-2015 AIE implies a 0.24 percentage points annual decline in CorRER1, or a five-year cumulative reduction of 1.2 percentage points (approximately 15% of the mean). This trend is consistent with AI reaching operational maturity after 2015, allowing firms to reorganize workflows and meaningfully reduce their physical footprint. The weaker pre-2015 effects are consistent with the view that AI capabilities were less operationally mature earlier in the sample, thus producing only modest real estate adjustments.

As local labor markets and technology ecosystems may shape how firms respond to AI exposure, we next partition firms by the AI intensity of their headquarters state. Bonney et al. (2024) document that AI adoption varies substantially across U.S. states. Using the headquarters state reported in Compustat, we compute the average AIE of all Compustat firms headquartered in each state in each year, and sort states into annual terciles based on this state-year mean. A firm is classified as being in a *high-AI state* if its headquarters falls in the top tercile that year, and in a *low-AI state* otherwise. The classification is time-varying, allowing states to migrate across terciles as AI technologies diffuse. We adopt a top-tercile split rather than a median cut to concentrate the comparison on states with distinctly high AI exposure while preserving sample size in the comparison group. This geographic partition complements our industry- and firm-level heterogeneity cuts by isolating the role of local concentration in AI-intensive activity.

Panel B of Table 6 exploits geographic variation in AI ecosystems, with the underlying spatial dispersion of AI exposure illustrated in Figures 2 and 3. Among firms in high-AI states (top tercile of state-year average AI exposure), the coefficients are -0.0085 and -0.0052, the largest across all heterogeneity dimensions. Low-AI-state estimates are insignificant. A one-standard-deviation increase in AIE among high-AI-state firms implies a 0.41 percentage points annual decline in CorRER1. AI-driven real estate reductions are thus amplified where

AI ecosystems are more mature and competitive pressures to adopt asset-light strategies are strongest. Firms in these regions may benefit from agglomeration externalities (e.g., access to AI service providers, digital coordination tools, and a workforce accustomed to flexible work arrangements) that lower the adjustment costs of reducing physical space.

In sum, these heterogeneity results suggest that, across industry, firm, and geographic splits, the negative effect of AIE is concentrated in tradable industries, non-technology firms, firms with highly replaceable tasks, low-R&D firms, financially constrained firms, the post-2015 period, and high-AI states. Taken together, these patterns suggest that AI reduces corporate real estate most strongly where it plausibly substitutes for routine labor and lowers the value of maintaining a large physical footprint.

3 Evidence from 10-K Disclosures

The balance-sheet evidence in Section 2 establishes that AI-exposed firms reduce the book value of owned real estate relative to total assets. A natural question is whether this pattern reflects actual changes in firms' physical footprint or merely accounting reclassifications. To provide direct evidence, we turn to Item 2 ("Properties") of the SEC Form 10-K, which requires registrants to describe the location and general character of their principal physical properties, including owned and leased facilities. Although this disclosure is qualitative and varies in detail across firms, it offers direct evidence on firms' property portfolios that complements the Compustat-based measures.

The Item 2 analysis serves two purposes. First, it provides direct evidence on whether AI-exposed firms reduce their physical footprint, as measured by disclosed property counts and square footage, complementing the balance-sheet-based CorRE measures. Second, it captures restructuring activities (facility closures, subleasing) that may not be fully reflected in PP&E line items, thereby documenting the operational channel through which AI exposure translates into reduced space demand.

3.1 Data and Sample Construction

We extract structured property information from Item 2 disclosures using a large language model (GPT-4o-mini) applied to the Item 2 text sections of 10-K filings obtained from EDGAR. For each firm-year, the extraction identifies the total number of properties disclosed, the count of owned versus leased properties, aggregate square footage (where reported), and indicators for property-related restructuring activities such as consolidations, closures, or subleasing.

To examine whether AI exposure leads to medium-term changes in firms' disclosed physical footprint, we construct five-year changes in Item 2 outcomes. We use non-overlapping five-year windows because Item 2 disclosures are not fully standardized from year to year and corporate real estate adjusts infrequently; longer differences therefore reduce reporting noise and better capture economically meaningful changes in firms' property portfolios. Specifically, we define non-overlapping five-year windows (2004–2009, 2009–2014, 2014–2019, 2019–2024) and compute the change in each Item 2 measure between the beginning and end of each window. These five-year differences are then regressed on beginning-of-window AI exposure, instrumented by the shift-share IV, with industry and year fixed effects and firm-level clustering similar to our previous analysis.

3.2 Results

Table 7 Panel A reports IV estimates of five-year changes in firms' disclosed property portfolios, estimated over non-overlapping five-year windows with industry and year fixed effects. The results are uniformly negative and statistically significant. A one-unit increase in AIE is associated with a reduction of 5.2 properties over a five-year horizon, comprising 2.11 fewer leased properties and 0.99 fewer owned properties. The geographic footprint also contracts: per unit of AIE firms reduce their presence by 0.4 states.

To gauge the economic magnitude, consider moving from the 25th to the 75th percentile of AIE (an interquartile range of 0.81 units): this implies a five-year reduction of approximately 4.2 total properties, including 1.7 fewer leased and 0.8 fewer owned locations. That both owned and leased counts decline, with the leased reduction roughly twice as large, suggests that

AI-exposed firms reduce overall space demand rather than merely shifting between ownership structures. The simultaneous contraction in geographic presence (0.32 fewer states under this interquartile move) is consistent with AI enabling centralized coordination that reduces the need for dispersed facilities.

While Panel A focuses on the extensive margin of adjustment: how many properties firms operate and how geographically dispersed they are, restructuring activities such as subleasing, leasing shifts, and square-footage reductions are disclosed more unevenly in narrative form and often appear only when a material event occurs. We therefore measure these margins with indicator variables, and Panel B reports estimates for the composition and mode of adjustment. The first such measure, *Shifted Toward Leasing*, captures discrete restructuring events in firms' property portfolios. Specifically, we classify each firm's portfolio at the start and end of a five-year window on an ordinal scale ranging from entirely owned to entirely leased, based on the ownership composition of properties disclosed in Item 2 ("Properties") of the firm's 10-K filings. The indicator equals one if the firm's portfolio moves at least one step up this scale over the window, meaning that the composition of its reported facilities has become meaningfully more lease-heavy, and zero otherwise. This binary measure complements the continuous CorRE outcomes by isolating episodes in which firms visibly restructure their property footprint, rather than gradual adjustments on the balance-sheet.

The firm-level IV estimates show that a one-unit increase in AIE raises the probability of shifting toward leasing (away from ownership) by 5.5 percentage points and increases the probability of initiating subleasing by 3.5 percentage points. At the shock level, using the BHJ inference procedure of Borusyak et al. (2022), the subleasing effect is confirmed at 4.6 percentage points, and AI-exposed firms are 16.5 percentage points more likely to experience a decrease in total square footage.

Taken together, the Item 2 evidence indicates that AI exposure is associated with active restructuring of firms' physical footprint: reducing the number of owned and leased properties, contracting their geographic presence, shifting toward leasing over ownership, and initiating subleasing arrangements. These patterns complement the balance-sheet evidence in Tables 2–3 by showing how the adjustment occurs: through discrete consolidations and restructuring of the physical footprint.

4 Evidence from Commercial Lease Transactions

The preceding analyses rely on publicly disclosed corporate real estate data recorded at historical cost. While well-suited for identifying the asset-side effects of AI exposure, these measures have two limitations. First, they cover only publicly traded firms, excluding the vast majority of tenants (e.g., private firms) who collectively account for the bulk of commercial space demand. Second, balance-sheet measures of owned real estate conflate firms' space demand decisions with their collateral and investment motives: a firm may hold real estate for collateral value or price appreciation rather than purely as a productive input (Chaney et al., 2012; Cvijanović, 2014). To address these limitations, we turn to leasing decisions: when a company leases less square footage or reduces its rent commitments, it directly signals lower demand for usable space, free of the collateral and investment motives that complicate balance-sheet measures.

We collect lease transaction data from CompStak, which consists of verified commercial lease transactions from a network of commercial real estate brokers across the U.S. The CompStak data offer three advantages. First, they cover both public and private tenants at the individual lease level, substantially broadening the scope of the analysis beyond publicly traded firms. Second, lease transactions directly proxy for tenants' demand for physical space: the decision to lease a given quantity of square footage at a negotiated rent reflects the tenant's marginal valuation of workspace, largely free of the balance-sheet and investment considerations that complicate the interpretation of owned real estate. Third, the granularity of lease-level data, including square footage, rent, and tenant industry, allows us to track tenants' space use in a timely manner. We therefore first construct a tenant-year panel and estimate within-tenant demand responses to AI exposure over time.

4.1 Data and Sample Construction

We expand each CompStak lease to annual observations spanning its contractual term and collapse the data to the tenant-year level, summing total leased square footage and total rent payments across all active leases for each tenant in each year.[4] Because the tenant-year panel is inferred from lease contracts rather than observed occupancy, and CompStak does not fully capture early terminations, partial give-backs, subleases, or mid-lease renegotiations, the exact annual level of leased square footage and rent is measured with nontrivial noise. We therefore focus on indicator outcomes that capture the direction of adjustment rather than its precise magnitude. Specifically, *SF Decrease* equals one if a tenant's total leased square footage declines year over year, and *Rent Decrease* equals one if total rent payments decline. We merge industry-level $AIIE$ to each tenant-year observation based on the tenant's four-digit NAICS code and retain observations from 2002 to 2023. The resulting panel covers 242,556 unique tenants and 1,410,603 tenant-year observations (Table A7). The unconditional rate of annual space contraction is 5.3%, and the mean $AIIE$ is 0.367 (SD = 0.664), indicating substantial cross-industry variation in AI exposure.

4.2 Results

Table 8 reports OLS and IV estimates. Specifically, a one-standard-deviation increase in $AIIE$ raises the annual probability of a space decline by 0.46 percentage points ($= 0.0069 \times 0.664$). A one-standard-deviation increase in $AIIE$ raises the annual probability of a rent decline by 0.48 percentage points ($= 0.0073 \times 0.664$). The IV estimates (columns 3–4) instrument $AIIE$ with a leave-one-out peer mean of AI exposure within the same four-digit NAICS industry. The IV coefficients roughly double the OLS magnitudes: a one-unit increase in $AIIE$ raises the probability of a square footage decline by 1.24 percentage points and a rent decline by 1.35 percentage points. That the IV estimates exceed OLS mirrors the pattern in the balance-sheet regressions (i.e., Tables 2–3), consistent with classical measurement error attenuating the OLS coefficients toward zero.

[4] CompStak records lease terms at signing but does not capture early terminations, subleases, or mid-lease renegotiations. Our panel therefore assumes each lease remains active for its full contractual term. To the extent that AI-exposed tenants terminate or downsize leases before expiration, this assumption biases our estimates toward zero.

The CompStak evidence adds support to the earlier results in two ways. First, the effect is not confined to publicly traded firms; it also appears in the broader tenant population covered by commercial lease transactions. Second, because the outcomes are reductions in leased space and rent commitments rather than changes in owned property, the findings mitigate the concern that the balance-sheet results are driven by changes in real estate investment motives (e.g., collateral for borrowing) rather than genuine reductions in workspace demand. Together with the Compustat and Item 2 evidence, the lease-market results indicate that AI exposure reduces physical space demand rather than merely altering the accounting or portfolio treatment of real estate holdings.

5 Conclusion

This paper studies how artificial intelligence reshapes firms' demand for corporate real estate. Using a panel of U.S. publicly traded firms from 2002 to 2023, we show that firms with greater AI exposure reduce their holdings of owned real estate over time. The effect is economically meaningful and robust to a shift-share IV design that isolates plausibly exogenous variation in firm-level AI exposure, suggesting that the decline in corporate real estate reflects a causal response to technological change rather than simple correlation. In this sense, AI affects not only how firms produce, but also how much physical space they choose to occupy.

The magnitudes are substantial for a slow-moving balance-sheet item. Our IV estimates imply that a one standard deviation increase in AI exposure reduces the ratio of owned real estate to total assets by about 0.14 percentage points per year. Over a five-year horizon, this effect cumulates to roughly 0.7 percentage points, or about 7% of the sample mean. The effect is strongest in settings where AI is most likely to substitute for labor and where maintaining underutilized space is especially costly, including firms with highly replaceable tasks, low R&D intensity, high leverage, and low cash flow, as well as in the post-2015 period and in high-AI states.

Two additional analyses support this interpretation. Using Item 2 property disclosures from 10-K filings, we show that more AI-exposed firms reduce the number of disclosed properties, contract their geographic footprint, and become more likely to sublease space and shift toward leasing. Using lease transaction data from CompStak, we further show that tenants in more AI-exposed industries, both public and private ones, are more likely to reduce leased square footage. Together, these results indicate that the balance-sheet evidence reflects genuine contractions in space demand rather than accounting reclassification or portfolio reshuffling alone.

Our findings have implications for both corporate finance and commercial real estate. For corporate finance, they suggest that the same technological forces that raise the importance of intangible capital may also reduce firms' holdings of pledgeable real assets, potentially weakening the traditional link between tangible assets and financing capacity. For commercial real estate markets, they point to a persistent technological headwind to space demand, especially in locations and sectors most exposed to AI-enabled reorganization. More broadly, the results show that technological change can reshape firm boundaries not only through labor and intangible investment, but also through firms' demand for physical space.

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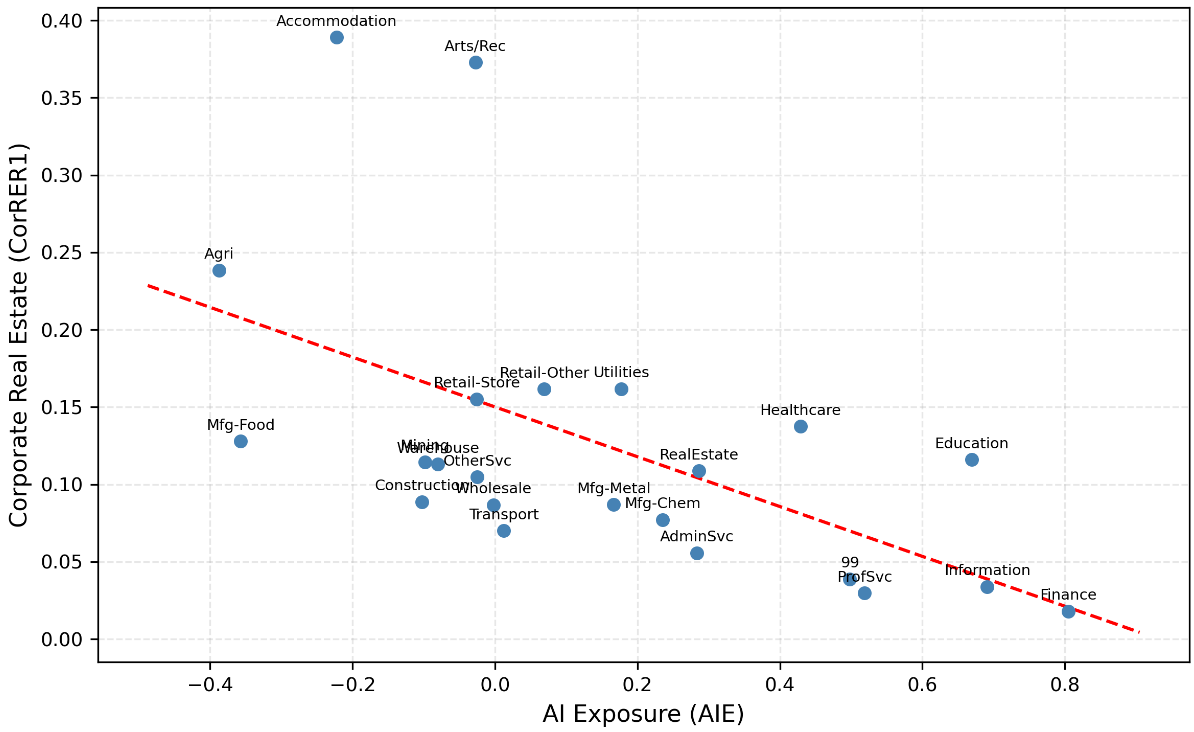
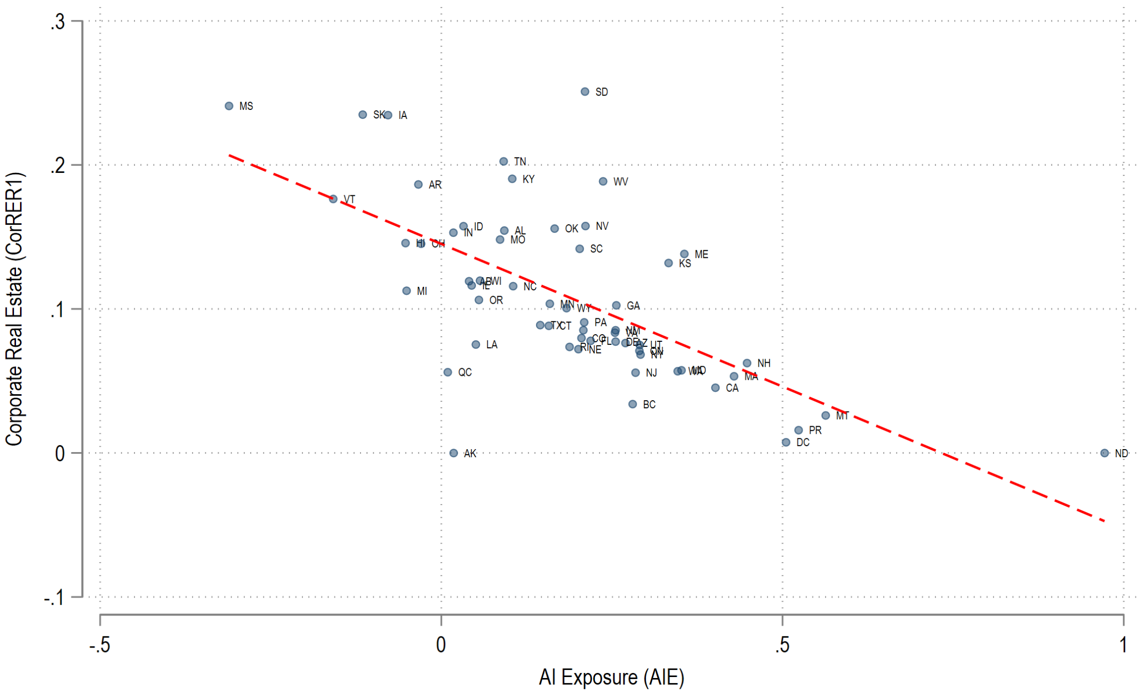
Figure 1: Industry-Level Corporate Real Estate and AI Exposure



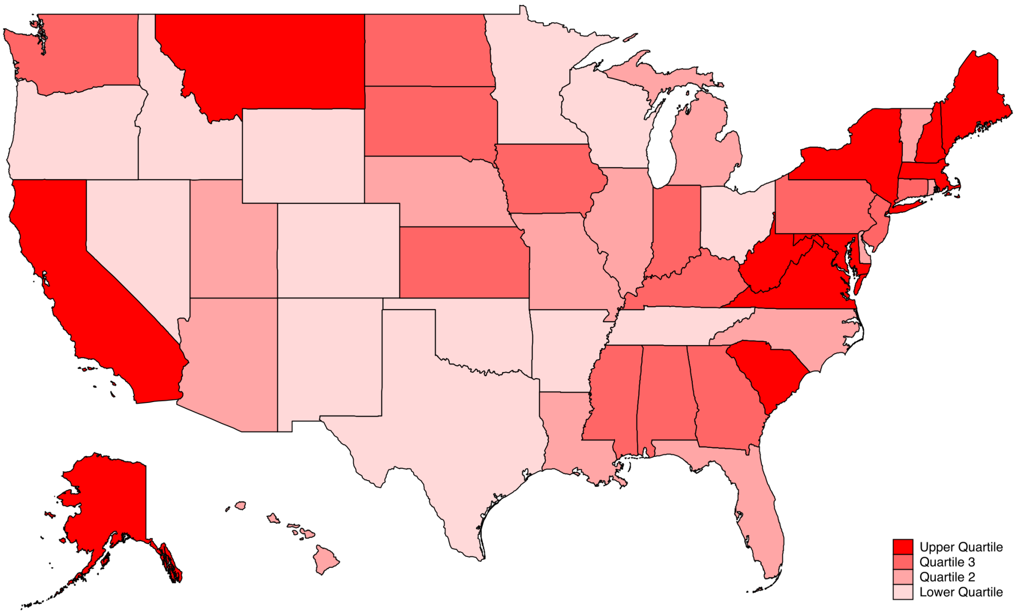
Notes: This figure plots industry-level averages of corporate real estate intensity (CorRER1, vertical axis) against industry-level averages of firm AI exposure (AIE, horizontal axis) across two-digit NAICS industries. CorRER1 is defined as buildings, construction in progress, and land and improvements, divided by adjusted total assets. AIE is the firm-level AI exposure measure constructed by aggregating Felten et al. (2021) ability-level AI scores to occupations and industries, then mapped to firms using the Hoberg and Phillips (2025) text-based segment weights, as described in Section 2.1.3. The sample consists of Compustat firm-year observations from 2002 to 2023 used in Table 2, collapsed to industry means. Each point represents one two-digit NAICS industry, labeled with its sector abbreviation. The dashed line shows the fitted linear relationship.

Figure 2: State-Level Corporate Real Estate and AI Exposure



Notes: This figure plots state-level averages of corporate real estate intensity (CorRER1, vertical axis) against state-level averages of firm AI exposure (AIE, horizontal axis) across U.S. states, where the state is defined by firm headquarters location. CorRER1 and AIE are defined as in Table 1. The sample consists of Compustat firm-year observations from 2002 to 2023 used in Table 2, collapsed to state means. Each point represents one state, labeled with its postal abbreviation. The dashed line shows the fitted linear relationship.

Figure 3: Geographic Dispersion of AI Exposure Across U.S. States



Notes: This figure displays the geographic distribution of average firm-level AI exposure (AIE) across U.S. states. AIE is defined as in Table 1. States are shaded into quartiles based on the mean AIE of Compustat firms headquartered in each state, computed over 2002–2023. Darker shading indicates higher average AI exposure.

Table 1: Summary Statistics

	Mean	SD	P25	Median	P75	N
Panel A: Corporate Real Estate Measures						
CorRER1	0.081	0.154	0.000	0.004	0.105	105,161
CorRER2	0.072	0.145	0.000	0.000	0.089	105,912
ΔCorRER1	0.001	0.051	−0.000	0.000	0.002	96,749
ΔCorRER2	0.001	0.044	0.000	0.000	0.000	97,546
Panel B: AI Exposure						
AIE	0.319	0.484	−0.069	0.351	0.738	119,054
Panel C: Firm Controls						
Log Assets	5.656	3.104	3.757	5.973	7.788	174,509
Leverage	0.979	2.901	0.007	0.191	0.680	154,842
Cash Flow	−0.361	1.744	−0.100	0.030	0.103	157,999
Tobin's Q	3.782	11.568	0.685	1.143	2.210	154,303

Notes: This table reports summary statistics for the panel of U.S. publicly traded firms in Compustat from 2002 to 2023. Each variable uses its own non-missing sample. CorRER1 is defined as buildings (*fatb*) plus construction in progress (*fatc*) plus land and improvements (*fatp*), divided by adjusted total assets. CorRER2 is buildings (*fatb*) plus land and improvements (*fatp*), divided by adjusted total assets. ΔCorRER1 and ΔCorRER2 are the annual first differences of the corresponding ratios. AIE is firm-level AI exposure, constructed by aggregating ability-level AI exposure scores from Felten et al. (2021) to the occupation and then industry-year level using BLS employment weights, and mapping to firms using the text-based industry segment weights from Hoberg and Phillips (2025). See Section 2.1.3 for details. Log Assets is the natural logarithm of adjusted total assets (total assets net of right-of-use assets). Leverage is adjusted long-term debt plus adjusted debt in current liabilities, divided by market value of equity, where debt is net of capitalized lease liabilities to maintain comparability across ASC 842 adoption. Cash Flow is net income plus depreciation, divided by lagged adjusted total assets. Tobin's Q is market value of equity plus adjusted total debt, divided by adjusted total assets. All CorRE measures are winsorized at the 1st and 99th percentiles by fiscal year. Control variables are winsorized at the 1st and 99th percentiles within SIC 3-digit industry $\times$ year levels.

Table 2: OLS Baseline Results

	(1) ΔCorRER1	(2) ΔCorRER1	(3) ΔCorRER2	(4) ΔCorRER2
AIE	−0.0015***	−0.0018***	−0.0008**	−0.0012***
	(0.0005)	(0.0005)	(0.0004)	(0.0004)
Log Assets		−0.0002**		−0.0002***
		(0.0001)		(0.0001)
Leverage		−0.0000		−0.0000
		(0.0000)		(0.0000)
Cash Flow		0.0000		0.0000
		(0.0000)		(0.0000)
Tobin's Q		−0.0000***		−0.0000***
		(0.0000)		(0.0000)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Sample Period	2002–2023	2002–2023	2002–2023	2002–2023
Observations	74,993	72,426	75,536	72,945
Number of Firms	9,799	9,433	9,821	9,455
Adjusted R^2	0.0023	0.0024	0.0031	0.0031

Notes: This table reports OLS estimates of the relationship between firm-level AI exposure and annual changes in corporate real estate holdings among U.S. publicly traded firms from 2002 to 2023. The dependent variable is the annual first difference in CorRER1 (columns 1–2) or CorRER2 (columns 3–4); see Table A1 for variable definitions. The main independent variable is AIE, a firm-level AI exposure measure constructed by aggregating ability-level AI scores from Felten et al. (2021) to the firm level using the text-based product-market segment weights of Hoberg and Phillips (2025). Columns (1) and (3) include no firm-level controls. Columns (2) and (4) add the natural logarithm of total assets, leverage, cash flow, and Tobin's Q. All specifications include two-digit NAICS industry fixed effects and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Instrumental Variable Results: Shift-Share IV

	(1) ΔCorRER1	(2) ΔCorRER2
AIE	-0.0028^{***}	-0.0020^{**}
	(0.0010)	(0.0009)
Firm Controls	Yes	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Observations	63,245	63,705
Number of Firms	8,730	8,752

Notes: This table reports two-stage least squares (2SLS) estimates of the effect of firm-level AI exposure on annual changes in corporate real estate holdings among U.S. publicly traded firms from 2002 to 2023. The dependent variable is the annual first difference in CorRER1 (column 1) or CorRER2 (column 2). The endogenous variable AIE is instrumented with a shift-share instrument that decomposes firm-level AI exposure into pre-determined product-market segment weights from Hoberg and Phillips (2025) (shares) and time-varying changes in industry-level AI intensity (shifts), where industry-level AIIE is constructed by aggregating occupation-level AI exposure scores to industries using BLS employment weights. See Table A1 for detailed variable definitions. All specifications control for log assets, leverage, cash flow, and Tobin's Q, and include two-digit NAICS industry fixed effects and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: IV Heterogeneity: Industry Characteristics

	ΔCorRER1	ΔCorRER2
Panel A: Tradable vs. Non-Tradable		
Non-Tradable	−0.0003	0.0011
	(0.0066)	(0.0060)
Tradable	−0.0027***	−0.0022***
	(0.0009)	(0.0008)
Panel B: Tech vs. Non-Tech		
Non-Tech	−0.0029***	−0.0019**
	(0.0010)	(0.0009)
Tech	−0.0013	−0.0031
	(0.0041)	(0.0035)
Panel C: High vs. Low Replaceability (R-shares)		
Low R-shares	−0.0033	−0.0023
	(0.0039)	(0.0035)
High R-shares	−0.0036***	−0.0032***
	(0.0011)	(0.0010)
Firm Controls	Yes	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: This table reports 2SLS estimates of the effect of AIE on annual changes in corporate real estate holdings, estimated separately for industry subsamples. The instrument is a shift-share IV; see Table 3 for instrument details. Panel A splits by tradability following the classification in Mian and Sufi (2014). Panel B defines technology firms as those in NAICS sectors 51 (Information) and 54 (Professional, Scientific, and Technical Services). Panel C splits at the fiscal-year median of the Replaceability share (R-shares) from occupation-level automation vulnerability scores. See Table A1 for detailed variable definitions. All specifications control for the natural logarithm of total assets, leverage, cash flow, and Tobin's Q, and include two-digit NAICS industry fixed effects and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: IV Heterogeneity: Firm Characteristics

	ΔCorRER1	ΔCorRER2
Panel A: High vs. Low R&D Intensity		
Low R&D	-0.0044^{**}	-0.0035^{**}
	(0.0020)	(0.0017)
High R&D	-0.0015	0.0010
	(0.0033)	(0.0028)
Panel B: High vs. Low Leverage		
Low Leverage	-0.0018	-0.0004
	(0.0016)	(0.0014)
High Leverage	-0.0035^{**}	-0.0028^{*}
	(0.0016)	(0.0015)
Panel C: High vs. Low Cash Flow		
Low Cash Flow	-0.0080^{***}	-0.0064^{***}
	(0.0021)	(0.0018)
High Cash Flow	-0.0014	-0.0012
	(0.0013)	(0.0012)
Firm Controls	Yes	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: This table reports 2SLS estimates of the effect of AIE on annual changes in corporate real estate holdings, estimated separately for firm-characteristic subsamples. The instrument is a shift-share IV; see Table 3 for instrument details. Panel A splits by R&D intensity, defined as R&D expenditure divided by total assets; firms not reporting R&D are classified as zero following Koh and Reeb (2015). "Low" and "High" denote the bottom and top terciles, computed within two-digit NAICS industry × fiscal year cells. Panel B splits at the fiscal-year median of leverage. Panel C splits at the fiscal-year median of cash flow. See Table A1 for detailed variable definitions. All specifications control for the log assets, leverage, cash flow, and Tobin's Q, and include two-digit NAICS industry fixed effects and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: IV Heterogeneity: Time and Geography

	ΔCorRER1	ΔCorRER2
Panel A: Pre-2015 vs. Post-2015		
Pre-2015	-0.0021^{*}	-0.0016
	(0.0012)	(0.0011)
Post-2015	-0.0049^{**}	-0.0035^{**}
	(0.0019)	(0.0016)
Panel B: High-AI vs. Low-AI States		
Low-AI States	-0.0016	-0.0011
	(0.0011)	(0.0010)
High-AI States	-0.0085^{***}	-0.0052^{**}
	(0.0025)	(0.0022)
Firm Controls	Yes	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: This table reports 2SLS estimates of the effect of AIE on annual changes in corporate real estate holdings, estimated separately by time period and geography. The instrument is a shift-share IV; see Table 3 for instrument details. Panel A splits the sample at 2015, corresponding to the commercial maturation of deep learning and cloud-based AI infrastructure. Panel B classifies a firm as headquartered in a "High-AI State" if its state-year average AIE falls in the top tercile of the state-year distribution; all remaining firms are classified as "Low-AI States." See Table A1 for detailed variable definitions. All specifications control for the log assets, leverage, cash flow, and Tobin's Q, and include two-digit NAICS industry fixed effects and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Item 2 Property Disclosure Evidence

Panel A: 5-Year Changes in Property Footprint

	IV
5-Year Change in Number of Properties	-5.196^{***}
	(1.494)
5-Year Change in Leased Properties	-2.113^{**}
	(0.839)
5-Year Change in Owned Properties	-0.991^{**}
	(0.453)
5-Year Change in Geographic Footprint	-0.397^{***}
	(0.139)
Firm Controls	Yes
Industry FE	Yes
Year FE	Yes

Panel B: Property Restructuring

	Shifted Toward Leasing	Sublease Mention	SqFt Decreased
Firm IV	0.055^{***}	0.035^{**}	0.050
	(0.020)	(0.014)	(0.034)
BHJ	0.069	0.046^{*}	0.165^{**}
	(0.042)	(0.027)	(0.066)
Firm Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: This table reports 2SLS estimates of the effect of AIE on property-level outcomes extracted from Item 2 (Properties) disclosures in 10-K filings using a large language model. Panel A reports firm-level IV estimates of five-year changes in firms' disclosed property portfolios, estimated over non-overlapping five-year windows. The dependent variables are the five-year change in total number of properties, number of leased properties, number of owned properties, and number of states in which the firm reports property. Panel B reports firm-level IV and shock-level IV estimates following Borusyak et al. (2022) for binary restructuring indicators: whether the firm shifted toward leasing, initiated subleasing, or experienced a decrease in total square footage. See Table A1 for detailed variable definitions. All specifications control for the log assets, leverage, cash flow, and Tobin's Q, and include two-digit NAICS industry and year fixed effects. Standard errors clustered at the firm level are reported in parentheses for firm-level IV; shock-level standard errors account for correlation across industry-level shocks. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Tenant Space Demand Declines

	OLS		IV	
	SF Decrease	Rent Decrease	SF Decrease	Rent Decrease
	(1)	(2)	(3)	(4)
AIIE	0.0069*	0.0073**	0.0124***	0.0135***
	(0.0036)	(0.0036)	(0.0044)	(0.0044)
Tenant Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,410,603	1,410,603	1,410,603	1,410,603
Number of Tenants	242,556	242,556	242,556	242,556

Notes: This table reports estimates of the effect of industry-level AI exposure on tenant-level space demand declines using individual lease transaction records from CompStak covering 2002–2023. The dependent variables are binary indicators equal to one if a tenant's total leased square footage (SF Decrease) or total rent payments (Rent Decrease) declined year over year. The independent variable $AIIE$ is the AI Industry Exposure measure, assigned to each tenant based on the tenant's four-digit NAICS code. Columns (1)–(2) report OLS estimates. Columns (3)–(4) report 2SLS estimates instrumenting $AIIE$ with a leave-one-out peer mean of AIIE within the same four-digit NAICS industry, excluding the tenant's own industry contribution. Summary statistics are reported in Table A7. See Table A1 for detailed variable definitions. All specifications include tenant fixed effects and year fixed effects. Standard errors clustered at the tenant level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Disrupted Spaces: How Automation and Artificial Intelligence Reshape Corporate Real Estate Demand

Appendix Tables

Table A1: Variable Definitions

Variable	Definition
Panel A: Corporate Real Estate Measures (Dependent Variables)	
CorRER1	(Buildings + Construction in Progress + Land and Improvements) / Adjusted Total Assets. Buildings (*fatb*), construction in progress (*fatc*), and land and improvements (*fatp*) are from Compustat PP&E subcomponents. Adjusted total assets equal total assets minus right-of-use assets ($at - ROUANT$) to maintain comparability across the ASC 842 adoption. Winsorized at the 1st and 99th percentiles by fiscal year.
CorRER2	(Buildings + Land and Improvements) / Adjusted Total Assets. Excludes construction in progress from the CorRER1 numerator, isolating stabilized, operational real estate assets.
CorRER3	(Buildings + Land and Improvements + Leases) / Adjusted Total Assets. Adds capitalized finance lease assets (*fatl*) to the CorRER2 numerator, capturing all structures used in the firm's operations including those held under finance leases.
CorRER4	(Buildings + Construction in Progress + Land and Improvements + Leases) / Adjusted Total Assets. The broadest book-value CorRE definition.
Panel B: AI Exposure (Treatment Variable)	
AIE	Firm-year AI exposure. Constructed by (i) scoring each O*NET ability on its exposure to AI using the Felten et al. (2021) AI-ability mapping, (ii) aggregating ability-level scores to occupations using ONET ability importance and level weights, (iii) aggregating occupation-level scores to four-digit NAICS industry-year level using BLS Occupational Employment Statistics employment weights, and (iv) mapping to firms using text-based industry segment weights from Hoberg and Phillips (2025).
$AIIE$	Industry-level AI exposure assigned to CompStak tenants based on the tenant's four-digit NAICS code. Constructed from steps (i)-(iii) of the AIE pipeline without the Hoberg-Phillips firm-level weighting.
Panel C: Firm-Level Control Variables	

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Table A1 — *Continued from previous page*

Variable	Definition
Log Assets	Natural logarithm of adjusted total assets ($at - ROUANT$). Winsorized at the 1st and 99th percentiles within three-digit SIC × fiscal year cells.
Leverage	(Debt in current liabilities + long-term debt) / equity market capitalization, where debt is adjusted for capitalized lease liabilities ($dlc - LLC$, $dltt - LLLT$). Winsorized within SIC3 × year.
Cash Flow	(Net income + depreciation) / lagged adjusted total assets. Winsorized within SIC3 × year.
Tobin's Q	(Equity market capitalization + adjusted total debt) / adjusted total assets. Winsorized within SIC3 × year.
Panel D: Item 2 Property Disclosure Variables	
Properties	Total number of properties disclosed in Item 2 of the 10-K filing, extracted via large language model.
Leased Properties	Number of properties identified as leased in Item 2.
Owned Properties	Number of properties identified as owned in Item 2.
Geographic Footprint	Number of distinct U.S. states in which the firm discloses property.
Shifted Toward Leasing	Binary indicator equal to one if the firm's ownership-mix category (an ordinal scale from all-owned to all-leased, based on Item 2 disclosures) shifted toward the leasing end over the five-year window.
Sublease Mention	Binary indicator equal to one if the firm initiated subleasing activity over the five-year window.
SqFt Decreased	Binary indicator equal to one if the firm's total disclosed square footage decreased over the five-year window.
Panel E: CompStak Tenant-Level Variables	
SF Decrease	Binary indicator equal to one if a tenant's total leased square footage declined relative to the prior year.
Rent Decrease	Binary indicator equal to one if a tenant's total rent payments declined year over year.

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Table A1 — *Continued from previous page*

Variable	Definition
Total Leased SF	Sum of square footage across all active leases for each tenant-year, measured in square feet.
Total Rent	Sum of rent payments across all active leases for each tenant-year, measured in dollars.
Panel F: Heterogeneity Indicators	
Tradable	Binary indicator for tradable industries based on the Mian and Sufi (2014) classification using four-digit NAICS employment patterns.
Tech	Binary indicator equal to one if the firm's two-digit NAICS code is 51 (Information) or 54 (Professional, Scientific, and Technical Services).
High Replaceability	Binary indicator equal to one if the firm's occupational replaceability (R-share) is above the sample median.
High R&D Intensity	Binary indicator equal to one if the firm is in the top tercile of R&D expenditures scaled by total assets within NAICS two-digit industry and fiscal year; non-reporting firms are set to zero.
High Leverage	Binary indicator equal to one if the firm's leverage exceeds the within-fiscal-year median.
Low Cash Flow	Binary indicator equal to one if the firm's cash flow is below the within-fiscal-year median.
Post-2015	Binary indicator equal to one if the fiscal year is after 2015.
High-AI State	Binary indicator equal to one if the firm is headquartered in a state in the top tercile of state-level mean AIE within each year.
Panel G: Instrumental Variables	
Shift-share IV	Shift-share IV: $Z_{it} = \sum_j w_{ij,0} \times \Delta AIIE_{jt}$, where $w_{ij,0}$ is firm i's pre-period text-based industry weight from Hoberg and Phillips (2025) and $\Delta AIIE_{jt}$ is the change in industry-level AI exposure.

Leave-one-out shift-share IV	Same as Shift-share IV but excluding each firm's own contribution to the industry-level AI exposure measure.

This table defines the variables used in the empirical analysis. Panel A describes four asset-scaled corporate real estate measures constructed from Compustat PP&E subcomponents. Panel B describes the AI exposure variables. Panel C describes firm-level controls drawn from Compustat. Panel D describes property-level outcomes extracted from 10-K Item 2 filings via large language model. Panel E describes tenant-level lease variables from CompStak. Panel F describes the binary heterogeneity indicators used in subsample analyses. Panel G describes the instrumental variables. All Compustat-based variables refer to the fiscal year 2002–2023 sample period. Detailed construction procedures are described in Sections 2.1.2–2.1.3.

Table A2: OLS Baseline: Alternative CorRE Measures

	(1) ΔCorRER3	(2) ΔCorRER3	(3) ΔCorRER4	(4) ΔCorRER4
AIE	−0.0012	−0.0020**	−0.0020**	−0.0026***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Log Assets		−0.0009***		−0.0009***
		(0.0001)		(0.0001)
Leverage		−0.0000		−0.0000
		(0.0000)		(0.0000)
Cash Flow		−0.0000		−0.0000
		(0.0000)		(0.0000)
Tobin's Q		−0.0000***		−0.0000***
		(0.0000)		(0.0000)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Sample Period	2002–2023	2002–2023	2002–2023	2002–2023
Observations	64,795	62,647	64,400	62,270
Adjusted R^2	0.0273	0.0285	0.0246	0.0258

Notes: This table reports OLS estimates of the relationship between AIE and annual changes in alternative corporate real estate measures among U.S. publicly traded firms from 2002 to 2023. CorRER3 is buildings (*fatb*) plus land and improvements (*fatp*) plus capitalized leases (*fatl*), divided by adjusted total assets. CorRER4 is buildings (*fatb*) plus land and improvements (*fatp*) plus construction in progress (*fatc*) plus capitalized leases (*fatl*), divided by adjusted total assets. Columns (1) and (3) include no firm-level controls. Columns (2) and (4) add the log assets, leverage, cash flow, and Tobin's Q. All specifications include two-digit NAICS industry fixed effects and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A3: Alternative Instrumental Variable: Leave-One-Out

	(1) ΔCorRER1	(2) ΔCorRER2
AIE	-0.0020^{***}	-0.0015^{**}
	(0.0008)	(0.0007)
Firm Controls	Yes	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Observations	71,656	72,168

Notes: This table reports 2SLS estimates of the effect of AIE on annual changes in corporate real estate holdings using an alternative instrument. The endogenous variable AIE is instrumented with a leave-one-out peer mean of AIE within the same four-digit NAICS industry, excluding firm i's own AIE when computing the industry mean. The leave-one-out shift-share IV addresses potential reflection bias by ensuring that a firm's own AI exposure does not mechanically enter its instrument. All specifications control for the natural logarithm of total assets, leverage, cash flow, and Tobin's Q, and include two-digit NAICS industry fixed effects and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A4: Alternative Model Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	lnCorRE1	DlnCorRE1	CorRER1	ΔCorRER1	ΔCorRER1	ΔCorRER1
Specification	Log-Level	Indicator	Level	3-Year Diff	5-Year Diff	Baseline
AIE	-0.4578^{*}	-0.2039^{***}	-0.0410^{**}	-0.0345^{**}	-0.0460^{***}	-0.0028^{***}
	(0.2383)	(0.0208)	(0.0183)	(0.0166)	(0.0172)	(0.0008)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Firm + Year	NAICS2 + Year	Firm + Year	Year	Year	NAICS2 + Year
Clustering	Firm	Firm	Firm	Firm	Firm	NAICS4
Observations	63,055	91,744	63,055	40,126	29,886	63,245
KP F-statistic	337.4	2,602.7	337.4	399.5	300.7	230.9

Notes: This table reports 2SLS estimates of the effect of AIE on corporate real estate outcomes under alternative model specifications, all instrumented with shift-share IV. Column (1) uses the log-level of real estate holdings, lnCorRE1 $=$ ln(1 + Buildings + Construction in Progress + Land), with firm and year fixed effects. Column (2) uses an indicator variable (DlnCorRE1) equal to one if lnCorRE1 increased relative to the prior year, with NAICS two-digit industry and year fixed effects. Column (3) estimates a levels-on-levels specification for the CorRER1 ratio with firm and year fixed effects. Column (4) estimates three-year long differences with year fixed effects. Column (5) estimates five-year long differences with year fixed effects. Column (6) replicates the baseline first-difference specification but clusters standard errors at the four-digit NAICS level. All specifications include log assets, leverage, cash flow, and Tobin's Q as controls. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Alternative Samples (IV)

	ΔCorRER1	ΔCorRER2
Panel A: Exclude Post-2019 (COVID)		
AIE	-0.0025^{**}	-0.0020^{**}
	(0.0010)	(0.0009)
Observations	54,497	54,874
Panel B: Exclude Post-2018 (ASC 842)		
AIE	-0.0026^{**}	-0.0021^{**}
	(0.0011)	(0.0009)
Observations	52,444	52,799
Panel C: Drop NAICS 51 and 54		
AIE	-0.0029^{***}	-0.0019^{**}
	(0.0010)	(0.0009)
Observations	52,835	53,259
Firm Controls	Yes	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: This table reports 2SLS estimates of the effect of AIE on annual changes in corporate real estate holdings under alternative sample restrictions, all instrumented with the shift-share IV. Panel A excludes fiscal years after 2019 to remove the COVID-19 period. Panel B excludes fiscal years after 2018 to remove the post-adoption period of ASC 842, which capitalized operating leases onto the balance-sheet beginning in 2019. Panel C drops firms in NAICS sectors 51 (Information) and 54 (Professional, Scientific, and Technical Services), the two industries with the highest average AI exposure. All specifications control for the log assets, leverage, cash flow, and Tobin's Q, and include two-digit NAICS industry fixed effects and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A6: BHJ Shock-Level Inference (ΔCorRER1)

Panel A: Firm-Level vs. Shock-Level IV

	Firm-Level IV	BHJ Shock-Level IV
AIE	-0.0028^{***}	-0.0030^{*}
	(0.0010)	(0.0020)
Firm Controls	Yes	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
First-Stage F	—	771.3
Shock Observations	—	3,179
Observations	63,245	63,245

Panel B: BHJ Shock-Level Balance Test

Lagged Covariate	Coefficient	SE	t
L.CorRER1	−0.046	(0.112)	−0.41
L.CorRER2	0.109	(0.107)	1.01
L.Log Assets	−0.000	(0.004)	−0.07
L.AIE	0.144	(0.025)	5.72^{***}
Fixed Effects	NAICS4 + Year		
Dep. variable	g_{jt} (NAICS4 × year AI shock)		

Notes: This table reports shock-level inference for the shift-share IV following Borusyak et al. (2022). Panel A compares firm-level 2SLS estimates (column 1) with shock-level IV estimates (column 2), where the unit of observation in the shock-level regression is the four-digit NAICS industry × year cell. The first-stage F-statistic and the number of shock-level observations are reported for the shock-level specification. Panel A controls for the natural logarithm of total assets, leverage, cash flow, and Tobin's Q, and includes two-digit NAICS industry fixed effects and year fixed effects. Standard errors are clustered at the firm level (column 1) or account for shock-level correlation (column 2). Panel B reports a balance test at the industry-year level in which the dependent variable is the AI shock (g_{jt}), regressed on lagged industry-year means of CorRER1, CorRER2, log assets, and AIE. Lagged AIE is expected to be significant due to persistence in AI exposure; lagged CorRER1, CorRER2, and log assets should be insignificant if the shocks are balanced with respect to prior firm characteristics. Panel B includes four-digit NAICS industry fixed effects and year fixed effects, with standard errors clustered at the four-digit NAICS level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A7: Summary Statistics: CompStak Tenant-Year Panel

	N	Mean	SD	P25	Median	P75
Panel A: Dependent Variables						
SF Decrease	1,410,603	0.053	0.224	0	0	0
Rent Decrease	1,410,603	0.053	0.223	0	0	0
Panel B: Lease Characteristics						
Total Leased SF	1,410,603	37,045	186,449	3,025	7,730	23,418
Total Rent ($)	1,410,603	665,004	3,497,833	51,722	142,507	418,100
Panel C: AI Exposure						
AIIE (Current)	1,410,603	0.367	0.664	−0.194	0.491	0.978

Notes: This table reports summary statistics for the CompStak tenant-year panel used in Table 8, covering 2002–2023. The panel is constructed by expanding individual lease transactions to annual observations spanning each lease's contractual term and collapsing to the tenant-year level. SF Decrease is a binary indicator equal to one if a tenant's total leased square footage declined relative to the prior year. Rent Decrease is a binary indicator equal to one if a tenant's total rent payments declined year over year. Total Leased SF is the sum of square footage across all active leases for each tenant-year, measured in square feet. Total Rent is the sum of rent payments across all active leases, measured in dollars. AIIE is the AI Industry Exposure measure from Felten et al. (2021), assigned to each tenant based on the tenant's four-digit NAICS code.

Table A8: Robustness: Excluding Financial Firms and Utilities

	Full Sample		Excl. Financials & Utilities	
	ΔCorRER1	ΔCorRER2	ΔCorRER1	ΔCorRER2
	(1)	(2)	(3)	(4)
Panel A: OLS				
AIE	−0.0018***	−0.0012***	−0.0020***	−0.0013***
	(0.0005)	(0.0004)	(0.0005)	(0.0005)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	72,426	72,945	65,189	65,689
Number of Firms	9,433	9,455	8,503	8,524
Adjusted R^2	0.0024	0.0031	0.0027	0.0037
Panel B: IV				
AIE	−0.0028***	−0.0020**	−0.0024***	−0.0019**
	(0.0010)	(0.0009)	(0.0009)	(0.0008)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	63,245	63,705	57,179	57,623
Number of Firms	8,730	8,752	7,871	7,892
KP F-statistic	2,008.3	2,043.9	2,133.3	2,170.4

Notes: This table compares the baseline OLS (Panel A) and IV (Panel B) results on the full sample (columns 1–2) with results obtained after excluding financial firms (SIC 6000–6999) and utilities (SIC 4900–4999) (columns 3–4). The dependent variable is the first-differenced corporate real estate ratio (ΔCorRER1 or ΔCorRER2). *AIE* is the firm-year AI exposure measure. All specifications include NAICS two-digit industry and year fixed effects, firm-level controls (log assets, leverage, cash flow, Tobin's Q, all SIC3×year winsorized at 1/99), and firm-clustered standard errors. The IV specifications instrument *AIE* using the shift-share instrument. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.