Datacenter Mortgages and Originate-to-Distribute *

Pedro Gete[†], Amparo Mercader[‡]

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Abstract

We construct a novel dataset that links mortgage records with detailed information on datacenter characteristics and tenant contracts. We show that banks with high securitization propensity, those more likely to sell, syndicate, or securitize loans, exhibit significantly weaker underwriting standards than banks that retain loans. Properties financed by high securitization propensity lenders carry substantially higher leverage, measured by debt per square foot, debt-to-rent ratios, and loan-to-value ratios. These patterns persist in matched samples and when restricting to single-property loans, indicating that they reflect systematic differences in screening rather than deal structure. Our findings extend evidence on originate-to-distribute moral hazard from residential mortgages to digital infrastructure finance, a rapidly growing market characterized by technological obsolescence risk and by collateral values that we show are meaningfully lower than total invested capital.

Keywords: AI, Banks, Datacenter, Leverage, Debt, Credit Risk, Mortgages

JEL Classification: G12, G21, G23, R31.

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[†]IE University. Email: pedro.gete@ie.edu.

[‡]IE University and Georgetown University. Email: mercada@georgetown.edu

1 Introduction

The rapid expansion of artificial intelligence (AI) and cloud computing has driven unprecedented demand for digital infrastructure. Datacenters are the physical facilities that house the servers, networking equipment, and storage systems powering modern digital services and have emerged as critical assets in the global economy. As AI applications proliferate and data processing requirements intensify, investment in datacenter capacity has accelerated sharply. This growth has been accompanied by an equally dramatic expansion in datacenter-secured lending: approximately $113 billion in property-secured debt has been originated over the past five years, with the pace of origination accelerating after 2021. Despite the economic importance of datacenters and the rapid growth of associated credit markets, little is known about the underwriting practices and risk characteristics of datacenter mortgages. This gap is particularly important given that datacenters represent a novel asset class with distinctive features: highly specialized collateral, rapid technological obsolescence, concentrated tenant bases, and intensive capital requirements. These characteristics raise fundamental questions about credit risk assessment and the incentives facing lenders in this emerging market.

This paper examines whether originate-to-distribute (OTD) incentives influence lending standards in datacenter mortgage lending. The OTD model, in which lenders originate loans with the intention of selling, syndicating, or securitizing them rather than holding them to maturity, has been extensively studied in the context of residential mortgages and corporate lending. A substantial body of research documents that when lenders can transfer credit risk to third parties, they may have weaker incentives to screen borrowers carefully or maintain rigorous underwriting standards (Dell'Ariccia et al., 2012; Keys et al., 2010; Piskorski et al., 2010; Purnanandam, 2011). This moral hazard problem was central to the deterioration of lending standards that preceded the 2007-2008 financial crisis, particularly in subprime mortgage markets where securitization was widespread.

The question of whether similar dynamics operate in datacenter lending is both theoretically and practically important. Theoretically, the information-intensive nature of datacenter credit requiring assessment of technology infrastructure, power capacity, cooling systems, network connectivity, and tenant creditworthiness suggests that screening costs are high and information asymmetries between lenders and secondary market participants may be substantial. These features could amplify the moral hazard inherent in OTD models. Practically, the concentration of datacenter debt among a small number of large lenders and the growing role of securitization and syndication in financing digital infrastructure raise concerns about systemic risk and credit quality.

To investigate these issues, we constructed a novel property-loan-level dataset that links datacenter mortgage originations to detailed information on property characteristics, tenant contracts, ownership structures, and lender balance sheets. Our database combines commercial real estate records from CoStar, covering approximately 1,850 datacenter properties in the United States as of November 2025, with mortgage origination data and regulatory information on lender characteristics from quarterly Call Report data, accessed via the Federal Reserve Bank of New York data products. This integration allows us to observe underwriting outcomes at an unprecedented level of granularity, including loan-to-value ratios (LTV), debt service coverage metrics, and borrower concentration, matched to lender-specific measures of securitization propensity. Our empirical strategy exploits variation across lenders in their propensity to distribute credit risk.

Following (Purnanandam, 2011) we construct bank-level OTD measures using regulatory balance sheet data, specifically the ratios of loan assets, trading assets, and repurchase agreements to total assets. These ratios capture the extent to which banks operate an originate-to-hold versus OTD business model. We classify lenders into high and low securitization propensity groups based on these measures and test whether lending outcomes differ systematically across lender types for otherwise comparable properties.

Our main findings provide evidence that OTD incentives shape credit supply in datacenter lending in ways consistent with moral hazard. Loans originated by high securitization propensity banks exhibit significantly higher leverage than loans from low securitization propensity banks. Specifically, properties financed by high securitization lenders have approximately 3.5 times higher debt per square foot and 3.5 higher debt-to-rent ratios compared to properties financed by other lenders, conditional on property characteristics, location, and origination year. The higher leverage ratios associated with high securitization lenders suggest that underwriting standards may be relaxed when lenders anticipate distributing loans rather than retaining them on balance sheet.

These differences persist in matched comparisons that restrict attention to high- vs. low-securitization banks and enforce common support in observables. They also remain economically large when we restrict the sample to single-property loans, ruling out that the results are driven by high-securitization lenders disproportionately originating multi-property (portfolio) deals.

High-securitization-propensity lenders are also more likely to finance undiversified datacenter borrowers, specialized datacenter landlords whose revenues are concentrated in a single asset class, relative to diversified owners such as large technology firms and other diversified infrastructure or financial owners. This borrower-type pattern is clear and statistically significant when securitization propensity is measured continuously using the balance-sheet OTD scores.

Our results contribute to several strands of literature. First, we extend the empirical evidence on OTD lending beyond residential mortgages and corporate loans to commercial real estate, specifically digital infrastructure finance. Prior work has documented the link between securitization and lending standards in residential mortgage markets (Dell'Ariccia et al., 2012; Keys et al., 2010; McGowan et al., 2024; Mian and Sufi, 2009; Piskorski et al., 2010), subprime lending (Purnanandam, 2011), and corporate credit (Bord and Santos, 2015; Ivashina and Sun, 2011). We show that similar patterns emerge in a specialized commercial real estate segment characterized by rapid growth, technological complexity, and concentrated ownership.

Second, we contribute to the literature on bank lending and risk transfer by providing micro-level evidence on how lenders' business models affect underwriting in an emerging asset class. Our use of regulatory balance sheet measures to proxy for OTD incentives follows Loutskina and Strahan (2009) and Purnanandam (2011), and relates to recent evidence on the securitize-versus-price margin in credit markets (McGowan and Nguyen, 2023), but applies these methods to a setting where collateral is highly specialized and secondary markets are developing. The finding that distribution incentives are associated with higher leverage and greater borrower concentration suggests that information frictions in digital infrastructure lending may amplify moral hazard problems.

Third, we provide the first systematic empirical analysis of datacenter debt markets. While prior research has examined credit risk in commercial real estate broadly (see, e.g., Ghent and Kudlyak (2011)) and the role of securitization in specific property types, datacenter lending has received little academic attention despite its growing economic importance. Our database and empirical findings establish baseline facts about the scale, composition, and underwriting characteristics of datacenter-secured credit.

The evidence we present raises important policy questions about credit risk in digital infrastructure markets. The concentration of datacenter lending among high securitization propensity banks, combined with elevated leverage ratios and borrower concentration, suggests potential vulnerabilities. If a significant fraction of datacenter debt has been originated under weak underwriting standards and subsequently distributed to investors with limited information about underlying credit quality, the resulting credit losses could be substantial. While datacenters have exhibited strong performance to date, the rapid pace of technological change, the potential for supply-demand imbalances as capacity additions accelerate, and the concentration of facilities in a small number of geographic markets all represent sources of systematic risk.

The remainder of the paper proceeds as follows. Section 2 describes our data construction and presents summary statistics on the universe of U.S. datacenters and associated debt. Section 3 documents the recent expansion of datacenters in terms of capacity, geography, and ownership structure. Section 4 analyzes the scale and composition of mortgage debt associated with datacenters. Section 5 examines the composition of datacenter collateral and assesses leverage relative to recoverable asset values. Section 6 presents our main empirical analysis, testing whether lenders with high securitization propensity exhibit weaker underwriting standards. Section 7 concludes. Appendix A provides additional details on variable construction and data sources.

2 Database

We construct a novel property-loan-level dataset of U.S. datacenters by integrating commercial real estate records, loan origination data, and lender balance sheet information from multiple sources. The dataset links leveraged datacenter properties to their mortgage lenders, enabling us to measure underwriting outcomes at an unprecedented level of granularity for this asset class.

The core of the dataset comes from CoStar, which provides a national inventory of U.S. datacenter properties as of November 2025 (approximately 1,850 assets). For each property, we observe RBA, geographic location, development status, shell rent, property taxes, percent leased, year built, ownership information, and loan origination records. CoStar's loan records include origination amount, origination date, interest rate, loan type, and originating lender name. We observe 550 properties with positive mortgage balances, representing approximately $113 billion in outstanding debt.

We construct property-level leverage measures from these loan origination records. When a single loan is secured by multiple properties, we allocate the loan balance across collateral properties in proportion to each property's RBA. This allocation allows us to measure debt per square foot, debt-to-rent ratios, and loan-to-value ratios at the property level in a manner comparable across single-asset and portfolio loans.

We link lenders to quarterly Call Report data (FFIEC), accessed via the Federal Reserve Bank of New York data products covering 2022 to 2025. We match bank lenders to regulatory data and construct bank-level OTD scores following (Purnanandam, 2011). We classify lenders into high and low securitization propensity groups based on these measures. Earnings-call transcripts were used to validate lender classifications. The remaining observations include non-bank lenders (insurance companies, private credit funds) and government/cooperative lenders.

Table 1 reports summary statistics for the main variables. Appendix A provides complete variable definitions, data cleaning procedures, and details on the collateral valuation methodology used to construct loan-to-value ratios.

3 Datacenter Expansion

This section documents the recent expansion of U.S. datacenters in terms of capacity, geography, and ownership structure.

Figure 1 reports cumulative datacenter capacity by year built. The distribution shows that most capacity has been delivered recently, with particularly rapid growth in the last five years. This acceleration reflects the surge in demand for digital infrastructure driven by cloud computing adoption and, more recently, artificial intelligence applications.

Figure 2 maps total datacenter capacity at the county level. Capacity is highly concentrated in Northern Virginia and a small set of additional hubs including major metropolitan markets. This geographic concentration reflects the clustering of network infrastructure, power availability, and proximity to end users and internet exchange points.

4 Debt Associated with Datacenters

This section documents the scale, composition, and recent growth of mortgage borrowing associated with U.S. datacenters.

Figure 3 reports cumulative origination of property-secured datacenter debt, including mortgages and construction loans. Origination accelerates sharply after 2021, with approximately $113 billion originated over the last five years. This rapid growth in debt issuance parallels the expansion of datacenter capacity documented in the previous section, indicating that much of the recent build-out has been financed through secured lending rather than equity or balance sheet funding.

Figures 4 and 5 describe the evolution of loan sizes over time and across the distribution. The median loan size rises substantially after 2021, and the upper tail of the distribution thickens considerably. This reflects the emergence of multi-billion-dollar portfolio financings that collateralize multiple datacenter properties simultaneously. The distributional evidence in

Figure 5 highlights the growing concentration of aggregate debt in very large loans, including financings in the \$3 to \$7 billion range. These mega-loans represent a shift toward portfolio-level financing structures more commonly observed in other commercial real estate sectors, raising questions about underwriting practices and the extent to which individual property fundamentals are assessed when loans are originated at the portfolio level.

5 Collateral Values of Datacenter Mortgages

Unlike traditional commercial real estate, where mortgage debt is primarily secured by land and building structure, datacenter mortgages are often supported by specialized power, cooling, and network infrastructure. Because this equipment depreciates rapidly and can be costly to liquidate in distress, recoverable collateral value may be meaningfully lower than total invested capital. This section measures collateral values for leveraged datacenters and assesses collateral coverage relative to debt levels.

To measure collateral values empirically, we construct three valuation approaches for each property. First, we use government tax assessments from matched parcel records where available. Second, we compute discounted cash flow values by capitalizing shell (base) rent using a standard income approach. Third, we construct acre-based land values by multiplying each property's land area by an implied dollars-per-acre measure derived from assessed values in the same state. Loan-to-value (LTV) is defined as the ratio of a property's mortgage debt to collateral value. Our final collateral measure takes the maximum of these three approaches for each property, yielding a lower-bound estimate of LTV.

Table 2 reports collateral values and debt intensity across leveraged properties. Panel A reports collateral values per square foot under each valuation approach alongside total debt per square foot. Panel B reports implied loan-to-value ratios computed as debt divided by each collateral measure. Under the final collateral basis, the implied LTV distribution is highly right-skewed, and a substantial share of properties have leverage that exceeds conservative collateral values: 38.7% of properties have LTV>1.0.

Figure 6 assesses required revenue coverage across leveraged properties. For each property, we compute required revenue per square foot as the sum of annual interest expense and property taxes. Required revenues vary considerably across properties and rise sharply for the most highly leveraged facilities, highlighting potential vulnerabilities if rental income or tenant occupancy deteriorates.

6 Econometric Analysis

6.1 Owner Taxonomy

We classify datacenter owners into four categories based on business scope and revenue diversification. Undiversified Datacenters are firms whose primary business is owning and operating datacenter real estate, with revenues concentrated in datacenter leasing and related services. Big Tech owners are large technology firms (Amazon, Google, Microsoft) with substantial non-datacenter revenue streams. Government owners are public-sector entities. The residual category, Other, includes diversified private owners such as industrial REITs, institutional real estate investors, and other corporations with broader revenue bases. The key distinction for our analysis is between specialized datacenter landlords and diversified owners, as this affects both the borrower's risk profile and the lender's ability to assess creditworthiness.

Table 3 reports debt characteristics by owner diversification status. Undiversified datacenter landlords exhibit substantially higher debt intensity than diversified owners.

6.2 Lender Taxonomy

We classify lenders into four categories based on their propensity to distribute credit risk: high securitization propensity banks, low securitization propensity banks, non-bank lenders, and government/cooperative lenders. Table 4 reports debt volumes and loan size distributions by lender type. High securitization propensity banks account for the majority of aggregate datacenter debt and originate substantially larger loans compared to other lender types.

To construct the high- versus low-securitization classification for banks, we use regulatory balance sheet data from the Federal Reserve Bank of New York covering 2022 to 2025. Following Purnanandam (2011), we compute bank-year measures that proxy the extent to which banks operate an OTD model rather than retaining loans on balance sheet.

Specifically, for each bank-year, we compute three balance sheet ratios: loan assets to total assets, trading assets to total assets, and repurchase agreement (repo) assets to total assets. Loan assets proxy on-balance-sheet retention, while trading and repo positions proxy market-based intermediation consistent with loan distribution. Each ratio is standardized within year to ensure comparability across time. We then construct a composite OTD score as:

$$\text{OTD Balance Score} = -z(\text{Loan Assets}) + z(\text{Trading Assets}) + z(\text{Repo Assets}). \quad (1)$$

Higher scores indicate greater securitization propensity. Banks are ranked by their average OTD score over 2022 to 2025, corresponding to the primary datacenter loan origination period in our sample. Banks in the top two deciles are classified as high securitization propensity banks; banks in all other deciles are classified as low securitization propensity banks.

Table 5 reports group means of the underlying balance sheet ratios and the resulting OTD scores. High securitization propensity banks hold substantially lower shares of loan assets and substantially higher shares of trading and repo assets compared to low securitization propensity banks. The differences are statistically significant and economically large, validating the classification. Appendix Table A1 summarizes the resulting lender classification, mapping specific lender names to securitization propensity groups.

6.3 Securitization Propensity and Borrower Outcomes

We test whether high securitization propensity banks exhibit weaker underwriting standards by estimating the relationship between lender type and leverage outcomes. Our baseline specification compares properties financed by high securitization propensity banks to all other properties:

$$Y_i = \beta_H \, \text{HighSecPropBank}_i + \mathbf{X}_i'\theta + \gamma_{s(i)} + \delta_{t(i)} + \varepsilon_i, \tag{2}$$

where HighSecPropBank equals one if property i is financed by a high securitization propensity bank. The control vector $\mathbf{X}_i$ includes log RBA, tenancy type fixed effects, and property taxes per square foot. All specifications include state fixed effects, $\gamma_{s(i)}$, and loan origination year fixed effects, $\delta_{t(i)}$, with standard errors clustered at the lender level. We estimate this specification using four dependent variables: ln(DebtPSF), ln(DebtToRent), ln(LTV), and UndiversDC, an indicator equal to one if the borrower is an undiversified datacenter landlord.

We estimate an analogous specification for low securitization propensity banks:

$$Y_i = \beta_L \, \text{LowSecPropBank}_i + \mathbf{X}_i'\theta + \gamma_{s(i)} + \delta_{t(i)} + \varepsilon_i, \tag{3}$$

where LowSecPropBank_i equals one if property i is financed by a low securitization propensity bank.

Finally, we estimate a pooled specification that includes both indicators:

$$Y_i = \beta_H \, \text{HighSecPropBank}_i + \beta_L \, \text{LowSecPropBank}_i + \mathbf{X}_i'\theta + \gamma_{s(i)} + \delta_{t(i)} + \varepsilon_i, \tag{4}$$

where the omitted category is loans financed by lenders that are neither classified as high nor low securitization propensity banks.

Tables 6, 7, and 8 report the results. High securitization propensity banks originate loans with substantially higher leverage intensity across all measures. In the High-vs.-non-High specification (Table 6), the High indicator implies roughly 3.5× higher DebtPSF and Debt-to-rent, and about 3.5× higher LTV (Cols. (1)-(3)), with all three effects statistically significant at the 1% level. The coefficient on borrower type is positive (Col. (4)) but statistically indistinguishable from zero.

In contrast, low securitization propensity banks exhibit significantly lower leverage intensity than other lenders in the separate Low-vs.-non-Low specification (Table 7, Cols. (1)-(3)), while the borrower-type difference is small and statistically insignificant (Col. (4)).

In the pooled specification that includes both High and Low indicators (Table 8), the leverage effects are concentrated among high securitization propensity banks: the High coefficient remains large, positive, and statistically significant for ln(DebtPSF), ln(DebtToRent), and ln(LTV), whereas the Low coefficient is statistically insignificant across these outcomes. Wald tests reject equality of the High and Low coefficients in Cols. (1)-(3) (Table 8 notes), while differences in borrower type are not statistically distinguishable.

6.4 High vs. Low Securitization Propensity: Matched Comparison in Debt Intensity

This subsection focuses on a clean comparison between High and Low securitization-propensity banks. We restrict the sample to these two lender groups and enforce overlap in observables (common support) so that High and Low-financed loans are comparable on the baseline covariates.

We first estimate the probability that a loan is financed by a high securitization-propensity bank using a probit model with the same baseline controls and fixed effects as Equation (2). Let

$$\hat{p}_i \equiv \Pr(\text{HighSecPropBank}_i = 1 \mid \mathbf{X}_i, \gamma_{s(i)}, \delta_{t(i)}), \tag{5}$$

where $\mathbf{X}_i$ includes ln(RBA) and tenancy-type fixed effects, and $\gamma_{s(i)}$ and $\delta_{t(i)}$ denote state and loan-origination year fixed effects. We restrict the estimation sample to the overlap region in $\hat{p}_i$ (common support) and then estimate the High-Low difference in outcomes using weighted least squares, where Low observations receive weights based on $\hat{p}_i$ so that their covariate distribution matches the High group.

As a complementary approach, we implement coarsened exact matching (CEM) by forming strata defined by state and binned ln(RBA). We keep only strata that contain at least one High and one Low observation (overlap strata), and estimate the High-Low difference using weighted least squares with within-stratum weights. Bins for ln(RBA) are defined using quartile cutoffs in the combined High+Low sample so that bin definitions are predetermined by the observed size distribution.

Table 9 reports matched comparisons between loans originated by High versus Low securitization propensity banks, restricting the sample to these two lender groups and to the region of overlap in observables. For debt intensity (ln(DebtPSF)), the estimates imply that DebtPSF is about 2.13× higher for High relative to Low lenders under the propensity-score approach and about 1.98× higher under coarsened exact matching (roughly +113% and +98%, respectively). For leverage (ln(LTV)), the estimates imply that LTV is about 2.45× higher under the propensity-score approach and about 2.08× higher under coarsened exact matching (roughly +145% and +108%). In the exact-matching design, about 85% of High observations remain in overlap strata, indicating that most High loans have comparable Low counterparts. Overall, the matched comparisons confirm that High-Low differences in leverage intensity are economically large.

6.5 Robustness: Single-Property Loans

A related concern is that high securitization-propensity banks may systematically participate in different types of transactions, such as portfolio loans secured by multiple properties, which could reflect different underwriting, borrower selection, or deal structuring rather than differences in leverage intensity per se. To assess whether our results are driven by these multi-property collateral structures, we conduct a robustness check that restricts attention to loans with a common collateral structure.

As a robustness check, we restrict the sample to single-property loans, defined as loans collateralized by exactly one property. This restriction eliminates the need to allocate balances across collateral properties and yields a one-to-one mapping between each loan and its financed property. We then re-estimate Equation (2) using the same baseline controls and fixed effects.

Table 10 reports the results. The estimated effects of high securitization-propensity banks on debt intensity and leverage remain economically large and statistically significant: the coefficients imply substantially higher ln(DebtPSF), ln(DebtToRent), and ln(LTV) for properties financed by High lenders relative to other lenders, even in this restricted sample. The estimate for UndiversDC remains positive but statistically indistinguishable from zero. Overall, restricting to single-property loans confirms that our main findings are not driven by the balance allocation in multi-property collateral structures.

6.6 Robustness: Continuous Securitization Propensity

Our main specifications classify lenders into high versus non-high securitization propensity groups. As a complementary robustness check, we replace this discrete classification with a continuous measure of securitization propensity based on lenders' balance-sheet originate-to-distribute activity. Specifically, we estimate regressions analogous to Equation (2), but substitute the indicator HighSecPropBank_i with the lender's continuous OTD score, OTDz_i, while keeping the same baseline controls and fixed effects.

Table 11 reports the results. Higher OTDz is associated with significantly greater debt intensity: a one-unit increase in OTDz predicts higher ln(DebtPSF) and ln(DebtToRent) (Cols. 1–2). The association with leverage is also positive, with a marginally significant effect on ln(LTV) (Col. 3). OTDz also predicts borrower type: a one-unit increase in OTDz is associated with a 1.8 percentage point higher likelihood that the financed property is owned by an undiversified datacenter landlord (Col. 4). Overall, using a continuous securitization-propensity measure yields patterns consistent with the main High-vs.-non-High design, reinforcing the conclusion that greater lender securitization propensity is linked to materially higher leverage intensity.

7 Conclusion

This paper provides the first systematic empirical evidence on OTD incentives in datacenter lending. Using a novel loan-level dataset linking datacenter mortgage originations to lender balance sheet characteristics, we show that banks with a high propensity to securitize or distribute loans originate datacenter loans with significantly weaker underwriting standards than banks that primarily retain loans on balance sheet.

High-securitization lenders originate loans with roughly 3.5 times higher debt per square foot and debt-to-rent ratios, and are more likely to finance undiversified datacenter operators. These patterns are consistent with moral hazard: when lenders expect to transfer credit risk, incentives to screen borrowers and maintain conservative underwriting weaken.

Our findings extend the OTD literature from residential mortgages to commercial real estate and digital infrastructure finance, a rapidly growing market characterized by specialized collateral and developing secondary markets. We document additional vulnerabilities, including high leverage, thin coverage based on base rent, borrower concentration, geographic clustering, and the emergence of multi-billion-dollar loans that amplify concentration risk.

The results have important implications for credit risk and regulation in digital infrastructure markets. While datacenters have performed well during the AI-driven expansion, the combination of OTD incentives, information-intensive assets, technological obsolescence risk, and concentrated exposures suggests that underwriting standards and risk distribution warrant close monitoring. As datacenter debt markets mature, greater transparency around underwriting practices and ultimate risk holders will be critical for maintaining financial stability.

Several important questions remain for future research. First, our analysis focuses on ex-ante lending standards and does not directly observe ex-post loan performance. Second, our classification of lenders by securitization propensity uses balance sheet proxies rather than direct observation of loan-level distribution decisions. While this approach follows established methods in the literature (Loutskina and Strahan, 2009; Purnanandam, 2011) and allows us to classify lenders consistently over time, more granular data on which specific loans are retained versus distributed would strengthen causal inference. Third, our analysis does not directly address the welfare implications of OTD lending in datacenters. While our evidence suggests that OTD incentives lead to weaker ex-ante standards, the overall efficiency of credit allocation depends on whether distributed loans flow to investors with comparative advantage in monitoring or bearing risk.

In conclusion, this paper documents that OTD incentives shape credit supply in datacenter lending in ways consistent with moral hazard and weaker underwriting standards. As digital infrastructure continues to expand and as datacenter debt markets mature, monitoring the interaction between lender business models and credit quality will be essential for maintaining financial stability in this critical sector of the modern economy. The rapid growth of datacenter lending, the concentration of origination among high securitization propensity banks, and the elevated leverage ratios we document all warrant continued attention from researchers, regulators, and market participants.

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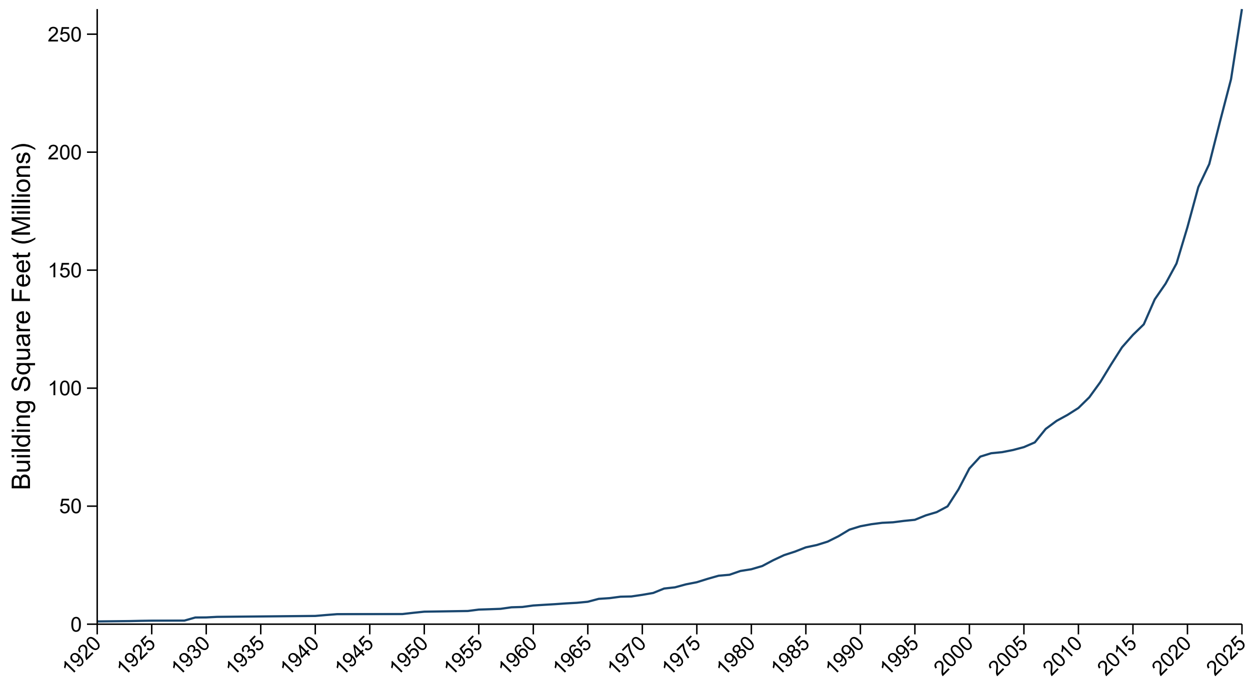

Figure 1: **Datacenter Capacity by Year Built (Cumulative)**

This figure reports cumulative datacenter capacity measured in rentable building area (RBA). Properties are grouped by year built. For each year, cumulative capacity is computed by adding the RBA of all properties built in that year and in all earlier years. The sample includes properties in the CoStar national datacenter inventory as of November 2025, with RBA measured in square feet.

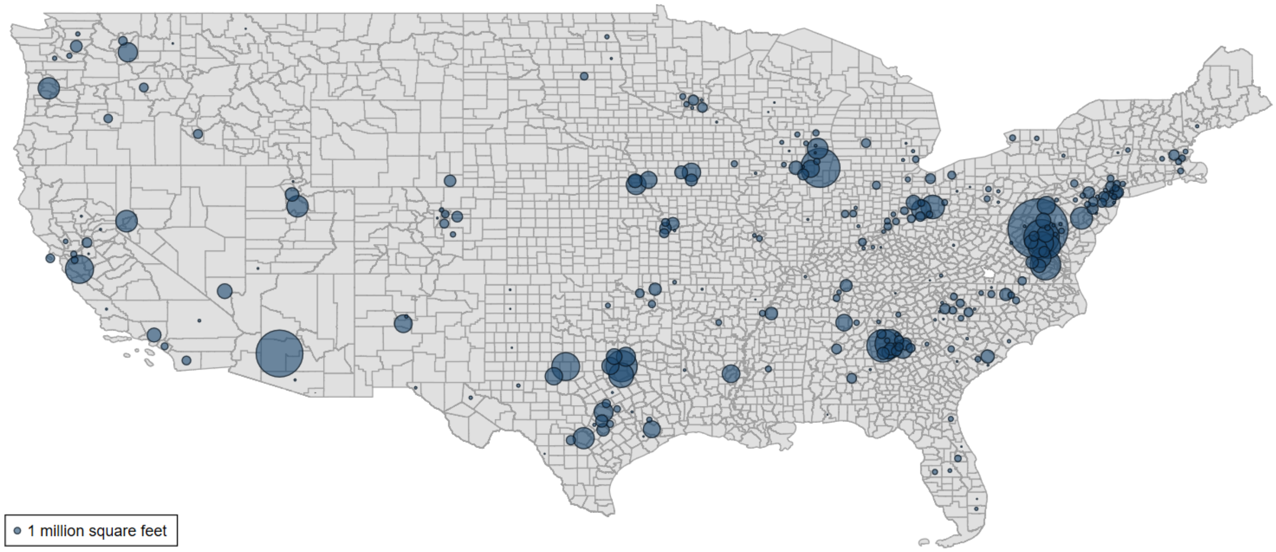

Figure 2: **Geographic Distribution of Datacenter Capacity**

This figure maps county-level datacenter capacity using the CoStar national datacenter inventory as of November 2025. For each property, capacity is measured as rentable building area (RBA) in square feet. We aggregate RBA to the county level, summing across all properties in the inventory, including both existing and under-construction facilities. The figure plots one marker per county, with marker size proportional to total county RBA.

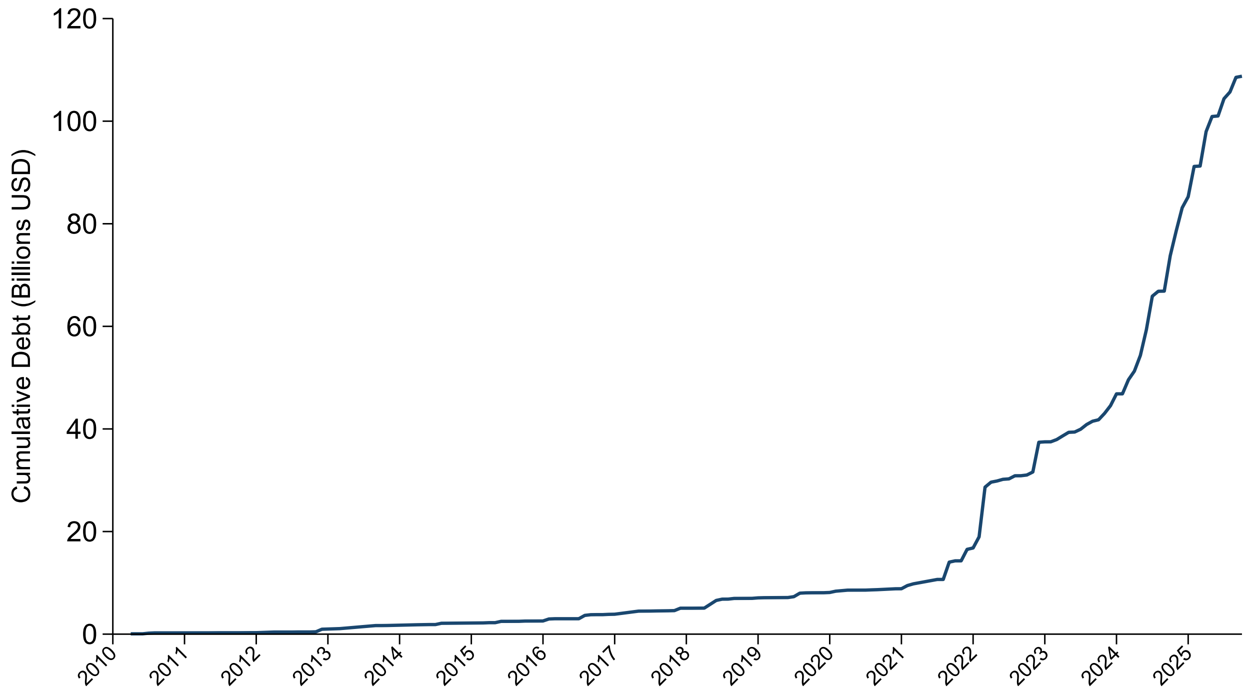

Figure 3: **Datacenter Mortgage Origination (Cumulative)**

This figure plots the cumulative origination of property-secured datacenter debt, including mortgages and construction loans. Loan amounts are aggregated at the monthly level, and then cumulatively aggregated over time. The figure shows that most of the approximately $113 billion in outstanding datacenter debt, with the majority originated after 2021

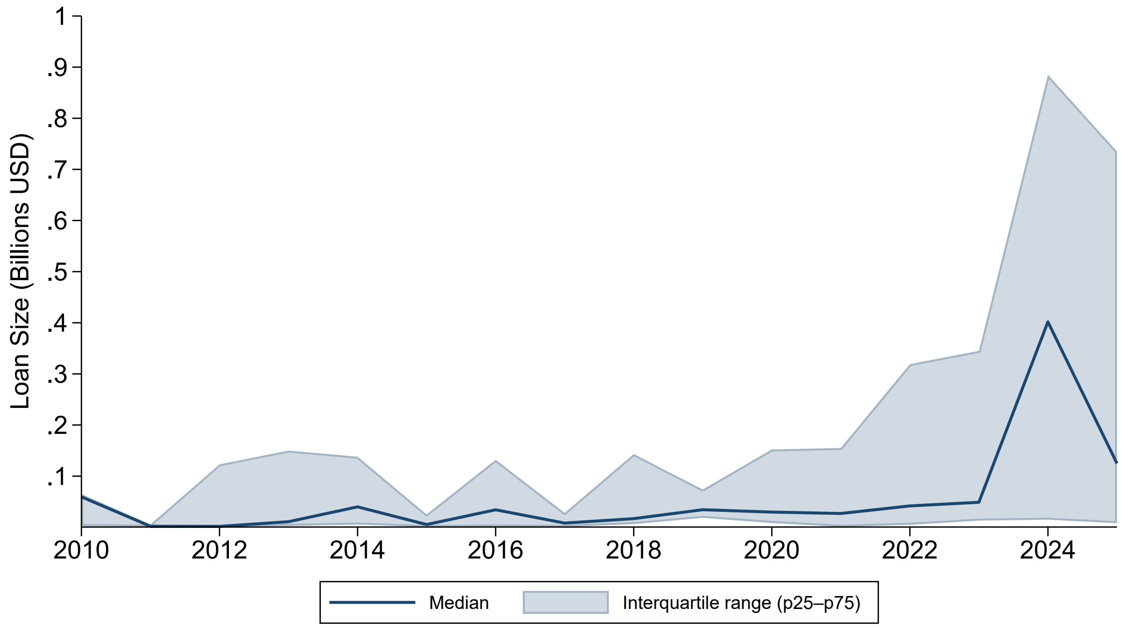

Figure 4: **Datacenter Loan Size over Time**

This figure plots the annual distribution of property-level datacenter loan sizes. The solid line reports the median loan size by origination year, while the shaded band shows the interquartile range (25th–75th percentiles). Loan sizes are measured in billions of U.S. dollars and are constructed at the loan level, with each loan counted once in its origination year.

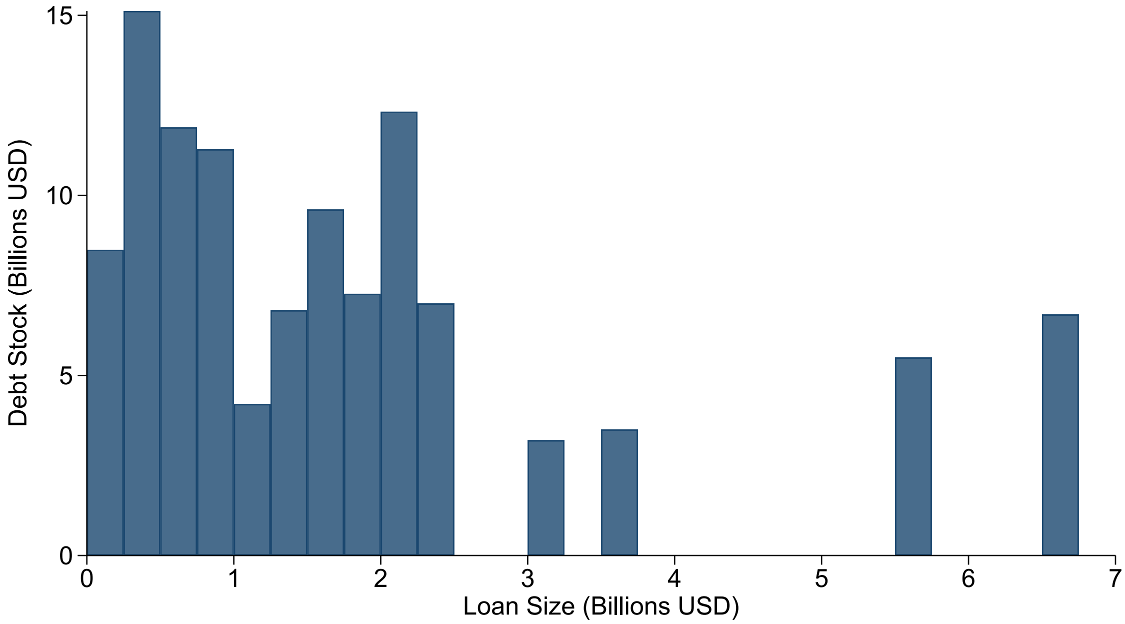

Figure 5: **Aggregate Datacenter Debt by Loan Size**

This figure plots the distribution of aggregate datacenter debt across loan-size bins. Each bar shows the total outstanding debt (in billions of U.S. dollars) within $0.25 billion loan-size bins, aggregated across all loans originated between 2010 and 2025.

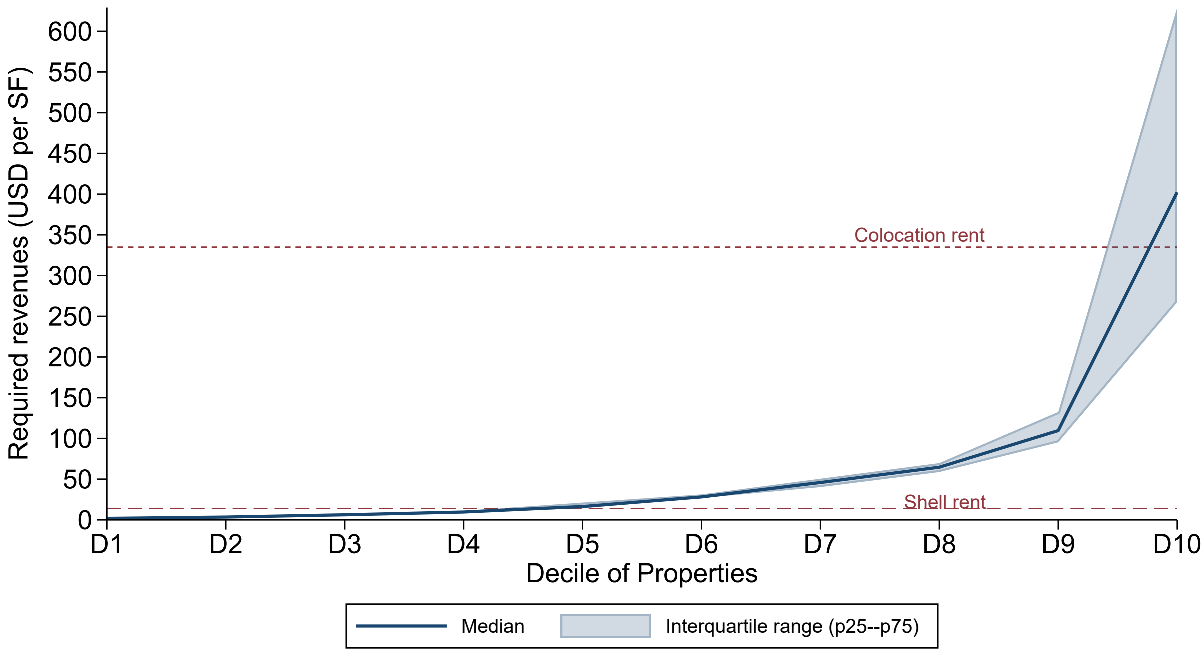

Figure 6: **Required Revenue to Cover Tax and Interest by Property Decile**

This figure plots required revenue per square foot to cover property taxes and interest payments across deciles of debt-backed datacenter properties. Properties are sorted by required revenue per square foot and grouped into deciles, with Decile 1 containing properties with the lowest required revenue and Decile 10 containing those with the highest. Each point reports the median required revenue per square foot within a decile, where required revenue is defined as the sum of interest expense per square foot and property taxes per square foot.

Table 1: **Summary Statistics**

Variable	N	Mean	SD	Min	Max
Rentable building area (SF)	550	223,909.1	383,397.7	6,757.0	6,500,000.0
Rent per square foot (USD)	550	14.5	11.2	3.6	201.4
Taxes per square foot (USD)	550	4.1	5.4	0.0	89.1
Debt per square foot (USD)	550	1,531.8	4,873.7	0.0	62,413.8
Loan-to-value ratio	550	6.3	25.4	0.0	368.6
Years since origination	550	6.3	7.1	0.0	33.0

Note: The table reports summary statistics for datacenter properties with positive mortgage balances. Rentable building area is the total leasable square footage of the property. Rent per square foot refers to shell (base) rent, excluding colocation usage charges and other operating pass-throughs. Taxes per square foot includes property taxes and other real estate assessments. Debt per square foot is constructed from mortgage balances; when a loan is secured by multiple properties, the loan balance is allocated across collateral properties in proportion to each property's rentable building area prior to computing debt per square foot. Loan-to-value ratios are computed using property-level collateral values based on tax assessment, discounted cash flow, and acre-based land valuation methods described in the text. Years since origination is the number of years elapsed between the loan origination date and 2025.

Table 2: **Collateral Value at Risk**

Variable	N	Mean	SD	Min	Max
Panel A: Collateral and Debt per Square Foot (USD)					
Tax assessment value per square foot (USD)	381	579.9	1,728.2	12.0	29,574.2
Discounted cash flow value per square foot (USD)	507	173.0	137.9	42.4	2,385.5
Acre based land value per square foot (USD)	540	618.6	1,321.4	1.5	17,491.7
Collateral value per square foot (USD)	550	856.4	1,849.5	31.8	29,574.2
Debt per square foot (USD)	550	1,531.8	4,873.7	0.0	62,413.8
Panel B: Implied Loan-to-Value Ratios					
Tax assessment basis	381	20.7	100.0	0.0	1,665.0
Discounted cash flow basis	507	12.0	38.3	0.0	466.3
Acre-based land value basis	540	14.0	52.2	0.0	824.9
Final collateral basis	550	6.3	25.4	0.0	368.6

Note: Panel A presents collateral values and debt expressed per square foot of rentable building area (RBA). Tax assessment value is computed from matched parcel assessments aggregated to the property level. Discounted cash flow value is computed by capitalizing shell rent using the discounted cash flow procedure described in the text. Acre-based land value is computed by multiplying the property land area in acres by an implied dollars per acre value, where the implied value per acre is the state median from properties with matched assessments. Collateral value is computed as the maximum of the three valuation approaches (tax assessment, discounted cash flow, and acre-based land value), taking the highest available value for each property to provide the most conservative loan-to-value calculation. Debt equals the total mortgage balance per square foot of RBA. Panel B presents loan-to-value ratios computed as total debt divided by each collateral measure. Under the final collateral basis, 38.7% of properties have LTV>1.0.

Table 3: **Debt Characteristics: Diversified vs. Undiversified Owners**

	Undiversified Datacenter Owners	Diversified Owners	All Owners
Number of Properties	113	437	550
Mean Debt per SF (USD)	1,824.2	1,456.3	1,531.8
Median Debt per SF (USD)	1,003.9	216.6	332.2
Mean Loan-to-Value Ratio	5.5	6.5	6.3
Median Loan-to-Value Ratio	0.9	0.5	0.6

Note: The table reports debt characteristics by owner diversification status using CoStar data through November 2025. Debt per square foot is defined as each property's allocated mortgage balance divided by rentable building area (RBA). When a loan is secured by multiple properties, the loan balance is allocated across collateral properties in proportion to RBA. Loan-to-value ratios are computed as total debt divided by property-level collateral values constructed using tax assessment, discounted cash flow, and acre-based land valuation methods described in the text.

Table 4: **Debt Characteristics by Lender Securitization Propensity**

	High securitization propensity banks	Low securitization propensity banks	High − Low
Number of Properties	250	183	67
Median Property Debt (USD M)	148.7	10.3	138.4
Median Debt per SF (USD)	896.3	143.2	753.2
Median Loan-to-Value Ratio	1.4	0.4	0.9

Note: This table reports median debt characteristics by lender securitization propensity, using CoStar data through November 2025. Banks are classified as high or low securitization propensity based on their originate-to-distribute (OTD) scores. Debt per square foot is computed as property-level mortgage balances divided by rentable building area (RBA). Loan-to-value ratios are computed using property-level collateral values based on tax assessment, discounted cash flow, and acre-based land valuation methods described in the text. The final column reports the difference in medians between high and low securitization propensity banks.

Table 5: **Originate-to-Distribute Metrics by Lender Type**

	High securitization propensity banks	Low securitization propensity banks	High-Low
Loan assets to assets (%)	38.66	69.63	-30.97***
OTD score	5.80	-0.60	6.40***
Repo to assets (%)	8.12	0.27	7.86***
Trading assets to assets (%)	3.57	0.09	3.48***

Notes: This table reports group means of regulatory ratios that proxy banks' originate-to-distribute (OTD) activity, constructed from quarterly Call Report data aggregated to the bank-year level for 2022-2025. Loan assets are inversely related to OTD activity, while trading assets and repo positions are positively related. All ratios are expressed as a percentage of total assets. Following Purnanandam (2011), we construct a composite OTD score based on balance-sheet proxies for originate-to-distribute activity, where each component is standardized within year. The final column reports the High−Low difference in means; stars indicate statistical significance from tests of equality using bank-year observations with standard errors clustered at the bank level and year fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 6: **High Securitization Propensity Banks and Borrower Outcomes**

	(1)	(2)	(3)	(4)
	ln(DebtPSF)	ln(DebtToRent)	ln(LTV)	UndiversDC
High sec. prop. bank	1.239***	1.265***	1.263***	0.109
	(0.277)	(0.271)	(0.276)	(0.069)
Controls	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.351	0.345	0.336	0.279
Observations	550	550	550	550

Notes: This table reports estimates from Equation (2). The dependent variables are ln(DebtPSF), ln(DebtToRent), ln(LTV), and UndiversDC, an indicator equal to one if the financed property is owned by a datacenter-landlord (Undiversified Datacenter). HighSecPropBank equals one if the lender is classified as a high securitization propensity bank. All specifications include the baseline control set (log rentable building area, tenancy-type fixed effects, and taxes per square foot), as well as state fixed effects and loan-origination year fixed effects. Standard errors are clustered at the lender level and reported in parentheses. Relative to properties financed by non-high lenders, the coefficient in Col. (1) implies about 3.5× higher DebtPSF; Col. (2) about 3.5× higher Debt-to-rent; Col. (3) about 3.5× higher LTV; and Col. (4) a 10.9 percentage point higher probability of financing a datacenter-landlord borrower. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 7: **Low Securitization Propensity Banks and Borrower Outcomes**

	(1)	(2)	(3)	(4)
	ln(DebtPSF)	ln(DebtToRent)	ln(LTV)	UndiversDC
Low sec. prop. bank	-0.462*	-0.498**	-0.497*	-0.076
	(0.244)	(0.243)	(0.262)	(0.055)
Controls	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.314	0.308	0.303	0.272
Observations	550	550	550	550

Notes: This table reports estimates from Equation (3). The dependent variables are ln(DebtPSF), ln(DebtToRent), ln(LTV), and UndiversDC, an indicator equal to one if the financed property is owned by a datacenter-landlord (undiversified borrower type). LowSecPropBank_i equals one if the lender is classified as a low securitization propensity bank. All specifications include the baseline control set (log rentable building area, tenancy-type fixed effects, and taxes per square foot), as well as state fixed effects and loan-origination year fixed effects. Standard errors are clustered at the lender level and reported in parentheses. Relative to properties financed by non-low lenders (i.e., lender_low_only=0), Col. (1) implies about 37% lower DebtPSF and Col. (2) about 39% lower Debt-to-rent; Col. (3) implies about 39% lower LTV; and Col. (4) shows a statistically insignificant difference in borrower type (about −7.6 percentage points). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 8: **High vs. Low Securitization Propensity Banks: Borrower Outcomes**

	(1) ln(DebtPSF)	(2) ln(DebtToRent)	(3) ln(LTV)	(4) UndiversDC
High sec. prop. bank	1.561***	1.568***	1.566***	0.104
	(0.385)	(0.382)	(0.390)	(0.078)
Low sec. prop. bank	0.553	0.521	0.521	-0.008
	(0.352)	(0.348)	(0.376)	(0.051)
Controls	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.356	0.349	0.340	0.279
Observations	550	550	550	550

Notes: This table reports pooled regressions that include both High and Low Sec. Prop. Bank indicators in the same specification (Equation (4), augmented to include the Low-bank indicator). Columns (1)–(4) correspond to ln(DebtPSF), ln(DebtToRent), ln(LTV), and UndiversDC (an indicator equal to one if the financed property is owned by a datacenter-landlord / undiversified borrower type). All specifications include the baseline control set (log rentable building area, tenancy-type fixed effects, and taxes per square foot), as well as state fixed effects and loan-origination year fixed effects. Standard errors are clustered at the lender level and reported in parentheses. The omitted category is the set of loans financed by lenders that are neither classified as high- nor low-securitization propensity banks. Wald tests of equality of the High and Low coefficients yield p-values of 0.0002 (Col. 1), 0.0001 (Col. 2), 0.0002 (Col. 3), and 0.117 (Col. 4). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 9: **High vs. Low Securitization Propensity Banks: Matching Estimates**

	ln(DebtPSF)		ln(LTV)	
	(1)	(2)	(3)	(4)
	Propensity score	Exact	Propensity score	Exact
High sec. prop. bank (vs. Low)	0.755**	0.681*	0.896**	0.732**
	(0.346)	(0.348)	(0.362)	(0.347)
Controls	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Common support/overlap enforced	Yes	Yes	Yes	Yes
R^2	0.266	0.412	0.281	0.396
Observations	375	347	375	347

Notes: This table compares loans originated by High versus Low securitization-propensity banks, restricting the sample to these two lender groups (other lender types excluded). Columns (1) and (3) use propensity scores from a probit model of High (vs. Low) on the baseline controls and fixed effects; the estimation sample is restricted to common support based on overlap in predicted scores (support interval: [0.163, 0.970]), and the outcome is estimated by a reweighted (ATT-IPW) regression including the baseline controls and fixed effects. Columns (2) and (4) implement coarsened exact matching by defining strata as State $\times$ binned ln(RBA) (four bins), retaining only strata containing both High and Low observations, and estimating the outcome using within-stratum weights. All outcome regressions include the baseline control set consistent with the main specification (log rentable building area and tenancy-type fixed effects), as well as state fixed effects and loan-origination year fixed effects. Standard errors are clustered at the lender level and reported in parentheses. For propensity-score overlap, common support retains 248 of 250 treated observations (99.2%) and 127 controls, for a total of 375 matched observations; 2 treated observations (0.8%) fall outside overlap and are excluded. For exact matching, the final matched sample retains 213 of 250 treated observations (85.2%) and 134 controls, for a total of 347 matched observations; 37 treated observations (14.8%) are excluded for lack of overlap strata. Interpreting coefficients in logs, Column (1) implies about 2.13$\times$ higher DebtPSF (112.8%), Column (2) about 1.98$\times$ (97.6%); Column (3) implies about 2.45$\times$ higher LTV (145.1%), and Column (4) about 2.08$\times$ (108.0%). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 10: **Robustness: High Securitization Propensity Banks and Borrower Outcomes for Single-Property Loans**

	(1) ln(DebtPSF)	(2) ln(DebtToRent)	(3) ln(LTV)	(4) UndiversDC
High sec. prop. bank	1.168***	1.207***	1.185***	0.033
	(0.412)	(0.401)	(0.412)	(0.047)
Controls	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.350	0.345	0.342	0.284
Observations	360	360	360	360

Notes: This table replicates Table 6 restricting the sample to single-property loans (i.e., loans collateralized by exactly one property), eliminating any need to allocate loan balances across multiple collateral properties. The dependent variables are ln(DebtPSF), ln(DebtToRent), ln(LTV), and UndiversDC, an indicator equal to one if the financed property is owned by a datacenter-landlord (Undiversified Datacenter). HighSecPropBank equals one if the lender is classified as a high securitization propensity bank. All specifications include the baseline control set (log rentable building area, tenancy-type fixed effects, and taxes per square foot), as well as state fixed effects and loan-origination year fixed effects. Standard errors are clustered at the lender level and reported in parentheses. Relative to properties financed by non-high lenders, the coefficient in Col. (1) implies about 3.21× higher DebtPSF; Col. (2) about 3.34× higher Debt-to-rent; and Col. (3) about 3.27× higher LTV. Col. (4) implies a 3.3 percentage point higher probability of financing a datacenter-landlord borrower but is statistically indistinguishable from zero. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 11: **Robustness: Continuous Securitization Propensity and Borrower Outcomes**

	(1)	(2)	(3)	(4)
	ln(DebtPSF)	ln(DebtToRent)	ln(LTV)	UndiversDC
OTDz (continuous)	0.055**	0.062**	0.054*	0.018**
	(0.026)	(0.027)	(0.028)	(0.009)
Controls	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.352	0.346	0.340	0.363
Observations	381	381	381	381

Notes: The dependent variables are ln(DebtPSF), ln(DebtToRent), ln(LTV), and UndiversDC, an indicator equal to one if the financed property is owned by a datacenter-landlord (Undiversified Datacenter). OTDz is the lender's continuous balance-sheet-based originate-to-distribute (OTD) score (standardized; `OTD_balance`). All specifications include the baseline control set (log rentable building area, tenancy-type fixed effects, and taxes per square foot), as well as state fixed effects and loan-origination year fixed effects. Standard errors are clustered at the lender level and reported in parentheses. A one-unit increase in OTDz is associated with about 5.6% higher DebtPSF (Col. 1), 6.4% higher Debt-to-rent (Col. 2), and 5.6% higher LTV (Col. 3). The estimate in Col. (4) implies about a 1.8 percentage point higher likelihood of being a datacenter-landlord property per one-unit increase in OTDz. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendix A: Detailed Description of Database

This appendix describes the data sources, cleaning procedures, and construction of key variables used in the analysis.

A.1 Data Sources and Sample Construction

CoStar datacenter inventory. The starting point is the CoStar national inventory of U.S. datacenter properties as of November 2025. The unit of observation in the main analysis is a property, identified by CoStar. For each property, CoStar reports physical characteristics (rentable building area, year built, and development status), location (state, county, market and submarket), leasing outcomes (shell rent and percent leased), and tax-related fields. Table 1 reports summary statistics for the resulting property universe.

Loan origination records. CoStar also provides loan origination information for a subset of properties, including origination amount, origination date, loan type, interest rate fields, and the originating lender name. The loan information is used to construct property-level leverage outcomes. Because a single loan may be collateralized by multiple properties, loan balances are allocated across collateral properties prior to constructing per-square-foot measures (see Appendix A.3).

Lender originate-to-distribute (OTD) measures. We link lenders to regulatory Call Report data to obtain an OTD-based securitization propensity measure; Section 6 describes construction of the OTD score and the high versus low classification.

A.2 Cleaning and Harmonization of Property Variables

Duplicates and normalization. We eliminate duplicate property records and retain one observation per property in the main property-level file. Descriptive fields (address, market, submarket, county, and owner names) are trimmed and normalized (case and punctuation) to ensure consistent matching and reporting across sources.

Rent per square foot. CoStar reports shell rent as `rentsfyr` (a string field). We convert this field into a numeric rent per square foot measure. For summary statistics and regressions, rent is interpreted as shell (base) rent and excludes colocation usage charges and other operating pass-throughs.

Property taxes per square foot. CoStar reports property taxes as `taxespersf` (string) and/or `taxestotal`. We construct a numeric taxes-per-square-foot measure by removing punctuation and currency symbols and converting to a numeric value. When `taxespersf` is not reported, we impute taxes per square foot using the mean of observed `taxespersf` among datacenters in the same county.

Percent leased. CoStar reports percent leased as `percentleased` (string). We harmonize this field into a numeric 0-100 measure by stripping percent symbols and converting to numeric values. Values between 0 and 1 are treated as fractions and scaled to percentages. Values outside the 0-100 range are set to missing.

Building age. CoStar provides building age measured as of 2025 (`age_2025`). We use this variable directly and interpret it as the number of years since construction, measured as of 2025. Observations with implausible values (negative ages or ages exceeding 150 years) are set to missing.

A.3 Construction of Property-Level Debt and Leverage Measures

Debt allocation for multi-property loans. Loan origination records may correspond to a loan secured by multiple properties. To construct property-level debt intensity measures, we apportion each loan's balance across collateral properties in proportion to each property's rentable building area (RBA). Formally, if loan ℓ is secured by properties $i \in \mathcal{I}_\ell$ with RBA RBA_i, the debt allocated to property i from loan ℓ is

$$Debt_{i\ell} = Debt_\ell \times \frac{RBA_i}{\sum_{j \in \mathcal{I}_\ell} RBA_j}.$$

Property-level debt is the sum of allocated balances across loans collateralized by that property.

Debt per square foot. Debt per square foot is computed as allocated property debt divided by property RBA. This measure is defined for the subset of properties with positive allocated mortgage balances.

Debt-to-rent and related coverage measures. Debt-to-rent ratios are constructed using shell rent per square foot. When reporting interest-and-tax coverage measures, we compute required revenue per square foot as the sum of interest expense per square foot and property taxes per square foot, using harmonized CoStar fields.

Loan-to-value (LTV). We measure leverage using a loan-to-value ratio defined as the property's mortgage balance divided by an estimate of recoverable collateral value. For loans secured by multiple properties, we allocate the loan balance across collateral properties in proportion to each property's RBA and compute LTV at the property level using the allocated balance.

To measure collateral value, we construct three valuation approaches for each property: (i) government tax assessment value from matched parcel records (when available), (ii) an income-based value computed by capitalizing CoStar shell (base) rent (our discounted cash flow (DCF) measure), and (iii) an acre-based land value computed as land area multiplied by an implied dollars-per-acre measure (the state median among properties with matched assessments). Our final collateral value is defined as the maximum of the available valuations for each property,

$$\text{Value}_i \equiv \max\left\{\text{Assess}_i,\ \text{DCF}_i,\ \text{Land}_i\right\},$$

which yields the most conservative (lowest) LTV for a given debt balance. Formally,

$$\text{LTV}_i = \frac{\text{AllocatedDebt}_i}{\text{Value}_i}.$$

Origination timing and years since origination.

CoStar reports the loan origination date as `originationdate` (string). We parse this string into a daily date when possible and extract the origination year. Years since origination is defined as

$$\text{YearsSinceOrigination}_i = 2025 - \text{OriginationYear}_i,$$

and is measured as of 2025. This variable is computed for the subset of properties for which an origination date is available and successfully parsed.

Transformations used in estimation. In the regressions, we use log transformations of continuous outcomes to reduce skewness and interpret coefficients in semi-elasticity units. Specifically, we use ln(DebtPSF), ln(DebtToRent), and ln(LTV) as dependent variables, and include ln(RBA) as a baseline control. When constructing logged outcomes, we restrict to observations with strictly positive values of the underlying variable. All level definitions and allocation rules are as described above.

A.4 Owner and Lender Classification

Owner types. We classify owners into four groups: Undiversified Datacenters (specialized datacenter landlords), Big Tech, Government, and Other private owners. The classification uses standardized owner names and owner group labels derived from CoStar ownership fields.

The indicator UndiversDC equals one for properties owned by undiversified datacenter landlords and is used as a borrower-type outcome in the lending standards analysis.

Lender mapping and lender types. The loan records report a lender name (originator). We standardize lender names (case normalization and removal of punctuation and legal suffixes) and map them to lender identifiers used for the regulatory OTD measures. Lenders are then assigned to one of the lender types used in the paper: high securitization propensity banks, low securitization propensity banks, non-bank lenders, and government/cooperative lenders. When lender identifiers are unavailable or a lender cannot be matched reliably, the observation is excluded from specifications requiring OTD-based classification.

Originate-to-distribute (OTD) measures. We measure lenders' propensity to originate loans for distribution using regulatory balance-sheet information. We obtain quarterly Call Report data from the Federal Reserve Bank of New York's dataset and aggregate items to the bank-year level for the period 2022-2025, which corresponds to the main datacenter origination window in our sample. For each bank-year, we compute three ratios, each expressed as a percentage of total assets: (i) loan assets to total assets, (ii) trading assets to total assets, and (iii) repurchase agreement assets to total assets. Loan assets proxy on-balance-sheet retention, while trading and repo positions proxy greater use of market-based intermediation consistent with loan distribution activity. To ensure comparability across years, each ratio is standardized within year.

We then construct a composite OTD balance-sheet score that increases with trading and repo intensity and decreases with loan intensity. This score provides a continuous measure of securitization propensity derived solely from regulatory data. Within each year, banks that appear as datacenter lenders are ranked by this score and assigned to deciles. Our baseline classification uses each lender's average rank over 2022-2025: banks in the top two deciles are classified as high securitization propensity banks, and banks in lower deciles are classified as low securitization propensity banks. Table 5 reports group means of the underlying ratios and the resulting OTD scores. In the main regressions, we link the OTD classification to datacenter loan originations using the standardized lender mapping described above, and we cluster standard errors at the lender level in specifications that use the OTD-based indicators.

Table A1: **Lender Classification by Securitization Propensity**

High securitization propensity	**Low securitization propensity**	**Non-bank lenders**	**Government lenders**
Wilmington Trust	U.S. Bank	Computershare	CoBank ACB
Toronto Dominion Bank	Truist Bank	Lawyers Title Realty Services	Farm Credit Mid-America FLCA
Goldman Sachs	Citizens Bank	GLAS USA	Farm Credit of the Virginias ACA
Wells Fargo	Société Générale	New York Life Insurance	Badgerland Financial FLCA
JPMorgan Chase	Huntington National Bank	Acore Capital Mortgage	Compeer Financial
Sumitomo Mitsui Banking	KeyBank	American General Life Insurance	Small Business Administration
Citibank	SunTrust Bank	Principal Life Insurance	
Morgan Stanley	First Citizens Bank & Trust	AIG Asset Management US	
BNP Paribas	Bank of Montreal	Fidelity Guaranty Life Insurance	
Deutsche Bank	Mizuho Bank	Argentic Real Estate Finance	
Bank of America	First Citizens Bank	Column Financial	
Barclays	Standard Chartered Bank	Thorofare Asset Based Lending	
Fifth Third Bank	Hancock Whitney Bank	Guggenheim Real Estate	
UBS Real Estate Securities	Webster Bank	Ladder Capital Finance	
Lehman Brothers Holdings	Prosperity Bank	Nationwide Life Insurance	
Commerce Bank	MUFG Bank	*Other non-bank lenders*	
Cit Bank N.A.	Sunflower Bank		
Eurohypo AG New York Branch	Pacific Western Bank		
	Berkshire Bank		
	Royal Bank of Canada		
	CIBC		
	Natixis New York Branch		
	BankUnited		
	Blue Sky Bank		
	SouthTrust Bank		
	First International Bank & Trust		
	Valley National Bank		
	Texas Capital Bank		
	Simmons Bank		
	First Bank		
	PNC Bank		
	Other low securitization lenders		

Notes: This table reports the lender classification used throughout the analysis and the corresponding lender labels observed in the datacenter loan data. Banks are grouped into high and low securitization propensity categories based on originate-to-distribute (OTD) activity as proxied by Call Report balance-sheet ratios used to construct the OTD score (Equation 1) and ranked by their average score over 2022-2025. Non-bank lenders include insurance companies, private credit funds, and other non-depository lenders. Government lenders include public or cooperative credit institutions and similar programs. Syndicated loans and CMBS instruments are treated as high securitization propensity lenders.