Pricing Government Contract Risk Premia: Evidence from the 2025 Federal Lease Terminations*

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January 2026

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Abstract

Are government contracts a safe investment? We investigate this question using unanticipated Department of Government Efficiency (DOGE) cancellations of federal leases as a shock to commercial mortgage default risk. Offices with DOGE-notified leases experience a persistent 21% net operating income decline, with large, negative spillovers to CMBS prices and rental cash flows tied to nearby private-tenant leases in Washington, D.C. Spillovers are driven by increased vacancy from tenants with high exposure to procurement contracts involving disrupted federal agencies. Simulations of office property value losses from early lease terminations indicate substantial market-wide repricing of government contract risk.

Keywords: commercial real estate, government contracts, CMBS, lease contingencies, production externalities, credit risk, arbitrage pricing

JEL Classifications: G18, G21, H83, R38

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*We thank Natee Amornsiripanitch, Jiakai Chen, Andreas Christopoulos, Sean Flynn, Marco Giacoletti, Stefano Giglio, Paul Goldsmith-Pinkham, Robert Jarrow, Felipe Netto, Alex Priest, Franklin Qian, Tim Riddiough, Jacob Sagi, Nathan Seegert, Todd Sinai, Alexei Tchistyi, and Chongyu Wang (discussant); as well as seminar and workshop participants at Yale, Northeastern University, University of Oklahoma, FSU RMI Research Symposium, REALPAC/TMU Research Symposium, AREUEA Virtual Seminar, and the UNC CREDA Real Estate Symposium for helpful comments and discussions. The Trepp CMBS/FEED, Moody's Analytics CRE, Advan Weekly Patterns (c/o Dewey Data), and WRDS TRACE data used in this paper are licensed through Yale University Library. We thank representatives from Trepp, especially Ben Kater, for answering our questions about their data products. This research was financially supported by the Yale International Center for Finance and the Tobin Center for Economic Policy. We thank a diligent team of RAs for their excellent work, including Fernando Reyes De La Luz, Aurel Rochell, Dharshan Venu, and Peter Williams. First draft: June 2025.

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1 Introduction

Across the OECD, government spending on private procurement – which includes contracts for goods and services, grants, and real estate – amounts to $13 trillion per year, or 13% of 2023 GDP (OECD, 2025). Many of these contracts offer stable payments which continue even in the event that the federal government is temporarily shutdown. For landlords, creditors, and CMBS investors, federal leases provide easily forecasted cash flows due to long lease terms relative to private leases and regularly exercised renewal options. However, because government contracts are backed by the full faith and credit of the federal government, they are still subject to risks of political regime changes and sovereign default, raising the question of how safe these investments really are and whether such risks are salient to investors in advanced economies.

In early 2025, the newly created Department of Government Efficiency (DOGE) initiated the largest wave of federal lease terminations in U.S. history. Unlike standard federal contracts that include termination for convenience clauses, General Services Administration (GSA) leases operate under different regulations and rely on early termination options (ETOs) that can only be exercised during the "soft term" period of leases, typically after the initial ten-year "firm term" with 90 to 120 days advance notice. DOGE's actions resulted in the cancellation of hundreds of leases within months, affecting nearly 9 million square feet of office space (Trepp Research, 2025). This was in sharp contrast to the COVID-19 pandemic period when federal agencies largely maintained existing leases despite widespread remote work. The rapid and extensive use of previously dormant ETO provisions represented a fundamental shift in federal leasing practices and created significant disruptions to both government agency operations and the commercial real estate (CRE) market (Yahoo Finance, 2025).

We use the sudden onset of the DOGE lease cancellations and the large-scale nature of the shock to CRE markets as a natural experiment to estimate risk premia associated with government contracts.[1] In the immediate aftermath of the DOGE announcements, market observers speculated that the cancellations would ripple through U.S. CMBS markets, leading to increased default and loss risk (Bloomberg, 2025). We show that these fears were well-founded, with sharp cuts in prices commanded by the most junior CMBS tranches and declines in net operating income and debt coverage among directly impacted GSA-linked properties. We also find evidence of large negative spillovers to the performance of nearby non-GSA properties and their loans. Simulating the tail risks from ETO exposure across terminated, nearby non-terminated, and private-tenant leases, we find total property valuation losses for the Washington, D.C. market alone exceed taxpayer savings from canceled lease payments.

[1] As of February 2025, Fitch-rated CMBS bonds with GSA leases included as a top five tenant total $19.1 billion, across 280 loans and 344 properties (Fitch Ratings, 2025). Based on our calculations from GSA lease inventory data, as of December 2024, half of the federal government's 7,535 leases are up for renewal in the next five years, with the initial wave of cancellations leading to uncertainty about further fallout of the GSA-linked market.

To motivate our empirical analysis, we extend the arbitrage pricing framework of Jarrow (2018, 2021) and Choi et al. (2025), applying contingency option pricing theory to CMBS backed by federal leases with ETOs. We compare two otherwise identical properties: one ignores the ETO, assuming zero probability of exercise, while the other accounts for its positive probability (ETO-salient). We show that treating the ETO as dormant leads to lower rents charged by landlords, indicating systematic underpricing of government contract risk. We quantify the resulting property-level value loss as the difference in risk-adjusted values under the two assumptions and derive a closed-form expression assuming independent Poisson processes for ETO notification and re-leasing. We also derive the insurance premium that would be required to fully hedge against ETO risk.

Our model generates three key predictions. First, a more aggressive federal lease cancellation policy leads to greater expected property value losses, which translate to lower CMBS bond prices, reflecting a repricing of previously mispriced government contract risk premia and increased salience of ETOs. Second, properties that receive ETO notifications experience lower cash flows and values than comparable properties due to premature terminations, higher vacancy risk, and reduced rental income. Third, properties located near ETO-notified buildings exhibit declines in CMBS bond prices and net operating income, relative to otherwise comparable properties, reflecting significant negative spatial and capital market spillover effects from a market-wide wake-up call that also impacts private tenants.

We test these predictions using detailed data from Trepp combined with GSA lease inventory and hand-collected data from DOGE on lease cancellation event dates. We match properties across the datasets using multiple criteria, including address similarity, geospatial proximity, and exact matches on square footage and lease terms, with manual validation of potential matches. To confirm the plausibility of our match rates, we isolate the universe of office properties in the Moody's CRE database and document that GSA offices are significantly overrepresented in CMBS pools relative to non-GSA offices, particularly in Washington, D.C. This new stylized fact underscores the importance of government contract risk to the broader CRE debt market, and reinforces prior findings that properties with the lowest expected default probabilities are more likely to be securitized (Black et al., 2020).

Our empirical setting comes with several features that make it particularly well-suited for causal identification of government contract risk premia. Government termination actions occurred in quick succession, with most announcements concentrated on February 18, 2025 when the DOGE website first went live, and notification dates spanning a narrow window from January 30 to March 4, 2025. This concentrated timing around February 2025, combined with the substantial size of affected leases, motivates our difference-in-differences (DiD) analysis. We focus on the D.C. metro area, which ranks first among metro areas in average square footage subject to early termination notifications while maintaining relatively high single-tenancy concentration, thus providing a compelling natural experiment to examine government contract risk repricing in CMBS markets.[2]

Adopting a DiD research design that compares ETO-exercisable leases receiving termination notifications in the first wave of cancellations in February 2025 against similar soon-to-be ETO-eligible leases that did not receive notifications, we uncover evidence of immediate market adjustment to this policy shock. CMBS bond prices in first-loss group tranches declined by 3.4% following ETO notifications, while property-level net operating income (NOI) fell by 21.2% relative to untreated properties with a similar lease structure. These effects remain robust across multiple fixed effects specifications that control for location, temporal, structural, and bond-level characteristics. Due to the drop in NOI, debt service coverage ratios (DSCR) also fall, with all notified properties being delinquent on their mortgage payments for several months after April 2025.

Our choice of soon-to-be ETO-eligible leases as a control group is motivated by the idea that these leases are among the least exposed to the DOGE announcement shock while at the same time not being so new that the characteristics of the mortgages and properties differ substantially from those of the treatment group. Our design is therefore akin to staggered DiD designs exploiting random assignment of units into earlier vs. later treatment cohorts (Goodman-Bacon, 2021), where assignment in this case is based on the plausibly exogenous time between the end of the lease's firm term and DOGE's creation date. We show there is no pre-treatment divergence in bond prices, NOI, or DSCR, confirming that the policy shock to individual leases was likely unanticipated by market participants. On top of estimating no statistically significant pre-trends relative to DOGE notification, our results are robust to the pretest of pre-trends recommended by Roth (2022). Further, we allow for potential violations of parallel trends as in Rambachan and Roth (2023), but even under conservative assumptions about such violations we still obtain statistically significant effects of the DOGE actions on CRE markets.

The fact that bond prices and NOI for impacted properties remain depressed as of 2025Q3 suggests that DOGE's rescission of termination notices later in the year for properties outside our sample did not spark a market rebound in either bond prices or re-leasing activity. For instance, the number of leases listed for cancellation by DOGE declined from a high of 793 in March 2025 to 384 as of September 30, 2025. Rather, the creation of DOGE signaled the federal government's intent to downsize its investment in the real estate sector going forward, leading to market-wide repricing of risk from cash flow exposure to government contracts.

The cancellation of federal leases could also create negative spillovers to surrounding leases and properties through a combination of factors, including a drop in foot traffic to surrounding businesses due to a reallocation of federal workers and reduction in demand for the goods and services provided by local contractors to GSA tenants. Using standard

[2]As of December 2024, canceled D.C. GSA leases in our sample average 150,000 rented square feet and total 1.8 million rented square feet.

spatial difference-in-differences approaches (e.g., Gupta et al., 2022; Chen et al., 2024) comparing properties linked to private-tenant leases in properties close vs. far away from a DOGE-terminated lease, we document a 11.9% drop in NOI backed by nearby properties with non-federal tenants. Decomposing this spillover effect, we do not find evidence that it is driven by contagion effects transmitting to non-ETO exercised leases packaged within the same bond pool alongside a DOGE-notified lease. This result holds even after controlling for local neighborhood time trends at various levels of geographic granularity, helping us combat a common challenge in such "ring" research designs in which selection into treatment status depends on distance cutoffs which may simply reflect other secular changes to neighborhoods rather than the local event of interest (Diamond and McQuade, 2019; LaPoint, 2022).

Our evidence is consistent with negative spillovers to purely private-tenant properties being driven by negative production externalities instead of consumption externalities. Examining weekly foot traffic patterns to businesses nearby properties with terminated leases, we observe no discernible changes in visits to retail or non-retail establishments. This null result holds for a battery of robustness checks, including controlling for neighbor and subsector-specific time trends, estimating Poisson regressions, and comparing early vs. late-notified rings to account for the fact that canceled leases are geographically selected. The lack of any break in foot traffic is not due to DOGE targeting federal agencies with more generous work-from-home policies, as we show average days worked from home are comparable to those in the hybrid work environments offered by private sector firms (Flynn et al., 2024) and similar across agencies with terminated and non-terminated leases.

To test for production externalities, we combine hand-collected, tenant-level data from CoStar with historical government contract awards from `USASpending.gov`. Comparing DOGE-proximal properties with high vs. low contract exposure within tenants' industry segment, post-DOGE occupancy sharply drops among the most exposed properties. At the same time, there is a small increase in rent per square foot of roughly 3% for nearby, DOGE contract-exposed properties, indicating that landlords partially offset losses by raising rents for their remaining tenants. These spillover effects are not simply driven by businesses with prior dealings with the federal government leaving Washington, D.C. due to post-2024 election pessimism. In a placebo test where we recompute the exposure measure based on all prior government contract awards, rather than only those tied to agencies with canceled leases, we find no differential effects on occupancy or rent.

Feeding in our reduced form estimates of the decline in NOI from GSA and non-GSA leases stemming from early termination risk exposure, we simulate implied property valuation losses from our arbitrage pricing framework for the securitized portion of the Washington, D.C. office market. We compute two measures to capture tail risk: the minimum loss incurred in the worst 5% of simulated outcomes (i.e., the 95% Value at Risk) and the average loss conditional on being in the worst 5% of outcomes (i.e., the expected shortfall). We calculate property value destruction, in a 95% Value at Risk sense over a five-year period, of $57 million for ETO-eligible lease properties, $333 million for DOGE-notified lease properties, and $2.16 billion for non-GSA properties experiencing negative spillovers.

In the median scenario, the combined total expected shortfall for securitized offices is $2.29 billion, implying an additional $43 million loss in terms of local property tax revenues. The median expected loss translates to 5.7% of D.C. office market value, rising to 6.7% of market value in tail-risk scenarios and to 9.5% in median-loss cases if we scale up our estimates to include potential losses to non-securitized properties. The value losses we project exceed the entire savings from canceled lease payments nationwide and dwarf savings from the D.C. metro area of between $75 million and $100 million reported during the peak termination period in March 2025. Hence, the sudden shift in federal real estate policy generates larger private asset value erosion than it does taxpayer savings.

We contribute to several literatures at the intersection of real estate, finance, and political economy. The commercial real estate literature does not isolate lease contingency clauses – such as the ETOs we study – as a distinct driver of CMBS or commercial debt pricing, and any lease-related effects appear only as part of broader risk and contract structure analyses. For instance, Mooradian and Yang (2000) document in a small sample of commercial leases that tenants who select into leases with a downsizing option tend to pay higher rents. Similar to tenant exercises of downsizing options, Glancy and Wang (2023) show that even prior to the pandemic, lease expirations increase downside risk to a property's occupancy and income. Cheng et al. (2022) study how lease structures, including the negotiation of contingency clauses, change following the introduction of a new lease accounting rule (ASC 842) in private debt markets.

With the exception of Allen et al. (1997), who compare federal government to private-market office lease pricing in two U.S. states, there is no empirical work isolating the GSA lease segment of the market. Studying government agency leases is important in its own right given the large average size of the leases, large dollar values of attached loans, and the potential for spillovers to local economies through employment and foot traffic.[3]

Prior work in urban economics underscores the special role of anchor tenants in the retail sector on lease (Pashigian and Gould, 1998; Choi et al., 2025) and product pricing (Konishi and Sandfort, 2003). Spatial spillovers of underperformance in real estate markets arise due to hyper-local agglomeration economies in CRE (Rosenthal and Strange, 2020), with consumption externalities spread across retail tenants due to shoppers following travel itineraries to run errands between home and work (Miyauchi et al., 2025). The failure of anchor tenants can also lead to agglomeration of bankruptcy cases (Benmelech et al., 2018). Even conditional on the within-submarket geographic proximity of properties to a terminated lease, local foot traffic, and

[3] According to the Office of Personnel and Management's (OPM) FedScope data, 2.3 million workers, accounting for roughly 2% of the U.S. civilian workforce, were employed across all federal agencies as of September 2024. See `https://www.fedscope.opm.gov/` for the most current snapshot of federal employment counts

other neighborhood business health metrics, we conclude CMBS repricing due to government policy risk can propagate through capital markets to nearby non-GSA-linked leases.

By studying a new natural experiment consisting of realized political risk to the real estate sector, we contribute to work quantifying adverse economic consequences of political uncertainty. This literature has largely focused on government shutdowns or the threat of shutdowns. Baker and Yannelis (2017) report a marked decline in household consumption during the 2013 shutdown. Gelman et al. (2020) estimate a spending reduction of 58 cents per dollar lost in liquidity during the same period. Herpfer et al. (2023) describe declines in government productivity – such as reduced accounting processing and patent creation – that persist up to four years post-shutdown. Baker et al. (2016) show more generally beyond shutdowns that policy uncertainty indexed throughout a century of U.S. newspaper data predicts declines in real aggregate activity and other major economies, echoing previous findings of delayed corporate investment spending during election years (Julio and Yook, 2012). For the purpose of quantifying government risk premia, our empirical setting has an advantage of clear "treatment" dates relative to the lengthy disputes related to Congressional budget appropriations or election-related uncertainty,[4] in the sense that individual government contracts are directly notified of termination on known dates, while other leases are not.

A large finance literature estimates how investors price political risk into securities markets. Pástor and Veronesi (2012) and Pástor and Veronesi (2013), respectively, show through the lens of general equilibrium models how stock prices negatively react to policy announcements and policy uncertainty generates a sizable risk premium. Consistent with these predictions, Brogaard and Detzel (2015) conclude that the economic policy uncertainty index of Baker et al. (2016) positively forecasts short-term abnormal returns on equities. Several empirical studies report that election uncertainty lowers liquidity and trading volume (Pasquariello and Zafeiridou, 2014) as well as firm valuations and productivity (Col et al., 2017), while raising option-implied volatility and hedging costs (Goodell and Vähämaa, 2013; Saiegh, 2023). Hassan et al. (2019) use firm-level textual analysis to show that higher political risk coincides with increased stock return volatility, a rise in risk dispersion, and a large uptick in lobbying activity. Kelly et al. (2016) emphasize that equity options spanning political events tend to be more expensive, as they offer a hedge against political tail risks. Similarly, our results indicate that the implicit put options represented by federal ETOs which are currently vested are cheaper because of the heightened loss exposure they carry.

A key distinction of our paper vis-à-vis extant research on the financial pricing of political uncertainty is our analysis of debt markets rather than equity markets. Moreover, relative to settings such as Congressional budget debates or contentious elections, the temporal clustering of government termination actions and the absence of pre-trends support our causal

[4] Prior to the Fall 2025 shutdown episode which lasted 43 days, the three longest shutdown events in U.S. history lasted 35 days (2018–2019), 21 days (1995–1996), and 16 days (2013). Several weeks of political gridlock over budget reconciliation preceded each of these events.

interpretation that DOGE's intervention served as a "wake-up call," revealing latent exposure in CMBS structures to federal lease terminations. Our results highlight how previously dormant contractual provisions can become salient sources of credit risk once activated, demonstrating the need for more explicit pricing of government contract risk in securitized products.

Finally, the negative consequences for debt markets we document from the regime shift in government lease contracts may magnify risk exposure of regional banks following the collapse of office real estate values due to the transition towards remote work after the pandemic (Gupta et al., 2025). Indeed, our simulation exercises point to sizable office property value destruction from government contract risk exposure. Jiang et al. (2025) simulate risks of insolvency for up to 300 banks due to losses on CRE loans amplified by the sharp monetary policy tightening cycle between 2022 and 2023 (Jiang et al., 2024). On top of regional banks, Brown et al. (2024) argue that major life insurance companies hold as much as 16% of their portfolio in CRE debt, of which roughly one-third includes CMBS investments, with GSA-concentrated Washington, D.C. ranked third in terms of the underlying property location of life insurers' book value mortgage exposure. Such trends may lead banks most exposed to CRE debt to reduce their credit supply to non-CRE investments, thus hampering economic growth in other sectors (Anenberg et al., 2025).

2 Background on Federal Lease Terminations

In early 2025, federal leasing policy underwent a significant transformation, marked by a sharp increase in the termination of leases administered by the General Services Administration (GSA). In contrast to standard federal procurement contracts governed by the Federal Acquisition Regulation (FAR), which often incorporate termination for convenience clauses, such as FAR 52.249-2, GSA leases are governed by the General Services Administration Acquisition Regulation (GSAR) and generally do not include such provisions (Federal Acquisition Regulation, 2025). Instead, the GSA can exercise *an early lease termination option* (ETO) within a pre-defined period of the lease term. In the post-2015 GSA lease inventory, every lease contract has a termination right date.

As shown in Figure 1, GSA leases are structured into two sequential phases. The *firm term*, usually encompassing the first ten years, prohibits early termination and provides cash flow certainty for lessors. The subsequent *soft term*, typically five years in length, allows the GSA to unilaterally terminate the lease provided that it issues an advance notice of 90 to 120 days (U.S. General Services Administration, 2023, 2024). Consequently, among contracts that were subject to the 2025 wave of federal lease cancellations, 85% had already transitioned into the soft term. In nearly all of the remaining 15% of cases the agency's operations were either shut down or the agency approved of the termination in an effort to downsize.[5] Figure 3 provides

[5]In two-thirds of all terminated leases, DOGE describes the termination on their website as being conducted via "mass modification," a method for modifying lease contracts under the GSA's Multiple Award Schedule (MAS) program, whereby government agencies receive services at pre-negotiated prices from private contractors.

examples of the termination right clauses in the standardized lease contract (form L100) that GSA uses when negotiating with private landlords.

Leases announced as terminated by DOGE are geographically dispersed, with each state having at least two federal leases canceled (Figure 4). However, the square footage of terminated leases is highly concentrated in a small handful of states, particularly Washington, D.C., California, and Georgia (Figures 5 and 6). For single-tenant leases, termination counts are greatest in larger states (Figure 7). Savings, as measured by total rent payments which will no longer be paid, are more geographically dispersed due to regional differences in per square foot rents (Figure 8).[6] Tenants of terminated leases span nearly one-hundred different federal agencies.

The scale of lease terminations initiated in 2025 is unprecedented in federal leasing history. Based on historical GSA inventory lists available from 2015, one-year GSA lease termination rates fluctuated between 2% and 3% before spiking above 5% in the first half of 2025 (Figure 9). The spike in termination rates is even more pronounced when computed over the subset of GSA leases which are in the soft term, whereby the lease is eligible for early termination in the absence of force majeure or agency closure; for soft term leases, one-year cancellation rates spiked from their historical 3-4% average to 12% in March 2025 (Figure 10).[7]

The jump in termination rates for ETO-eligible leases supports the notion that the cancellation option embedded in government leases would have been viewed by market participants as a rarely exercised, dormant clause. Notably, during the COVID-19 pandemic, despite widespread remote work, federal agencies largely maintained existing leases, citing the absence of cancellation clauses and potential costs of early termination. In contrast, the 2025 termination involved hundreds of leases spanning millions of square feet of office space and widespread disruption of federal agency operations.

Figure 11 shows how the number of leases slated for termination by DOGE evolved since the DOGE website's publication on February 18, 2025. The number of canceled leases peaked at 793 between March 13, 2025 and March 18, 2025, dropping down to 384 leases as of September 30, 2025. These cancellations are relative to an inventory of 7,535 GSA leases as of December 2024.[8] Many of the leases which were at one point listed as terminated on the DOGE savings website but then subsequently removed either remain vacant or have since been leased out

[6]DOGE calculates a contract's value using a federal contracting concept known as "total potential value," which includes any remaining lease payments left on the current term of the lease, plus any payments in the event all remaining lease renewal options are exercised (CBS News, 2025).

[7]These calculations assume that DOGE announcements eventually lead to removal of the lease from the GSA inventory list after the 90 to 120 day grace period for ETO-exercised leases. As shown in Figure 11, some leases were eventually removed from the DOGE savings webpage, leading to ambiguity about whether such a lease will eventually be removed from the government's inventory. Therefore, our series captures the perceived spike in cancellation rates as of 2025Q1 but not necessarily finalized terminations.

[8]The DOGE website does not provide a unique identifier to track leases over time. We create a lease panel identifier based on a combination of the city-level location, government agency tenant, and square footage. We do this after correcting for misspellings/abbreviations in the agency name after cross-referencing with the historical GSA lease inventory list (e.g., "EPA" vs. "Environmental Protection Agency").

to a new, non-governmental tenant. The ebb and flow of DOGE decisions also allows us to test for effects on the CMBS market of moving between regimes with higher vs. lower lease cancellation risk. In the next section, we theoretically model such transitions and derive testable implications for the commercial real estate market.

3 Arbitrage Pricing Framework for CMBS Market

Our framework extends the contingency option pricing model of Choi et al. (2025). Using the arbitrage pricing model, we compare two otherwise identical properties that differ only in the perceived ETO exercise probability: zero vs. strictly positive. When ETO exercise is treated as impossible, rents are lower, implying an underpriced government contract risk premium.

3.1 Model Setup

We adopt the arbitrage pricing framework developed in Jarrow (2018, 2021) and Choi et al. (2025) to evaluate commercial lease contingencies. Given that federal leases have finite terms, we assume a continuous trading model with a finite horizon T^*. We formalize the characterization of uncertainty in the model with a filtered probability space $(\Omega, \mathscr{F}, \mathcal{F} = (\mathscr{F}_t)_{t\in[0,T^*]}, \mathbb{P})$ where Ω is the state space, $\mathscr{F}$ is a σ-algebra of events, $\mathcal{F} = (\mathscr{F}_t)_{t\in[0,T^*]}$ is an information filtration, and $\mathbb{P}$ is the statistical probability measure. The traded assets are a default-free money market account and default-free zero-coupon bonds. We denote the time t price of a zero-coupon bond maturing at T and always paying a dollar as $p(t,T)$, and r_t is the default-free spot rate of interest. Define the time t value of a money market account as

$$B(t) = e^{\int_0^t r_u du}$$

Since we assume the market to be arbitrage-free, the First and Third Fundamental Theorems of Asset Pricing are satisfied. The theorems imply that there is an equivalent probability (i.e., risk-netural probability) measure $\mathbb{Q}$ with respect to $\mathbb{P}$ such that

$$p(t,\mathbb{T})e^{-\int_0^t r_u du} \tag{3.1}$$

is a martingale for all $\mathbb{T} \in [0,T]$.[9] We model the exercise of an ETO by a federal tenant as a stopping time $\tau \in [0,T]$ with respect to the underlying information filtration, where $T < T^*$, and T denotes the original lease expiration date.[10]

[9]The formal notion of an arbitrage-free market is known as a market that satisfies the principle of *No Free Lunch with Vanishing Risk* (Jarrow, 2018).

[10]To accommodate specific times of key events in an exercised ETO episode, we equate the finite time period $[0,T]$ with $[t_0,t_m]$ for $m \in \mathbb{N}$. For the time t valuation, it implies the fixed horizon is $[t_j,T]$ for $j \in \mathbb{N}$.

From the landlord's perspective and thus for the CMBS pool, the key credit event occurs when a federal tenant exercises its ETO and delivers formal notice at time τ, triggering the contractual advance-notice period α (typically 90–120 days) during which rent is generally still owed and the landlord can prepare for vacancy.[11] After the notice period expires, the lease terminates and the space becomes vacant, shifting the contract rent shortfall onto the landlord until re-tenanting at time η, with the interval $[\tau + \alpha, \eta)$ generating the associated NOI loss (see Figure 2).

3.2 Rental Cash Flows

Consider two otherwise identical properties that differ only in the salience of the ETO exercise probability: one property assumes the early termination option (ETO) exercise event has zero probability while the other assumes a strictly positive probability of exercise. The no-arbitrage market value of the property for which the ETO is assumed to have zero probability is:[12]

$$\frac{V(t)}{B(t)} = \mathbb{E}_{\mathbb{Q}}\left[\sum_{s=t+1}^{T}\frac{R}{B(s)} + \frac{V(T)}{B(T)}\right] \tag{3.2}$$

Intuitively, the current discounted value of the property with a dormant ETO equals the risk-adjusted discounted sum of all future rent payments plus the terminal liquidation value of the property.

Consider another property with a strictly positive probability of ETO exercise. This introduces a friction whereby space rendered vacant by a prematurely terminated lease cannot be leased out again until a certain period, $\eta > \tau$, has passed. This implies that the ETO-salient property's market value is:

$$\frac{\widetilde{V}(t)}{B(t)} = \mathbb{E}_{\mathbb{Q}}\left[\sum_{s=t+1}^{\tau}\frac{\widetilde{R}}{B(s)} + \sum_{s=\eta+1}^{T}\frac{\widetilde{R}}{B(s)} + \frac{V(T)}{B(T)}\right] \tag{3.3}$$

The next proposition characterizes how correctly pricing an ETO yields higher rent.

Proposition 1. *The rent payments ($\widetilde{R}$) associated with a lease that has a strictly positive probability of ETO exercise are higher than the rents under a lease without an ETO (R). Hence,*

$$\widetilde{R} - R > 0 \quad \textit{with } \widetilde{R} = R\left[1 + \frac{\sum\limits_{s=t+1}^{T} p(t,s)\mathbb{Q}(\tau < s)\mathbb{Q}(s \leq \eta)}{\sum\limits_{s=t+1}^{T} p(t,s)\left[\mathbb{Q}(s \leq \tau) + \mathbb{Q}(\eta < s)\right]}\right] \tag{3.4}$$

[11] In practice, additional rent abatement may apply if the tenant vacates before the notice period ends (see the "vacant premises" clause in Panel B of Figure 3); for simplicity, our baseline sets $\alpha = 0$.

[12] The baseline environment assumes no grace period, $\alpha = 0$, and that the landlord faces no lapse in re-leasing if the ETO is perceived as a zero-probability event. We refer to this as a dormant ETO. In addition, the baseline model treats the exercise and notification of the ETO equivalently.

where $p(t,s) = \mathbb{E}_{\mathbb{Q}}\left(\frac{1}{B(s)}\right)B(t)$, *and ETO notification and re-leasing follow Poisson processes with respective intensities* λ_τ *and* λ_η *under* $\mathbb{Q}$*.*

Proof. See Appendix C.1 for the derivations. □

3.3 Property Value Loss

Recognizing that the current property value reflects the risk-adjusted sum of discounted cash flows and the liquidation value, we formalize the loss in property value arising from the underpricing of government contract risk associated with the ETO. Under the assumption of independence among the ETO notification, re-leasing, and the zero-coupon bond price processes, we derive a closed-form expression for the loss in property value.

Proposition 2. *Suppose the time* t *value of a property without ETO pricing is* $V(t)$*, and with ETO pricing the value is* $\widetilde{V}(t)$*. Denote the time* t *discounted value loss induced by mispricing the ETO as* $L(t) = \frac{V(t)-\widetilde{V}(t)}{B(t)}$*. With ETO notification and re-leasing following Poisson processes having respective intensities* λ_τ *and* λ_η *under* $\mathbb{Q}$*, the closed-form solution of the loss is*

$$L(t) = \frac{R}{B(t)} \sum_{s=t+1}^{T} p(t,s) \left[e^{-\lambda_\eta s} - e^{-(\lambda_\tau+\lambda_\eta)s}\right] \tag{3.5}$$

Proof. See Appendix C.2 for the derivations. □

3.4 CMBS Bond Price Adjustment

We consider a pool of N otherwise identical properties that differ only in the perceived probability (salience) of exercising an ETO. A fraction θ_0 of the properties are assumed to have a dormant ETO (i.e., a zero probability of exercise) while the remaining fraction $\theta_1 = 1-\theta_0$ have a strictly positive probability of ETO exercise. Each dormant-ETO (respectively, ETO-salient) property generates rent R ($\widetilde{R}$) per period and a terminal liquidation value $V(T)$ ($\widetilde{V}(T)$) at maturity T, conditional on the lease remaining active.[13]

This structure implies that the expected contribution of the ETO-sensitive portion of the pool is simply the corresponding cash flow multiplied by the survival probability from t to the relevant date, while the dormant-ETO portion remains unaffected. Aggregating across properties then yields a closed-form no-arbitrage pricing for the CMBS bond price

$$\phi(t) = N\left[\sum_{s=t+1}^{T} p(t,s)\big(\theta_0 R + \theta_1 \widetilde{R} e^{-\lambda_\tau(s-t)}\big) + p(t,T)\big(\theta_0 V(T) + \theta_1 \widetilde{V}(T) e^{-\lambda_\tau(T-t)}\big)\right] \tag{3.6}$$

[13]We abstract from other elements commonly featured in CMBS pricing models, such as prepayment and vacancy risks, default risk, and heterogeneous recovery rates, as a full treatment of CMBS bond pricing is beyond the scope of this paper. For comprehensive discussions of CMBS pricing frameworks incorporating these additional dimensions, see, for example, Christopoulos et al. (2008) and Diener et al. (2012).

The following proposition establishes that a marginal increase in the ETO notification arrival intensity (i.e., an increased likelihood of exercising ETOs) has a negative effect on the CMBS bond price.[14]

Proposition 3. *Let $\phi(t)$ denote the arbitrage-free price of a CMBS bond backed by a pool of N properties, where a fraction θ_1 is subject to early termination option (ETO) risk with Poisson intensity λ_τ. Then $\phi(t)$ is strictly decreasing in λ_τ, that is,*

$$\frac{\partial \phi(t)}{\partial \lambda_\tau} < 0 \tag{3.7}$$

Proof. See Appendix C.3 for the derivations. □

3.5 Regime Switching

We extend our baseline model by allowing the ETO notification arrival intensity, λ_τ, to follow a two-state continuous-time Markov chain, capturing a low-intensity (L) and a high-intensity (H) federal lease cancellation regime. The low-intensity state reflects the baseline policy environment prevailing before the DOGE initiative, while the high-intensity state represents the aggressive exercise of ETOs under the DOGE-driven exit strategy. The regime process $X_t \in \{L, H\}$ has the transition probability matrix:

$$Q = \begin{pmatrix} -q_{LH} & q_{LH} \\ q_{HL} & -q_{HL} \end{pmatrix}, \quad \lambda_\tau(t) = \begin{cases} \lambda_\tau^L & X_t = L \\ \lambda_\tau^H & X_t = H \end{cases}$$

Economically, q_{LH} reflects the hazard of federal leasing policy becoming more aggressive in the *exit regime* (e.g., the beginning of the 2025 DOGE-led terminations), while q_{HL} reflects reversion to the *baseline regime* (e.g., the rescission of some DOGE terminations).

To let ETO risk vary with macro-financial conditions, we model the economy as occupying an observable regime $X_t = i$ with regime-specific termination intensity λ_τ^i and regime-switching rates q_{ij}, which together imply a regime-dependent lease survival probability $\widehat{\pi}(s, i)$. Replacing the baseline survival term $e^{-\lambda_\tau(s-t)}$ with $\widehat{\pi}(s, i)$ in the pooled cash-flow and terminal-value expressions yields the regime-conditional no-arbitrage bond price

$$\widehat{\phi}(t, i) = N \left[\sum_{s=t+1}^{T} p(t, s) \big(\theta_0 R + \theta_1 \widetilde{R} \widehat{\pi}(s, i) \big) + p(t, T) \big(\theta_0 V(T) + \theta_1 \widetilde{V}(T) \widehat{\pi}(T, i) \big) \right] \tag{3.8}$$

The following proposition establishes that the CMBS bond price declines with a higher transition rate into the exit regime (i.e., aggressive ETO-canceling regime), but increases with a higher transition rate back to the baseline regime.

[14] In subsequent analyses, we maintain the following regularity conditions: the collateral pool is non-empty and contains a strictly positive share of loans with a dormant ETO. Rents and terminal property values are strictly positive.

Proposition 4. *Let $\widehat{\phi}(t,i)$ denote the arbitrage-free price of a CMBS bond backed by a pool of N properties at time t in regime $i \in \{L, H\}$, where a fraction θ_1 are subject to ETO risk under a regime-switching intensity process with transition rates q_{LH} (from L to H) and q_{HL} (from H to L), and baseline and exit regime hazard levels are λ_τ^L and λ_τ^H, respectively. Then, we obtain the following comparative statics:*

$$\frac{\partial \widehat{\phi}(t,i)}{\partial q_{LH}} < 0 \quad \textit{and} \quad \frac{\partial \widehat{\phi}(t,i)}{\partial q_{HL}} > 0. \tag{3.9}$$

Proof. See Appendix C.4 for the derivations. □

3.6 Spatial Spillovers to Private Leases

We extend the regime-switching framework to incorporate a *spillover effect* of ETO notifications, whereby cash flows of nearby properties, including those without direct ETO exposure, are also adversely impacted. For tractability, we modify the original pool setup in Section 3.4 such that private-tenant properties (share θ_0) earn safe cash flows $\bar{R}$ and valuation $\bar{V}(T)$ which are reduced proportionally by a contagion factor:

$$\Gamma_{\text{Private}}(s,i) = \theta_0 \bar{R} \varsigma\, \mathbb{1}_{\{\tau < s\}} \qquad \Psi_{\text{Private}}(T,i) = \theta_0 \bar{V}(T) \varsigma\, \mathbb{1}_{\{\tau < T\}}$$

For tractability, we assume private-tenant properties generate baseline cash flows $\bar{R}$ and terminal value $\bar{V}(T)$ that are reduced following realized ETO exercise. Specifically, define the spillover adjustment factor $\Xi(s,i) \equiv 1 - \varsigma\big(1 - \widehat{\pi}(s,i)\big)$ where $\varsigma > 0$ denotes the proportional ETO-induced spillover loss rate experienced by private-tenant properties.[15] We can derive the arbitrage-free contagion-adjusted price of the CMBS bond at time t, conditional on starting in regime i as

$$\widehat{\phi}_c = N \left\{ \sum_{s=t+1}^{T} p(t,s) \left[\theta_0 \bar{R}\, \Xi(s,i) + \theta_1 \widetilde{R}\, \widehat{\pi}(s,i) \right] + p(t,T) \left[\theta_0 \bar{V}(T)\, \Xi(T,i) + \theta_1 \widetilde{V}(T)\, \widehat{\pi}(T,i) \right] \right\} \tag{3.10}$$

Proposition 5. *Let $\widehat{\phi}_c(t,i)$ denote the arbitrage-free price of a CMBS bond at time t, conditional on starting in regime i, in the presence of regime-switching ETO risk and spillover effects at rate ς. Then,*

$$\frac{\partial \widehat{\phi}_c(t,i)}{\partial \varsigma} < 0 \qquad \textit{and} \frac{\partial \widehat{\phi}_c(t,i)}{\partial \Xi} > 0.$$

Proof. See Appendix C.5 for the derivations. □

The second part of the proposition motivates our use of a bond pool-level exposure share in empirically estimating spillover effects ς.

[15]The parameter ς measures the *sensitivity of nearby (private-tenant) properties* to the observed (delivered) ETO notifications. If $\varsigma = 0$, then private-tenant properties are fully insulated from the negative spillover effects induced by ETO notifications. Therefore, we suppose that spillovers bind with positive probability so that ς has a non-trivial effect on the bond valuation.

In practice, negative spillover effects to income generated by nearby non-ETO properties can occur through several channels. First, the relocation of government employees can reduce foot traffic to nearby businesses from workers traveling to and from the office to run errands (Miyauchi et al., 2025). In Section 6.4, we find no evidence in support of this consumption externality mechanism in our analysis of retail foot traffic data. However, there could also be positive production spillovers to local contractors from having GSA tenants nearby (Duranton and Kerr, 2018), in which case lease cancellations could limit agglomeration effects on the margin of business entry and exit, thus increasing vacancy rates for non-GSA properties in the same neighborhood. In Section 6.5 we decompose the rent vs. occupancy response for nearby office buildings leased to private tenants with varying levels of exposure to federal government spending based on historical contract awards. In doing so, we find support for this production externality hypothesis, with the drop in NOI for non-GSA properties driven by a sharp decline in occupancy for buildings with the tenants most exposed to disrupted government agencies.

3.7 Testable Hypotheses

Building on the key results from the preceding sections, we formulate our three main empirically testable hypotheses.

Hypothesis 1 *A more aggressive federal lease cancellation policy, which increases the salience of early termination risk, leads to greater expected losses at the property level, which translates into lower CMBS bond prices.*

This testable prediction is directly motivated by Proposition 3 and Proposition 4. It implies that the CMBS bond price $\phi(t)$ declines as the early termination intensity λ_τ increases, since heightened termination risk reduces the expected stream of property-level cash flows. Consequently, an increase in λ_τ, driven by more aggressive DOGE policy actions, disproportionately erodes the value of properties with embedded ETOs through elevated expected losses. These losses propagate to the CMBS market by lowering the risk-adjusted present value of the pooled cash flows, thereby depressing bond prices.

Hypothesis 2 *Properties that receive ETO notifications exhibit a decline in net operating income (NOI), relative to otherwise comparable properties, reflecting the direct operational impact of government lease termination risk on property-level cash flows.*

This prediction is grounded in Proposition 1 and Proposition 2, which formalize the loss in property value arising from the mispricing of government contract risk embedded in the ETO. These results demonstrate that the present value of property-level cash flows declines when the risk of ETO exercise is underestimated, as reflected in higher expected losses due to premature lease terminations and uncertain re-leasing outcomes. This mechanism operates through a reduction in expected rental income streams and an increase in vacancy risk, both of which lower the landlord's net operating cash flows. Properties subject to ETO risk experience direct operational disruptions as leases terminate earlier than anticipated and re-leasing takes time, during which rent income is forgone. These property-level income shortfalls aggregate up to large declines in net operating income, property values, and ultimately CMBS bond prices, as we show via simulations in Section 7.

Hypothesis 3 *Properties located near ETO-notified buildings exhibit a decline in net operating income (NOI), property values, and associated CMBS bond prices, relative to otherwise comparable properties, reflecting the spillover impact of government lease termination risk on nearby, non-notified assets.*

The intuition behind this prediction is captured by Proposition 5, which formalizes the adverse spillover effects of ETO notifications on nearby, non-notified properties through a contagion mechanism. These results demonstrate that the present value of property-level cash flows and valuations for non-notified assets decline as the spillover intensity increases, reflecting market perceptions of heightened vacancy risk and reduced tenant demand in the surrounding area. Economically, this mechanism operates through localized deterioration in property market fundamentals, as nearby tenants reassess location desirability and avoid DOGE-notified areas altogether. Non-notified properties experience indirect income disruptions as occupancy and rental rates weaken, even if no direct lease termination occurs. We show in Section 7 that the vast majority of total value destruction in tail-risk scenarios originates from spillovers to non-notified leases.

4 Commercial Property Market Data

Our sample consists of three main datasets: (i) government cancellation notices from the DOGE website, (ii) bond, loan, and property information from Trepp, and (iii) federal lease inventory information from the General Services Administration (GSA). As of writing, our data cover the months up to and including September 2025.

DOGE dates. Since March 23, 2025, we have hand collected twice per day (once in the morning and once in the evening) the DOGE website's information listed under its real estate savings section (`https://doge.gov/savings`). The website provides the main agency, location, square footage under lease contract, and an estimated total savings amount involved in an early cancellation or lease non-renewal. Crucially, we collect the notification-sent date of the early termination option that the government plans to exercise, which is the basis for our treatment definition in the regression analysis. We use various media sources, plus website snapshots from the Wayback Machine and the JLL Federal Lease Termination Tracker, to backfill date announcements and lease information since the initial publication of savings on DOGE's website on February 18, 2025.[16]

CMBS price data. We use the Trepp CMBS dataset which offers month-end bond values at the CUSIP level. Trepp applies a model of loan default risk to impute prices for CMBS bonds in each month. Trepp's valuation model takes as inputs dealer inventory, rating agency actions, delinquency and modifications, and the financial performance of the underlying collateral (Trepp, 2022). We focus on the valuation data from Trepp rather than data on CMBS spot markets from the Financial Industry Regulatory Authority's (FINRA) Trade Reporting and Compliance Engine (TRACE), since the TRACE panel is unbalanced at monthly frequency due to lack of liquidity in CRE debt markets. Restricting to a balanced panel is important for the interpretation of our results to the extent that bond pools may be restructured in response to DOGE announcements, meaning that we may not be able to plausibly separate mortgage composition effects from the role played by the activation of the dormant ETO clause in the repricing of the CMBS market.[17]

Trepp FEED data. To construct a comprehensive panel dataset of government real estate investments and property performance, we supplement the CMBS bond pricing data from Trepp with the set of four tables contained in their FEED data: the *bond*, *deal*, *loan*, and *property* tables. The combined table results in a table of CMBS bonds matched to mortgages in the bond pool and the properties those mortgages help finance. We relegate details of how we perform this merge to Appendix D.1.

Merging across all five Trepp tables allows us to recover measures of performance, such as net operating income (NOI) or net cash flow (NCF), at both the loan level and averaged across properties within the same bond deal, and at different points in time (e.g., as of securitization vs. as of the last CMBS reporting date) to measure lease characteristics as close to DOGE announcements as possible. We drop from the sample the roughly one-fifth of loans where the NOI is only reported as of the securitization date, since for such loans we cannot isolate changes in cash flow performance. To account for skewness in the distributions, we take logs of bond prices and cash flow-related variables, such as NOI and debt service coverage ratios (DSCR); these variables are strictly positive for all observations in our sample.

CMBS bond ratings. We follow the classification scheme suggested by Flynn and Ghent (2018) to divide bonds into three seniority categories (first-loss group, mezzanine, and senior). We define

[16] Media commentators have criticized the accuracy of the cost savings reported on the DOGE website (CBS News, 2025). There are also reports suggesting that some of the leases DOGE claimed to have terminated were already canceled prior to 2025 but still within their grace period (New York Times, 2025). For this reason, in our research designs we only use information on the *timing* of notification dates from the DOGE website for leases which can be uniquely matched to the official GSA inventory list as of December 2024. We analyze DOGE's cost savings and adjust them for discrepancies in Section 7.3.

[17] We match 87% of CUSIPs in Trepp to their transaction history in TRACE. Nearly all of the CUSIPs which do not appear in TRACE are linked to a GSA tenant. Further, the TRACE data are typically released with a three to four-month lag. Given the real-time nature of our exercise, this is another reason why we use the monthly Trepp CMBS data to form our main bond price panel.

the first-loss group (FLG) as consisting of tranches which have a rating of CCC, or CCC+, or those which are unrated. In cases where the bond receives multiple agency ratings, we use the S&P rating. If the S&P rating is unavailable, we use the Fitch rating. If both the S&P and Fitch ratings are unavailable, we adopt the Moody's rating.[18] We refrain from using Kroll and Morningstar DBRS ratings in our baseline setup given 2023 SEC charges against these agencies regarding record-keeping failures for CMBS transactions.[19] In Table 2, we report summary statistics by tranche and lease type for our key outcomes of interest.

GSA leases. The U.S. General Services Administration (GSA) publishes its lease inventory information on a monthly basis. GSA lease inventory consists both of space leased by federal agencies as well as by private contractors engaged in government business. We compile a panel of GSA leases from January 2015 to the present. We collapse the GSA lease inventory panel to the unique geolocation level and separately record lease effective, expiration, and DOGE termination dates for individual leases within the same property. We then many-to-one match on the standardized property address the collapsed GSA inventory panel to the bond-loan-property table for use in our loan-level analysis.

To link GSA leases with properties in the Trepp CMBS dataset, we generate candidate matches using multiple criteria: (i) string similarity between standardized GSA and Trepp addresses, (ii) geospatial proximity between GSA and Trepp coordinates (the latter obtained from the Google Maps API), (iii) exact matches in square footage for the five largest tenants, and (iv) exact matches in lease expiration dates for these same tenants. We manually review approximately 400 potential matches for the Washington, D.C. market to validate correct pairings. This procedure yields 96 matched leases (seven terminated) for D.C. and 45 leases (six terminated) for Atlanta, corresponding to average match rates of roughly 37%. The lower match rate in D.C. is primarily due to the fact that Trepp only covers CMBS-securitized properties, rather than match quality, given the broad criteria used to define the initial match pool.

In Table 1, we list the federal agencies who are tenants in DOGE-notified and ETO-eligible leases by cross-referencing their Trepp property address with online listings from CoStar. The agencies with office space within DOGE-terminated leases contained in a securitized pool include, on top of GSA divisions, Housing and Urban Development (HUD), Veteran's Affairs, Department of Homeland Security, Federal Emergency Management Agency (FEMA), Department of the Treasury, Internal Revenue Service (IRS), Department of Energy, Federal Energy Regulatory Commission, and Federal Aviation Administration (FAA) offices. Leases in our estimation sample for Washington, D.C. span 36 distinct federal agencies.

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[18]We obtain similar tranche classifications – and therefore quantitatively similar results – if we instead divide up bonds into tranches based on the consensus grouping across rating agencies. The tranche group classifications overlap in 86% of cases between S&P and Fitch, 89% of the time between S&P and Moody's, and in 76% of cases between Fitch and Moody's.

[19]See the official SEC press release here: `https://www.sec.gov/newsroom/press-releases/2023-211`. That said, our results are similar and our sample size is larger if we include the Kroll ratings to classify bonds.

In Figure 12 we map the spatial distribution of canceled leases relative to the overall CMBS-linked property market in Washington, D.C. The seven canceled leases are clustered in the downtown areas of the city around the National Mall.[20] These seven terminated leases are attached to 74 unique CMBS CUSIPs. On top of the seven leases which actually received a letter from DOGE, ETO-eligible leases in the D.C. area span 285 CUSIPs across 15 bond pools on the eve of DOGE's formation, pointing to the potentially broader impact of DOGE's announced terminations despite the small number of leases involved.

In what follows, we will distinguish currently ETO-eligible leases from soon-to-be ETO-eligible leases. We define soon-to-be-eligible leases those which will enter the soft term of the lease at any point during the current presidential administration, or between January 2025 and January 2029. We indicate "close" properties within a 1-mile radius of the affected leases and relatively "far" properties in the metro area but still within a 5-mile radius. In our analysis of spillovers, we control for proximity to the seven canceled leases tied to five securitized properties, as well as six additional rings corresponding to six leases attached to non-securitized properties. These 11 rings form the basis for our implementation in Section 5.3 of a difference-in-differences strategy to isolate spatial spillovers of the DOGE actions.[21]

Moody's CRE data. We use the Moody's Analytics CRE database to estimate securitization rates for commercial office buildings. Comparing the number of office properties matched to Trepp records to the set of corresponding Moody's offices yields a measure of securitization rates for the non-GSA segment of the office market. We successfully link 96 out of the 291 GSA leases in the 2020–2024 inventory for Washington, D.C. to 577 Trepp office properties, yielding a match rate of 33.0%. For terminated GSA leases in D.C., the implied securitization rate is 41.2%; for D.C. GSA leases which are ETO-eligible but not terminated, the securitization rate is 50.0%. In contrast, for purely private-tenant leased offices, the securitization rate is (577 - 96)/(1,995 - 291) = 28.2%. These tabulations suggest that GSA properties are overrepresented in the CMBS universe relative to non-GSA leased properties. In Section 7.3, we use these securitization rates to extrapolate our value loss projections to compute an overall market-wide loss. We do this because NOI is only observable for securitized properties.

SafeGraph/Advan foot traffic. In our analysis of the spillover effects of DOGE cancellations to neighboring properties, we obtain data from Advan Weekly Patterns (Advan Research, 2022), formerly SafeGraph, to measure foot traffic to nearby businesses. Advan offers foot traffic for points of interest (POI) such as retail chains and local businesses and amenities based on anonymized geolocated cell phone "pings."[22] We first identify POIs located within a radius of

[20] Two sets of canceled leases are located in the same building complex, meaning there are five unique properties implicated.

[21] See the augmented map with locations of all canceled Washington, D.C. leases in Figure E.1.

[22] See recent applications of the SafeGraph data to study agglomeration spillovers from grocery store openings (Qian et al., 2024) and disparities in bank branch access (Sakong and Zentefis, 2025). Hou et al. (2025) discuss advantages and best practices for using this dataset in corporate finance applications.

terminated GSA leases. We then isolate the weekly number of visits to each POI within the radius, restricting to a balanced panel of businesses with strictly positive weekly foot traffic in the 24 months prior to DOGE's formation. To isolate retail POIs and test for consumption externalities, we use the 2-digit NAICS codes corresponding to *Retail Trade*, *Arts, Entertainment, and Recreation*, and *Accommodation and Food Services*.

Tenant-level data. Trepp does not provide tenant-level information other than the names of the top five tenants by leased square footage within each securitized property. To overcome this limitation, we hand-collect data on the identity and industry classification of nearby office tenants from CoStar and match tenants to their historical government contract awards reported in `USAspending.gov`. We use this information in Section 6.5 to construct a measure of business exposure to DOGE contract terminations and evaluate the influence of negative production externalities on the performance of nearby office buildings. We offer more details on our data collection process in Appendix D.2.

5 Empirical Strategies

We adopt several difference-in-differences (DiD) research designs to test the two main hypotheses of the model outlined in Section 3.7. We define the treatment group as those leases for which the government officially issued an early termination option (ETO) notification, while the control group consists of otherwise similar leases which are soon-to-be past their termination right date and thus did not receive such a notification. The core identification logic rests on the premise that the issuance of an official ETO notice serves as a salient signal of the government's intent to invoke contract flexibility, thereby prompting an immediate market reassessment of risk.

To ensure valid comparisons across treatment and control groups, we focus on GSA leases with an exercisable ETO and those associated with first-loss group tranches of CMBS bonds in our analysis of bond prices. This sampling strategy is motivated by the assumption that the salience of government contract risk is most pronounced in settings where leases retain the legal flexibility for early termination and where the corresponding bond tranches are most sensitive to fluctuations in net operating income (NOI).

To isolate spillovers to the other groups of leases, such as already ETO-eligible leases and non-GSA leases, we use soon-to-be ETO-eligible leases as a common control group. Our choice of control group follows the logic that the latter set of leases is tied to debt contracts among the least exposed to the DOGE announcement shock. We validate this assumption by conducting contamination bias tests proposed by Goldsmith-Pinkham et al. (2024), and find no evidence of statistical cross-contamination of effects on bond prices or cash flows in comparing the directly notified and spillover groups to the not-yet eligible group of leases.[23]

We implement a spatial triple difference-in-differences (DDD) design to test whether the negative impact of government lease cancellations on CMBS valuations is disproportionately concentrated among properties in immediate proximity to the ETO-notified leases. The objective of this exercise is to test whether repricing of government contract risk is driven by a market-wide increase in risk, particularly through negative spillover effects to non-GSA leases located near ETO-impacted properties. We estimate the average effect of government lease cancellations on CMBS bond prices for non-GSA leases located within 5 miles of a canceled lease relative to federal leases in the same region. Such a design captures the overall spatial spillover effect of government exit risk on private tenants.

5.1 Pooled Difference-in-Differences

Our main specification is a pooled difference-in-differences (DiD) regression of the form:

$$Y_{i,c,t} = \beta \cdot DOGE_{i,c} \times Post_t + \gamma \cdot Post_t + \eta \cdot DOGE_{i,c} + \xi' \cdot \mathbf{X_{i,c}} + \delta_{i,y} + \varepsilon_{i,c,t} \tag{5.1}$$

In this equation, $Y_{i,c,t}$ denotes the log of the bond price, net operating income, or debt service coverage ratio (DSCR) associated with deal i, bond CUSIP c, and time t.[24] The variable $DOGE_{i,c}$ is an indicator equal to one if the underlying lease is notified by DOGE for early termination, as indicated by the DOGE website and corroborated by other industry sources monitoring the website in real time. $Post_t$ equals one in periods following the initial wave of DOGE announcements in February 2025 or later.

The interaction term $DOGE_{i,c} \times Post_t$ is our key variable of interest. The coefficient β on the interaction term captures the average treatment effect of the DOGE notification on bond prices (or property performance) for tranches that are ETO-eligible relative to those that are not. The vector of pre-DOGE characteristics $\mathbf{X_{i,c}}$ controls for pre-existing differences in bond prices between DOGE-notified vs. non-notified tranches, such as initial differences in square footage, delinquency rates, and mortgage features.[25] In our most stringent specifications, we include 5-digit property zip code and deal closing year or bond CUSIP fixed effects, which absorb these

[23]To further inspect robustness to potential contamination bias, we provide results which are quantitatively similar if we refine the definition of soon-to-be ETO-eligible leases to exclude leases which enter the soft term during the post-DOGE sample period – that is, those that become eligible between January 2026 and January 2029 instead of between January 2025 and January 2029.

[24]Note that loan-level NOI and DSCR are always strictly positive in our sample, so the log transformation does not result in us dropping any observations.

[25]DOGE-terminated leases tend to occupy large spaces and have higher debt service coverage for the attached mortgage, than their non-terminated but ETO-eligible counterparts, but higher loan-to-value ratios, 30-day loan delinquency rates, and longer delinquency spells conditional on missing a loan payment.

control variables and the $Post_t$ dummy.[26] The vector of deal closing year dummies $\delta_{i,y}$ strips out any temporal variation in past CRE debt market conditions that might drive differences in the *ex post* performance of CMBS bonds.

Because our underlying data used to estimate (5.1) are at the bond-deal-property level, we experiment with clustering the standard errors at various levels. Standard practice would be to cluster at the level of treatment (Bertrand et al., 2004), which in this case is a lease contract. Yet, leases are not a unit of analysis in Trepp; individual leases can only be inferred based on tenants reported as occupying a property in a given quarter. We therefore ultimately cluster the standard errors at the bond CUSIP level for CMBS prices as the outcome variable, as doing so yields more conservative confidence intervals and accounts for the fact that the same bond can be tied to multiple leases in the dataset to the extent that the loan pools are not fully geographically diversified.[27] Analogously, for loan-level outcomes like NOI or DSCR, we cluster at the loan level, as the same loan can finance a property with several leases.

We consider treatment to be both absorbing and to have common timing across all CMBS bonds. Hence, $DOGE_{i,c}$ is not indexed by t, and $Post_t$ is not indexed by i. We justify this simplifying assumption on the grounds that for the Washington, D.C. sample where many of the nationwide set of terminated leases are concentrated, DOGE sent all cancellation notices to landlords and tenants within a two-week timespan between January 30 and February 13, 2025. Given that our main data source covering CMBS prices and property fundamentals is at the monthly frequency, this effectively means treatment occurs within the same month for the directly affected units.

An alternative notion of treatment timing would use the date that terminated leases were listed under the "savings" section of the DOGE website. For many leases notified in the first wave of letters sent on January 30, the lease was not listed on the DOGE website until late March. Given that information about terminated leases would have already become common knowledge among investors in the intervening period – especially given extensive media coverage of the topic starting in early February (e.g., Associated Press, 2025; CoStar News, 2025a) – we consider the original information provided to the market on January 30 as the realized shock to the dormant ETO clause. To the extent that our main analysis uses monthly frequency data, using the DOGE website initiation date of February 18 as the timing cutoff would generate identical results.

[26]Given the small number of securitized CRE properties relative to residential properties, including finer geographic fixed effects leads to many singleton cells. Therefore, we adopt 5-digit property zip code fixed effects as our baseline set of neighborhood fixed effects.

[27]For our cash flow-based outcomes of interest, we verify that our results quantitatively hold even if we collapse the panel down to the property level and estimate versions of (5.1).

5.2 Parallel Trends and Non-Anticipation

Our identification strategy relies on the parallel trends assumption that CMBS prices and loan and property performance metrics would have evolved similarly across the notified and non-notified groups of leases if not for the DOGE cancellations. We strengthen the credibility of this assumption by restricting the sample used to estimate (5.1) to leases that are subject to ETO provisions. Our choice of soon-to-be ETO-eligible leases as a control group is motivated by the idea that these leases are among the least exposed to the DOGE announcement shock while at the same time not being so recently issued that the characteristics of the mortgages and properties differ substantially from those of the treatment group. Our design is therefore akin to staggered DiD designs exploiting random assignment of units into earlier vs. later treatment cohorts (Goodman-Bacon, 2021), where assignment in this case is based on the plausibly exogenous time between the end of the lease's firm term and DOGE's creation date.[28]

For CMBS prices, we isolate the first-loss group (FLG) tranches by excluding mezzanine and senior tranches in our estimation sample; the latter are less exposed to losses in the event a commercial mortgage defaults, a potential outcome in cases where delinquency is induced by prolonged vacancy after a sudden lease cancellation. Ashcraft et al. (2019) show that buyers of B-pieces (low-rated CMBS tranches) act as gate-keepers in the CMBS market since they re-underwrite all the loans in the underlying pool, and for this reason B-pieces are more informationally sensitive. Restricting to the FLG allows us to zoom in on a segment of the CMBS market that would be the most likely to react to the increased salience of the ETO clause embedded in GSA leases.

To assess the validity of the parallel trends assumption after making our sample restrictions, we estimate an event study version of our baseline specification (5.1) that includes leads and lags of treatment and plot the resulting event-time coefficients β_t:

$$Y_{i,c,t} = \sum_{t=-4, t\neq -1}^{+8} \beta_t \cdot DOGE_{i,c} + \mu_{(i,c)} + \delta_{i,y} + \varepsilon_{i,c,t} \tag{5.2}$$

where $\mu_{(i,c)}$ refers to a set of fixed effects capturing different dimensions of the deal-bond combination, such as 5-digit property zip code, census block group, or CUSIP fixed effects. We set $t = -1$ to be the reference period, corresponding to January 2025. Because the first set of DOGE terminations for the Washington, D.C. area was sent to landlords and tenants on January 30, 2025, the first month in which the market could react to the notifications is February 2025 ($t = 0$). Previewing the results, with or without our most stringent set of fixed effects,

[28] An alternative approach would be to estimate a regression discontinuity where the running variable is the difference in months between DOGE's creation in January 2025 and the date when a lease passes its termination right date. We lack the statistical power to estimate these more localized treatment effects in our setting. For instance, out of the 7,535 GSA leases active as of December 2024, only 598 are within a 6-month symmetric window of the running variable cutoff. Of these, only 17 are located in D.C., none of which received a cancellation notice from DOGE.

Figures 13 and 14 show no evidence of pre-treatment divergence for either bond prices or NOI. The same is true for DSCR in Figure 15.

A second identifying assumption is non-anticipation, which posits that market participants did not revise their expectations about lease termination risk prior to the observed announcement or notification dates. In our setting, this assumption is justified by the temporal clustering of ETO notifications and the widespread perception prior to the event that ETO clauses were legally available but operationally dormant. The low historical volatility and levels of early lease cancellation rates depicted in Figure 10 bolster our interpretation of lack of ETO salience in the pre-DOGE period. Hence, any observed bond price responses are likely triggered by the government's formal signaling of intent, rather than by market speculation or information leakage.

5.3 Spatial Difference-in-Differences

To account for the possibility of spillovers across space and CRE debt markets, we estimate spatial difference-in-differences regressions, distinguishing between GSA and non-GSA lease performance:

$$Y_{i,c,r,t} = \beta \cdot Spillover_{i,c,r} \times Post_t + \gamma \cdot Post_t + \eta \cdot Spillover_{i,c,r} + \mu_{(i,c)} + \chi_{r,t} + \varepsilon_{i,c,r,t} \tag{5.3}$$

The dependent variables, subscripts, and $Post_t$ follow the same definitions as described for equation (5.1). The treatment variable in the spatial difference-in-differences is $Spillover_{i,c,r}$, an indicator equal to one if two criteria are satisfied: (i) the bond-deal involves only private tenants, and (ii) the underlying space being rented is located within a 1-mile radius of an ETO-exercised lease. The interaction term $Spillover_{i,c,r} \times Post_t$ captures the average spillover effect of DOGE lease cancellations on bonds or loans not linked to GSA-leased properties relative to more distant units within a 5-mile radius of ETO-exercised leases in the D.C. metro area. The index r emphasizes the fact that observations are connected to a particular ring r with the location of a DOGE-canceled tenant as its centroid.

As shown in the map of Figure 12, a property can be contained within multiple rings. We account for neighborhood-specific time trends that may overlap with the geography-based definition of treatment by including ring-by-time fixed effects $\chi_{r,t}$. While our baseline analysis studying the direct effects on terminated lease properties relies on the Trepp data, in estimating (5.3) we include rings defined by non-securitized leases which were also canceled by DOGE (see the map in Figure E.3).

We further decompose the *Spillover* dummy in (5.3) via a spatial triple difference-in-differences (DDD) design to determine whether there is any incremental impact of proximity to canceled leases within the innermost 1-mile radius relative to those in the surrounding 1-to-5 mile band. Equation 5.3 conflates two notions of treated status: one based on spatial proximity, and another based on whether the lease involves a private tenant. A natural question arises of which spillover margin is quantitatively more prominent. We answer this question by estimating the following equation:

$$\begin{aligned} Y_{i,c,r,t} = \beta \cdot (Ring_{i,c,r} \times Private_{i,c} \times Post_t) + \gamma_1 \cdot Post_t + \gamma_2 \cdot Private_{i,c} + \gamma_3 \cdot Ring_{i,c,r} \\ + \gamma_4 \cdot (Private_{i,c} \times Post_t) + \gamma_5 \cdot (Ring_{i,c,r} \times Post_t) + \gamma_6 \cdot (Ring_{i,c,r} \times Private_{i,c}) \\ + \mu_{(i,c)} + \chi_{r,t} + \varepsilon_{i,c,r,t} \end{aligned} \tag{5.4}$$

where $Ring_{i,c,r}$ is an indicator equal to one if the property lies within one-mile radius of the ETO-exercised D.C. properties, and $Private_{i,c}$ indicates that the deal involves a non-GSA lease. The new coefficient of interest, β, captures the differential post-treatment effect for properties located within the treatment radius (1 mile), relative to other private-tenant properties located further away (between 1 and 5 miles). Our results are quantitatively similar but estimated with wider confidence intervals if we use a more stringent outer ring radius (e.g., 3 miles), given that most securitized office properties are located in the downtown area where the canceled leases are clustered.

6 Main Results

We now present our main empirical results using the notification of DOGE cancellations of GSA leases as a natural experiment to test the hypotheses implied by our arbitrage pricing framework.

6.1 Results on Bond Pricing

Table 3 presents the main results from our difference-in-differences regression (5.1) examining the impact of early termination option (ETO) notifications on log CMBS bond prices. The coefficient on the interaction term, $DOGE \times Post$, captures the differential change in bond prices following the ETO notification for notified leases relative to not-yet eligible ones. Across most specifications, which sequentially include fixed effects for property zip code, deal-year and bond-month, bond CUSIP, the estimated treatment effect is negative and statistically significant at the 10% level. The estimated decline in bond prices ranges from 3.0 to 3.4 log points, suggesting that markets priced in heightened government contract risk immediately following the receipt of an ETO notice.

As indicated by the event study for bond prices in Figure 13, the negative effects are persistent up to eight months after DOGE, with more precisely estimated coefficients in the first two quarters of 2025. Including CUSIP fixed effects compares leases with vs. without a DOGE termination notice but bundled within the same tranche issue. The fact that the within-CUSIP effect on bond prices in column (3) is attenuated suggests that some bond pools may have been restructured to diversify away from federal government procurement. This is another form of repricing of government contract risk.

These empirical findings lend direct support to **Hypothesis 1**, confirming that an increase in government lease termination intensity λ_τ, realized through DOGE's ETO notifications, leads to a decline in CMBS bond prices. The observed repricing is consistent with the theoretical prediction that heightened policy-induced termination risk lowers the expected present value of property-level cash flows, which in turn diminishes the valuation of securitized tranches exposed to this risk. The results validate the mechanism formalized in Proposition 3 and Proposition 4, demonstrating how mispriced contractual risk embedded in federal leases is revealed and incorporated into market prices through the DOGE policy shock.

We show in Appendix F that the repricing of government contract risk through DOGE's actions is also reflected in the prices and abnormal returns for REIT equities. We compare publicly-traded REITs holding D.C. office properties that are more or less exposed to the termination announcements based on the fraction of their *ex ante* NOI or leased square footage accounted for by GSA tenants. For the GSA-exposed REITs, cumulative abnormal returns (CARs) drop by 5% below normal levels, as measured in the months prior to the 2024 presidential election. The control group of D.C. office REITs with little to no GSA tenant exposure experiences a 2% increase in their CAR, reflecting that investors price the government contract risk rather than a general shift in fundamentals for the D.C. office market writ large.

6.2 Results on Property and Loan Performance

Table 4 reports results from estimating (5.1) with log net operating income (NOI) as the outcome. The coefficient on the interaction term, *DOGE* $\times$ *Post*, is consistently negative and statistically significant across all four specifications. The estimates imply that properties receiving ETO notifications experience a 19 to 28 log points decline in NOI, relative to comparable untreated properties, even after controlling for combinations of property zip code, deal, tranche, and bond-level fixed effects.

The dynamic event study (5.2) shows a sharp drop in March 2025 ($t = 0$) NOI which has persisted up to September 2025, with a flat trend in cash flows prior to the creation of DOGE (Figure 14). The delayed drop in NOI relative to DOGE's creation matches the end of the standard 90-day grace period, which begins after the government exercises its ETO. The persistent negative effects on NOI are consistent with CoStar data showing vacancy rates of over 30% in buildings with early terminated GSA leases as of 2025Q4 – far above the overall D.C. office submarket vacancy rate which exhibits a flat trend throughout 2025 (Figure 16).

Some of the initial decline in NOI could be due to other features of GSA leases. First, the grace period is negotiable, and some leases applied to agencies which were immediately disbanded (e.g., USAID). Second, as shown in Panel B of Figure 3, during the grace period the government is entitled to a rent abatement at either a pre-negotiated rate, or, in the case of net leases, at a rate based on a reduction in the operating expenses component of the rental payment in proportion to the leasable area being vacated. The typical rent abatement for a GSA lease subject to the vacant premises clause is between \$1.50 and \$2.00 per square foot (Holland & Knight, 2025). Under early 2025 estimates of market rent of \$60 per square foot for grade A office space in D.C., NOI would fall by roughly 3% due to the rent abatement, even without any immediate vacancy or changes to the property's operating costs. Hence, only a small portion of the initial drop in NOI we observe is due to rent abatement, and the remainder is caused by agencies which left within months of receiving a DOGE termination notice.

Declines in NOI for properties with terminated leases are mirrored in declines in debt service coverage ratios (DSCR), computed as the ratio of NOI to annual debt service at the loan level. We uncover a robust effect in Table 5 of a 15 to 21 log points drop in DSCR for loans tied to DOGE-notified leased properties, with corresponding event study results in Figure 17. Similar to the event study for NOI, there is a sharp drop in DSCR in March 2025 for bonds exposed to a DOGE-notified lease.[29] Since creditors can call in their capital if DSCR falls below a threshold negotiated by the lender and any co-lenders in the inter-creditor agreement, a deterioration of DSCR signals potential future covenant violations. This is an important concern due to the current high interest rate environment which has led to a tightening of interest coverage limits and constraints on firms' debt issuing capacity (Greenwald, 2019). While we do not have the DSCR covenant information for loans in our sample, we find that all loans attached to ETO-notified properties are delinquent as of April 2025, and 90% of them are still delinquent at the end of our sample period in September 2025.

Since NOI is updated for most loans at a less than monthly frequency, our estimates for the effect of DOGE cancellations on NOI and on DSCR are attenuated towards zero. For instance, in a typical month in the months leading up to the creation of DOGE, NOI experiences a month-on-month change for less than 10% of the loan sample. However, this fraction steadily rises in the post-DOGE period, peaking at 25% in May 2025. Based on lease effective dates and term lengths in the GSA lease inventory data, annual start dates for GSA leases active as of December 2024 are almost uniformly distributed across months in the year; leasing years are slightly less likely to start between February and March (when most DOGE announcements were concentrated) and more likely to start in August through October. Hence, the observed decline in NOI for terminated leases is due to DOGE actions rather than seasonality related to how frequently the loan reports cash flows for the underlying property. The lack of month-to-month changes in NOI in the pre-period leads to near zero coefficients in the months prior to DOGE.

Our empirical results are consistent with **Hypothesis 2**, supporting the prediction that underestimated government lease termination risk materially depresses property-level cash flows when exercised. We validate the characterization in Proposition 1 and Proposition 2 in which mispriced contractual risk embedded in federal leases translates into operational disruptions and diminished cash flow realizations at the property level.

[29] We obtain qualitatively and quantitatively similar results if we instead use DSCR as a function of net cash flow (NCF) instead of NOI as the outcome variable.

6.3 Spillover Effects to Nearby Properties

Table 6 and event study Figure 17 present results from spatial difference-in-differences regressions estimating the impact of DOGE lease cancellations on CMBS bond prices. The analysis focuses on properties that are not directly leased to the GSA and lie within a 5-mile radius of the canceled leases in Washington, D.C. The interaction term, $Spillover \times Post$, exhibits a consistently negative and highly significant coefficient in the first two model specifications. When we include more stringent fixed effects, the results are statistically significant at the 1% level. The estimates indicate that bond prices of first-loss tranches decline by between 9 and 12 log points compared to otherwise similar, unaffected tranches tied to private-tenant leases, even after controlling for property, ring-time, and bond-level fixed effects. The magnitudes of these bond price declines are larger than the direct impacts on DOGE-notified GSA leases, as estimated in the preceding subsection.

Table 7 documents the spatial triple difference-in-differences regression results from estimating the decomposed spillover equation (5.4). The analysis focuses on properties that are not directly leased to the GSA and lie within a 1-mile radius of the seven canceled leases in Washington, D.C.[30] As before, we subset the sample to properties located within a 5-mile radius buffer and the first-loss tranche group. As illustrated in Figure 12, this produces a set of treatment groups comprising leases located in the inner black rings and a control group situated between the inner black and outer purple rings.

The insignificant coefficient estimates on the triple interaction term, $Ring \times Private \times Post$, indicate that the price declines documented in the DiD estimates are not statistically stronger for properties located within the innermost 1-mile radius compared to those in the surrounding 1–5 mile band. In other words, while the baseline DiD results demonstrate economically and statistically significant price declines for private-sector properties in the broader treated area, the DDD estimates suggest that the negative impact is not stronger at closer distances. This finding is consistent with the interpretation that the spillover effects of federal lease cancellations are broadly felt within the 5-mile zone. Although we do not currently model intra-pool spillovers in our theoretical framework, the fact that the estimated negative coefficient on $Post \times Private$ drops by over one-third with the inclusion of bond fixed effects in Table 7 suggests that spillovers are not solely driven by contagion across leases securitized into the same pool.

One plausible explanation for the insignificant triple-difference estimates is that the DOGE lease cancellation shock functions more as a market-wide increase in the salience of early termination options rather than as a hyper-local shock to economic activity. Rather than affecting only the properties in the immediate 1-mile vicinity of a canceled lease, the DOGE initiative may have served as a systemic wake-up call to investors, triggering a broad reappraisal of federal lease risk across the Washington, D.C. commercial real estate market. The visibility

[30] Trepp classifies 95% of the properties in our spillover sample as being majority office use. Therefore, our analysis of spillovers within the CRE debt market is restricted to mostly office and mixed-use retail.

and policy significance of the DOGE cancellations likely amplified investor attention to the ETO risk, even for properties that were not directly leased to the federal government. As a result, market participants may have repriced CMBS bonds across the entire 5-mile radius in a relatively uniform manner, reflecting heightened perceptions of risk, tighter underwriting expectations, or anticipations of reduced liquidity.

Our results in this subsection validate **Hypothesis 3** by showing that the sensitivity of CMBS bond prices to observed ETO notifications is empirically reflected in the price adjustments of securities backed by private-tenant leases in the vicinity of ETO-exercised buildings. Our results underscore a pronounced spatial spillover effect, whereby government lease termination risk depresses the valuation of CMBS tranches collateralized by nearby, non-ETO properties. These findings are consistent with Proposition 5, which predicts that government lease cancellations trigger significant and economically meaningful declines in CMBS bond prices through the propagation of contract risk across space.

6.4 Testing for Consumption Externalities Using Retail Foot Traffic

The previous set of tests show that the distinction between relatively near vs. far non-GSA properties matters little for the magnitude of negative spillovers, pointing to a market-wide shock acting through debt markets. One possibility is that negative consumption externalities to nearby non-GSA leases are limited due to hybrid work modes put in place at terminated agency offices after the COVID-19 pandemic. Hybrid work policies are now widespread among private, publicly-listed firms (Flynn et al., 2024). If agency offices subject to DOGE lease termination feature hybrid work environments with a large fraction of hours worked from home, then there is little scope for spillovers to surrounding businesses arising from fewer employees making trips to and from the office.

To evaluate this conjecture, we classify federal agency tenants in Table 1 based on their return-to-office (RTO) policies listed in the August 2024 OMB Congressional Report (Office of Management and Budget, 2024). Both canceled and non-canceled but ETO-eligible federal tenants in the D.C. metro area are under RTO mandates stipulating that employees average between two and three days in the office each week. The limited cross-agency variation in telework mandates suggests that DOGE did not target leases for offices with substantially lower in-person attendance.

To directly test for the consumption externality channel, we implement a spatial DiD regression similar to (5.3) that compares the evolution of foot traffic for retail establishments located inside an inner ring to those located inside an outer ring. Specifically, for a given pair of radii $(\mathfrak{r}_{inner}, \mathfrak{r}_{outer})$ we estimate the following regression specification:

$$Y_{j,r,s,t} = \sum_{t=-10,t\neq-1}^{+10} \beta_t \cdot Spillover_{j,t} + \mu_j + \chi_{r,t} + \delta_{s,t} + \epsilon_{j,t,r,s} \tag{6.1}$$

In this equation, $Y_{j,r,s,t}$ denotes the volume of visits to POI j, located in outer ring r and belonging to 3-digit NAICS subsector s, during week t. The variable $Spillover_{j,t}$ is an indicator equal to one if the POI is located inside an inner ring (i.e., if the distance to a terminated DOGE lease is less than $\mathfrak{r}_{inner}$) and if the relative time to the termination of that DOGE lease equals t. μ_j and $\chi_{r,t}$ denote POI and ring-by-week fixed effects, respectively, and $\delta_{s,t}$ represents week-by-subsector fixed effects that absorb subsector-specific seasonality. We define the control group as those POIs that are located in an outer ring of radius $\mathfrak{r}_{outer}$ around a DOGE terminated lease by excluding POIs from the estimation that are located further than $\mathfrak{r}_{outer}$ away from a termination.

We account for the fact that our outcome of interest in (6.1) is a count variable using two alternative approaches. Our first approach uses a fixed-effects Poisson regression, as recommended by Cohn et al. (2022), and thus explicitly assumes that the outcome is sampled from a Poisson distribution. In our second approach we instead use OLS but with the log of weekly visits as the outcome, assuming that this transformed outcome is asymptotically normal distributed. For both approaches, we test for spillovers at different levels of proximity by varying the pair of inner and outer radii $(\mathfrak{r}_{inner}, \mathfrak{r}_{outer})$ from $(0.25, 0.5)$ miles to $(0.5, 1)$ miles.[31] Figure E.1 gives a visual presentation of the resulting rings. Throughout, we use Conley (2008) standard errors that are robust to the strong spatial autocorrelation present in the foot traffic data.[32]

Figure 18 displays a null effect on foot traffic after estimating (6.1) by either Poisson regression (Panel A) or OLS (Panel B), regardless of the choice of inner and outer radii. If anything, there is a slightly positive, but statistically insignificant trend in retail foot traffic in the weeks after DOGE announces a termination. We probe this null result further in Appendix E, but ultimately find that it holds even in a version of (6.1) in which we compare effects across early vs. late cohorts of DOGE terminations using the Callaway and Sant'Anna (2021) estimator (Figure E.4) or when we estimate ring DiD models for non-retail foot traffic (Figure E.2).

Overall, our analysis of RTO policies and foot traffic to nearby retail and non-retail establishments casts doubt on a consumption externality channel driving negative performance spillovers to non-GSA properties. Rather, the DOGE shock generated a revaluation of the office stock by activating a long-dormant contractual clause in leases.

6.5 Production Externalities from Tenants' Contract Exposure

Our previous analyses suggest that local consumption spillovers are unlikely to be the primary mechanism behind the adverse effects of DOGE lease cancellations on nearby non-GSA

[31] Precisely estimating spillovers at finer levels of proximity is not possible, as the effective number of observations in the small inner circle is insufficient due to spatial correlation. Estimating spillovers at coarser levels of proximity is possible, but such estimates are likely contaminated by time-varying differences in foot traffic between the city center and the surrounding, less dense areas.

[32] In all estimations, we vary the maximal cutoff for spatial autocorrelation from 0.05 miles to 0.5 miles in 0.05 mile increments and report the standard errors that are the most conservative. Alternatively, clustering standard errors by ring-time or Census block group yields tighter confidence intervals across most specifications.

properties. In this section, we test a production externality channel: lease terminations disrupt local federal agency operations, leading to lower public procurement demand. Lower government contract spending, in turn, lowers demand for space at nearby private-tenant office buildings, reducing cash flows on those properties and valuations for the related CMBS bonds.

We construct a local tenant-level panel by combining Trepp, CoStar, and `USAspending.gov` for securitized private-tenant office buildings within one mile of ETO-notified leases in Washington, D.C. We use pre-DOGE tenant composition and historical federal award linkages to classify buildings by their exposure to government contract risk, focusing on procurement contracts initiated by agencies which received lease cancellation notices. We describe the construction of the tenant panel in Appendix D.2. We then estimate building–quarter difference-in-differences models to ask whether occupancy and rent dynamics deteriorate for higher government contract-exposed buildings after DOGE's announcements.

Government Contract Exposure. We first construct a tenant-level government contract exposure measure from federal awards: for each tenant j, let $GovExp_j$ denote the tenant's historical award exposure over 2015–2024. Our results are quantitatively similar if we instead restrict to contracts awarded in the post-COVID period, 2020 to 2024. We then aggregate $GovExp_j$ to the building level using pre-DOGE square-footage (SF) weights. For tenant j in building i, define the weights as:

$$w_{i,j} = \frac{\mathrm{SF}_{ij}^{\mathrm{PreDOGE}}}{\sum_{k \in \mathcal{J}_i} \mathrm{SF}_{ik}^{\mathrm{PreDOGE}}} \tag{6.2}$$

where $\mathcal{J}_i$ is the set of tenants in building i. Building-level government dependence is then

$$GovDep_i = \sum_{j \in \mathcal{J}_i} w_{i,j}\, GovExp_j = \frac{\sum_{j \in \mathcal{J}_i} \mathrm{SF}_{ij}^{\mathrm{PreDOGE}}\, GovExp_j}{\sum_{j \in \mathcal{J}_i} \mathrm{SF}_{ij}^{\mathrm{PreDOGE}}} \tag{6.3}$$

which captures the intensity of federal contracting exposure embedded in the building's pre-period tenant composition. We classify a building as a high government contract exposure building ($HighGovExp = 1$) if it falls in the top 20% of the building-level distribution of government exposure. We use $HighGovExp$ to construct a placebo test of whether negative spillover effects are driven by tenants exiting the Washington, D.C. market due to general pessimism about doing business with the government after the 2024 election rather than a DOGE-specific effect.

DOGE Contract Exposure. To capture whether a building's tenant mix is disproportionately linked to DOGE-related vs. non-DOGE federal business, we construct a building-level DOGE exposure measure. For each tenant j, let $DOGEShare_j$ and $NonDOGEShare_j$ denote the tenant's historical shares of federal award dollars over 2015–2024 that are attributable to (i) agencies subject to ETO notifications and (ii) all other agencies, respectively. Tenants with a larger $DOGEShare_j$ have greater reliance on agency demand for their goods and services that is plausibly disrupted by the early termination activity, so their exposure is more likely to transmit to local real estate cash flows through reduced business activity and knock-on effects on downstream contract linkages. We aggregate tenant-level shares to the building level via square-footage–weighted averages:

$$Share_i^D = \sum_{j \in \mathcal{J}_i} w_{i,j}\, DOGEShare_j, \qquad Share_i^N = \sum_{j \in \mathcal{J}_i} w_{i,j}\, NonDOGEShare_j \tag{6.4}$$

and define the building's DOGE tilt as

$$Tilt_i = Share_i^D - Share_i^N \tag{6.5}$$

We define an indicator for high DOGE exposure buildings based on positive tilt towards DOGE-impacted agencies:

$$HighDogeExp_i = \mathbb{1}\{Tilt_i > 0\} \tag{6.6}$$

We estimate two DiD specifications comparing buildings with high vs. low contract exposure using the two measures defined above:

$$Y_{i,t} = \beta^{DOGE} \cdot \left(HighDogeExp_i \times Post_t\right) + \mu_i + \delta_t + \Gamma' \cdot \mathbf{Z_{i,t}} + \varepsilon_{i,t} \tag{6.7}$$

$$Y_{i,t} = \beta^{GOV} \cdot \left(HighGovExp_i \times Post_t\right) + \mu_i + \delta_t + \Gamma' \cdot \mathbf{Z_{i,t}} + \varepsilon_{i,t} \tag{6.8}$$

The coefficients β^{DOGE} and β^{GOV} are the DiD estimates of interest; they capture the incremental post-period change in occupancy or rent for high government and DOGE-impacted agency exposure buildings relative to low-exposure ones, after controlling for observable building characteristics and absorbing common shocks and persistent differences through the time and unit fixed effects. The vector $\mathbf{Z_{i,t}}$ includes hedonic controls that proxy for baseline building quality (rentable building area, CoStar StarRating), physical form and vintage (year built, floor number), and accessibility (distance from the property to nearest transit stop).[33] We additionally include the lagged counterpart outcome to hold the price margin fixed when studying occupancy and to hold the quantity margin fixed when studying rents. We cluster standard errors at the building level.

Figure 19 plots the time series of quarterly average rent per square foot and occupancy rates, splitting the properties based on *HighDogeExp*. Both outcomes exhibit parallel trends across the high and low DOGE exposure groups. Occupancy rates sharply diverge starting in 2025Q1 when DOGE was created, with the most exposed properties experience an immediate 19 p.p. drop

[33] CoStar's StarRating is based on the CoStar Building Rating System, a nationally standardized 1 to 5-star measure of a property's overall physical quality (e.g., design, utilities, amenities, and site attributes), where 5-star indicates the highest-quality assets within the relevant property type. See `https://www.costar.com/costar-building-rating-system` for details.

in occupancy rates that does not rebound as of 2025Q3. Meanwhile, the low DOGE-exposure properties do not experience a sharp decline in occupancy. Rents show a much more muted divergence across the two groups, with rents increasing by 2% in the high exposure group relative to the low-exposure group.

Table 8 reports the regression estimates after adjusting for covariate differences across the treatment and control groups. Panel (A) shows that high DOGE-exposure buildings experience a 15 p.p. greater decline in occupancy after the initial wave of ETO notifications. In contrast, the pre-period level difference is small and statistically insignificant, indicating that DOGE exposed and non-exposed buildings are broadly comparable prior to the notifications and that the divergence emerges sharply in the post period. The occupancy effect remains stable as we progressively enrich the specification with time, location, and loan vintage fixed effects, together with hedonic controls. For rents, we document the opposite pattern.

We estimate a 3% relative increase in per-square foot rents for high DOGE-contract exposure buildings. Landlords partially offset losses by raising rents for tenants who remain in the space. The fact that rents increase is consistent with the predictions of our arbitrage pricing framework. Proposition 1 states that rents are greater for properties with salient probability of contract cancellation to compensate landlords for the cash flow risk in the event that they need to re-lease the space.

In Panel (B), we do not observe a comparable post-period decline among buildings with high overall government contract exposure. The interaction term is small and statistically indistinguishable from zero for both occupancy and rents. This contrast is informative because it suggests that the local contraction documented in Panel (A) is not a generic federal exposure effect that would mechanically arise under a broader political shift in the government contracting environment. Taken together, these findings suggest that local spillovers from the ETO notifications operate through a localized production externality mechanism rather than a broad-based repricing of public procurement-dependent real estate.

7 Implied Property Value Losses

We analyze the property valuation consequences of government contract risk exposure using a simulation disciplined by the coefficient estimates from our main empirical results for the Washington, D.C. market to quantify the aggregate value losses implied by Proposition 2. Specifically, we quantify the key tail risks associated with ETO exposure by addressing two central questions: (i) what is the minimum loss incurred in the worst α% of simulated outcomes, corresponding to the Value at Risk (VaR) at some percentile $1-\alpha$, and (ii) what is the average loss conditional on being in this worst α% of outcomes, known as the expected shortfall (ES)[34]

[34]This is also referred to as the Value at Risk at the $1-\alpha$% level.

Together, these risk measures allow us to assess the potential market-wide magnitude of adverse outcomes stemming from DOGE's lease termination actions.

7.1 Modeling ETO-induced NOI Volatility

We provide complete details for the simulation algorithm in Appendix G, but summarize the key steps here. First, we numerically simulate the portfolio-level distribution of losses $L(t)$ under stochastic ETO risk, as defined by expression (3.5). We do this for three mutually exclusive exposure groups: (i) ETO-eligible leases not exercised (unrealized risk),[35] (ii) DOGE-notified ETO exercises (realized losses), and (iii) nearby non-GSA properties (spillovers). This partition spans direct and indirect channels of policy-driven disruption.

Following the ETO regime-switching intensities described in Section 3.5, for each group we model the evolution of property values using a jump-diffusion process. The Brownian motion component captures continuous market volatility, while the Poisson jump component with arrival intensity λ_τ represents abrupt lease terminations. We calibrate λ_τ to observed DOGE notification rates. We project losses out over various horizons of $T \in \{1, 2, 3, 4, 5\}$ years, which pins down the degree of shock persistence. Simulation parameters are disciplined by our empirical estimates in Section 6.2 and auxiliary regressions reported in Appendix G. We estimate group-specific treatment effects for ETO-eligible and spillover properties according to equation (5.3) and map these coefficients into the jump and drift components used in the simulation.

Each jump induces a proportional decline in asset value consistent with the empirically estimated 21.2% reduction in NOI for ETO-notified properties, as reported in Table 4. To account for spillover effects to the already ETO-eligible and non-GSA lease groups, we scale jump magnitudes by our DiD-estimated declines in NOI for each of those groups (1.6% and 11.9%, respectively). This means the group of soon-to-be ETO-eligible leases (the control group in our empirical setting) acts as a reference category in the simulation. We conduct 50,000 Monte Carlo iterations, sampling with replacement from our estimation sample, to generate empirical loss distributions for both directly impacted and spillover assets. From these portfolio-level distributions, we compute the VaR and ES measures and compare losses to estimates of the overall value of office properties in the Washington, D.C. market and to implied taxpayer savings from canceled GSA lease payments.

We initialize baseline property values $V(0)$ using a hedonic pricing model in Appendix G.1; these baseline values define the counterfactual valuation path $V(t)$ in the absence of ETO-induced repricing (i.e., the baseline regime in Section 3.5). We use quality-adjusted property values obtained as fitted values from a hedonic regression to approximate steady-state fundamental values, rather than loan appraisal values or historical transaction prices which may simply reflect

[35] This group consists of federal leases with termination right dates prior to the creation of DOGE whose ETOs were not exercised.

market conditions as of a point in time. We follow the set of covariates used in our hedonic estimations from the production externality analysis in Section 6.5, including construction year, rentable building area (RBA), CoStar StarRating, and number of stories. We conduct several goodness-of-fit tests for our hedonic model in Appendix G.2.

7.2 Simulation Results

We document that properties which are ETO-eligible or subject to spatial spillover effects are critical determinants of tail risk in property value declines. Figure 20 presents the simulated distribution of five-year property value losses under early termination option (ETO) risk across three groups: already ETO-eligible properties (gray), ETO-notified properties (pink), and private-lease properties within a 5-mile radius subject to spatial spillovers (green). The estimated 95% Value at Risk (VaR) is $333 million for ETO-notified properties, and smaller for the ETO-eligible sample at $57 million. Private-lease properties account for 85% of the 95% VaR at $2.16 billion, reflecting the vulnerability of assets indirectly exposed to ETO terminations via disruptions to procurement contracts initiated by federal agencies. The unified distribution underscores that while direct ETO exposure is consequential, secondary spillovers may pose even greater tail risks under federal lease repricing conditions.

We report the full set of VaR and expected shortfall estimates for different assumptions about the projection horizon in Table G.4. Our one-year estimates correspond to the sample time period underlying our DiD estimates used to calibrate the size of the NOI shocks. If the drop in NOI were to persist after five years since DOGE, the 95% VaR would be four times larger than the one-year losses. A horizon of five years reflects the typical length of the soft term of a federal lease, during which the government can exercise its early termination option.

The simulation results reveal meaningful differences in the loss distributions, particularly with respect to the emergence of fatter left tails in the spillover group. These fat-tailed outcomes indicate elevated probability mass in the extreme loss region, suggesting non-linear amplification of risk among indirectly affected assets. Since the presence of such fat tails implies that risk cannot be fully captured by the first and second moments, it is important to quantify the expected shortfall for stress testing a portfolio of ETO-exposed assets in a region.

7.3 Systemic Tail Risk and Market-Level Exposure

The Value at Risk (VaR) provides a threshold for losses in extreme scenarios. What would be the expected magnitude of losses conditional on exceeding that threshold, that is, the average market-wide loss in the worst $1-\alpha$% of simulated outcomes? We compute the corresponding expected shortfall (ES) in the worst α% of outcomes given a positive loss, denoted as $\mathrm{ES}_{1-\alpha}(L)$, separately for each group of properties (i.e., ETO-notified, ETO-eligible, and spillover):

$$\mathrm{ES}_{1-\alpha}(L) = \mathbb{E}\left[L \mid L \geq \mathrm{VaR}_{1-\alpha}(L)\right] \tag{7.1}$$

We report VaR and expected shortfalls for different levels of α% in Table 9. The 50%-level (median) expected shortfalls for ETO-eligible (non-exercised), ETO-notified, and spillover properties are \$45 million, \$251 million, and \$2 billion, respectively. The total expected shortfall across the three groups is \$2.29 billion. In tail-risk scenarios ($\alpha = 5\%$), five-year expected shortfalls total \$2.68 billion across the three groups of properties. The losses accruing to the two spillover groups of ETO-eligible and non-GSA-leased properties account for the bulk of total tail-risk losses. The Washington, D.C. metro area office real estate market spans roughly 158.6 million square feet and is valued at \$40 billion based on price per square foot charged in recent transactions (BNP Paribas Real Estate, 2025; CommercialEdge, 2025; Cushman & Wakefield, 2025).[36] Our simulated total loss from the securitized office market represents 5.7% of total market capitalization in the worst half of scenarios. Losses rise to 6.7% of market value in the 95% ES tail-risk scenarios.

Our average loss estimates are conservative for three main reasons. First, for each group of properties, our estimates of the average drop in NOI are attenuated towards zero due to loan cash flows in Trepp updating at a quarterly frequency for most loans. This empirical moment is the key parameter underlying the jump processes in the simulation. Second, our arbitrage pricing framework does not incorporate possible general equilibrium forces of lease cancellations. For instance, vacancies triggered by ETO-exercised buildings can initiate a cascading sequence of additional vacancies *within* the same building due to input-output networks (Duranton and Kerr, 2018) and/or hyper-local consumption spillovers (Miyauchi et al., 2025). Still, our results in Section 6.4 demonstrating no negative impact of DOGE cancellations on foot traffic suggest that the local consumption externalities of government contract risk are limited, at least in our setting.

A third factor that leads us to underestimate value losses for the entire office market is that our reduced form empirical results and simulation analysis pertain to securitized properties. To the extent that negative spillovers can occur to non-CMBS properties, the market-wide losses will be larger. Using the securitization rates for the three property groups computed in Section 4, we can inflate up value loss estimates based on Trepp properties to a market-wide loss measure under the assumption that the distribution of cash flow losses, conditional on the baseline property characteristics included in our hedonic model (see Appendix G.1), is otherwise identical for non-securitized offices.

[36] The August 2025 CoStar Office Market Report for Washington, D.C. presents estimated total office asset values for the East End, CBD, and Tysons Corner areas of approximately \$49.8 billion.

A key difference between the securitized and non-securitized market which would impact the losses in nominal terms is that non-securitized properties are much smaller on average.[37] To estimate losses in the non-securitized market, we therefore apply an inflation factor for each group equal to the product of the inverse group-specific securitization rate and the ratio of average square footage for non-securitized to securitized office properties. Based on our calculations in Moody's CRE, the latter ratio is 70,182/361,537 = 0.195. For instance, this would mean inflating the private spillover group's nominal losses by 0.195/0.282 = 70%. After scaling up the $\alpha = 50\%$ ES losses for the securitized market in this fashion, we obtain an overall office market loss of $3.81 billion, or 9.5% of office market value.

7.4 Cost-Benefit Analysis

Another way to contextualize the broader market exposure from ETO-induced value losses is to compare them against the magnitude of cost savings accruing to the federal government. At the peak of its lease termination campaign in March 2025, the Department of Government Efficiency reported approximately $660 million in savings from federal lease cancellations and non-renewals nationwide (Politico, 2025). Notably, this figure is dwarfed by the $2.3 billion in aggregate expected securitized property value losses we simulate from *only the D.C. area* in the worst 50% of scenarios. Based on annual contract payments reported in the GSA lease inventory, at the height of lease terminations listed on the DOGE website as of mid-March 2025 the total savings based on the implied (non-discounted) annual lease payments remaining until lease expiration amount to $220 million, or $76.2 million when only including terminations in the broader D.C. metro area including Maryland, Virginia, and West Virginia. While the reported DOGE savings reflect meaningful fiscal relief on the public balance sheet, they come at the cost of potentially larger private-sector value erosion.

The value destruction from the sudden shift to a high lease termination rate environment also erodes property tax revenues from commercial properties. Suppose the D.C. office market suffers the total median expected valuation loss of $2.3 billion. Applying the standard 1.89% statutory rate and the fact that assessment ratios are nearly 100% in D.C. results in local revenue losses of $43.5 million.[38] To the extent buildings may be left fully vacant by reversals in government investments, some of the lost property tax revenues may be recouped by vacancy taxes.[39]

[37]There are two main reasons for this. One is that smaller offices do not have as many loans in the capital stack. Another is that safer properties are more likely to be securitized. Large buildings are more likely to have major companies as tenants, who sign longer-term leases and make rent payments in advance, increasing cash flow stability.

[38]The Washington, D.C. Office of Tax and Revenue reports commercial property tax brackets and assessment ratios here: `https://otr.cfo.dc.gov/page/real-property-tax-rates`. Nearly all properties in our Trepp sample have an *ex ante* value greater than $10 million, corresponding to the 1.89% statutory tax bracket. This calculation assumes property value losses translate to lower tax assessments one-for-one in the first tax year and remain thereafter.

[39]In D.C., there is a 5% tax rate for commercial properties which are assessed as 100% vacant. As of December 2025, none of the 15 D.C. properties with terminated leases in our sample are completely vacant.

We caution against drawing aggregate welfare conclusions from our results on government real estate investments for two main reasons. First, our results are based on the transition of the office market from a high to low lease cancellation regime. We lack a counterfactual to address the question of whether asset value losses would have been similar under a less abrupt shift in expected cancellation probabilities. Second, our cost-benefit analysis is partial equilibrium. For instance, the multiplier effect from rebating a dollar to federal taxpayers may exceed that from rebating the same dollar to local taxpayers, and the latter multiplier may be heterogeneous across locations with different degrees of exposure to government contracts.

Estimates of state-level government spending multipliers on output based on cross-sectional experiments from defense contracts in the post-1960s period fall between 1 and 2 (Nakamura and Steinsson, 2014; Auerbach et al., 2020).[40] Conservative estimates imply an annualized *local asset value multiplier* of roughly 10.41 = ($2.29 billion/$220 million), meaning that for every federal taxpayer dollar saved through a lease termination, at least $10.41 in office market value is destroyed.[41] Translating this asset multiplier to a real government spending multiplier would require a general equilibrium model incorporating real estate inputs to firm production, additional assumptions about how the DOGE shock maps to agents' expectations of future government spending, and estimates of re-leasing hazard rates for government-tenant offices.

8 Conclusion

We offer new empirical evidence of how contractual risk embedded in federal lease agreements is priced in the commercial real estate debt market. We study the market's response to the federal government's large-scale exercise of early termination options (ETOs) during the 2025 policy shift led by the Department of Government Efficiency (DOGE). While ETOs had long existed as a legal clause in General Services Administration (GSA) leases, they were widely perceived as operationally dormant, rarely invoked, and thus ignored in risk assessments and bond pricing. The sudden wave of terminations in early 2025 represents a plausibly exogenous policy shock that reactivated this dormant contractual risk.

Using a new dataset linking DOGE notifications, GSA lease records, and CMBS valuations, we find that early termination option (ETO) notifications lead to a 3.4% decline in CMBS bond prices and a 21.2% drop in property-level NOI, consistent with predictions of an arbitrage pricing framework for lease contingencies. These effects generate large negative spillovers across local markets driven by production externalities from severed procurement contract linkages.

[40] Dupor and Guerrero (2017) emphasize the sensitivity of multiplier estimates to the inclusion of particular historical episodes when only defense contract spending is used. Suárez Serrato and Wingender (2016) and Chodorow-Reich (2019) compute cross-sectional multipliers closer to 2 based on population-indexed federal program and American Recovery and Reinvestment Act spending, respectively. Contractionary multipliers, such as reductions in spending due to DOGE's contract cancellations, are larger than expansionary ones (Barnichon et al., 2022).

[41] This calculation uses the securitized 50% expected loss estimates from Table G.4.

Simulations imply median total office property valuation losses of \$3.8 billion in Washington, D.C., overwhelming the fiscal savings from canceled GSA leases.

Our findings demonstrate that previously ignored contractual clauses can become salient sources of credit and pricing risk once activated, and that federal policy shifts can generate significant asset valuation effects through this channel. Our results also call attention to the need for more explicit pricing of government contract risk in securitized credit products. In this setting, the DOGE intervention served as a wake-up call, revealing the latent exposure of CMBS structures to federal lease terminations.

As government leasing continues to evolve in the post-pandemic period, our analysis provides a foundational framework for understanding how public-sector behavior interacts with private capital markets through embedded contractual options. The negative risk exposure to government leases we document has the potential to magnify the troubles of regional banks suffering losses due to cratering commercial office valuations after the pandemic. As of 2021, 33% of agency and GSE-backed MBS investments were made by depository institutions (Fuster et al., 2025). Future work will explore implications of exposure to real estate policy uncertainty for the stability of the overall banking sector and credit provision.

References

Advan Research, 2022, Foot Traffic / Weekly Patterns [Dataset]. Dewey Data, https://doi.org/10.82551/X1PP-1F65.

Allen, Marcus T., Ronald C. Rutherford, and Larry J. Warner, 1997, A Comparison of Federal Government Office Rents with Market Rents, *Journal of Real Estate Finance and Economics* 15, 183–196.

Anenberg, Elliot, You Suk Kim, and Erica Moszkowski, 2025, Work-From-Home, Commercial Real Estate Risk and Credit Supply: Evidence from a Large Sample of Bank Loan Portfolios, *SSRN Working Paper* 5200882.

Ashcraft, Adam B., Kunal Gooriah, and Amir Kermani, 2019, Does Skin-In-The-Game Affect Security Performance, *Journal of Financial Economics* 134, 333–354.

Associated Press, 2025, Trump and Musk Demand Termination of Federal Office Leases Through General Services Administration.

Auerbach, Alan, Yuriy Gorodnichenko, and Daniel Murphy, 2020, Local Fiscal Multipliers And Fiscal Spillovers in the USA, *IMF Economic Review* 68, 195–229.

Axios Local, 2024, Office buildings in D.C. Sit Empty As Sales Slump.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis, 2016, Measuring Economic Policy Uncertainty, *The Quarterly Journal of Economics* 131, 1593–1636.

Baker, Scott R., and Constantine Yannelis, 2017, Income Changes and Consumption: Evidence from the 2013 Federal Government Shutdown, *Review of Economic Dynamics* 23, 99–124.

Barnichon, Regis, Davide Debortoli, and Christian Matthes, 2022, Understanding the Size of the Government Spending Multiplier: It's in the Sign, *The Review of Economic Studies* 89, 87–117.

Benmelech, Efraim, Nittai Bergman, Anna Milanez, and Vladimir Mukharlyamov, 2018, The Agglomeration of Bankruptcy, *Review of Financial Studies* 32, 2541–2586.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, 2004, How Much Should We Trust Differences-In-Differences Estimates?, *Quarterly Journal of Economics* 119, 249–275.

Black, Lamont K, John R Krainer, and Joseph B Nichols, 2020, Safe Collateral, Arm's-Length Credit: Evidence from the Commercial Real Estate Market, *Review of Financial Studies* 33, 5173–5211.

Bloomberg, 2025, DOGE's Lease Exits Put $12 Billion of Loans at Risk: Barclays.

BNP Paribas Real Estate, 2025, Market Research - Washington, D.C.

Brogaard, Jonathan, and Andrew Detzel, 2015, The Asset-Pricing Implications of Government Economic Policy Uncertainty, *Management Science* 61, 3–18.

Brown, Jordan, Ralf Meisenzahl, and Andy Polacek, 2024, Life Insurers' Exposure to Commercial Real Estate, *Federal Reserve Bank of Chicago Economic Perspectives* 5.

Callaway, Brantly, and Pedro H.C. Sant'Anna, 2021, Difference-in-Differences with Multiple Time Periods, *Journal of Econometrics* 225, 200–230.

CBS News, 2025, DOGE Says It Has Canceled Thousands of Federal Contracts, Grants and Leases. Here's a Searchable List.

Chen, Yifan, Sean Wilkoff, and Jiro Yoshida, 2024, Amazon Is Coming to Town: Sequential Information Revelation in the Housing Market, *Real Estate Economics* 52, 277–323.

Cheng, Lin, Jacob Jaggi, Mark Yuzhi Yan, and Spencer Young, 2022, Debt Contracting and Changes to the Accounting for Leases: Implications of Accounting Standards Codification 842, *SSRN Working Paper* 4203733.

Chodorow-Reich, Gabriel, 2019, Geographic Cross-Sectional Fiscal Spending Multipliers: What Have We Learned?, *American Economic Journal: Economic Policy* 11, 1–34.

Choi, Soon Hyeok, Robert A. Jarrow, Daniel Lebret, and Crocker H. Liu, 2025, Pricing the Upside Potential to Downside Risk, *SSRN Working Paper* 5201008.

Christopoulos, Andreas D., Robert A. Jarrow, and Yildiray Yildirim, 2008, Commercial Mortgage-Backed Securities (CMBS) and Market Efficiency with Respect to Costly Information, *Real Estate Economics* 36, 441–498.

Cohn, Jonathan B., Zack Liu, and Malcolm I. Wardlaw, 2022, Count (and Count-Like) Data in Finance, *Journal of Financial Economics* 146, 529–551.

Col, Burcin, Art Durnev, and Alexander Molchanov, 2017, Foreign Risk, Domestic Problem: Capital Allocation and Firm Performance Under Political Instability, *Management Science* 64, 2102–2125.

Colliers Insights, 2018, GSA Lease Terminations: How Often Do They Occur?

CommercialEdge, 2025, CBD Office Markets Struggle Amid High Vacancies, Discounted Sales and Slowed Development.

Conley, Timothy G., 2008, Spatial Econometrics, in Steven N. Durlauf, and Lawrence E. Blume, eds., *Microeconometrics*, 303–313 (London: Palgrave Macmillan).

CoStar News, 2025a, Federal Government Scraps Multiple Office Leases, Looks for More Across Country.

CoStar News, 2025b, US Government Has Now Canceled About One in 10 Federal Real Estate Leases.

Cresa, 2025, Washington, DC Market Report - Q2 2025.

Cushman & Wakefield, 2025, Washington, D.C. Office MarketBeat.

Diamond, Rebecca, and Tim McQuade, 2019, Who Wants Affordable Housing in Their Backyard? An Equilibrium Analysis of Low-Income Property Development, *Journal of Political Economy* 127, 1063–1117.

Diener, Nicolas, Robert Jarrow, and Philip Protter, 2012, Relating Top-Down with Bottom-Up Approaches in the Evaluation of ABS with Large Collateral Pools, *International Journal of Theoretical and Applied Finance* 15, 1250011.

Dupor, Bill, and Rodrigo Guerrero, 2017, Local And Aggregate Fiscal Policy Multipliers, *Journal of Monetary Economics* 92, 16–30.

Duranton, Gilles, and William Kerr, 2018, Chapter 18: The Logic of Agglomeration, in *The New Oxford Handbook of Economic Geography*, 347–365 (Oxford University Press).

Federal Acquisition Regulation, 2025, Termination for Convenience of the Government (Fixed-Price).

Fitch Ratings, 2025, U.S. CMBS with Govt Lease Exposure Face Increased Default, Loss Risk.

Flynn, Sean, and Andra Ghent, 2018, Competition and Credit Ratings After the Fall, *Management Science* 64, 1672–1692.

Flynn, Sean, Andra C. Ghent, and Vasudha Nair, 2024, Determinants and Consequences of Return to Office Policies, *SSRN Working Paper* 4757876.

Fuster, Andreas, David Lucca, and James Vickery, 2025, Mortgage-Backed Securities, *FRB of Philadelphia Working Paper* 25-10.

Gelman, Michael, Shachar Kariv, Matthew D. Shapiro, Dan Silverman, and Steven Tadelis, 2020, How Individuals Respond to a Liquidity Shock: Evidence from the 2013 Government Shutdown, *Journal of Public Economics* 189, 103917.

Glancy, David, and J. Christina Wang, 2023, Lease Expirations and CRE Property Performance, *FRB of Boston Working Paper* 23-10.

Goldsmith-Pinkham, Paul, Peter Hull, and Michal Kolesár, 2024, Contamination Bias in Linear Regressions, *American Economic Review* 114, 4015–4051.

Goldsmith-Pinkham, Paul, and Tianshu Lyu, 2025, Causal Inference in Financial Event Studies, Technical report, Available at arXiv:2511.15123.

Goodell, John W., and Sami Vähämaa, 2013, US Presidential Elections and Implied Volatility: The Role of Political Uncertainty, *Journal of Banking & Finance* 37, 1108–1117.

Goodman-Bacon, Andrew, 2021, Difference-In-Differences with Variation in Treatment Timing, *Journal of Econometrics* 225, 254–277.

Greenwald, Daniel, 2019, Firm Debt Covenants and the Macroeconomy: The Interest Coverage Channel, *SSRN Working Paper* 3535221.

Gupta, Arpit, Vrinda Mittal, and Stijn Van Nieuwerburgh, 2025, Work From Home and the Office Real Estate Apocalypse, *forthcoming, American Economic Review* .

Gupta, Arpit, Stijn Van Nieuwerburgh, and Constantine Kontokosta, 2022, Take the Q Train: Value Capture of Public Infrastructure Projects, *Journal of Urban Economics* 129.

Hassan, Tarek A., Stephan Hollander, Laurence van Lent, and Ahmed Tahoun, 2019, Firm-Level Political Risk: Measurement and Effects, *Quarterly Journal of Economics* 134, 2135–2202.

Herpfer, Christoph, Gonzalo Maturana, and Andrew Teodorescu, 2023, Intrinsic Motivation, Human Capital, and Productivity: Evidence from Government Shutdowns, *SSRN Working Paper* 3962279.

Holland & Knight, 2025, GSA Lease Terminations: Lessorsâ Rights and Responsibilities.

Hou, Young, Christopher Poliquin, Mariko Sakakibara, and Marco Testoni, 2025, Using Smartphone Location Data for Strategy Research, *SSRN Working Paper* 4796679.

Jarrow, Robert A., 2018, *Continuous-Time Asset Pricing Theory*, first edition (Springer International Publishing).

Jarrow, Robert A., 2021, The Economics of Insurance: A Derivatives-Based Approach, *Annual Review of Financial Economics* 13, 79–110.

Jiang, Eric Xuewei, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2024, Monetary Tightening and U.S. Bank Fragility in 2023: Mark-to-Market Losses and Uninsured Depositor Runs?, *Journal of Financial Economics* 159.

Jiang, Eric Xuewei, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2025, Monetary Tightening, Commercial Real Estate Distress, and US Bank Fragility, *forthcoming, Journal of Political Economy Macroeconomics* .

Julio, Brandon, and Youngsuk Yook, 2012, Political Uncertainty and Corporate Investment Cycles, *Journal of Finance* 67, 45–83.

Kelly, Bryan, Luboš Pástor, and Pietro Veronesi, 2016, The Price of Political Uncertainty: Theory and Evidence from the Option Market, *Journal of Finance* 71, 2417–2480.

Konishi, Hideo, and Michael T. Sandfort, 2003, Anchor Stores, *Journal of Urban Economics* 53, 413 – 435.

LaPoint, Cameron, 2022, Property Tax Sales, Private Capital, and Gentrification in the U.S., *SSRN Working Paper* 4219360.

Miyauchi, Yuhei, Kentaro Nakajima, and Stephen J. Redding, 2025, The Economics of Spatial Mobility: Theory and Evidence Using Smartphone Data, *forthcoming, Quarterly Journal of Economics* .

Mooradian, Robert M., and Shiawee X. Yang, 2000, Cancellation Strategies in Commercial Real Estate Leasing, *Real Estate Economics* 28, 65–88.

Nakamura, Emi, and Jón Steinsson, 2014, Fiscal Stimulus in a Monetary Union: Evidence From US Regions, *American Economic Review* 104, 753–792.

New York Times, 2025, How Did DOGE Disrupt So Much While Saving So Little?

Newey, Whitney K., and Kenneth D. West, 1987, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703–708.

OECD, 2025, Chapter 11: Procurement, in *Government at a Glance 2025*, 145–156 (OECD Publishing).

Office of Management and Budget, 2024, OMB Report to Congress on Telework and Real Property Utilization.

Pashigian, B. Peter, and Eric D. Gould, 1998, Internalizing Externalities: The Pricing of Space in Shopping Malls, *Journal of Law and Economics* 41, 115–142.

Pasquariello, Paolo, and Christina Zafeiridou, 2014, Political Uncertainty and Financial Market Quality, *Michigan Ross School of Business Working Paper Series* 1232.

Pástor, Luboš, and Pietro Veronesi, 2012, Uncertainty about Government Policy and Stock Prices, *Journal of Finance* 67, 1219–1264.

Pástor, Luboš, and Pietro Veronesi, 2013, Political Uncertainty and Risk Premia, *Journal of Financial Economics* 110, 520–545.

Politico, 2025, Inside GSA's Mass Lease Terminations.

Qian, Franklin, Qianyang Zhang, and Xiang Zhang, 2024, Identifying Agglomeration Spillovers: Evidence from Grocery Store Openings, Technical report, UNC Chapel Hill.

Rambachan, Ashesh, and Jonathan Roth, 2023, A More Credible Approach to Parallel Trends, *Review of Economic Studies* 90, 2555–2591.

Rosenthal, Stuart S., and William C. Strange, 2020, How Close Is Close? The Spatial Reach of Agglomeration Economies, *Journal of Economic Perspectives* 34, 27–49.

Roth, Jonathan, 2022, Pretest with Caution: Event-Study Estimates after Testing for Parallel Trends, *American Economic Review: Insights* 4, 305–322.

Saiegh, Sebastian M., 2023, Fear and Loathing on Wall Street: Electoral Risk Hedging in the United States (1986-2020), *Journal of Political Economy and Political Institutions* 4, 311–331.

Sakong, Jung, and Alexander Zentefis, 2025, What Drives Disparities in Bank Branch Use? A Geospatial Analysis, *SSRN Working Paper* 4621778.

Suárez Serrato, Juan Carlos, and Philippe Wingender, 2016, Estimating Local Fiscal Multipliers, Working Paper 22425, National Bureau of Economic Research.

Trepp, 2022, Trepp Pricing Service: Daily CMBS Valuation and Coverage, Product memo, Trepp, LLC, Accessed 2026-01-14.

Trepp Research, 2025, DOGE Cuts Begin on GSA-Leased Office Space: February Data Update.

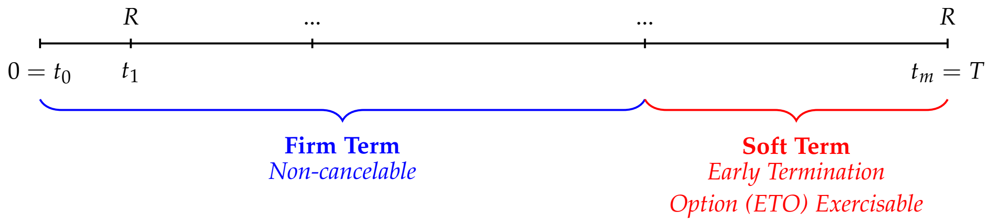
U.S. General Services Administration, 2023, Lease Offer Submission Guide (LOSG).

U.S. General Services Administration, 2024, GSA Lease Policies and Templates.

Yahoo Finance, 2025, Government Looks To Cut 100 Federal Leases In D.C. Causing Market Disruption.

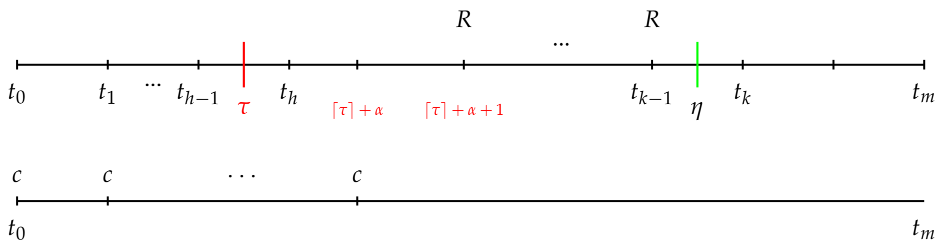
FIGURES

FIGURE 1. Federal Lease Term Structure with an Early Termination Option (ETO)



Notes: The figure plots the timing of a typical lease term divided into a ten-year firm term and a five-year soft term. During the firm term, the lease is non-cancelable and the early termination option is unavailable. In the soft term, the tenant may exercise the early termination option. The timeline lengths reflect that for the median federal lease contract, the firm term lasts ten years, and the soft term lasts five years.

FIGURE 2. Timeline of Key Events with an Exercised ETO



Notes: The figure plots the sequence of key events following an exercised ETO during the soft term of a federal lease. In the above timeline, the initial event, denoted by τ, marks the time at which the federal tenant issues formal notice of its intent to terminate, subject to the required advance notice period α. Upon expiration of this notice period, the landlord assumes responsibility for the vacated rent obligation until a replacement tenant is secured at a subsequent date, denoted by η. The bottom timeline illustrates that federal tenants pay an insurance premium c for holding a long position on their ETO.

FIGURE 3. Termination Right and Rent Abatement Clauses for GSA Leases

A. Termination Rights and (Non-)Renewal Clauses

1.05 TERMINATION RIGHTS (OCT 2016)

The Government may terminate this Lease, in whole or in parts, at any time effective after the Firm Term of this Lease, by providing not less than XX days' prior written notice to the Lessor. The effective date of the termination shall be the day following the expiration of the required notice period or the termination date set forth in the notice, whichever is later. No rental shall accrue after the effective date of termination.

1.06 RENEWAL RIGHTS (OCT 2016)

A. This Lease may be renewed at the option of the Government for a term of XX **YEARS** at the following rental rate(s):

	OPTION TERM, YEARS XX - XX	
	ANNUAL RENT	ANNUAL RATE / RSF
SHELL RENTAL RATE	$XX	$XX
OPERATING COSTS	OPERATING COST BASE SHALL CONTINUE FROM THE EFFECTIVE YEAR OF THE LEASE. OPTION TERM IS SUBJECT TO CONTINUING ANNUAL ADJUSTMENTS.	

provided notice is given to the Lessor at least XX days before the end of the original Lease term or any extension thereof; all other terms and conditions of this Lease, as same may have been amended, shall remain in full force and effect during any renewal term.

NOTE: REVISE SUB-PARAGRAPH B IF THE INTENT IS TO SEEK FIRM TERM RENEWAL OPTIONS.

B. Termination rights outlined in the "Termination Rights" paragraph apply to all renewal terms.

B. Rent Abatement Clauses

ACTION REQUIRED: USE IF THERE IS A NEGOTIATED AMOUNT FOR THE VACANT LEASED PREMISES.

NOTE: ALWAYS ATTEMPT TO NEGOTIATE AN ADJUSTMENT FOR VACANT PREMISES PRIOR TO LEASE AWARD. IDEALLY, NEGOTIATE OUT ALL NON-REQUIRED SERVICES AND UTILITIES IN THE VACANT SPACE.

1.15 RATE FOR ADJUSTMENT FOR VACANT LEASED PREMISES (SEP 2013)

In accordance with the paragraph entitled "Adjustment for Vacant Premises," if the Government fails to occupy or vacates the entire or any portion of the Premises prior to expiration of the term of the Lease, the operating costs paid by the Government as part of the rent shall be reduced by $XX.XX per ABOA SF of Space vacated by the Government.

NOTE: ALWAYS ATTEMPT TO NEGOTIATE SOME KIND OF ADJUSTMENT FOR VACANT PREMISES PRIOR TO LEASE AWARD. IDEALLY, NEGOTIATE OUT ALL NON-REQUIRED SERVICES AND UTILITIES IN THE VACANT SPACE.

2.08 GSAR 552.270-16 ADJUSTMENT FOR VACANT PREMISES (DEVIATION) (SEP 2022)

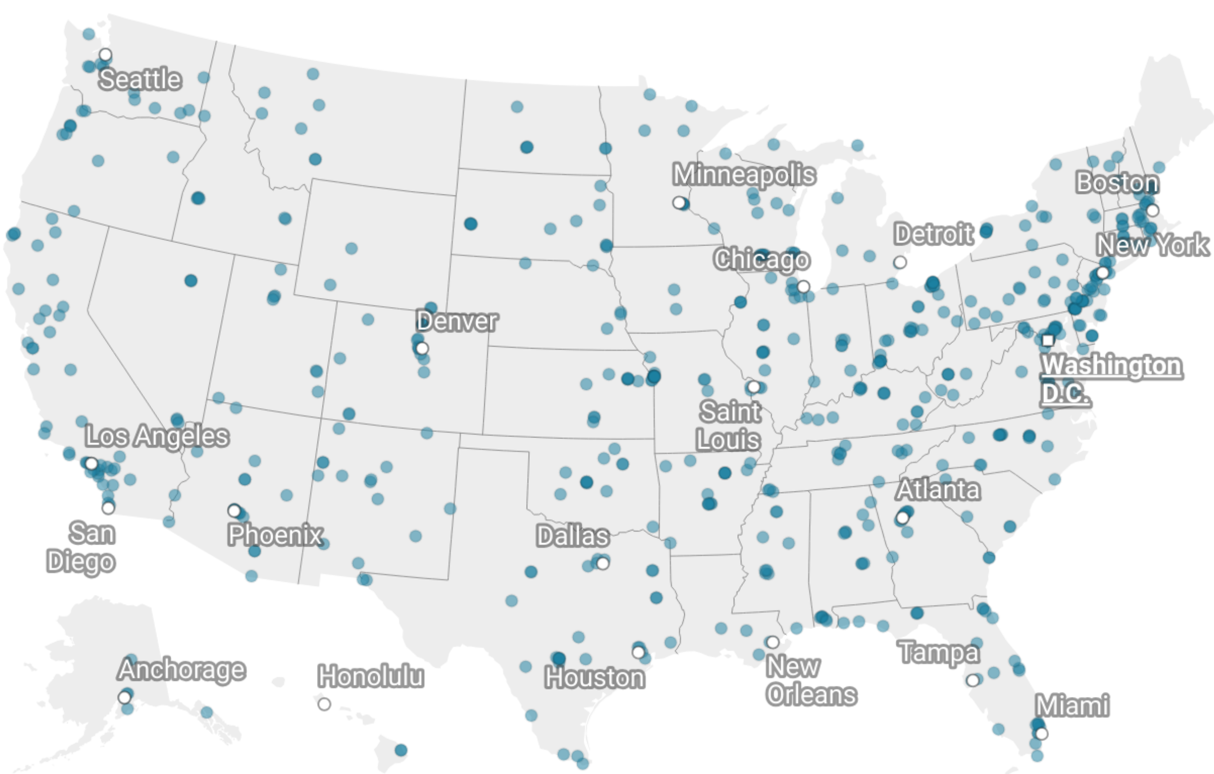
(a) If the Government fails to occupy any portion of the leased premises or vacates the premises in whole or in part prior to expiration of the term of the lease, the rental rate and the base for operating cost adjustments will be reduced using the figure specified in the "Rate for Adjustment for Vacant Leased Premises" paragraph of this Lease.

(b) If no rate reduction has been established in this lease, the rate will be reduced by that portion of the costs per ABOA square foot of operating expenses not required to maintain the space.

(c) Said reduction shall occur after the Government gives 30 calendar days' prior notice to the Lessor and shall continue in effect until the Government occupies the vacant premises or the lease expires or is terminated.

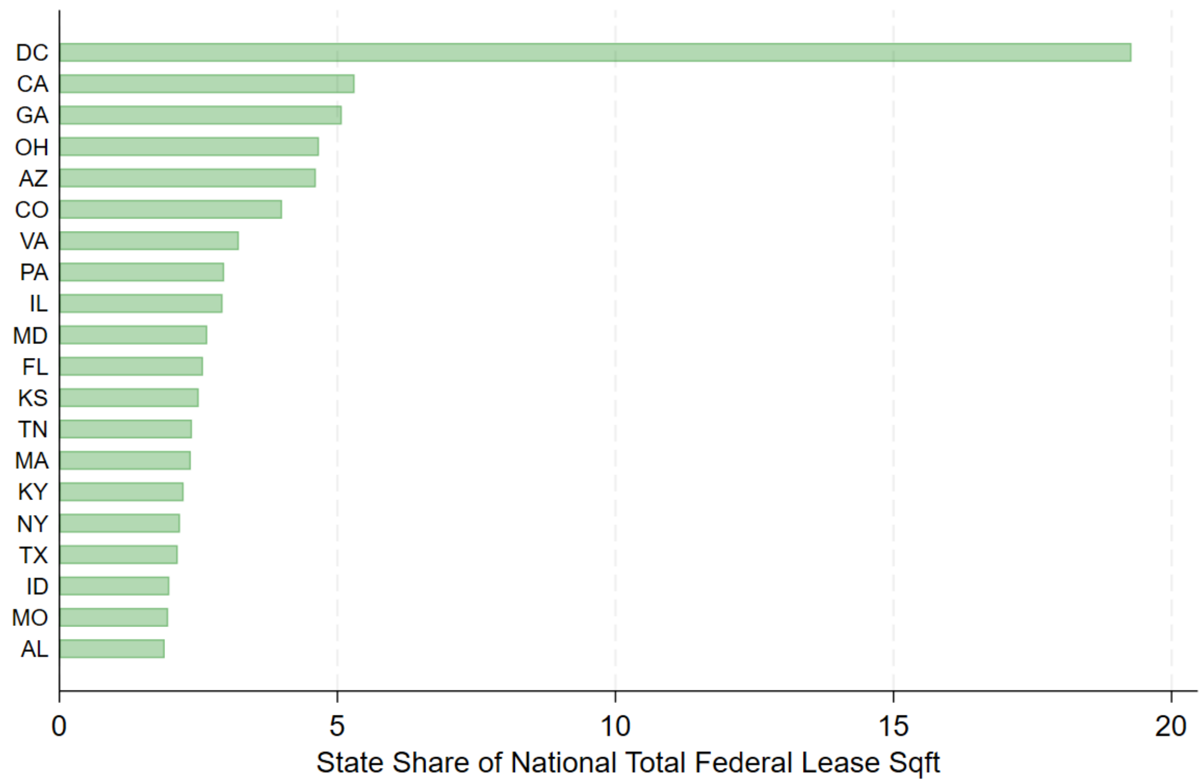
Notes: The figure consists of sample GSA termination right clauses in Panel A (§1.05 and §1.06) and the vacant premises clauses in Panel B (§ 1.15 and § 2.08). The §1.05 clause stipulates the terms of the government's early termination option (ETO). §1.06 indicates that, by default, termination rights apply to any renewal terms as well. The §1.15 clause provides a rent abatement if the federal tenant vacates the premise partially at any time before its expiration, including in the event that the government exits during the soft term of the lease by exercising its ETO. §2.08 clarifies that if the GSA and private contractor did not agree to rent abatement rate in §1.15, then the rent abatement is determined by the fraction of operating expenditures attributable to the leasable square footage (ABOA) occupied by the GSA tenant. ANSI/BOMA Office Area (ABOA) means the area "where a tenant normally houses personnel, and/or furniture, for which a measurement is to be computed," as stated by the American National Standards Institute/Building Owners and Managers Association (ANSI/BOMA) publication, Z65.1-1996. *Source*: GSA Global Lease Template L100, revised October 2023.

FIGURE 4. Federal Lease Termination Footprint by State



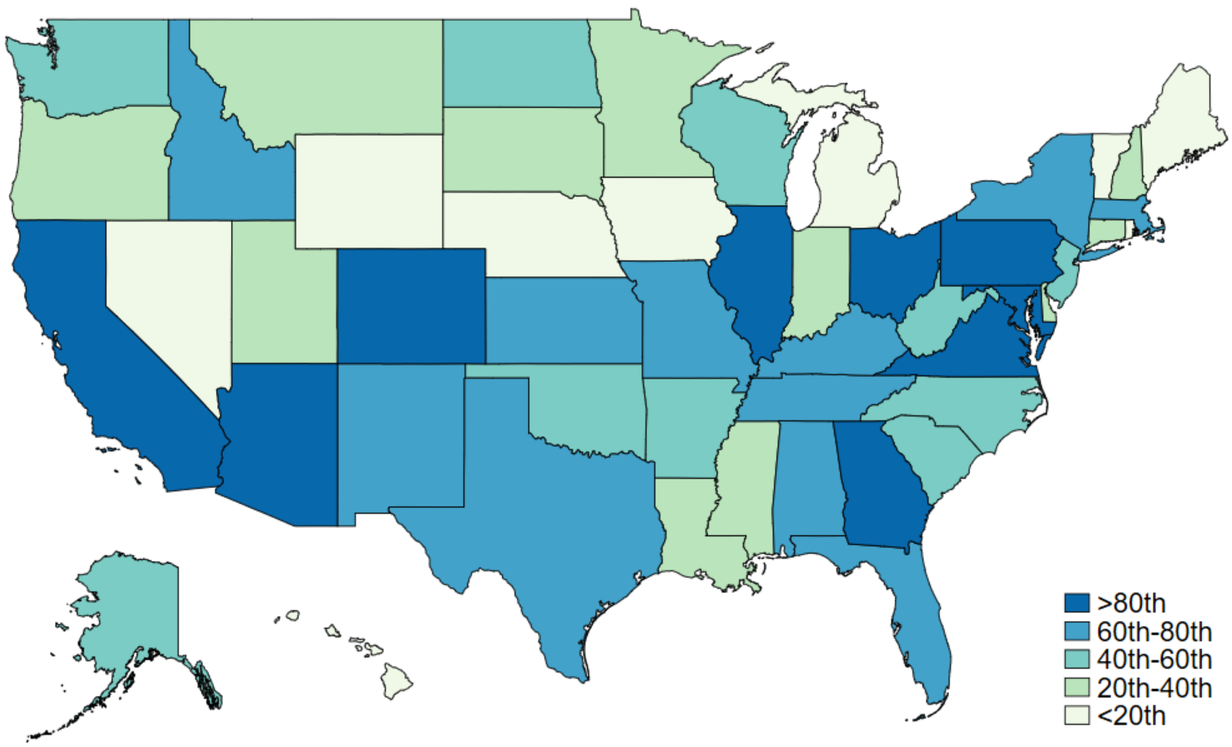
Notes: The map plots a snapshot of the DOGE-terminated federal leases as of March 24, 2025 using Datawrapper. On March 24, 2025, the number of terminated leases reached 679. *Sources*: Department of Government Efficiency, Arco Real Estate Solutions, JLL Federal Lease Termination Tracker.

FIGURE 5. Top States in Terminated Average Square Footage by Federal Lease



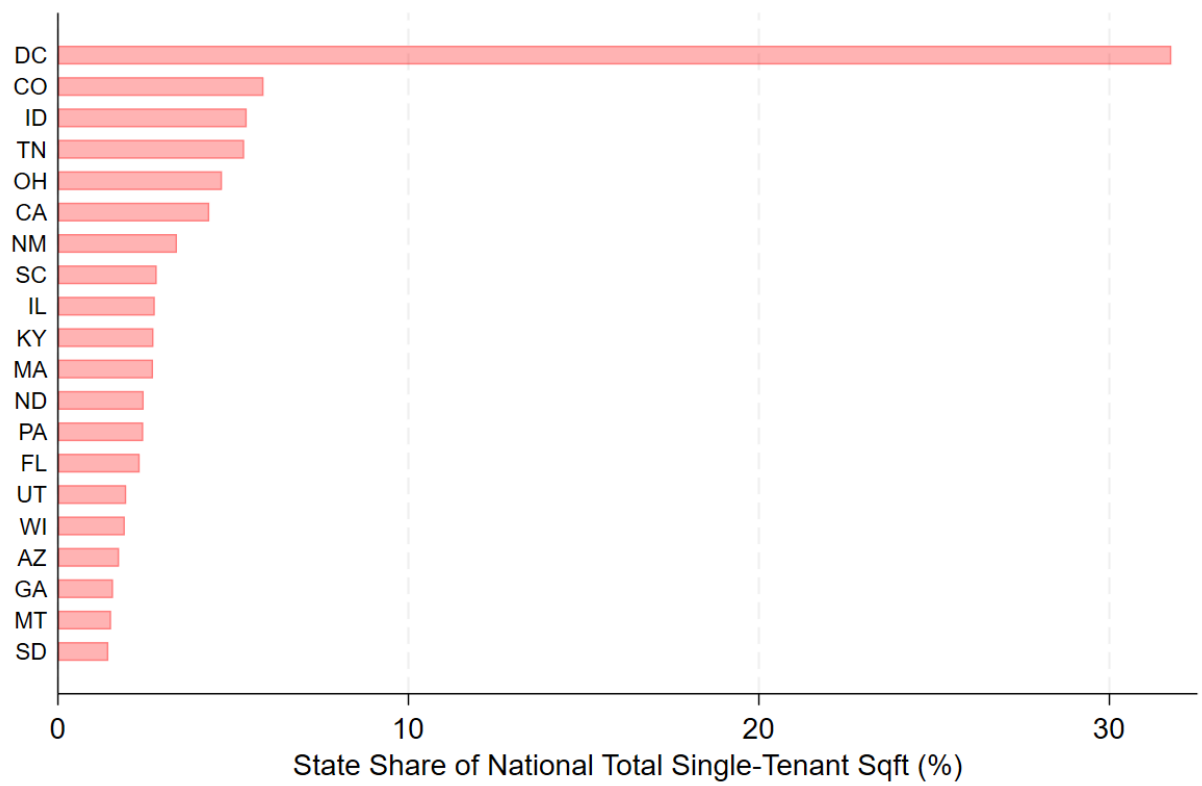
Notes: The bar plot reports the top 19 states and District of Columbia in descending order by share of the national total square footage of terminated federal leases, as of March 24, 2025. *Source*: Department of Government Efficiency, Arco Real Estate Solutions, JLL Federal Lease Termination Tracker.

FIGURE 6. Fraction of Total Square Footage Terminated by State



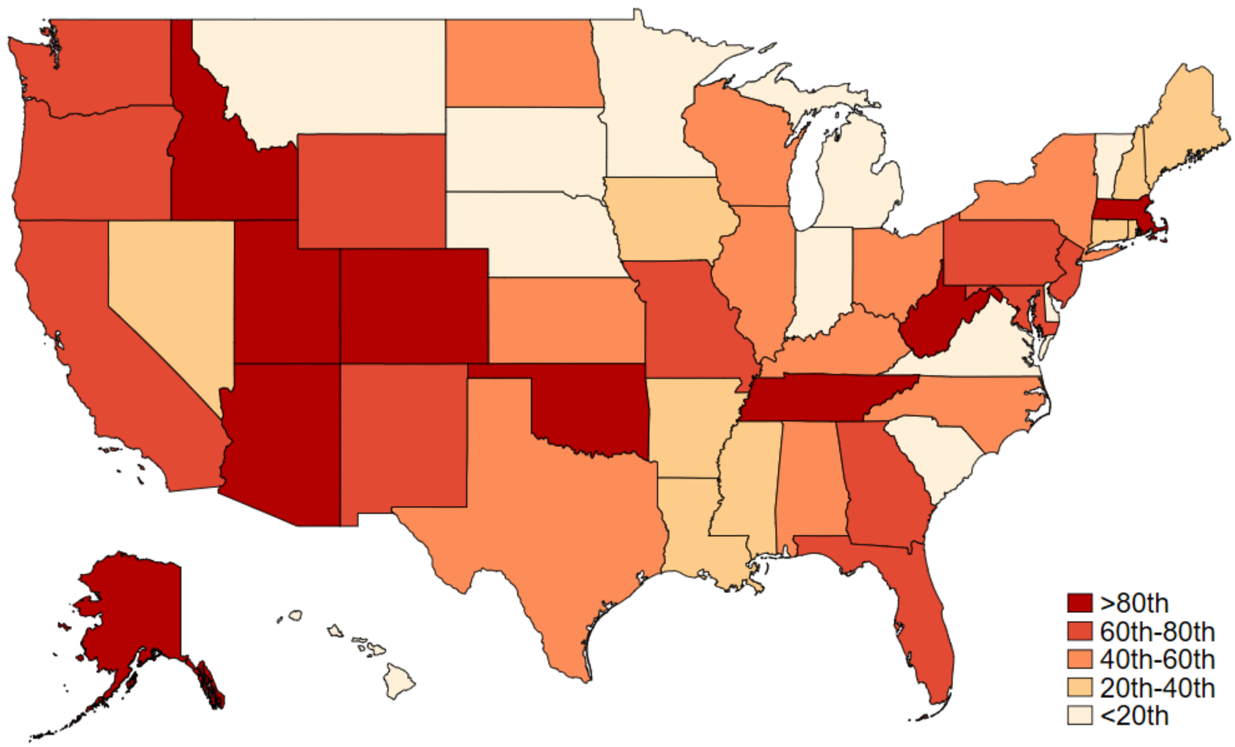
Notes: The map displays the fraction of total square footage in terminated federal leases by state in quintiles as of March 24, 2025. *Sources*: Department of Government Efficiency, Arco Real Estate Solutions, JLL Federal Lease Termination Tracker.

FIGURE 7. Top States in Single-Tenancy Federal Lease Concentration



Notes: The bar plot shows the top 19 states and District of Columbia in descending order by their share of the national total single-tenant federal-lease square footage, as of March 24, 2025. *Sources*: Department of Government Efficiency, Arco Real Estate Solutions, JLL Federal Lease Termination Tracker.

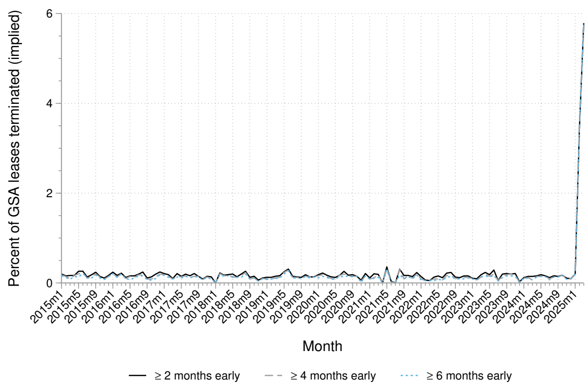
FIGURE 8. Fraction of Total Savings due to Terminated Federal Leases by State



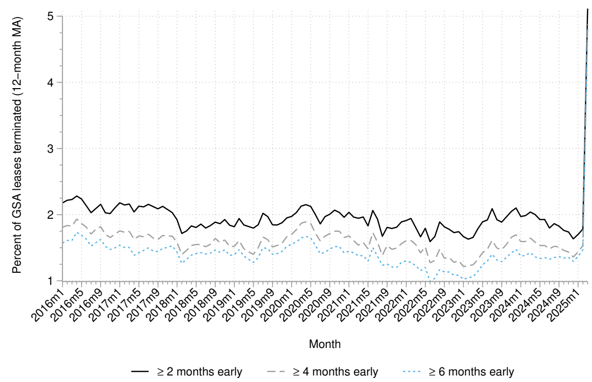
Notes: The map displays the fraction of total savings reported by the Department of Government Efficiency (DOGE) due to federal lease terminations by state in quintiles as of March 24, 2025. *Source*: Department of Government Efficiency, Arco Real Estate Solutions, JLL Federal Lease Termination Tracker.

FIGURE 9. GSA Lease Cancellation Rates Implied by GSA Inventory and DOGE Announcements

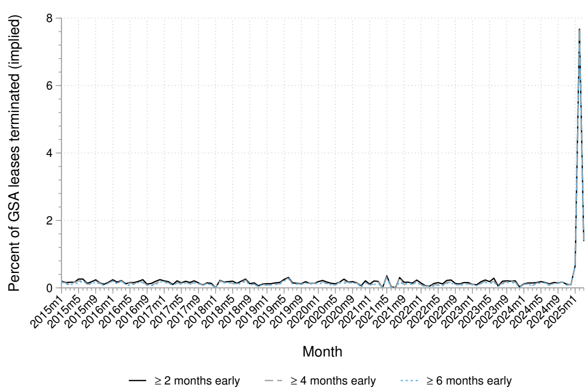
A. Monthly Rates: DOGE Website



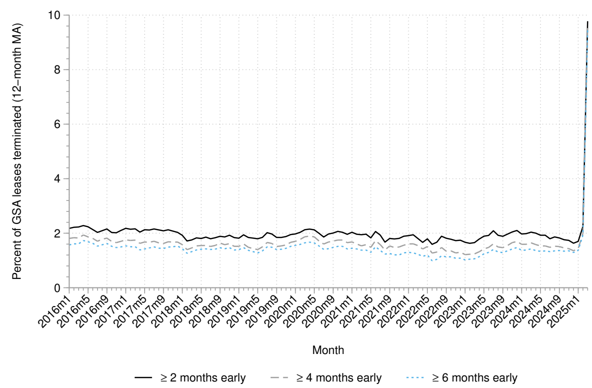
B. 12-Month Rates: DOGE Website



C. Monthly Rates: DOGE Letter

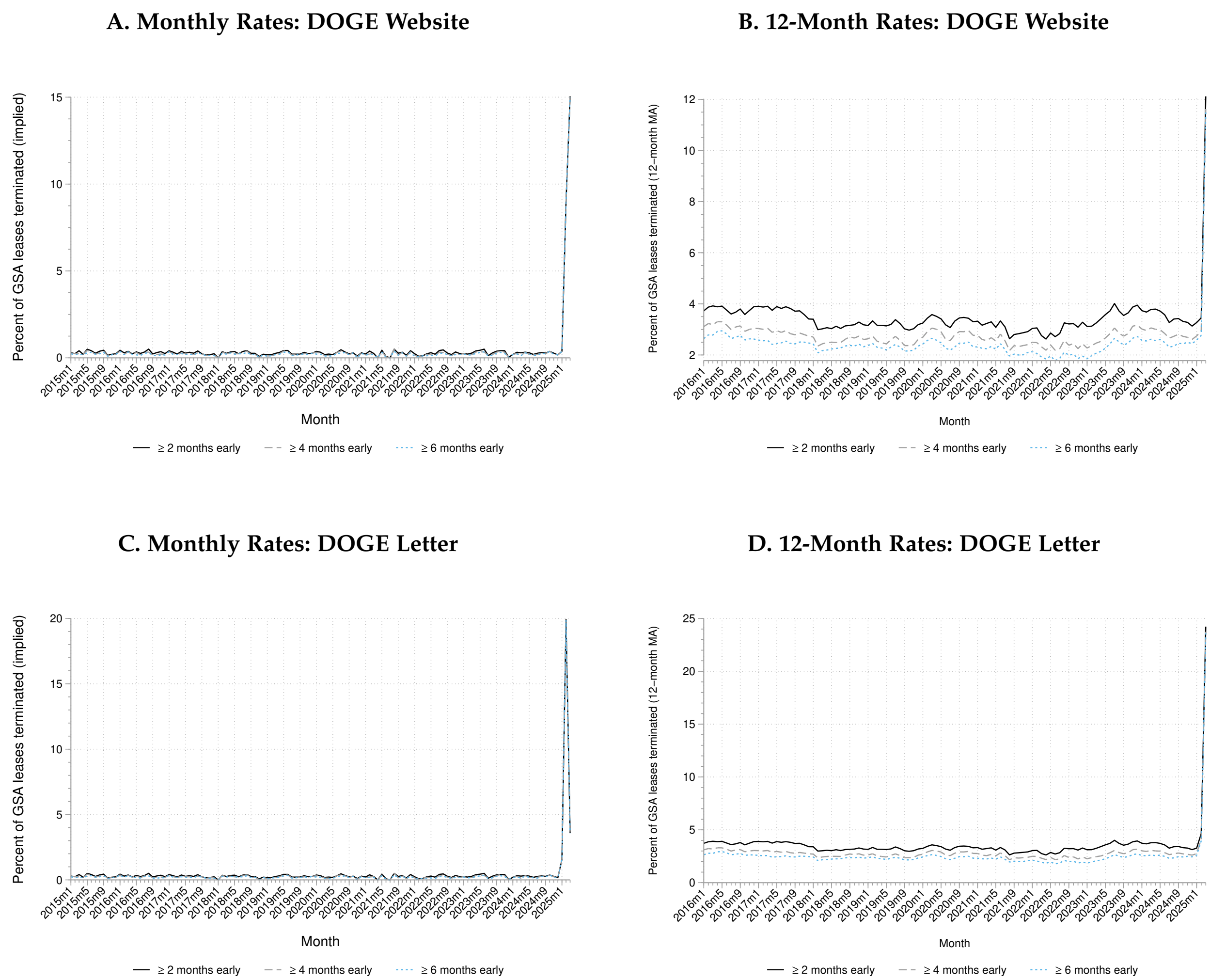


D. 12-Month Rates: DOGE Letter



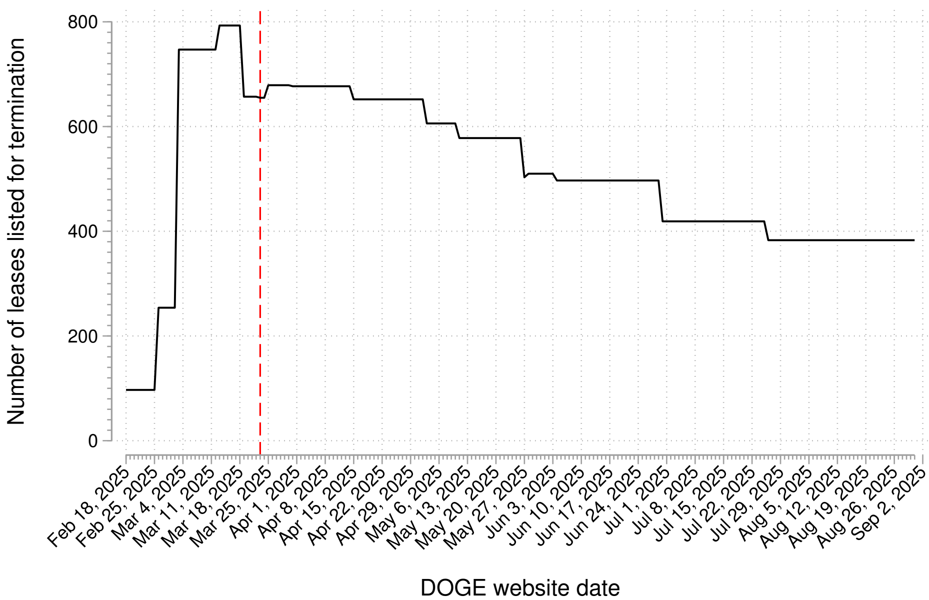
Notes: The figure plots measures of the empirical probability of a GSA lease being canceled before it expires. We plot the monthly termination rate in the left-hand side panels (Panels A and C), whereas Panels B and D plot the 12-month lagged sum of monthly termination rates to account for seasonality. We follow the procedures outlined by Colliers Insights (2018) to identify canceled leases from the historical GSA inventory lists. In particular, we drop leases which were superseded in the same property, or those that were short term or temporary leases which were originally executed with less than three years of firm term (i.e., pre-ETO eligibility period) or those with less than five years in the total term. We keep all leases in the sample regardless of their rentable square footage. We flag a lease as canceled and mark the last month it appears in the GSA inventory panel if it disappears from the panel at least x months prior to lease expiration, where for robustness we vary $x = \{2, 4, 6\}$ months in the figures above. For the months starting in January 2025 when DOGE was created, we add in the implied terminations due to either the timing of leases listed on the DOGE website (Panels A and B) or the timing of the notifications sent by DOGE to the tenants and landlords (Panels C and D). The series are therefore "implied" cancellation rates, because some leases were removed from the DOGE termination list after March 2025. *Sources*: Department of Government Efficiency, Inventory of GSA Owned and Leased Properties.

FIGURE 10. ETO-Eligible Cancellation Rates Implied by GSA Inventory and DOGE Announcements



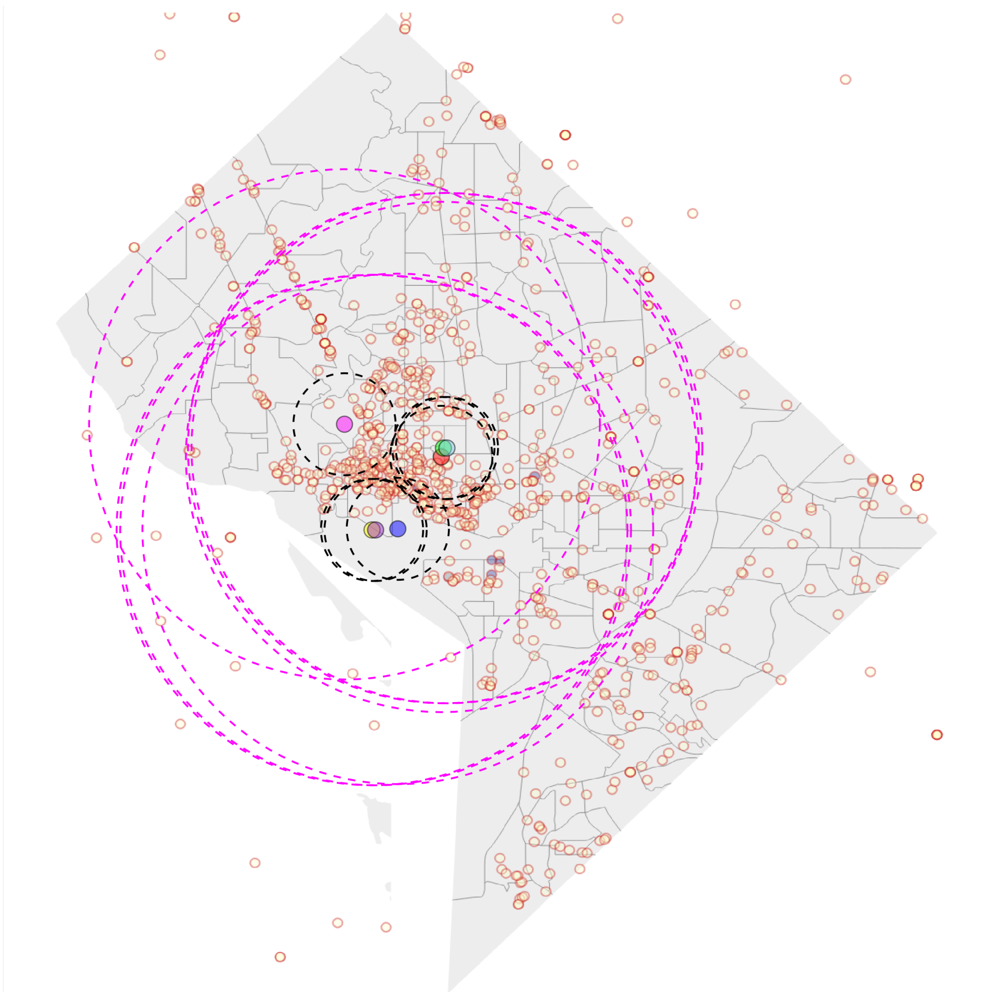
Notes: The figure plots measures of the empirical probability of a GSA lease being canceled before it expires. Relative to Figure 9, the procedures are identical except we now restrict attention to ETO-eligible leases, meaning those which are in the soft term where the date is after the termination right date. We plot the monthly termination rate in the left-hand side panels (Panels A and C), whereas Panels B and D plot the 12-month lagged sum of monthly termination rates to account for seasonality. We follow the procedures outlined by Colliers Insights (2018) to identify canceled leases from the historical GSA inventory lists. In particular, we drop leases which were superseded in the same property, or those that were short term or temporary leases which were originally executed with less than three years of firm term (i.e., pre-ETO eligibility period) or those with less than five years in the total term. We keep all leases in the sample regardless of their rentable square footage. We flag a lease as canceled and mark the last month it appears in the GSA inventory panel if it disappears from the panel at least x months prior to lease expiration, where for robustness we vary $x = \{2, 4, 6\}$ months in the figures above. For the months starting in January 2025 when DOGE was created, we add in the implied terminations due to either the timing of leases listed on the DOGE website (Panels A and B) or the timing of the notifications sent by DOGE to the tenants and landlords (Panels C and D). The series are therefore "implied" cancellation rates, because some leases were removed from the DOGE termination list after March 2025. *Sources*: Department of Government Efficiency, Inventory of GSA Owned and Leased Properties.

FIGURE 11. Number of Canceled GSA Leases Announced by DOGE: February 18, 2025 – August 31, 2025



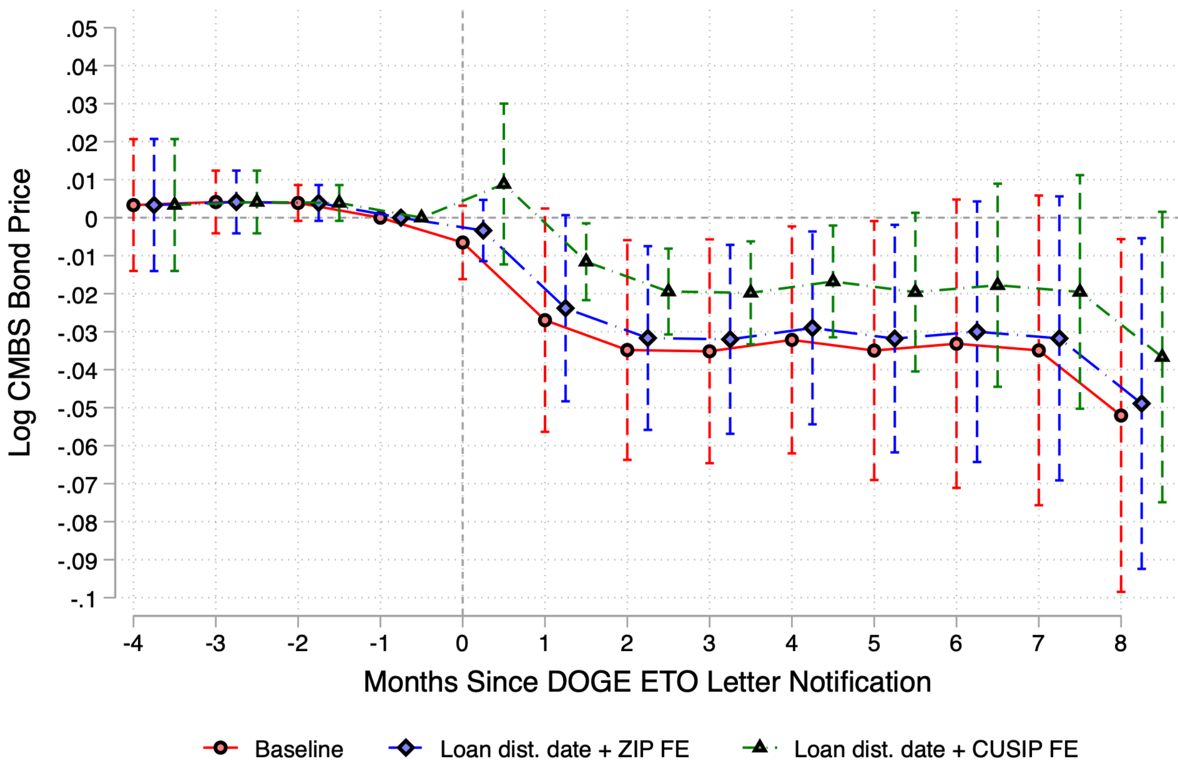
Notes: We plot the number of GSA leases listed as terminated on the DOGE lease savings website since the first date the information was published on February 18, 2025 up until August 31, 2025. The number of canceled leases peaked at 793 between March 13, 2025 and March 18, 2025. The dashed vertical red line indicates the date (March 23, 2025) that we started scraping the DOGE website. Information on canceled leases prior to March 23, 2025 obtained from the Wayback Machine and various real estate news sources. *Sources*: Department of Government Efficiency, Arco Real Estate Solutions, JLL Federal Lease Termination Tracker.

FIGURE 12. A 1-Mile Inner Ring and 5-Mile Outer Ring around Terminated Washington, D.C. Federal Agency-Leased Office Properties



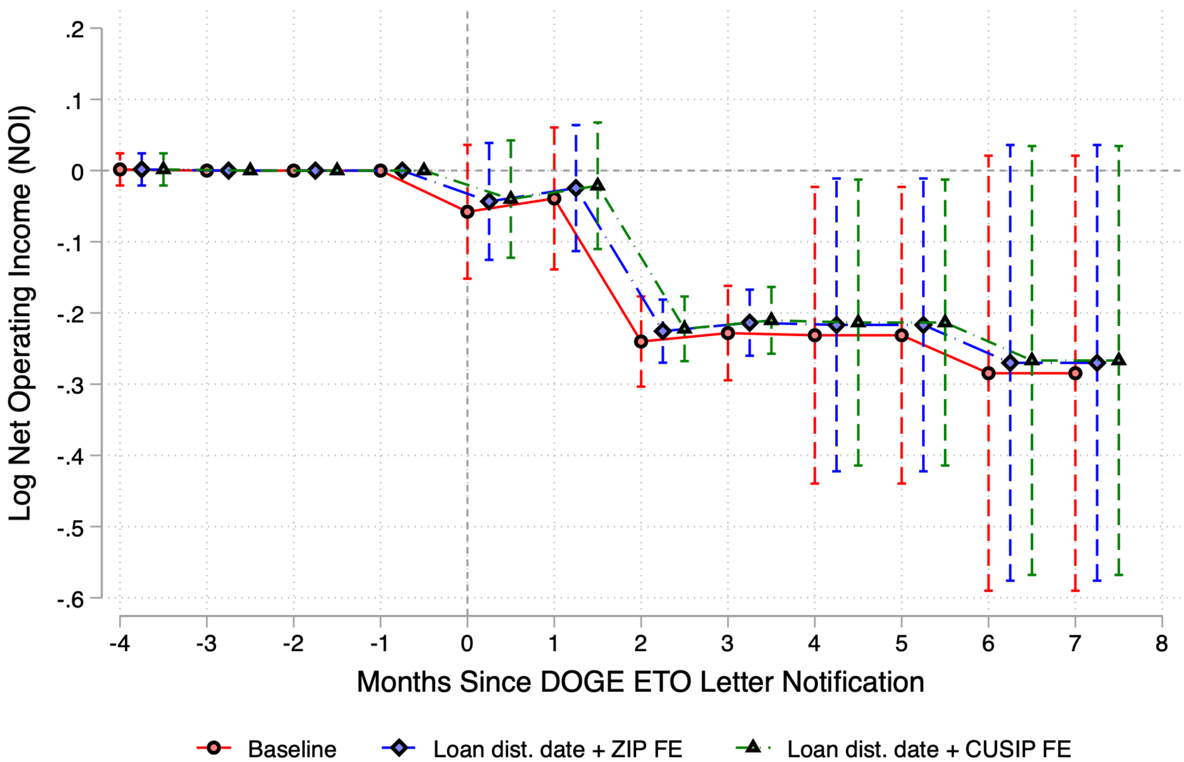
Notes: The map plots a set of 1-mile rings (black) around the seven terminated Washington, D.C. federal lease properties tied to a CMBS deal (with a 5-mile buffer, colored in purple) using Datawrapper. The ring radii correspond to the baseline parametrizations of our spatial difference-in-differences specification, as outlined in Section 5.3. Each colored, filled colored circles inside the black rings on the map represents a DOGE-terminated GSA lease which received formal notification. Yellow points indicate other securitized properties in the Trepp data which were not notified by DOGE. We include properties in the Washington, D.C. MSA, which includes counties in Maryland and Virginia. *Sources*: Department of Government Efficiency.

FIGURE 13. Event Study Effects for Log CMBS Bond Prices around DOGE Announcements



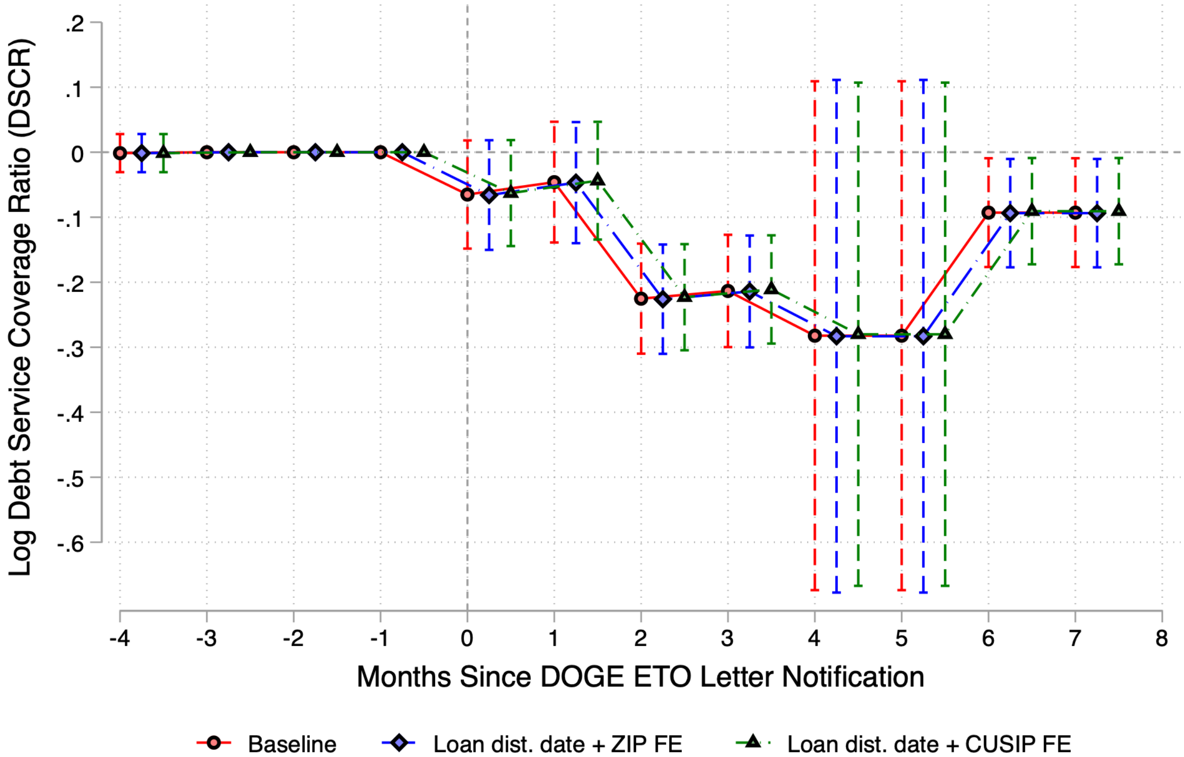
Notes: The figure plots the event study coefficients estimated from versions of equation (5.2) with log CMBS bond price as the outcome variable, applied to a window around the creation of DOGE. The control group includes any units tied to GSA leases which will become ETO eligible during the incoming presidential administration between January 2025 and January 2029. We plot the estimates from three specifications: one without any fixed effects ("Baseline"), then one adding in loan origination year cohort and 5-digit zip code fixed effects ("Loan Distribution Date + ZIP FE"), then replacing zip code with CUSIP fixed effects ("Loan Distribution Date + CUSIP FE"). In each specification, we set $t = -1$ to be the reference period, corresponding to January 2025. This reference period choice reflects the fact that the first set of DOGE terminations for the Washington, D.C. area was sent to landlords and tenants on January 30, 2025. The time window then corresponds to a full 12-month period spanning October 2024 to September 2025. We restrict our sample to the first-loss group (FLG) of tranches. We continue to follow Flynn and Ghent (2018) in defining the FLG as consisting of tranches which have a rating of CCC, or CCC+, or are unrated. 90% confidence intervals obtained from clustering standard errors at the bond CUSIP level.

FIGURE 14. Event Study Effects for Log NOI around DOGE Announcements



Notes: The figure plots the event study coefficients estimated from versions of equation (5.2) with the log net operating income (NOI) as the outcome variable, applied to a window around the creation of DOGE. The control group includes any units tied to GSA leases which will become ETO eligible during the incoming presidential administration between January 2025 and January 2029. We plot the estimates from three specifications: one without any fixed effects ("Baseline"), then one adding in loan origination year cohort and 5-digit zip code fixed effects ("Loan Distribution Date + ZIP FE"), then replacing zip code with CUSIP fixed effects ("Loan Distribution Date + CUSIP FE"). In each specification, we set $t = -1$ to be the reference period, corresponding to January 2025. This reference period choice reflects the fact that the first set of DOGE terminations for the Washington, D.C. area was sent to landlords and tenants on January 30, 2025. The time window then corresponds to a full 12-month period spanning October 2024 to September 2025. We measure NOI in Trepp as of the last reported date. 95% confidence intervals obtained from clustering standard errors at the loan id level.

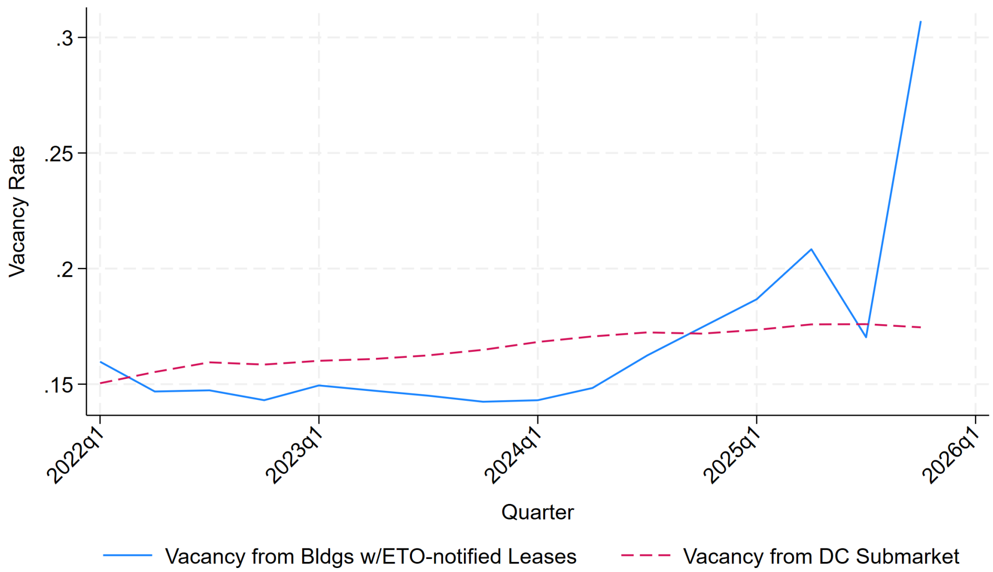
FIGURE 15. Event Study Effects for Log DSCR around DOGE Announcements



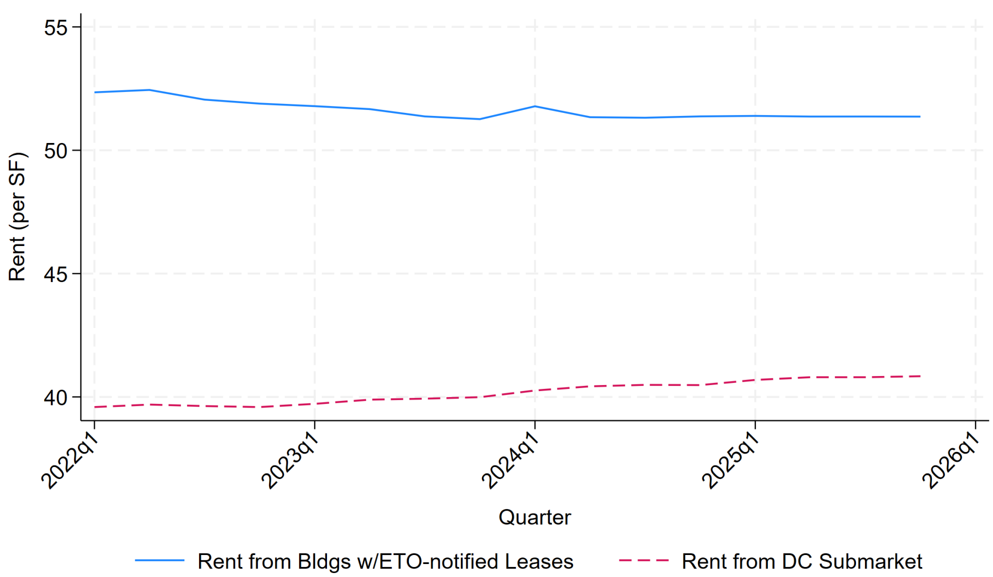
Notes: The figure plots the event study coefficients estimated from versions of equation (5.2) with the log debt service coverage ratio (DSCR) as the outcome variable, applied to a window around the creation of DOGE. The control group includes any units tied to GSA leases which will become ETO eligible during the incoming presidential administration between January 2025 and January 2029. We plot the estimates from three specifications: one without any fixed effects ("Baseline"), then one adding in loan origination year cohort and 5-digit zip code fixed effects ("Loan Distribution Date + ZIP FE"), then replacing zip code with CUSIP fixed effects ("Loan Distribution Date + CUSIP FE"). In each specification, we set $t = -1$ to be the reference period, corresponding to January 2025. This reference period choice reflects the fact that the first set of DOGE terminations for the Washington, D.C. area was sent to landlords and tenants on January 30, 2025. The time window then corresponds to a full 12-month period spanning October 2024 to September 2025. The loan DSCR is defined as the ratio of the underlying property's NOI to debt service for a particular mortgage loan. We measure DSCR in Trepp as of the last reported date. 95% confidence intervals obtained from clustering standard errors at the loan id level.

FIGURE 16. Average Vacancy Rates and Rent for Buildings with ETO-Notified Leases

A. Average Vacancy Rate

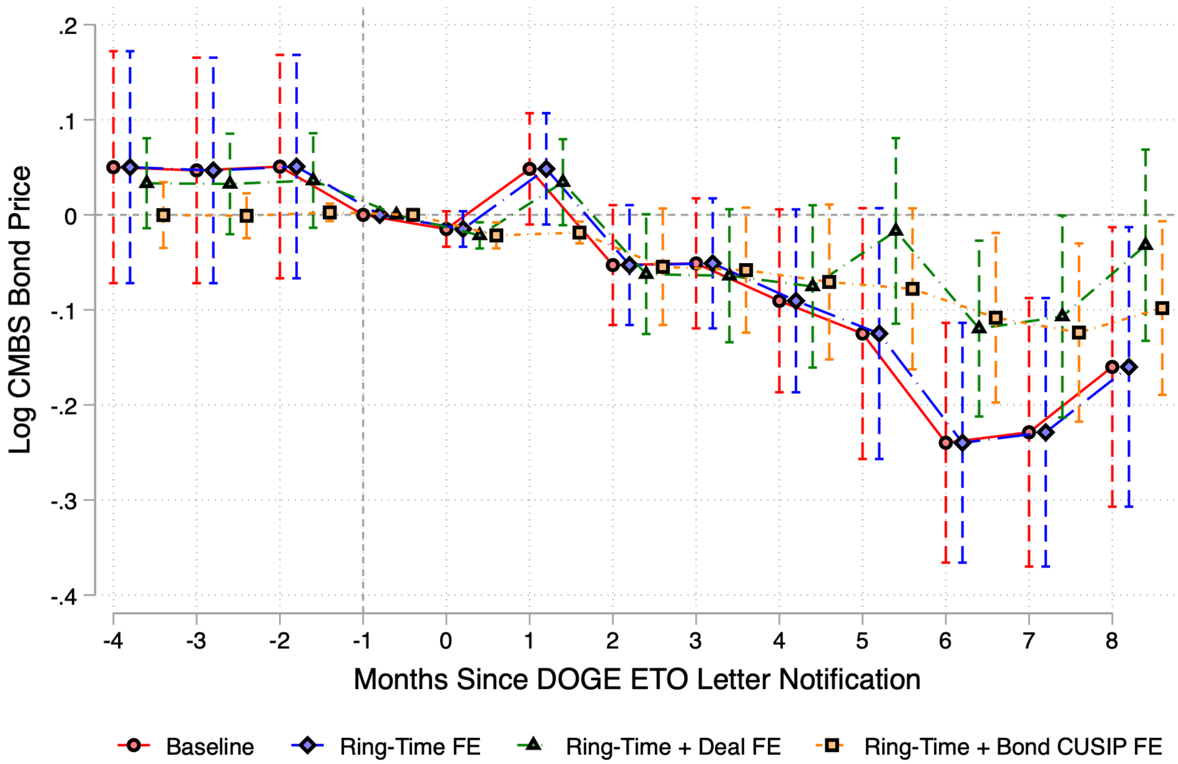


B. Average Rent Per Square Foot



Notes: The figure plots quarterly vacancy rates (Panel A) and rents per square foot (Panel B) for office buildings that contain ETO-notified leases (blue) and for the Washington, D.C. office submarket (red) over 2022Q1–2025Q4. For the ETO-notified sample, both the vacancy and rent series are computed as square-footage-weighted averages, using GSA square footage as weights. Data collected from CoStar as of January 2025.

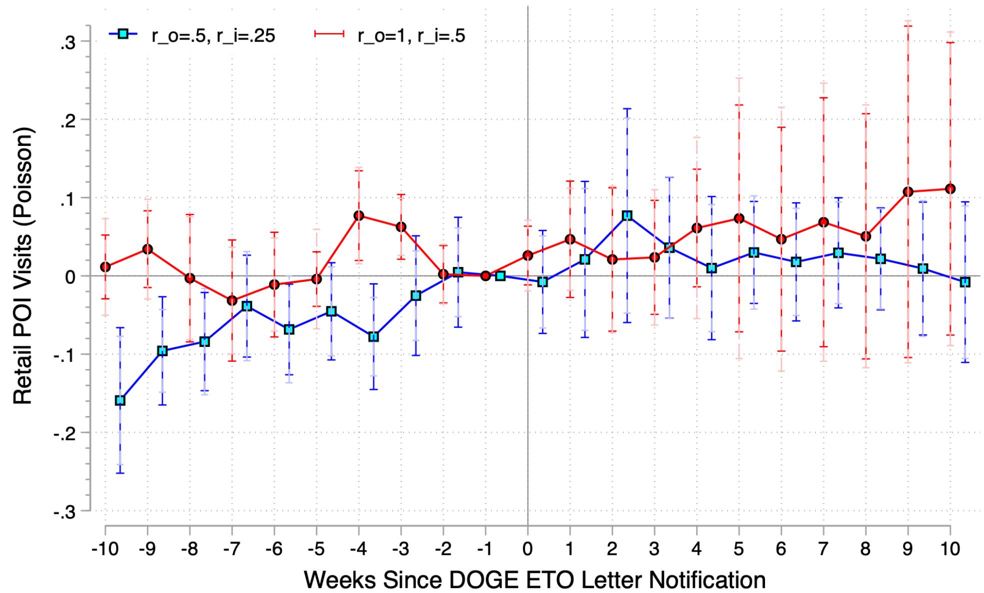
FIGURE 17. Spatial Event Study Effects for Log CMBS Bond Prices
Spillover: 5-mile Radius Private-Tenant Leased Properties



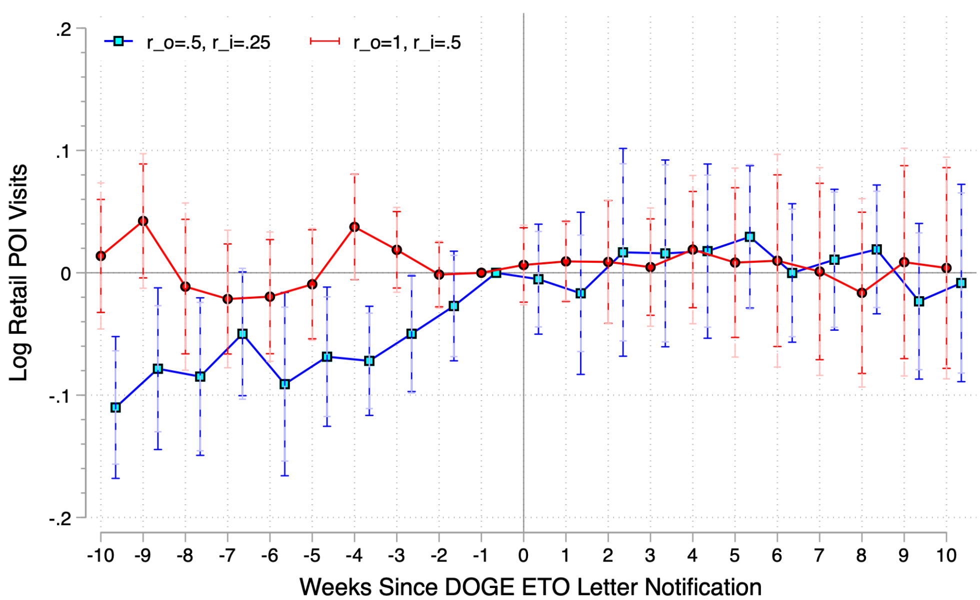
Notes: The figure plots the event study coefficients estimated from dynamic versions of the spatial DiD equation (5.3) with log CMBS bond price as the outcome variable, applied to a window around the creation of DOGE. We plot the estimates from four specifications: one without any fixed effects ("No FE"), then one adding in discrete distance band ring fixed effects and time fixed effects ("Ring-Time FE"), then adding CMBS deal fixed effects ("Deal"), then finally adding CUSIP fixed effects ("Bond CUSIP"). In each specification, we set $t = -1$ to be the reference period, corresponding to January 2025. This reference period choice reflects the fact that the first set of DOGE terminations for the Washington, D.C. area was sent to landlords and tenants on January 30, 2025. We restrict our sample to the first-loss group of tranches with properties that are within the set of 5-mile radii from the properties with the canceled federal leases in Washington, D.C. The time window then corresponds to a full 12-month period spanning October 2024 to September 2025. We restrict our sample to the first-loss group (FLG) of tranches. We continue to follow Flynn and Ghent (2018) in defining the FLG as consisting of tranches which have a rating of CCC, or CCC+, or are unrated. 95% confidence intervals obtained from clustering standard errors at the bond CUSIP level.

FIGURE 18. Null Effects of Terminated Federal Leases on Nearby Retail Foot Traffic

A. Poisson Regression Results



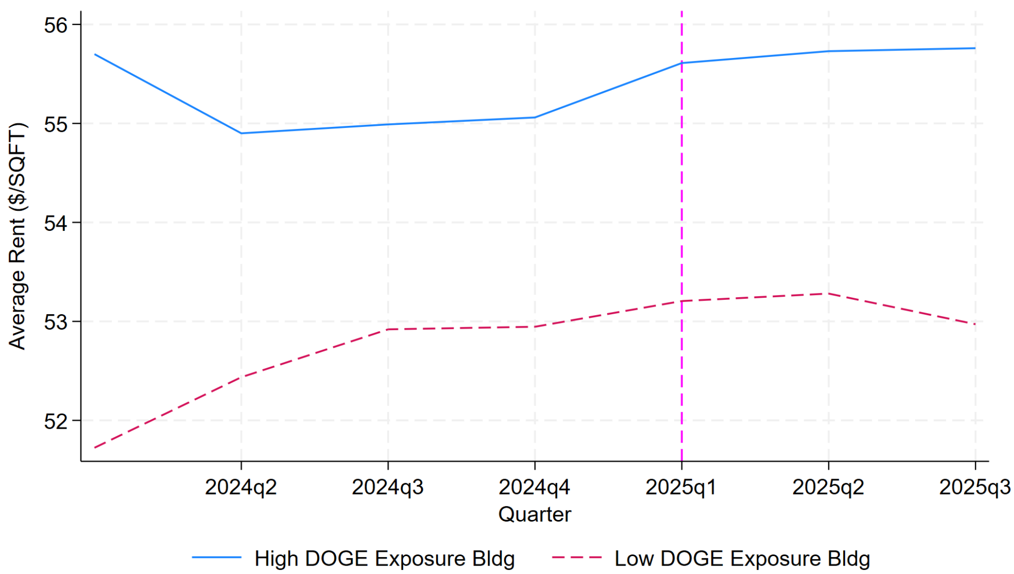
B. OLS Estimation Results



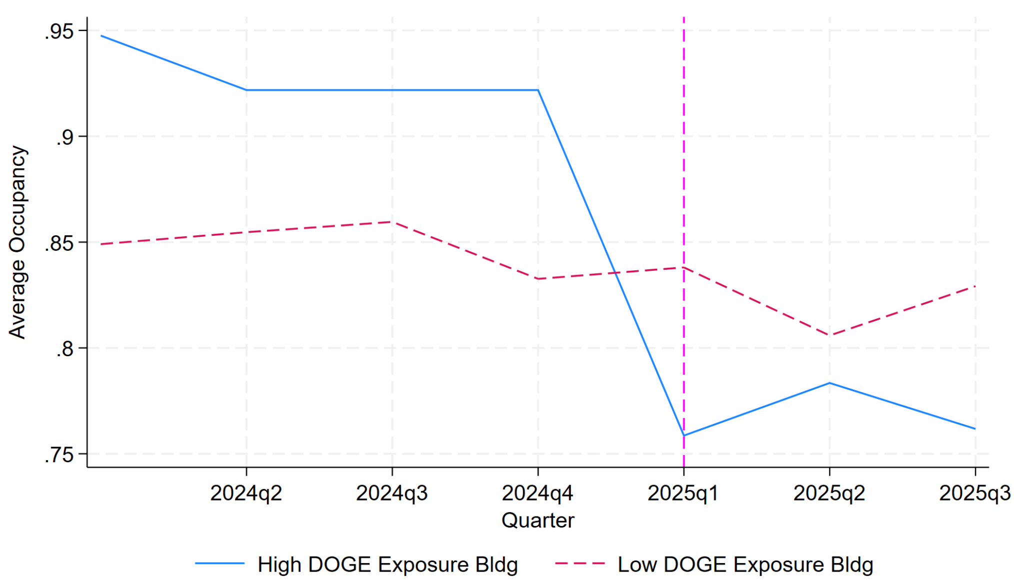
Notes: We plot event study coefficients from estimating the ring difference-in-differences specification (6.1) applied to the Advan Research (2022) foot traffic data for retail points of interest (POI). The outcome variable in all regressions is the number of visits to a POI in a given week t. In Panel A, we assume the number of visits is distributed in a Poisson fashion, following Cohn et al. (2022). In Panel B, we define the outcome as the log number of visits to a retail POI and estimate (6.1) by simple OLS. Since we restrict to a balanced panel of POIs with strictly positive foot traffic in each week, the log transform does not omit any observations. For both the Poisson and OLS approaches, we test for spillovers at different levels of proximity by varying the pair of inner and outer radii $(\mathfrak{r}_{inner}, \mathfrak{r}_{outer})$ from $(0.25, 0.5)$ miles to $(0.5, 1)$ miles. We identify POIs as retail establishments based on whether they belong to one of four two-digit NAICS sectors Retail Trade (sector codes 44–45), Arts, Entertainment, and Recreation (sector code 71) or Accommodation and Food Services (sector code 72). 95% confidence intervals in solid bars obtained from Conley (2008) standard errors with a maximal spatial correlation distance cutoff parameter determined for each set of inner and outer radii $(\mathfrak{r}_{inner}, \mathfrak{r}_{outer})$. 95% confidence intervals in lighter dashed bars obtained from clustering standard errors at the Census block group level.

FIGURE 19. Average Rent and Occupancy Rates for Non-GSA Tenant Properties (within 1-mile Ring of ETO-notified Leases)

A. Average Rent Per Square Foot

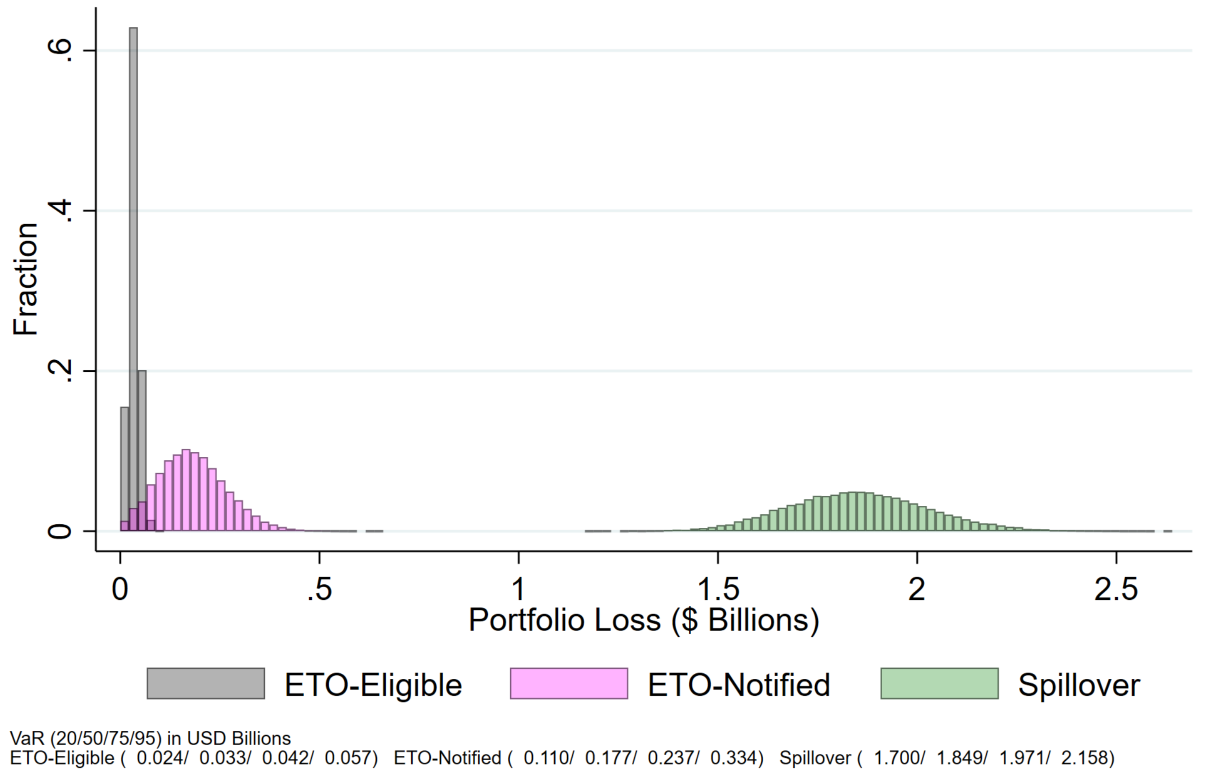


B. Average Occupancy Rate



Notes: The figure plots quarterly average rent per square foot and occupancy rates for private tenant buildings that are within the 1-mile ring of the ETO-notified leases from 2024Q1 to 2025Q4. The dashed vertical line represents 2025Q1. Buildings are classified as high DOGE exposure if their pre-DOGE SF-weighted average tenant's federal contract award share (2015-2024) by DOGE-impacted agencies exceeds the corresponding SF-weighted non-DOGE share, as defined by equations (6.4)–(6.6).

FIGURE 20. Simulated Loss Distributions over 5-Year Shock Horizon
ETO-Eligible (Non-Exercised) vs. ETO-Notified (Exercised) vs. Private Tenant



Notes: The figure plots the simulated portfolio loss distributions under early termination option (ETO) risk for three groups of properties: those that are eligible for ETO exercise but not notified (gray), those that have received formal ETO notifications (pink), and private-lease properties within a 5-mile radius of terminated leases which are indirectly affected through spatial spillovers (green). We define ETO-eligible leases as those which are already in the soft term of the lease as of January 2025 when DOGE was created. Losses are measured in billions of dollars, based on Monte Carlo simulations of property value declines over a one-year horizon using the jump-diffusion processes in (G.3)–(G.5) calibrated to observed termination rates and hedonic value baselines. We summarize the Value at Risk (VaR) for the $1-\alpha \in \{20\%, 50\%, 75\%, 95\%\}$ levels. See Appendix G for details.

Tables

TABLE 1. Telework Policies of Federal Agencies with Securitized GSA Leases in the Washington, D.C. Metro Area (DOGE-Notified & ETO-Eligible Leases)

Status	Agency	Days/Week In-Office (est.)
DOGE-notified	Department of Veterans Affairs (VA)	2.5
DOGE-notified	Federal Energy Regulatory Commission (FERC)	2
DOGE-notified	Department of Homeland Security (DHS)	3 (est.)
DOGE-notified	General Services Administration (GSA)	1-2 (est.)
DOGE-notified	Federal Emergency Management Agency (FEMA)	2
DOGE-notified	Department of Housing and Urban Development (HUD)	1
DOGE-notified	Department of the Treasury	2.5
DOGE-notified	Internal Revenue Service (IRS)	2.5
DOGE-notified	Department of Energy (DOE)	3
DOGE-notified	Federal Aviation Administration (FAA)	2
ETO-eligible	GSA National Capital Region 11	2 (est.)
ETO-eligible	U.S. Navy	3
ETO-eligible	Department of Housing and Urban Development (HUD)	1
ETO-eligible	U.S. Federal Labor Relations Authority	3 (est.)
ETO-eligible	The Public Defender Service	3 (est.)
ETO-eligible	U.S. Chemical Safety Board	3 (est.)
ETO-eligible	United States Postal Service (USPS)	3
ETO-eligible	AmeriCorps	3 (est.)
ETO-eligible	Federal Mediation and Conciliation Service	4 (est.)
ETO-eligible	U.S. Office of Government Ethics	1-2 (est.)
ETO-eligible	National Aeronautics and Space Administration (NASA)	2.5 (est.)
ETO-eligible	NASA Office of Inspector General	3 (est.)
ETO-eligible	Office of the Comptroller of the Currency (OCC)	3 (est.)
ETO-eligible	Federal Housing Finance Agency (FHFA)	1-2 (est.)
ETO-eligible	Federal Trade Commission (FTC)	3 (est.)
ETO-eligible	National Endowment for the Humanities (NEH)	1-2 (est.)
ETO-eligible	National Endowment for the Arts (NEA)	2.5 (est.)
ETO-eligible	National Institute for Occupational Safety and Health (NIOSH)	2.5 (est.)
ETO-eligible	Networking and Information Technology Research and Development (NITRD)	2.5 (est.)
ETO-eligible	National Transportation Safety Board (NTSB)	1-2 (est.)
ETO-eligible	Argonne National Laboratory	2.5 (est.)
ETO-eligible	Court Services and Offender Supervision Agency (CSOSA)	1-2 (est.)
ETO-eligible	Pretrial Services Agency for the District of Columbia (PSA)	2.5 (est.)
ETO-eligible	Public Defender Service for the District of Columbia (PDS)	2.5 (est.)
ETO-eligible	Federal Retirement Thrift Investment Board (FRTIB)	3 (est.)
ETO-eligible	U.S. Agency for International Development (USAID)	3
ETO-eligible	National Science Foundation (NSF)	2

Notes: The table reports average in-office days per week for federal agency employees attached to DOGE-notified and ETO-eligible (but not notified by DOGE) General Services Administration (GSA) leases in the Washington, D.C. metro area. We define ETO-eligible leases as those which will be in the soft term of the lease at any point during the current presidential administration, or between January 2025 and January 2029. We extract property addresses for DOGE-notified and ETO-eligible GSA leases in the Trepp data, which consists of properties with CMBS loans (see Section 4 for details). We identify the federal agency tenants located at Trepp GSA addresses from CoStar. We classify by hand estimated average days per week worked from home for each agency from the Appendix of the 2024 OMB Report to Congress on Telework and Real Property Utilization (Office of Management and Budget, 2024) If in-office days per week are not explicitly reported, we infer from the telework participation numbers from the OMB report and estimate the average days per week worked in the office; we denote such cases as ("est.").

TABLE 2. Summary Statistics for CMBS Prices, NOI, and DSCR, by Tranche

	First-loss	Mezzanine	Senior	All
Panel A: ETO Exercisable (Not Notified)				
$Log(P_{bond})$	3.017	3.614	3.476	3.499
$StdDev$	(1.957)	(1.374)	(2.284)	(1.881)
N	2,756	13,935	12,753	29,444
$Log(NOI)$	15.556	15.886	15.898	15.860
$StdDev$	(0.761)	(0.862)	(0.935)	(0.891)
N	2,756	13,386	12,551	28,693
$Log(DSCR)$	0.576	0.502	0.531	0.522
$StdDev$	(0.551)	(0.390)	(0.402)	(0.414)
N	2,714	13,314	12,430	28,458
Panel B: ETO Exercisable (Notified)				
$Log(P_{bond})$	3.019	3.741	3.600	3.566
$StdDev$	(1.232)	(1.407)	(2.113)	(1.731)
N	3,090	8,146	7,940	19,176
$Log(NOI)$	16.697	16.341	16.357	16.406
$StdDev$	(0.149)	(0.433)	(0.434)	(0.421)
N	3,090	8,083	7,665	18,838
$Log(DSCR)$	1.004	0.619	0.663	0.701
$StdDev$	(0.229)	(0.360)	(0.406)	(0.387)
N	3,090	7,969	7,551	18,610
Panel C: Non-GSA Leases				
$Log(P_{bond})$	3.136	3.889	3.547	3.707
$StdDev$	(1.923)	(1.244)	(2.206)	(1.734)
N	92,893	736,294	506,606	1,335,793
$Log(NOI)$	14.682	15.239	15.131	15.155
$StdDev$	(1.605)	(2.080)	(1.915)	(1.988)
N	86,861	619,231	479,258	1,185,350
$Log(DSCR)$	0.390	0.613	0.535	0.565
$StdDev$	(0.502)	(0.628)	(0.522)	(0.582)
N	86,502	599,613	465,892	1,152,007

Notes: The table reports summary statistics in our nationwide Trepp CMBS sample for the mean, standard deviation, and number of observations for the log of CMBS bond price, net operating income (NOI), and debt-service coverage ratio (DSCR). Panel (A), (B), and (C) represent bond-deal-property observations tied to leases that are ETO-exercisable (not notified), ETO-exercisable (notified), and private, respectively. Each column corresponds to the tranche group. We follow Flynn and Ghent (2018) in defining the tranche groups according to their bond ratings. The First Loss Group (FLG) as consists of tranches which have a rating of CCC, or CCC+. We classify mezzanine tranches as those rated below AAA but above CCC+. Senior tranches are those with a AAA rating. Unclassified bonds are those which are "unrated" but do not have a missing value for the rating provided by the rating agencies. In cases where the bond receives multiple agency ratings, we use the S&P rating. If the S&P rating is unavailable, we use the Fitch rating. Finally, if both the S&P and Fitch ratings are unavailable, we adopt the Moody's rating.

TABLE 3. Pooled Difference-in-Differences Regressions for Log CMBS Bond Prices

Control Group	Jan. 2025–Jan. 29 TRD			Jan. 2026–Jan. 29 TRD		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.031*			0.032**		
	(0.016)			(0.016)		
DOGE	-0.409	-0.344*		-0.353	-0.678*	
	(0.274)	(0.176)		(0.325)	(0.342)	
DOGE × *Post*	-0.033*	-0.030*	-0.019	-0.034*	-0.034*	-0.034*
	(0.018)	(0.016)	(0.012)	(0.018)	(0.018)	(0.018)
Adj-R^2	0.029	0.133	0.999	0.018	0.154	0.999
Observations	1,621	1,621	1,621	1,248	1,248	1,248
Property Zip FE		✓			✓	
Deal Year FE		✓	✓		✓	✓
Bond Time FE			✓			✓
Bond CUSIP FE			✓			✓

Notes: The table reports our pooled difference-in-differences regression results with log of CMBS bond prices as the outcome variable, estimated according to equation (5.1). *Post* equals 1 if a period is after January 2025, *DOGE* equals 1 if the U.S. government sent ETO notifications to a lease tied to a property in the bond pool. The sample consists of the leases that are in the first loss group of tranches, with soon-to-be ETO-eligible leases as a control group. Columns (1)–(3) define the control group based on termination right dates (TRD) from January 2025 to January 2029, while Columns (4)–(6) use TRD from January 2026 to January 2029 to avoid any overlap between the soft term of the lease and the post-DOGE sample period. Fixed effects are added cumulatively across specifications. Standard errors clustered by bond CUSIP in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

TABLE 4. Pooled Difference-in-Differences Regressions for Log NOI

Control Group	Jan. 2025–Jan. 29 TRD			Jan. 2026–Jan. 29 TRD		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.006	-0.018		0.060	0.063	
	(0.072)	(0.071)		(0.109)	(0.110)	
DOGE	0.440	-0.738***		1.47*	-0.064	
	(0.644)	(0.218)		(0.800)	(0.157)	
$DOGE \times Post$	-0.209**	-0.195**	-0.192**	-0.275**	-0.275**	-0.275**
	(0.072)	(0.070)	(0.068)	(0.109)	(0.109)	(0.110)
R^2	0.021	0.944	0.984	0.295	0.979	0.982
Observations	1,621	1,621	1,621	1,248	1,248	1,248
Property Zip FE		✓			✓	
Deal Year FE		✓	✓		✓	✓
Loan Time FE			✓			✓
Bond CUSIP FE			✓			✓

Notes: The table reports pooled difference-in-differences regression results with $Log(NOI)$ (NOI) as the outcome variable, estimated according to equation (5.1). *Post* equals 1 if a period is after January 2025, *DOGE* equals 1 if the U.S. government sent ETO notifications to a lease tied to a property in the bond pool. The sample consists of the leases that are in the first loss group of tranches, with soon-to-be ETO-eligible leases as a control group. Columns (1)–(3) define the control group based on termination right dates (TRD) from January 2025 to January 2029, while Columns (4)–(6) use TRD from January 2026 to January 2029 to avoid any overlap between the soft term of the lease and the post-DOGE sample period. Fixed effects are added cumulatively across specifications. Standard errors clustered by loan id are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE 5. Pooled Difference-in-Differences Regressions for Log DSCR

Control Group	Jan. 2025–Jan. 29 TRD			Jan. 2026–Jan. 29 TRD		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.062	-0.059		-0.011	-0.007	
	(0.058)	(0.060)		(0.093)	(0.095)	
DOGE	0.239	0.176		0.421	0.778	
	(0.211)	(0.277)		(0.362)	(0.578)	
DOGE $\times$ *Post*	-0.154**	-0.155**	-0.152**	-0.206*	-0.206*	-0.206*
	(0.058)	(0.059)	(0.056)	(0.094)	(0.094)	(0.094)
Adj-R^2	0.059	0.229	0.861	0.116	0.463	0.870
Observations	1,621	1,621	1,621	1,248	1,248	1,248
Property Zip FE		✓			✓	
Deal Year FE		✓	✓		✓	✓
Loan Time FE			✓			✓
Bond CUSIP FE			✓			✓

Notes: The table reports pooled difference-in-differences regression results with log weighted-average debt service coverage ratio (DSCR) as the outcome variable, estimated according to equation (5.1). *Post* equals 1 if a period is after January 2025, *DOGE* equals 1 if the U.S. government sent ETO notifications to a lease tied to a property in the bond pool. The sample consists of the leases that are in the first loss group of tranches, with soon-to-be ETO-eligible leases as a control group. Columns (1)–(3) define the control group based on termination right dates (TRD) from January 2025 to January 2029, while Columns (4)–(6) use TRD from January 2026 to January 2029 to avoid any overlap between the soft term of the lease and the post-DOGE sample period. Fixed effects are added cumulatively across specifications. Standard errors clustered by loan id are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE 6. Spatial Difference-in-Differences Regressions for Log CMBS Bond Prices

	(1)	(2)	(3)	(4)
Post	-0.114**			
	(0.057)			
Spillover	-0.442***	-0.441***	0.080***	0.072***
	(0.130)	(0.130)	(0.029)	(0.019)
Spillover $\times$ *Post*	-0.124*	-0.121*	-0.104***	-0.093***
	(0.067)	(0.066)	(0.037)	(0.024)
Adj-R^2	0.020	0.025	0.446	0.983
Observations	13,446	13,446	13,446	13,446
Ring-Time FE		✓	✓	✓
Deal FE			✓	
Bond CUSIP				✓

Notes: The table reports our spatial difference-in-differences regression results with log of CMBS bond prices as the outcome variable, estimated according to equation (5.3). *Post* equals 1 if a period is after January 2025, *Spillover* equals 1 if the bond-deal involves a private tenant and the underlying space being rented is located within a 5-mile radius of an ETO-exercised lease. The sample consists of the leases that are within a 5-mile radius of the DOGE-led canceled leases and which are to bonds in the first loss group of tranches. Ring-time, deal, and bond CUSIP fixed effects are cumulatively added in Columns (2), (3), and (4) respectively. Ring fixed effects refer to an indicator equal to one if the bond-deal (i, c) lies within the 1-mile radius of DOGE-canceled lease r. Standard errors clustered by bond CUSIP in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

TABLE 7. Spatial Triple Difference-in-Differences Regressions for Log CMBS Bond Prices

	(1)	(2)	(3)	(4)
Private $\times$ *Post*	-0.179***	-0.179***	-0.146***	-0.106***
	(0.066)	(0.067)	(0.043)	(0.037)
Ring $\times$ *Post*	-0.188***	-0.187***	-0.158***	-0.113***
	(0.063)	(0.063)	(0.048)	(0.041)
Ring $\times$ *Private* $\times$ *Post*	0.065	0.067	0.055	0.020
	(0.091)	(0.090)	(0.061)	(0.047)
Adj-R^2	0.025	0.030	0.439	0.985
Observations	14,833	14,833	14,833	14,833
Ring-Time FE		✓	✓	✓
Deal FE			✓	
Bond CUSIP				✓

Notes: The table reports our spatial difference-in-differences regression results with log of CMBS bond prices as the outcome variable, estimated according to equation (5.4). *Post* equals 1 if a period is after January 2025, *Private* equals 1 if the property has a private tenant (i.e., non-federal lease), and *Ring* equals 1 if the lease is within a 1-mile radius of ETO-canceled federal lease buildings in Washington D.C. The sample consists of the leases that are within a 5-mile radius of the DOGE-led canceled leases which are also tied to bonds in the first loss group of tranches. Ring and time, deal, and bond CUSIP fixed effects are cumulatively added in Columns (2), (3), and (4) respectively. Ring fixed effects refer to an indicator equal to one if the bond-deal (i, c) lies within the 1-mile radius of DOGE-canceled lease r. Standard errors clustered by bond CUSIP in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

TABLE 8. DiD Regressions Comparing High vs. Low Government Contract Exposure Properties

Panel (A)	Occupancy				Log Rent Per Square Foot			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.009				0.014*			
	(0.015)				(0.008)			
HighDogeExp	0.078***	0.078***	-0.009		0.034	0.034	0.046	
	(0.024)	(0.024)	(0.078)		(0.030)	(0.030)	(0.089)	
HighDogeExp × *Post*	-0.147***	-0.147***	-0.151***	-0.151***	0.029**	0.029**	0.025**	0.026*
	(0.019)	(0.019)	(0.019)	(0.020)	(0.012)	(0.012)	(0.011)	(0.014)
Adj-R^2	0.062	0.054	0.111	0.164	0.064	0.051	0.306	0.420
Observations	151	151	123	123	151	151	123	123
Quarter FE		✓	✓	✓		✓	✓	✓
Loan Vintage FE			✓	✓			✓	✓
Hedonic Controls			✓	✓			✓	✓
Property Zip FE				✓				✓

Panel (B)	Occupancy				Log Rent Per Square Foot			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.011				-0.011			
	(0.016)				(0.016)			
HighGovExp	0.013	0.013	-0.017	0.093	0.013	0.013	-0.064	-0.190***
	(0.071)	(0.072)	(0.082)	(0.097)	(0.071)	(0.072)	(0.044)	(0.051)
HighGovExp × *Post*	-0.031	-0.031	-0.035	-0.034	-0.031	-0.031	0.012	0.013
	(0.051)	(0.052)	(0.055)	(0.057)	(0.051)	(0.052)	(0.012)	(0.015)
Adj-R^2	0.058	0.050	0.097	0.160	0.058	0.050	0.311	0.478
Observations	151	151	123	123	151	151	123	123
Quarter FE		✓	✓	✓		✓	✓	✓
Loan Vintage FE			✓	✓			✓	✓
Hedonic Controls			✓	✓			✓	✓
Property Zip FE				✓				✓

Notes: The table reports production-externality difference-in-differences estimates based on regressions (6.7) and (6.8). The dependent variables are occupancy (Occ) and log rent per square foot ($\log(Rent)$). In Panel (A), the key regressor is $HighDogeExp_i \times Post_t$, where $HighDogeExp_i$ equals one for buildings with more SF-weighted DOGE contract exposure than non-DOGE government contract exposure, based on the tenant mix. In Panel (B), the key regressor is $HighGovExp_i \times Post_t$, where $HighGovExp_i$ equals one for buildings in the top quintile of pre-period, SF-weighted overall federal contract exposure. $Post_t$ indicates quarters after the onset of the ETO notifications. Time, loan-vintage, and 5-digit property zip code fixed effects are added progressively with hedonic controls added in the last two columns. The vector of hedonic variables collected from CoStar includes: rentable building area (RBA), the CoStar StarRating (discretized into a 5-point scale), age based on construction year, number of floors, and distance to the nearest transit stop. To separate the price and quantity margins, in all regressions with occupancy as the outcome, we include lagged log rent per square foot as a control. Similarly, we control for lagged occupancy when log rent per square foot is the outcome. Standard errors are clustered at the building level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

TABLE 9. Summary of Simulated Value at Risk (VaR) and Expected Shortfall (ES)
Washington, D.C. Office Property Value Losses ($ Billions)

5-Year Persistence	Value at Risk (VaR)				Expected Shortfall (ES)			
$1 - \alpha =$	20%	50%	75%	95%	20%	50%	75%	95%
ETO-eligible	0.024	0.033	0.042	0.057	0.039	0.045	0.051	0.064
	[0.033]	[0.047]	[0.059]	[0.079]	[0.054]	[0.062]	[0.071]	[0.089]
ETO-notified	0.107	0.176	0.236	0.333	0.210	0.251	0.296	0.378
	[0.158]	[0.260]	[0.348]	[0.491]	[0.310]	[0.369]	[0.436]	[0.557]
Spillover	1.700	1.849	1.971	2.158	1.915	1.996	2.085	2.240
	[2.876]	[3.128]	[3.334]	[3.650]	[3.238]	[3.376]	[3.526]	[3.788]
Total ($ Billions)	1.831	2.058	2.249	2.548	2.164	2.292	2.432	2.682
	[3.067]	[3.434]	[3.741]	[4.220]	[3.602]	[3.807]	[4.034]	[4.435]

Notes: The table summarizes the 5-year projected Value at Risk (VaR) and expected shortfall (ES) notions of office property valuation losses from the DOGE federal lease cancellations at various levels of the α% worst outcomes. We report losses in billions of dollars. Following the definitions used throughout the paper, ETO-eligible refers here to losses incurred by properties which are already eligible for early termination as of January 2025, ETO-notified refers to losses among properties with leases canceled by DOGE, and spillover refers to non-GSA properties within a 5-mile radius of those actually canceled. Numbers in brackets scale up the headline estimates to include losses to non-securitized offices, using the procedure outlined in the Section 7.4 text. We follow the simulation procedures described in Section 7, under the calibration outlined in Appendix G.3. We report the corresponding VaR and ES numbers projected at different horizons $T \in \{1, 2, 3, 4, 5\}$ in Appendix G.3 as well.

Online Appendix to

Pricing Government Contract Risk Premia: Evidence from the 2025 Federal Lease Terminations

Soon Hyeok Choi (Rochester Institute of Technology) & Cameron LaPoint (Yale SOM)

A Model Environment

A.1 CMBS Bond Pool

Based on Section 3.4, we provide the environment under which the CMBS bond price adjustments occur.

We assume that the ETO exercise time τ for positive-ETO properties follows a Poisson process with constant intensity λ_τ under the risk-neutral measure $\mathbb{Q}$. The survival probability of the lease to time s conditional on surviving up to t, is then:

$$\pi(s) = \mathbb{Q}(\tau > s \mid \tau > t) = e^{-\lambda_\tau (s-t)} \tag{A.1}$$

where $\pi(s) = 1$ for dormant-ETO properties. The aggregated cash flow from the pool at time $s > t$ and terminal date liquidation value are, respectively:

$$\Gamma(s) = N\left[\theta_0 R + \theta_1 \widetilde{R}\mathbb{1}_{\tau > s}\right] \tag{A.2}$$

$$\Psi(T) = N\left[\theta_0 V(T) + \theta_1 \widetilde{V}(T)\mathbb{1}_{\tau > T}\right] \tag{A.3}$$

The no-arbitrage price of the CMBS bond at time t, denoted $\phi(t)$, equals the risk-neutral expected present value of the aggregated future cash flows and terminal liquidation value:[1]

$$\phi(t) = B(t)\mathbb{E}_{\mathbb{Q}}\left[\sum_{s=t+1}^{T} \frac{\Gamma(s)}{B(s)} + \frac{\Psi(T)}{B(T)}\right] \tag{A.4}$$

Substituting in for $\Gamma(s)$ and $\Psi(T)$ in equation (A.4), we can write

$$\phi(t) = N\left[\sum_{s=t+1}^{T} p(t,s)\left(\theta_0 R + \theta_1 \widetilde{R} e^{-\lambda_\tau (s-t)}\right) + p(t,T)\left(\theta_0 V(T) + \theta_1 \widetilde{V}(T) e^{-\lambda_\tau (T-t)}\right)\right] \tag{A.5}$$

[1] In our empirical setting, we focus on the first-loss tranche, as it is the most junior in the CMBS waterfall structure and absorbs cash flow losses first when the market becomes ETO-salient.

A.2 CMBS Prices under Regime Switching

Define $u(s,i) = \mathbb{Q}(\tau > s \,|\, X_t = i)$ as the lease survival probability at time s in regime i, which satisfies the system of ordinary differential equations,

$$\frac{\partial u(s,i)}{\partial s} = -\lambda_\tau^i\, u(s,i) + \sum_{j\neq i} q_{ij}\big(u(s,j) - u(s,i)\big)$$

The term $-\lambda_\tau^i\, u(s,i)$ represents hazard-driven decay of survival in regime i, while the term $\sum_{j\neq i} q_{ij}\big(u(s,j) - u(s,i)\big)$ accounts for regime switching, with transition between states at rates q_{ij}. Incorporating these extensions into (A.1), we obtain the probability of the lease surviving to time s conditional on surviving up to t and being in regime i:

$$\widehat{\pi}(s,i) = \mathbb{Q}(\tau > s \mid \tau > t, X_t = i) \tag{A.6}$$

Applying the state-dependent conditional survival probabilities directly to aggregate cash flows in (A.2) and the terminal liquidation value in (A.3), we derive the no-arbitrage price of the CMBS bond at time t, conditional on starting in regime i, denoted $\widehat{\phi}(t,i)$:

$$\widehat{\phi}(t,i) = N\left[\sum_{s=t+1}^{T} p(t,s)\big(\theta_0 R + \theta_1 \widetilde{R}\widehat{\pi}(s,i)\big) + p(t,T)\big(\theta_0 V(T) + \theta_1 \widetilde{V}(T)\widehat{\pi}(T,i)\big)\right]. \tag{A.7}$$

B Model Extensions

B.1 Insurance Premia

Given losses stemming from the mispricing of the government contract risk premium associated with an early termination option (ETO), a natural question arises: if a market for ETO contingencies existed in the form of insurance what would be the price? To address this, we derive a closed-form solution for the insurance premium corresponding to an ETO contingency.

A federal lease is typically divided into a firm term and a soft term, each comprising roughly half of the contract term. As the firm term carries no credit risk due to its non-cancelable nature, our analysis focuses on the soft term. Suppose the soft term spans a fixed horizon, $[t_0, t_m]$ with $m \in \mathbb{N}$. The contract obligates the federal tenant to pay the base rent R from t_1 to t_m. Since the federal tenant holds a long position in the ETO (put option), it pays a regular insurance premium (c) to the landlord during the soft term. However, the federal tenant can exercise its ETO during any time in this soft term. The stopping time, τ, represents the period that the tenant officially notifies its intent to terminate the lease early, where $\tau \in (t_{h-1}, t_h]$ for $h \in \{1, ..., m\}$.

The advance notification period, denoted by α, serves as a grace period during which the landlord is formally informed of the tenant's intention to exercise the ETO. This notification initiates a transitional window allowing the landlord to commence re-leasing efforts in anticipation of the forthcoming vacancy, thereby partially mitigating the risk of rental income disruption. Throughout the interval $[t_h, \lceil\tau\rceil + \alpha]$, the federal tenant remains contractually obligated to continue rental payments. Upon the expiration of this notice period, starting at $\lceil\tau\rceil + \alpha + 1$, the financial responsibility for the vacant space shifts to the landlord, who must then absorb the rental cost until a replacement tenant is secured. Since the time of successful re-leasing is uncertain, $\eta \in (t_{k-1}, t_k]$ for $k > \lceil\tau\rceil + \alpha + 1$ denotes a stopping time marking the end of the vacancy period, beyond which the landlord ceases rent payments beginning at t_k. Figure 2 summarizes the timeline of key events with an exercised ETO.

Proposition 6. *Suppose there is one landlord and one federal tenant. Consider a soft term in which the tenant can exercise an early termination option (ETO). Suppose the tenant sends its ETO notification at* τ *with the grace period* α *and the random time* η *at which a replacement tenant can occur. Then the ETO insurance premium is:*

$$c = \frac{RE_{\mathbb{Q}}\left[\sum_{h=\lceil\tau\rceil+\alpha+1}^{\lceil\eta\rceil\wedge t_m} \mathbb{1}_{\{t_0<\tau\le t_m\}} e^{-\int_0^{t_h} r_u du}\right]}{E_{\mathbb{Q}}\left[\sum_{k=1}^{\lceil\tau\rceil+\alpha} p(0,t_k)\right]} \tag{B.1}$$

Proof. See Appendix C.6 for the derivations. □

C Proofs

C.1 Proof of Proposition 1

If the rent $\widetilde{R}$ correctly prices the government contract risk premium associated with the ETO:

$$\frac{V(t)}{B(t)} = \mathbb{E}_{\mathbb{Q}}\left[\sum_{s=t+1}^{\tau} \frac{\widetilde{R}}{B(s)} + \sum_{s=\eta+1}^{T} \frac{\widetilde{R}}{B(s)} + \frac{V(T)}{B(T)}\right] \tag{C.1}$$

$$\Longrightarrow \frac{V(t)}{B(t)} - \mathbb{E}_{\mathbb{Q}}\left[\frac{V(T)}{B(T)}\right] = \mathbb{E}_{\mathbb{Q}}\left[\sum_{s=t+1}^{\tau} \frac{\widetilde{R}}{B(s)} + \sum_{s=\eta+1}^{T} \frac{\widetilde{R}}{B(s)}\right] \tag{C.2}$$

$$\Longrightarrow \mathbb{E}_{\mathbb{Q}}\left[\sum_{s=t+1}^{T} \frac{R}{B(s)}\right] = \tilde{R}\,\mathbb{E}_{\mathbb{Q}}\left[\sum_{s=t+1}^{\tau} \frac{1}{B(s)} + \sum_{s=\eta+1}^{T} \frac{1}{B(s)}\right] \tag{C.3}$$

$$\Longrightarrow R\,\mathbb{E}_{\mathbb{Q}}\left[\sum_{s=t+1}^{\tau} \frac{1}{B(s)} + \sum_{s=\tau+1}^{\eta} \frac{1}{B(s)} + \sum_{s=\eta+1}^{T} \frac{1}{B(s)}\right] = \widetilde{R}\,\mathbb{E}_{\mathbb{Q}}\left[\sum_{s=t+1}^{\tau} \frac{1}{B(s)} + \sum_{s=\eta+1}^{T} \frac{1}{B(s)}\right] \tag{C.4}$$

$$\implies \widetilde{R} = R\,\mathbb{E}_{\mathbb{Q}}\left[1 + \frac{\sum_{s=\tau+1}^{\eta} \frac{1}{B(s)}}{\sum_{s=t+1}^{\tau} \frac{1}{B(s)} + \sum_{s=\eta+1}^{T} \frac{1}{B(s)}}\right] \tag{C.5}$$

$$\implies \widetilde{R} = R\left[1 + \frac{\sum_{s=t+1}^{T} p(t,s)\mathbb{Q}(\tau < s)\mathbb{Q}(s \le \eta)}{\sum_{s=t+1}^{T} p(t,s)\left[\mathbb{Q}(s \le \tau) + \mathbb{Q}(\eta < s)\right]}\right] > R \tag{C.6}$$

□

C.2 Proof of Proposition 2

$$L(t) = \frac{V(t) - \widetilde{V}(t)}{B(t)} = \mathbb{E}_{\mathbb{Q}}\left[\sum_{s=\tau+1}^{\eta} \frac{R}{B(s)}\right] \tag{C.7}$$

$$= \frac{R}{B(t)} \sum_{s=t+1}^{T} p(t,s)\,\mathbb{Q}(\tau \le s)\,\mathbb{Q}(s \le \eta). \tag{C.8}$$

$$\text{Note that } \mathbb{Q}(\tau \le s)\,\mathbb{Q}(s \le \eta) = \left(1 - e^{-\lambda_\tau s}\right)\left(e^{-\lambda_\eta s}\right) = e^{-\lambda_\eta s} - e^{-(\lambda_\tau + \lambda_\eta)s} \tag{C.9}$$

$$= \frac{R}{B(t)} \sum_{s=t+1}^{T} p(t,s)\left[e^{-\lambda_\eta s} - e^{-(\lambda_\tau + \lambda_\eta)s}\right] \tag{C.10}$$

□

C.3 Proof of Proposition 3

Using the independence termination and interest rates, noting that $\mathbb{E}_{\mathbb{Q}}\left[\mathbb{1}_{\tau > s}\right] = e^{-\lambda_\tau (s-t)}$ yields

$$\phi(t) = N \cdot \mathbb{E}_{\mathbb{Q}}\left[\sum_{s=t+1}^{T} \frac{\theta_0 R + \theta_1 \widetilde{R}\mathbb{1}_{\tau > s}}{B(s)} + \frac{\theta_0 V(T) + \theta_1 \widetilde{V}(T)\mathbb{1}_{\tau > T}}{B(T)}\right] \tag{C.11}$$

$$= N\left[\sum_{s=t+1}^{T} \mathbb{E}_{\mathbb{Q}}\left[\frac{B(t)}{B(s)}\right]\left[\theta_0 R + \theta_1 \widetilde{R} e^{-\lambda_\tau (s-t)}\right] + \mathbb{E}_{\mathbb{Q}}\left[\frac{B(t)}{B(T)}\right]\left[\theta_0 V(T) + \theta_1 \widetilde{V}(T) e^{-\lambda_\tau (T-t)}\right]\right]$$

$$= N\left[\sum_{s=t+1}^{T} p(t,s)\left[\theta_0 R + \theta_1 \widetilde{R} e^{-\lambda_\tau (s-t)}\right] + p(t,T)\left[\theta_0 V(T) + \theta_1 \widetilde{V}(T) e^{-\lambda_\tau (T-t)}\right]\right] \tag{C.12}$$

$$
\begin{aligned}
\frac{\partial \phi(t)}{\partial \lambda_\tau} &= N\left[\sum_{s=t+1}^{T} p(t,s)\left[\theta_1 \widetilde{R}\left[-(s-t)e^{-\lambda_\tau(s-t)}\right]\right] + p(t,T)\left[\theta_1 \widetilde{V}(T)\left[-(T-t)e^{-\lambda_\tau(T-t)}\right]\right]\right] \\
&= -N\theta_1\left[\sum_{s=t+1}^{T} p(t,s)\,\widetilde{R}\,(s-t)e^{-\lambda_\tau(s-t)} + p(t,T)\,\widetilde{V}(T)\,(T-t)e^{-\lambda_\tau(T-t)}\right]. \qquad \text{(C.13)}
\end{aligned}
$$

Hence, $\frac{\partial \phi(t)}{\partial \lambda_\tau} < 0$ if and only if $N > 0, T > t, \theta_1 > 0, \widetilde{V}(T) > 0, \widetilde{R} > 0$. □

C.4 Proof of Proposition 4

Since $\widehat{\phi}(t,i)$ is linear in $\widehat{\pi}(s,i)$, it suffices to show the marginal effects of the state transition probabilities and intensities on $\widehat{\pi}(s,i)$. First, increasing q_{LH} makes transitions from L (baseline regime) to H (exit regime) more likely. Since $\lambda_\tau^H > \lambda_\tau^L$, spending more time in the exit regime leads to a higher effective hazard rate. Hence, increasing q_{LH} increases the rate at which the survival probability decays:

$$
\frac{\partial \widehat{\pi}(s,i)}{\partial q_{LH}} < 0 \implies \frac{\partial \widehat{\phi}(t,i)}{\partial q_{LH}} < 0
$$

By the same intuition, spending more time in the baseline regime slows down the decay of survival probability:

$$
\frac{\partial \widehat{\pi}(s,i)}{\partial q_{HL}} > 0 \implies \frac{\partial \widehat{\phi}(t,i)}{\partial q_{HL}} > 0
$$

Regardless of the regime $i \in \{L,H\}$, increasing λ_τ^i directly increases the hazard rate in the exit regime without affecting the regime transition probability matrix Q. Whenever the system is in the exit regime, survival decays faster:

$$
\frac{\partial \widehat{\pi}(s,i)}{\partial \lambda_\tau^i} < 0 \implies \frac{\partial \widehat{\phi}(t,i)}{\partial \lambda_\tau^i} < 0
$$

□

C.5 Proof of Proposition 5

$$
\frac{\partial \widehat{\phi}_c(t,i)}{\partial \varsigma} = N\left[\sum_{s=t+1}^{T} p(t,s)\,\theta_0 \bar{R}\,\frac{\partial \Xi(s,i)}{\partial \varsigma} + p(t,T)\,\theta_0 \bar{V}(T)\,\frac{\partial \Xi(T,i)}{\partial \varsigma}\right] \qquad \text{(C.14)}
$$

$$
= -N\left[\sum_{s=t+1}^{T} p(t,s)\left[\theta_0 \bar{R}\big(1-\widehat{\pi}(s,i)\big)\right] + p(t,T)\left[\theta_0 \bar{V}(T)\big(1-\widehat{\pi}(T,i)\big)\right]\right] < 0. \qquad \text{(C.15)}
$$

$$\frac{\partial \widehat{\phi}_c(t,i)}{\partial \Xi(s,i)} = \begin{cases} N\,p(t,s)\,\theta_0 \bar{R} \;>\; 0, & s < T, \\ N\,p(t,T)\,\theta_0 \bar{V}(T) \;>\; 0, & s = T. \end{cases} \tag{C.16}$$

Hence,

$$\frac{\partial \widehat{\phi}_c(t,i)}{\partial \varsigma} < 0 \iff N > 0,\ \theta_0 > 0,\ T > t,\ \bar{R} \geq 0,\ \bar{V}(T) \geq 0,\ p(t,s) > 0\ \forall s \in \{t+1,\dots,T\},\ \text{and}$$

$$\left[\sum_{s=t+1}^{T} p(t,s)\bar{R}\big(1-\widehat{\pi}(s,i)\big) + p(t,T)\bar{V}(T)\big(1-\widehat{\pi}(T,i)\big) > 0\right].$$

$$\frac{\partial \widehat{\phi}_c(t,i)}{\partial \Xi(s,i)} > 0 \iff N > 0,\ \theta_0 > 0,\ p(t,s) > 0,\ \text{and} \begin{cases} \bar{R} > 0, & s < T, \\ \bar{V}(T) > 0, & s = T. \end{cases}$$

□

C.6 Proof of Proposition 6

Using the same argument as above:

$$V(0) = 0 \quad \text{given that the time } t = 0 \text{ fair value of the ETO contract is zero.}$$

$$0 = E_{\mathbb{Q}}\Big[\sum_{k=1}^{\lceil\tau\rceil+\alpha} c e^{-\int_0^{t_k} r_u du} - \sum_{h=\lceil\tau\rceil+\alpha+1}^{\lceil\eta\rceil\wedge t_m} R\mathbb{1}_{\{t_0<\tau\leq t_h\}} e^{-\int_0^{t_j} r_u du}\Big] \tag{C.17}$$

$$\implies c = \frac{RE_{\mathbb{Q}}\left[\sum_{h=\lceil\tau\rceil+\alpha+1}^{\lceil\eta\rceil\wedge t_m} \mathbb{1}_{\{t_0<\tau\leq t_m\}} e^{-\int_0^{t_h} r_u du}\right]}{E_{\mathbb{Q}}\left[\sum_{k=1}^{\lceil\tau\rceil+\alpha} p(0,t_k)\right]} \tag{C.18}$$

□

D Data Construction

This appendix provides more details on the construction of our estimation sample, including how we merged across tables in the Trepp database and our collection of tenant-level information from CoStar and `USAspending.gov`.

D.1 Merging Trepp and GSA Tables

We merge across tables in Trepp according to the following steps:

1. We match CUSIPs in the *bond* table to the corresponding panel of CUSIPs in the Trepp CMBS file to obtain a bond-price table. This step effectively filters our sample to include only loans securitized into bonds with transaction prices.

2. We then many-to-one join the bond-price table to the *deal* table based on the deal name and tape date to pick up information on the performance of the loans within each CMBS bond pool. Each deal can result in multiple bonds.

3. We merge the *property* and *loan* tables in a many-to-many fashion using the Trepp deal name, the unique loan identifier, and the distribution date. The merge is many-to-many because one property can have multiple loans used to finance it, and, in turn, the same loan can be used to finance several different properties.

4. Finally, we create a bond-loan-property table by many-to-many matching the property-loan table with the bond-deal table created in step 2, thus keeping only properties and loans corresponding to a bond-deal. We perform this match using the Trepp deal name contained in both sub-tables and by matching the loan distribution date to the bond tape date. The loan distribution date and bond tape date match in 100% of cases in Trepp.

Our main estimation sample includes only those observations for which we are able to merge underlying properties from our Trepp dataset to entries in the GSA inventory. Individual properties may have multiple lease agreements – up to seven in the Washington, D.C. sample. We keep track of the lease sequence and associated dates for each tenant tied to the property. We include all leases active at any point from 2020 to 2024, which captures both active and expired agreements. Given that cancellation rates in the pre-DOGE period were relatively low (see Figure 9), this means there are often multiple GSA leases located at the same property.

We record several key dates related to each lease. The DOGE announcement date captures the date a lease termination was first published on the DOGE website. We record any dates that a termination was formally rescinded. We also collect the date DOGE reportedly sent each termination notice, which typically precedes the public announcement on the website. This is the key determinant of treatment status in our analysis, as a formal notification commences the government's intent to exercise the early termination option, which influences CMBS bond prices and property net operating income immediately. These variables are supplemented by GSA inventory dates, including the lease effective, lease expiration, and termination right dates, which are available for all leases regardless of termination status.

D.2 Tenant-Level Data Collection

We construct a geographically localized panel of tenant information by integrating Trepp, CoStar, and `USAspending.gov` for 44 private-tenant office buildings located within one mile of ETO-notified federal leases in Washington, D.C. From Trepp, we identify 44 such buildings within a 1-mile radius of the ETO-notified buildings. We preserve each property's earliest observed loan origination date to capture loan vintage.

From CoStar, we hand-collect quarterly rent per square foot and occupancy series from 2023Q1 to 2025Q3, and enrich these outcomes with tenant composition measured in a November 2025 snapshot. Rent per square foot in CoStar is defined as total contract rents charged divided by rented square footage in that quarter. Occupancy is infrequently updated in the Trepp data, and rent per square foot can only be imputed as a residual measure based on NOI, operating expenditures, and rentable building area, with each component recorded at potentially different frequencies depending on the property.

Further, Trepp only records the name and square footage of the largest five tenants in each building according to leased area. In our CoStar tenant roll, we observe 343 unique tenants attached to the 44 buildings. Of these, 300 tenants (87%) have lease commencement dates prior to January 30, 2025, while 43 tenants (13%) commenced in February 2025 or later, indicating that the snapshot is largely representative of the pre-DOGE tenant mix. Hence, we consider the information about space occupied by these tenants to reflect conditions in the pre-DOGE period.[2] Since Trepp has no information on the physical characteristics (other than building age) of the properties attached to each mortgage, we download the full set of property attributes using CoStar's export feature. The set of additional variables we download includes: the number of stories, distance to the nearest transit stop, energy efficiency certifications, triple net status of the leases, and CoStar's 5-star rating based on an internal hedonic model. This allows us to control in equations (6.7) and (6.8) for differences in the quality of properties across groups of offices with high vs. low exposure to government contracts.

Using the CoStar tenant roster, we match each tenant to recipients listed on `USAspending.gov` to recover fiscal-year federal award histories for 2015–2024 and construct a balanced tenant–year panel. The primary linkage variable is the tenant name.[3] For non-unique or ambiguous names (e.g., Apple vs Apple Inc.), we validate matches using recipient headquarters addresses for large firms and, for small and local entities (e.g., boutique lobbying firms), by confirming that the recipient business address corresponds to one of the 44 buildings in our sample. This procedure yields a congruent tenant-name crosswalk between CoStar and `USAspending.gov`.

Next, we access the publicly available `USAspending.gov` API (v2) to recover each tenant's federal award dollars and awarding-agency identifiers over fiscal years 2015–2024. For each tenant, we submit a recipient-name search within each fiscal year window, collect award records, and aggregate the contract award amount (Total Obligation) by federal agency (Awarding

[2] Our results in Table 8 are materially unchanged if we exclude the 43 relatively new tenants from our calculation of the exposure share measures in Section 6.5.

[3] When a company conducts business with the U.S. federal government, it may obtain a Unique Entity ID (UEI), a 12-character alphanumeric identifier used in federal award systems. However, UEI coverage is not universal. Some entities transact using alternative identifiers (e.g., tax identifiers). Therefore, tenant name and address-based verification remains a more reliable step for increasing match and accuracy rates.

TABLE D.1. Summary Statistics: Government Contract Awards & Exposure

	Obs/Count	Mean	Std Dev	Fraction
Panel (A): Tenant-level				
Total obligations ($M)	356	8.172	132	
DOGE obligations ($M)	356	0.897	15.8	
Non-DOGE obligations ($M)	356	7.276	130	
High gov. exposure	352	0.142	0.350	
High DOGE exposure	352	0.063	0.242	
Panel (B): Building-level				
Total obligations ($M)	47	2.925	15.8	
DOGE obligations ($M)	47	0.312	1.97	
Non-DOGE obligations ($M)	47	2.613	15.6	
High gov. exposure	43	0.070	0.258	
High DOGE exposure	43	0.023	0.152	
Panel (C): Building-level overlap (High Gov vs. High DOGE)				
High gov exposure only	10			0.052
High DOGE exposure only	-			-
Both	5			0.026
Neither	179			0.923

Notes: The table reports Summary statistics for tenant- and building-level measures. Tenant obligation variables are annualized averages over fiscal years 2015–2024 and reported in millions of U.S. dollars ($M). Property-level exposure measures (High Gov, High DOGE) are constructed using pre-DOGE tenant space shares (square foot-weighted average).

Agency) to form a tenant-year-agency panel.[4] Then, we flag whether an observation's awarding federal agency is in the ETO-notified group. Finally, we aggregate based on each tenant's share of the property's occupied square footage to produce property-level government contract exposure measures, according to the procedures summarized by equations (6.2)–(6.5).

Table D.1 summarizes the distribution of government contract obligations. Panel (A) shows that tenant contract activity is sizable on average, but highly dispersed, with a standard deviation (132 million) far exceeding the mean (8.172 million), indicating substantial heterogeneity across tenants. The average tenant's DOGE-linked component (0.897 million) is smaller than the

[4]The `USAspending.gov` API (v2) does not systematically report office- or facility-level locations for awarding agencies; it primarily identifies the awarding entity at the agency or sub-agency level rather than the specific field office involved. For instance, FEMA is headquartered in Washington, D.C., but many of its operational activities are administered through regional offices outside the D.C. area. This limitation is unlikely to bias our setting. For large, nationally scoped contractors (e.g., Boeing) receiving multi-year awards from cabinet-level departments (e.g., the Department of Defense), assigning the awarding entity to the headquarters-level agency is appropriate because contracting authority and procurement attribution are organized at that level. Conversely, for local or place-based recipients (e.g., lobbying or professional services firms), repeated federal awards are typically associated with agencies and contracting offices concentrated in the Washington, D.C. market. Accordingly, using the highest-level (headquarters) awarding-entity identifiers provided by `USAspending.gov` is a reasonable and conservative approach for our D.C.-centric analysis.

non-DOGE component (7.276 million), yet both exhibit large heterogeneity. The exposure indicators are non-trivial in prevalence: 6.3% of observations fall into high DOGE contract exposure buildings and 14.2% into high government contract exposure buildings. Panel (B) reports analogous building-level aggregates for the matched building sample: average obligations are lower in level (2.925 million) yet remain highly dispersed (15.8 million). The exposure measures are concentrated in a subset of buildings, 2.3% for high DOGE contract exposure and 7.0% for high government contract exposure.

Panel (C) further motivates our two-specification design by showing that the DOGE-impacted exposure indicator is nested within overall government exposure in the building sample. In particular, all buildings classified as DOGE-impacted exposure are also classified as high government exposure, while a non-trivial set of buildings are high government exposure without being DOGE-impacted. This overlap structure implies that (6.7) isolates the post-period response of the most DOGE-intensive subset of government-exposed buildings, whereas (6.8) captures broader effects of government dependence that extend beyond DOGE exposure. Estimating both specifications therefore provides a transparent decomposition of post-period adjustments in occupancy and rents into a concentrated DOGE contract exposure and a broader government contract exposure.

E Additional Results for Foot Traffic Analysis

This appendix presents supplemental information about the Advan Research data on foot traffic and robustness checks corresponding to the tests for consumption externalities from Section 6.4.

E.1 Foot Traffic Sample Creation

We obtain data on foot traffic for points of interests (POIs) from Advan Research (2022). The data tracks the number of visits to POIs using cellphone pings from an anonymized panel of mobile devices, allowing us to observe weekly volume of visits and visitors. Our sample consists of a balanced panel of POIs for all weeks between June 2023 and June 2025. POIs in our data are *static* in the sense that our set of POIs and their characteristics are fixed as of June 2023, and we cannot add or drop POIs based on unobserved establishment turnover or openings. Instead, we exclude POIs that experience zero visits in any week of our sample period to avoid tracking POIs that experience business closure. Our main analysis further subsets to POIs that we identify as retail establishments based on belonging to one of four two-digit NAICS sectors *Retail Trade* (sector codes 44–45), *Arts, Entertainment, and Recreation* (sector code 71) or *Accommodation and Food Services* (sector code 72). We present robustness analyses on a non-retail sample that includes all other NAICS sectors in Appendix E.2.

A common concern with foot traffic data inferred from cellphone locations is that the underlying panel of mobile devices might not uniformly cover the area of interest (Hou et al., 2025). Given that we exclusively focus on the well-populated area of D.C., we expect this to be less of an issue in our application. However, our focus on a static panel of POIs with always non-zero foot traffic might induce selective coverage of POIs. For example, POIs further away from the more frequented areas in the center might experience visits less regularly and therefore could be more prone to exclusion from the sample. Figure E.1 maps out the share of POIs that are excluded from the sample due to having zero weekly foot traffic. Census tracts located further away from the central business district (CBD) are subject to a higher share of excluded POIs. Fortunately, 13 out of the 15 locations with DOGE terminated leases are located close to the CBD where POI coverage is the greatest. In addition, our spillover design limits variation in POI coverage by only comparing POIs in small concentric circles around DOGE terminated leases, among which POI coverage appears to be relatively stable. We exclude two more canceled leases which are located in high coverage rate areas but were canceled later in the sample after investors would have witnessed rescission decisions.

E.2 Robustness: Foot Traffic Responses of Non-Retail Establishments

As a sanity check, we re-estimate our specifications using the foot traffic data but for the sample of non-retail leases, defined by the complement set of any of the 2-digit NAICS codes not classified as retail. We use this non-retail definition rather than further defining office and industrial groups, as there is no clear way to map NAICS codes for the establishment into a use of the property. We again estimate the difference-in-differences specification in equation (6.1) by Poisson regression and OLS. We continue to find a statistically flat pattern of foot traffic around DOGE lease cancellation events. If anything, foot traffic to non-retail establishments slightly increases in the month after termination announcements.

E.3 Robustness: Early vs. Late Ring Difference-in-Differences

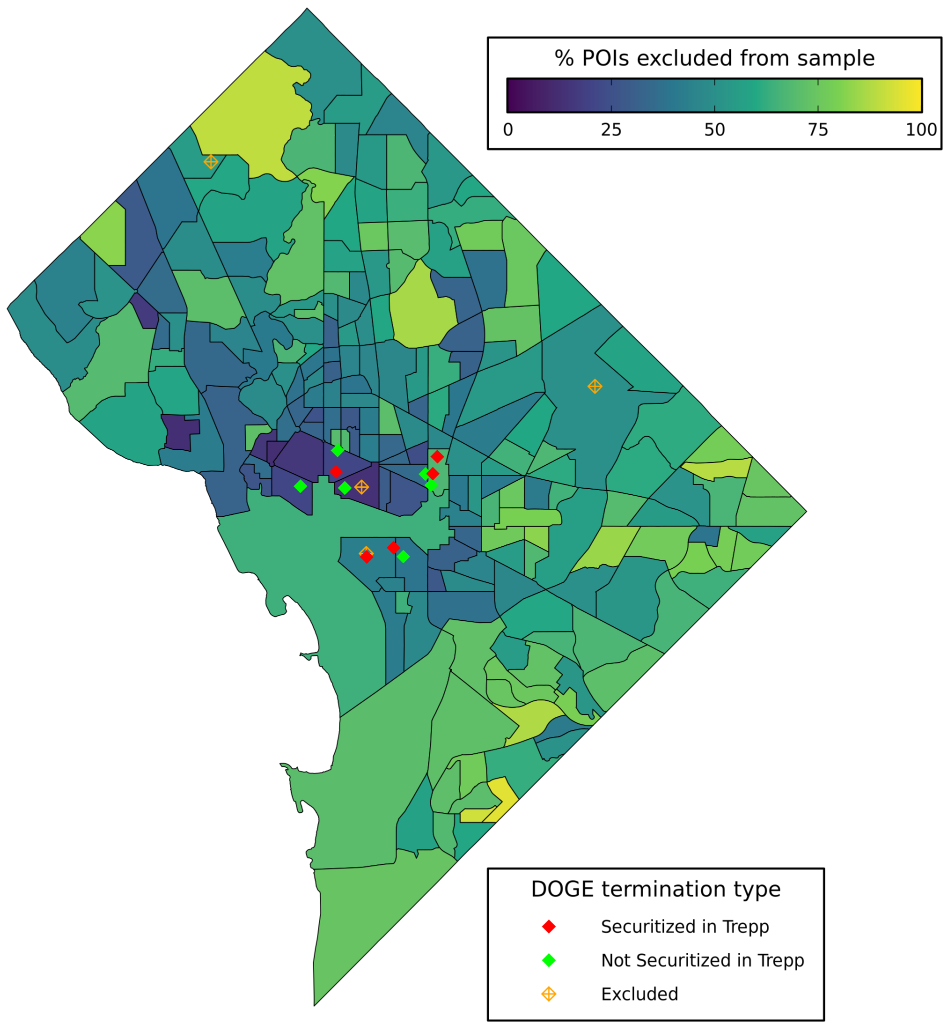
An alternative approach to estimating spillovers on foot traffic makes use of the staggered termination of leases, comparing the evolution of foot traffic around federal leases that DOGE terminated first to the evolution of foot traffic around federal leases terminated later. We can implement this research design with the Advan data which are at a weekly frequency, unlike our data on CMBS prices and property performance which are only available monthly and therefore do not divide up leases into clear treatment cohorts.

To implement this early vs. late design, we estimate the following regression specification:

$$Y_{j,r,s,t} = \sum_{t=-5, e\neq -1}^{+4} \beta_t \cdot Spillover_{i,t} + \mu_i + \delta_{s,t} + \epsilon_{j,r,s,t} \tag{E.1}$$

Quantities in this equation are defined as in equation (6.1), except for $Spillover_{i,t}$ which now takes value one if the POI is located within 0.5 miles or 0.25 miles of a terminated DOGE lease

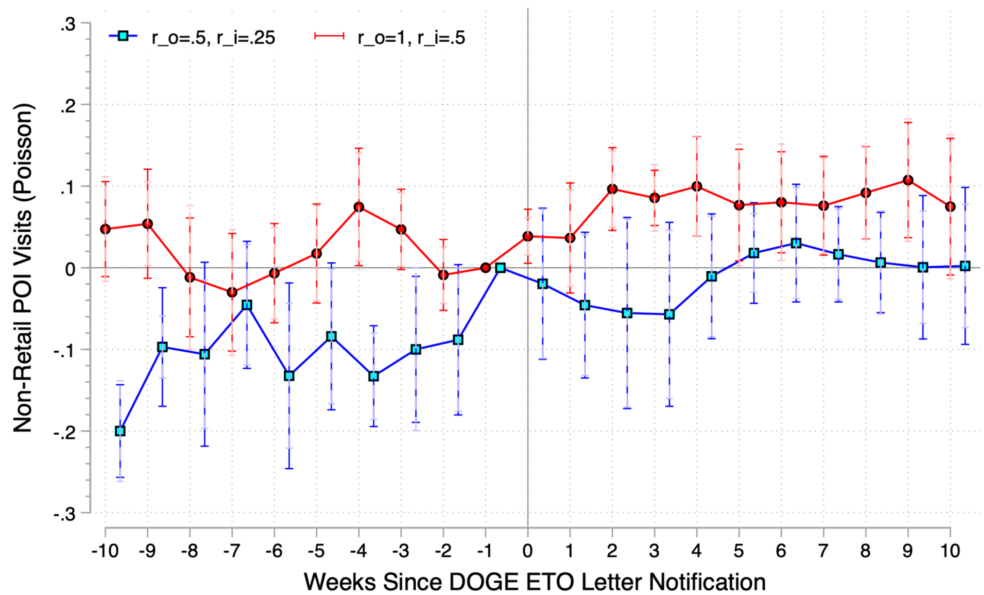
FIGURE E.1. Spatial Distribution of Points of Interest (POIs) Excluded from Advan Sample



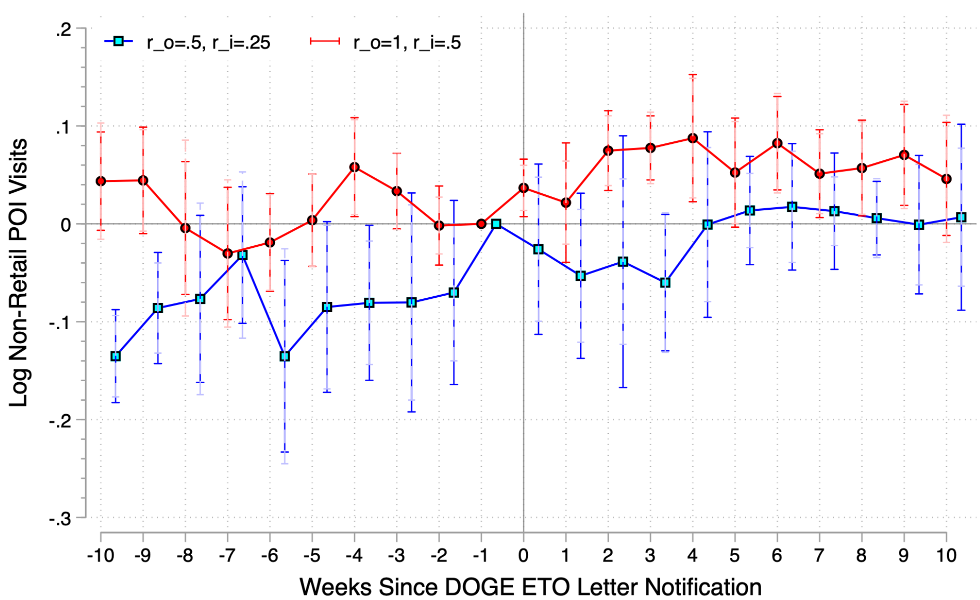
Notes: The map plots the percentage of points of interest (POIs) that are excluded from the Advan foot traffic analysis sample due to having zero foot traffic in at least one month during the sample period. Each polygon represents a census tract in Washington, D.C., with the color scale indicating the percentage of POIs located in the census tract that were excluded from the analysis sample. Red diamonds indicate the location of DOGE terminated federal leases that are included in our Trepp analysis sample, while the green diamonds indicate the non-securitized canceled leases which are not in Trepp. The four orange kites indicate the location of DOGE-terminated federal leases that we exclude from our analysis. We exclude the two leases on the periphery, as they fall outside a 5-mile ring boundary from the central business district and have weaker cell phone coverage. We exclude two rings in the center of the map corresponding to leases terminated in May 2025. Units attached to these later leases may have already been treated given that the market priced in the initial wave of DOGE announcements several months prior.

FIGURE E.2. Null Effects of Terminated Federal Leases on Non-Retail Foot Traffic

A. Poisson Regression Results



B. OLS Estimation Results



Notes: We plot event study coefficients from estimating the ring difference-in-differences specification (6.1) applied to the Advan Research (2022) foot traffic data for non-retail points of interest (POI). The outcome variable in all regressions is the number of visits to a POI in a given week t. In Panel A, we assume the number of visits is distributed in a Poisson fashion, following Cohn et al. (2022). In Panel B, we define the outcome as the log number of visits to a non-retail POI and estimate (6.1) by simple OLS. Since we restrict to a balanced panel of POIs with strictly positive foot traffic in each week, the log transform does not omit any observations. For both the Poisson and OLS approaches, we test for spillovers at different levels of proximity by varying the pair of inner and outer radii $(\mathfrak{r}_{inner}, \mathfrak{r}_{outer})$ from $(0.25, 0.5)$ miles to $(0.5, 1)$ miles. We identify POIs as non-retail establishments based on whether they do not belong to one of four retail two-digit NAICS sectors *Retail Trade* (sector codes 44–45), *Arts, Entertainment, and Recreation* (sector code 71) or *Accommodation and Food Services* (sector code 72). 95% confidence intervals in solid bars obtained from Conley (2008) standard errors with a maximal spatial correlation distance cutoff parameter determined for each set of inner and outer radii $(\mathfrak{r}_{inner}, \mathfrak{r}_{outer})$. 95% confidence intervals in lighter dashed bars obtained from clustering standard errors at the Census block group level.

and if the relative time to the termination of that DOGE lease equals t. We define the control group as those POIs which are close to a DOGE lease but which have not been terminated as of period t and will be in the future. Appendix Figure E.3 gives a visual representation of early and late-treated POIs. We exclude from the estimation rings defined by two leases canceled after March 2025, as such rings may differ from earlier cohorts due to the informational content of being listed on the DOGE website. For example, landlords for leases that were newly canceled in May 2025 may have already incorporated signals received from the rescission of leases between March and May, resulting in little change in the status quo of business patterns after the actual termination announcement. Our results are less precise but qualitatively similar – meaning we still find null effects on foot traffic – if we include these later cohorts of rings in the sample.

We adopt the estimator proposed by Callaway and Sant'Anna (2021), with log of weekly visits as outcome. We report standard errors clustered at the block group level that allow for spatial correlation of POIs located within the same block group. We plot the estimated event study coefficients in Figure E.4. We continue to find a statistically flat pattern for the response of retail (Panel A) and non-retail (Panel B) foot traffic, with the point estimates close to zero regardless of the ring radius parameterization.

F Cumulative Abnormal Returns of GSA Tenant-Exposed REITs

In this appendix, we design and implement a cumulative abnormal return (CAR) analysis to quantify how the pricing of equities of public real estate investment trusts (REITs) with different exposure to federal tenants reacts to the initial set of DOGE ETO notifications.

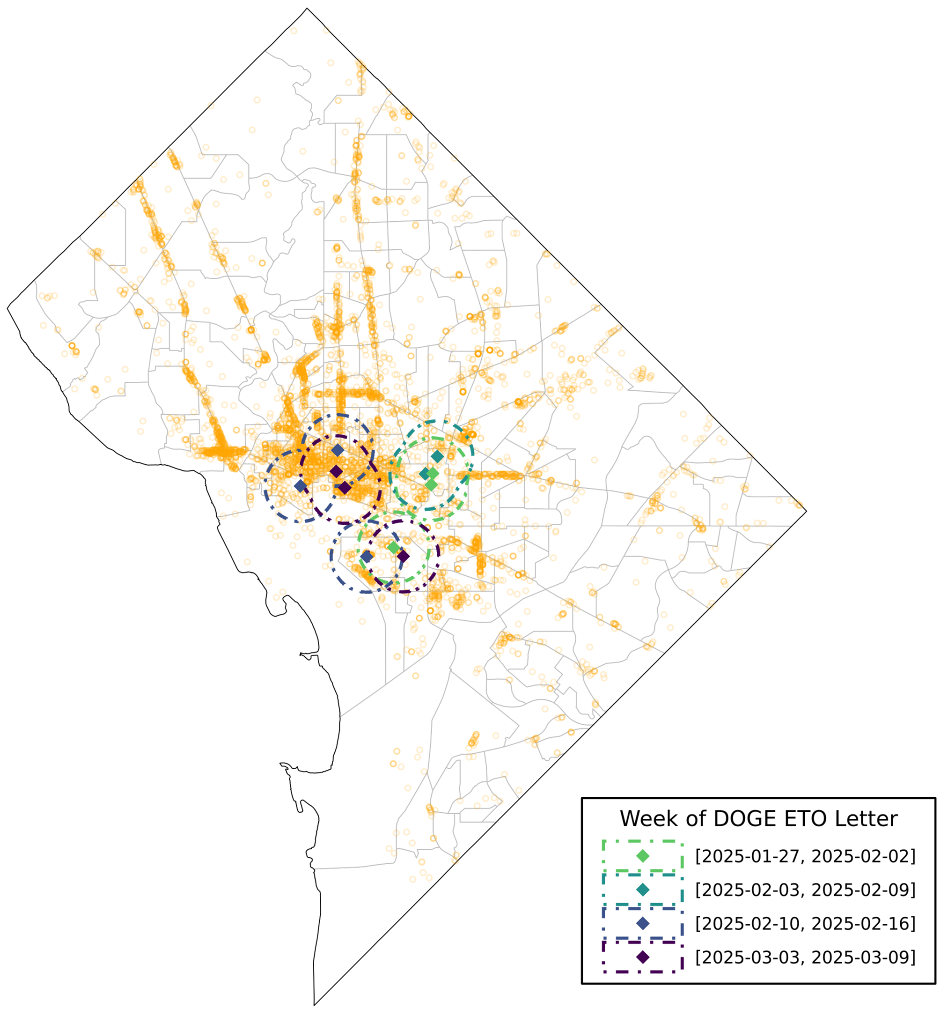
F.1 Event Studies of REIT Stock Prices and Returns

We track two portfolios of publicly traded REITs: a treated group with high direct U.S. federal tenant exposure to the D.C. metro office market (DEA, CDP, JBGS, OPI) and a control group holding D.C.-area assets but with little to no direct federal leasing exposure (BXP, FRT, ELME, AVB).[5] Let $P_{i,t}$ denote the closing stock price for REIT i on day t and $t_0 = 1/30/2025$ be the day DOGE first sent cancellation notifications to landlords. We re-base each series to 100 at t_0 and aggregate within portfolios such that

$$\tilde{P}_{it} \equiv 100 \times \frac{P_{i,t}}{P_{it_0}}.$$

[5] We classify REIT office exposure to federal tenants in D.C. based on 2024Q4 10-K (Schedule III supplemental) filings and investor materials. The treated group of REITs are heavily concentrated in buildings leased to federal agencies or to tenants whose revenue is closely tied to federal missions, especially in and around Washington D.C. The control group consists of large listed landlords with similar exposure to property, interest rate, and equity market risk but whose cash flows are primarily driven by private tenants rather than federal leases.

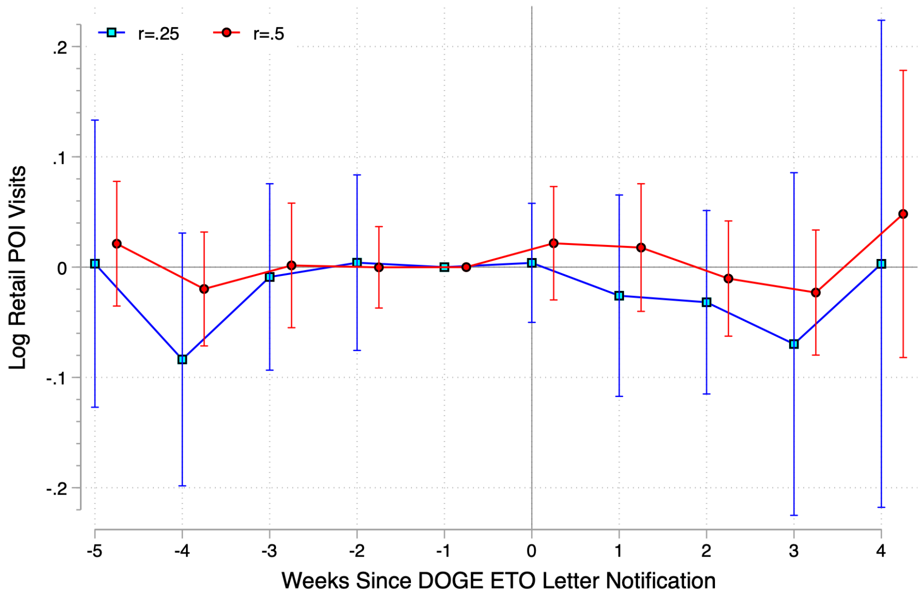
FIGURE E.3. Early and Late-Treated Rings around Terminated Washington, D.C. Federal Agency-Leased Office Properties



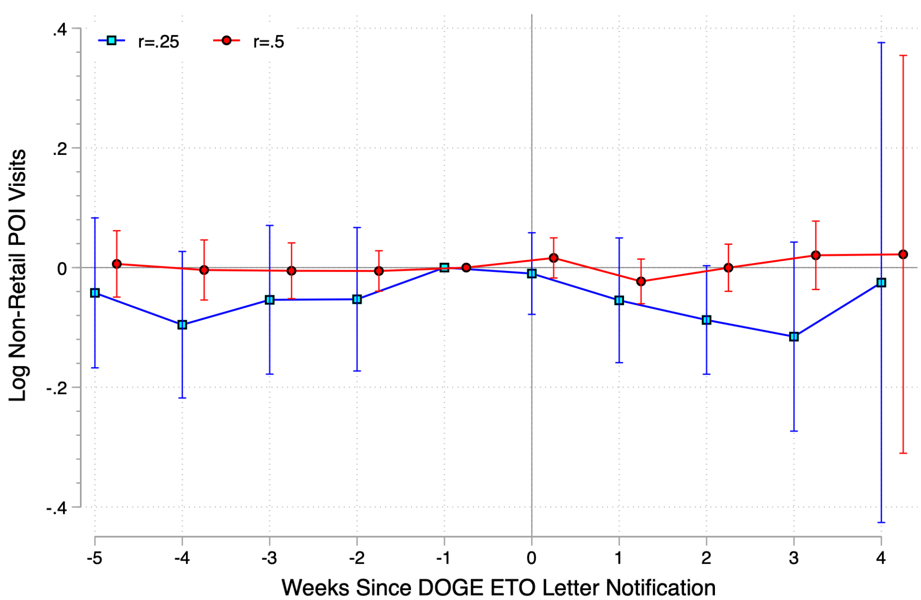
Notes: The map plots 0.5-mile rings around DOGE terminated leases that are included in the early-vs-late DiD estimation given by (E.1). Darker colors indicate rings defined by later termination cohorts, and POIs inside the darker circles serve as control group for POIs in proximity to earlier terminations, which are contained in the lightly colored circles. We restrict our sample to rings corresponding to leases terminated prior to the wave of rescissions occurring after mid-March, 2025. Orange points indicate the locations of retail POIs in the foot traffic analysis sample. Due to commercial zoning rules in Washington, D.C. most retail establishments are located on avenues, which results in clustering of retail POIs along the diagonal street grids radiating outwards from the central business district.

FIGURE E.4. Effects of Terminated Federal Leases on Foot Traffic: CSDID estimates

A. Retail POI Visits



B. Non-Retail POI Visits



Notes: We plot event study coefficients from estimating the early vs. late ring difference-in-differences specification (E.1) applied to the Advan Research (2022) foot traffic data for points of interest (POI). We estimate the event studies using the Callaway and Sant'Anna (2021) estimator, comparing foot traffic to POIs in the vicinity of an early-terminated lease to that of POIs in the vicinity of a late-terminated lease, as visualized in the map of Figure E.3. The outcome variable in all regressions is the number of visits to a POI in a given week t. In Panel A, we restrict to retail foot traffic; Panel B instead restricts to non-retail foot traffic. The outcome variable in each regression is the log number of visits to a POI. Since we restrict to a balanced panel of POIs with strictly positive foot traffic in each week, the log transform does not omit any observations. In both panels, we test for spatial spillovers at ring radii of 0.25 and 0.5 miles. We identify POIs as retail establishments based on whether they belong to one of four retail two-digit NAICS sectors *Retail Trade* (sector codes 44–45), *Arts, Entertainment, and Recreation* (sector code 71) or *Accommodation and Food Services* (sector code 72). 95% confidence intervals obtained from clustering standard errors at the Census block group level.

For the treated basket we form two indices using 2024Q4 fundamentals: (i) an NOI-weighted index, $I_t^{\text{NOI}} = \sum_{i \in \mathcal{T}} w_i^{\text{NOI}} \tilde{P}_{it}$, and (ii) a square-footage-weighted index, $I_t^{\text{SQFT}} = \sum_{i \in \mathcal{T}} w_i^{\text{SQFT}} \tilde{P}_{it}$, with $\sum_i w_i^{\cdot} = 1$ in each case. The control index is an equal-weighted mean across the control group of REITs, $I_t^{\text{CTRL}} = \frac{1}{4} \sum_{i \in \mathcal{C}} \tilde{P}_{it}$. The sample runs from January 1, 2024 to October 16, 2025. Vertical reference lines mark February 1, 2025 (DOGE policy shock) and September 15, 2025 (initial broad press coverage of federal government shutdown risk).

In Figure F.1, we document that stock prices for GSA tenant-exposed REITs react quickly and negatively around January 30, 2025, consistent with equity markets incorporating the newly announced and expected future lease cancellations. Consistent with the increased salience of vacancy risk, the depth of this price decline is larger under SQFT weighting than NOI weighting. Stock prices for the two groups of REITs trended similarly in the months leading up to the creation of DOGE, including around the November 2024 presidential election. The drop in prices around October 1, 2025, when the federal government temporarily shutdown due to a lapse in appropriations legislation suggests news-beta to Washington headlines rather than a reversal in fundamentals. Together, the patterns are consistent with the evidence presented for real estate debt markets; equity REITs concentrated in federal tenancy and D.C. office ownership incur a persistent discount relative to otherwise similar D.C. owners without federal lease dependence.

Next, we test whether the market processed the abrupt change in the federal leasing policy as an increased salience of government contract risk by investigating the cumulative abnormal return (CAR) of the aforementioned treatment and control REITs groups.[6] For each index (treated NOI-weighted, treated SQFT-weighted, control equal-weighted), we estimate a standard market model over an estimation window that runs from 360 to 90 days before the event date (from February 5, 2024 to November 1, 2024), regressing daily portfolio returns on the return of the broader stock market (S&P 500).[7] The fitted intercept and slope from this regression provide a benchmark for normal returns driven purely by usual co-movement with the market. Since the procedures are standard, we defer them to the next subsection (Appendix F.2).

Figure F.2 Panel A shows cumulative abnormal returns (CARs), obtained by summing up these daily abnormal returns from 15 trading days before to 15 days after the event, separately for the two treated indices and the control portfolio. By exploiting differential responses of high vs. low-government exposure REITs to the DOGE shock, where returns are benchmarked against the capitalization-weighted market return, we estimate a difference-in-differences-in-means

[6]We define the returns as a capital gain; however, our results are nearly unchanged if we instead compute total returns. All eight REITs in the sample are regular dividend payers, typically on a quarterly schedule. For example, OPI has an ex-dividend date on January 27, 2025 with payment on February 20, 2025, and DEA, CDP, and JBGS have recurring quarterly dividends. Over the relatively short event windows that we study (up to thirty trading days) the total dividend yield that falls inside a given window is on the order of tens of basis points to at most a few percent, and some windows contain no ex-dividend dates for several REITs. The large negative CARs we document for the treated indices are therefore mainly driven by price reactions.

[7]We cut the normal time window to end before November 2024 to avoid any market volatility around the resolution of political uncertainty associated with the outcome of the 2024 presidential election.

estimator. We compute CARs as an arithmetic average to avoid the need for parallel trends to hold in volatility of returns across the two groups of REITs, as noted by Goldsmith-Pinkham and Lyu (2025). Instead, parallel trends need only hold in terms of levels of returns, which is validated by the CARs being nearly identical prior to DOGE's announcements on January 30, 2025.

Panel B summarizes the same information in a more compact form by reporting cumulative abnormal returns over symmetric windows of different lengths around the notification date. The two panels show a sharp and persistent repricing of federal tenant exposure at the time of the initial DOGE ETO notifications. In Panel A, both treated indices experience a large drop in cumulative abnormal returns on the event date and remain roughly 3% to 5% below pre-event levels over the subsequent 15 trading days while the control portfolio rebounds and posts positive cumulative abnormal returns over the same horizon. Panel B reinforces this pattern: cumulative abnormal returns for the treated portfolios are negative and grow in magnitude as the window widens, whereas the control portfolio records modestly positive cumulative abnormal returns. Consistent with our debt market salience results, investors mark down landlords that rely on federal leases while leaving comparable REITs without such exposure largely unaffected providing equity market evidence of repricing of government contract risk.

F.2 Constructing Abnormal Returns: Steps

Define the daily capital gain for the stock price of REIT i as:

$$r_{i,t} = \log\left(\frac{P_{i,t}}{P_{i,t-1}}\right),$$

where $P_{i,t}$ is the price of REIT i on day t.

Then we can construct portfolio returns for the treated set of REITs as a weighted average of the capital gains, based on either NOI or square footage (SQFT) weights.

$$r_{T,\text{NOI},t} = \sum_{i\in\mathcal{T}} w_i^{\text{NOI}}\, r_{i,t}, \qquad r_{T,\text{SQFT},t} = \sum_{i\in\mathcal{T}} w_i^{\text{SQFT}}\, r_{i,t},$$

where $\mathcal{T} = \{\text{DEA}, \text{CDP}, \text{JBGS}, \text{OPI}\}$ is the treated set of REITs with GSA tenant exposure, and $\sum_{i\in\mathcal{T}} w_i^{\text{NOI}} = \sum_{i\in\mathcal{T}} w_i^{\text{SQFT}} = 1$.

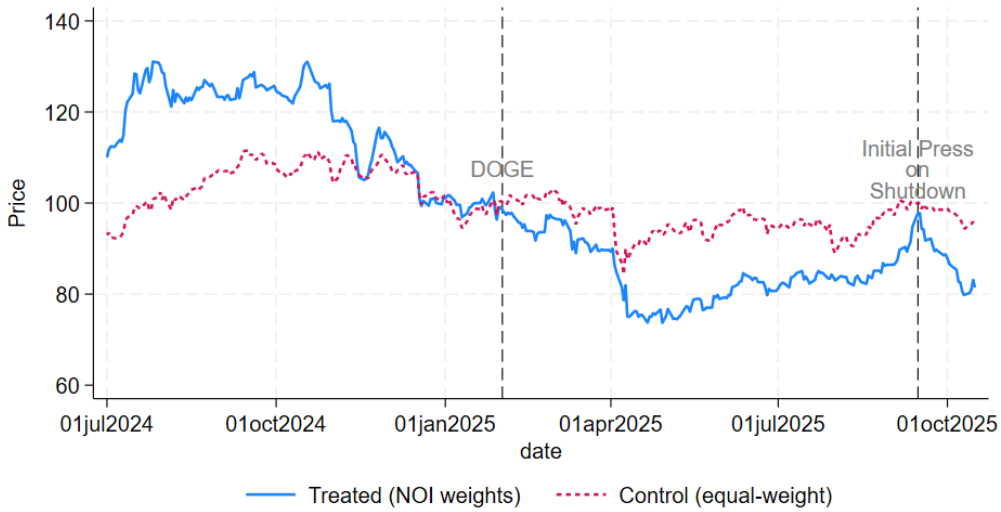
Similarly, the return on the portfolio of control REITs is an equal-weighted average of the capital gains for equities of REITs with little to no GSA tenant exposure:

$$r_{C,t} = \frac{1}{4}\left(r_{\text{BXP},t} + r_{\text{FRT},t} + r_{\text{ELME},t} + r_{\text{AVB},t}\right).$$

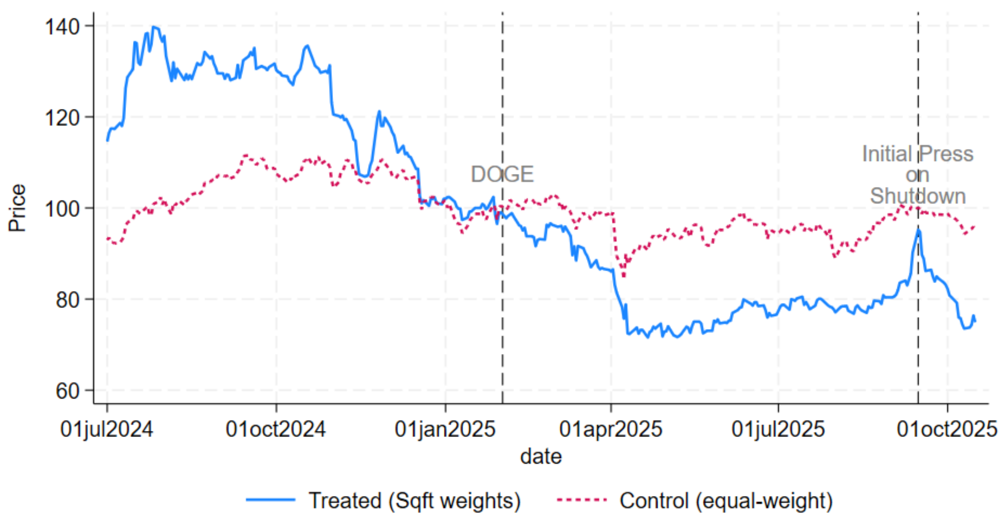
Let $r_{M,t}$ be the log market return on the S&P 500 on day t. For each portfolio $p \in \{T, \text{NOI};\ T, \text{SQFT};\ C\}$, we estimate the market model over the pre-event estimation window

FIGURE F.1. Time Series of Stock Prices for Treatment and Control Group D.C. REIT Indices

A. NOI-Weighted



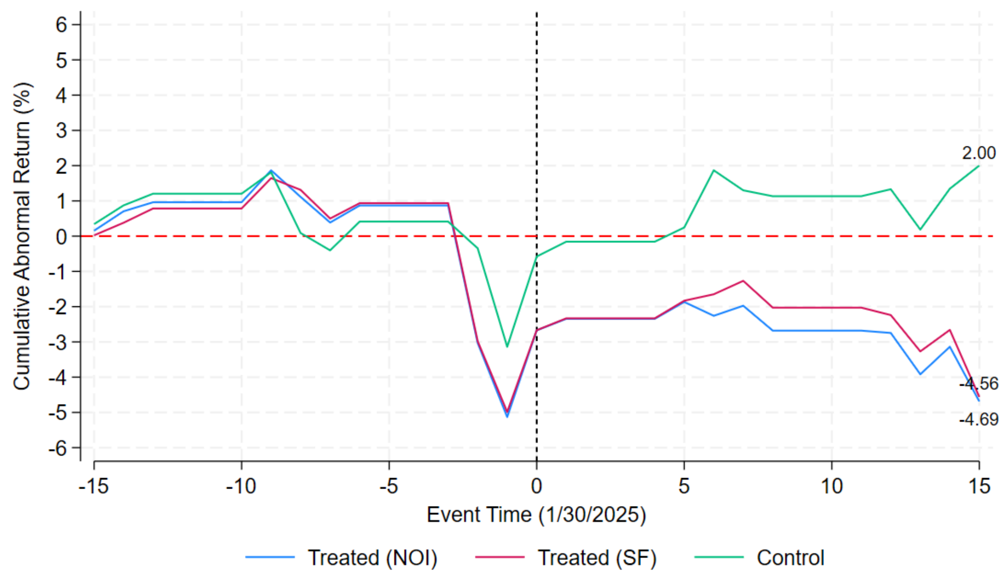
B. SQFT-Weighted



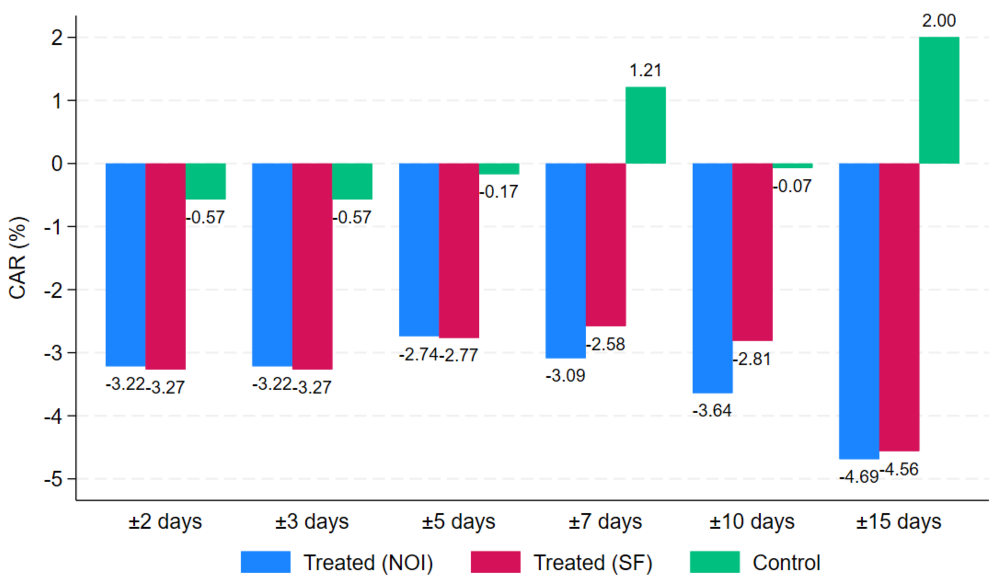
Notes: The figure plots the daily price indices for two REIT portfolios consisting of treated companies (DEA, CDP, JBGS, OPI; high D.C. office exposure) and control (BXP, FRT, ELME, AVB) REITs using prices from Jan 1, 2024 to Oct 16, 2025. Each constituent price is re-based to 100 on January 30, 2025, then aggregated. The treated portfolio yields two indices: NOI-weighted (Panel A) and SQFT-weighted (Panel B) based on the 2024Q4 10-K Schedule III information, while the control portfolio is equal-weighted. Vertical reference lines mark February 1, 2025 (DOGE-induced federal lease policy change) and September 15, 2025 (initial press coverage on the 2025 U.S. government shutdown).

FIGURE F.2. Cumulative Abnormal Returns for D.C. REITs

A. Cumulative Abnormal Returns for a Symmetric 15-day Window



B. Cumulative Abnormal Return at Various Horizons



Notes: The figure plots the cumulative abnormal return (CAR) analysis for two REIT portfolios with treated (DEA, CDP, JBGS, OPI; high D.C. office exposure) and control (BXP, FRT, ELME, AVB) groups using prices from February 5, 2024 to November 1, 2024 as the normal market return window and the symmetric windows of 2, 3, 5, 7, 10, and 15 trading days. Panel A plots the daily CARs with a symmetric 15-day window around January 30, 2025. Panel B plots the CARs for the aforementioned horizons.

$t \in [T_0, T_1] = [-360, -90]$:

$$r_{p,t} = \alpha_p + \beta_p r_{M,t} + \varepsilon_{p,t}, \quad t \in [T_0, T_1].$$

Using the estimated coefficients $(\hat{\alpha}_p, \hat{\beta}_p)$, we define the "normal" return and abnormal return for all event days t:

$$\widehat{r}_{p,t} = \hat{\alpha}_p + \hat{\beta}_p r_{M,t}, \qquad AR_{p,t} = r_{p,t} - \widehat{r}_{p,t}.$$

Here, event time is defined so that $t = 0$ is the event date of initial DOGE ETO notifications on January 30, 2025.

We compute standard errors for the estimate coefficients and corresponding abnormal returns (AR) using Newey-West standard errors with four lags to adjust for serial correlation and heteroskedasticity (Newey and West, 1987). We select the minimum possible lag order such that the estimator for the covariance matrix is consistent, or $\texttt{floor}(T^{1/4}) = \texttt{floor}(270^{1/4}) = 4$.

For a symmetric event window of half-width h days,

$$\mathcal{W}(h) = \{-h, -h+1, \ldots, -1, 0, 1, \ldots, h-1, h\},$$

the cumulative abnormal return (CAR) for portfolio p is

$$CAR_p(h) = 100 \sum_{t \in \mathcal{W}(h)} AR_{p,t} = 100 \sum_{t=-h}^{h} AR_{p,t},$$

for $h \in \{2, 3, 5, 7, 10, 15\}$.

G Loss Simulation Procedures

This appendix provides details about how we calibrate the simulation exercises in Section 7 based on our arbitrage pricing framework for valuing lease contingencies.

G.1 Hedonic Regression

We begin by dividing our Trepp CMBS property panel into ETO-notified, ETO-eligible, and spillover groups, as defined in our main regression specifications in Section 5. A practical limitation of the Trepp extract is that property values are missing for a subset of observations. To expand the set of properties with usable covariates and preserve statistical power, we hand-collect building characteristics from CoStar for all office addresses belonging to our three mutually exclusive exposure groups. We then merge these CoStar covariates with the Trepp property file using a standardized property address key, producing a unified property-level dataset covering 136 properties across the three groups, with only five properties included in our original difference-in-differences sample missing covariates.[8]

When appraisal values are available in Trepp, we compute for each property a lagged moving average of the four most recent appraisals observed prior to the securitization date as provided by Trepp:

$$\overline{V}_i = \frac{1}{4}\sum_{k=1}^{4} V_{i,t-k} \tag{G.1}$$

where $\overline{V}_i$ denotes the appraised value of property i at the k-th most recent observation. This average, $\overline{V}_i$, serves to mitigate idiosyncratic noise in any single observation and more closely approximates a steady state valuation for each property.

Next, we estimate a standard cross-sectional hedonic pricing model:

$$\begin{aligned} \log \overline{V}_i &= \beta_0 + \beta' \cdot \mathbf{X_i} + \varepsilon_i \\ \widehat{V}_i &= \exp\left(\widehat{\beta}_0 + \widehat{\beta}' \cdot \mathbf{X_i}\right) \end{aligned} \tag{G.2}$$

where $\overline{V}_i$ is the appraised value based on (G.1), $\mathbf{X_i}$ is a vector of covariates used in the production externality analysis including construction year, rentable building area (RBA), CoStar StarRating, and number of stories, and ε_i is an idiosyncratic error term. The estimated baseline value $\widehat{V}_i$ obtained from the regression fitted values captures both systematic pricing effects and property-specific deviations. We test the goodness-of-fit of our property value estimation via in-sample fit measures (e.g., adjusted R^2, RMSE, MAPE) in the next subsection. We adopt this parsimonious set of covariates to include to maximize our sample size while preserving explanatory power. The StarRating is available for most observations and is based on CoStar's own hedonic model which is a function of other building characteristics.

Among the explanatory variables, rentable building area (RBA), CoStar Star Rating, year built, and the number of stories are all statistically significant and positive; RBA and year built are significant at the 1% level and star rating and number of stories are significant at the 5% level. Properties that are larger, newer, higher-rated, and taller are associated with higher appraised values at securitization. These results suggest that the baseline valuation differences in this market are largely explained by a small set of structural and quality attributes, which we use to impute missing appraisals for otherwise comparable properties.

We use the estimated coefficients from (G.2) to impute baseline values for properties with missing Trepp appraisals. Specifically, for any property with a non-missing covariate vector $\mathbf{X}_i$

[8]These missing values lead us to slightly underestimate value losses accruing to the spillover group of private-tenant offices.

TABLE G.1. Hedonic Regression Results

Variable	Coefficient	Std. Error	t-Stat	p-Value
Rentable Building Area ('000s sq. ft.)	0.0030***	0.0007	4.10	0.000
Star Rating	0.3214**	0.1347	2.39	0.018
Year Built	0.0069***	0.0024	2.89	0.004
Number of Stories	0.0721**	0.0293	2.46	0.015
# Properties	136			
Adj-R^2	0.657			

Notes: Dependent variable is the natural logarithm of property value. Rentable area and prior-year NOI are expressed in thousands. Regression results are estimated using the sample of Washington, D.C. Trepp properties with non-missing covariates. Robust standard errors are clustered at the property level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

but a missing $\overline{V}_i$, we compute the predicted log appraisal

$$\widehat{\log \overline{V}_i} = \widehat{\beta}_0 + \widehat{\beta}'\mathbf{X}_i,$$

and recover the implied level baseline value as $\widehat{V}_i = \exp\left(\widehat{\log \overline{V}_i}\right)$. We then replace missing appraisal values with $\widehat{V}_i$ to obtain a completed baseline value series used as the initial valuation input in the simulation. The mark-to-market correction implied by our model results in a slight increase in our valuation of the securitized office market segment for Washington, D.C. The total value based on appraisals is \$12.80 billion, while the sum of the fitted values is \$12.95 billion. In Table 9 we scale up the portfolio-level losses to a market-wide loss measure using estimated securitization rates.

G.2 Hedonic Model Goodness-of-Fit Tests

Model Fit Statistics. As part of our goodness-of-fit assessment for the hedonic specification in (G.2), we report standard in-sample fit measures. The model attains an adjusted R^2 of 0.657, indicating that the included structural covariates explain a substantial share of the cross-sectional variation in log appraised values within the estimation sample. The regressors are jointly significant with an F-statistic of 48.45. The Root MSE is 0.752, reflecting the typical magnitude of residual variation in log-value units.

Mean Absolute Percentage Error (MAPE). Table G.2 reports absolute percentage error (APE) statistics for the overlap sample ($N = 136$). While the mean absolute percentage error (MAPE) is 71.6%, the median APE is substantially lower at 39.3%, indicating that prediction accuracy is considerably better for the typical property and that the mean is driven by a right-tailed set of outliers. This is consistent with idiosyncratic noise in point-in-time securitization appraisals and the mechanical sensitivity of percentage errors to small denominators; correspondingly, trimming the top 1% of APE observations reduces MAPE to 67.5%.

TABLE G.2. Hedonic Prediction Accuracy (APE / MAPE)

Metric	Value (decimal)	Value (%)
Observations used (N)	136	—
MAPE (mean APE)	0.716	71.6%
Median APE	0.393	39.3%
90th percentile APE	1.952	195.2%
95th percentile APE	3.450	345.0%
Trimmed MAPE (excluding top 1% APE)	0.675	67.5%

Notes: The table reports absolute percentage error (APE) statistics comparing hedonic-predicted baseline values $\widehat{V}_i$ to observed Trepp appraisals V_i for properties with both observed appraisals and non-missing covariates (overlap sample). $\text{APE}_i = \left|(\widehat{V}_i - V_i)/V_i\right|$. MAPE is the mean of APE. Trimmed MAPE excludes the top 1% of APE observations (above the 99th percentile) to reduce sensitivity to extreme outliers.

G.3 Simulation Dynamics

We simulate the evolution of property values under early termination risk using stochastic processes that incorporate both continuous market volatility and discrete policy shocks.

We conduct the simulation over a horizon of $T \in \{1, 2, 3, 4, 5\}$ years and repeatedly compute valuations and losses across 50,000 independent Monte Carlo draws for each group. We calibrate the model parameters in Table G.3 to reflect empirical features of commercial real estate markets and observed characteristics of federal lease terminations. A five-year horizon matches the typical length of the soft term for ETO-eligible leases, while a one-year horizon matches the time frame of our difference-in-differences estimates. The drift term is set to $\mu = 0.02$, representing modest long-run expected growth in property values under normal conditions. We set the volatility parameter to $\sigma = 0.10$, capturing annualized standard deviation in value consistent with historical CRE return data (Axios Local, 2024; Cresa, 2025).

Jump magnitudes are governed by $\beta_{DOGE} = 0.213$, $\beta_{ETO} = 0.016$, and $\beta_{SPILL} = 0.119$, corresponding to proportional NOI losses per DOGE-induced jump for the ETO-notified, ETO-eligible, and private-tenant spillover groups, respectively. We map these proportional effects into group-specific log jump sizes

$$J_g = \log\left(1 - \beta_g\right),$$

so that each realized jump scales value multiplicatively by $\exp\left(J_g\right) = 1 - \beta_g$. As in the empirical analysis, β_{DOGE} and β_{ETO} are obtained from the baseline difference-in-differences design, and β_{SPILL} is obtained from the spatial difference-in-differences design in equation (5.3) comparing private leases within a 5-mile radius of notified properties to the ETO-eligible group.

By simulating property values directly, we avoid taking a stand on terminal capitalization parameters such as the discount rate and long-run growth rate. Our empirical estimates identify group-specific proportional NOI effects per termination shock, β_g. Under a standard

TABLE G.3. Simulation Model Parameters

Symbol	Parameter	Value	Description
μ	Drift rate	0.020	Annual baseline growth in property values
σ	Valuation volatility	0.100	Annualized standard deviation of value (market risk)
β_{DOGE}	Jump size	0.213	Average proportional loss per jump for ETO-notified
β_{ETO}	Jump size	0.016	Average proportional loss per jump for ETO-eligible
β_{SPILL}	Jump size	0.119	Average proportional loss per jump for private-tenant
λ	Jump intensity	0.15	Annual probability of ETO execution (Poisson)
T	Simulation horizon	$\{1,2,3,4,5\}$	Horizon in years (shock persistence parameter)
N	Monte Carlo iterations	50,000	Number of random draws per group and horizon

income-capitalization framework (e.g., the Gordon growth model), a proportional cash-flow hit implies a proportional value hit when capitalization rates are held fixed. Hence, we implement shocks as multiplicative jumps in value of size $1 - \beta_g$ (i.e., $J_g = \log(1 - \beta_g)$). This provides a reduced-form mapping from empirically estimated cash-flow impacts into the value process used in the Monte Carlo analysis.

We set the jump intensity to $\lambda = 0.15$, and for each simulation horizon T we draw the number of jumps as $N_T \sim \text{Poisson}(\lambda \cdot T)$. This parameter is calibrated to match observed termination intensity in DOGE lease records and termination frequencies reported in Panels A and B of Figure 10, and is corroborated by industry reporting during the peak period of DOGE-listed cancellations (CoStar News, 2025b).[9]

We model the evolution of property value V_t over horizon T using stochastic differential equations tailored to each of three scenarios: ETO-notified, ETO-eligible, and private-tenant spillovers.

Scenario 1: ETO-Notified

$$dV_t = \mu V_t^- dt + \sigma V_t^- dW_t + V_t^- (J_{DOGE} - 1)\, dC_t \tag{G.3}$$

Here, C_t is a Poisson process with intensity λ, and J_{DOGE} represents the multiplicative impact of jumps. This specification captures the combination of continuous market volatility with sudden discontinuous declines triggered by federal lease cancellations.

Scenario 2: ETO-Eligible without Notification

$$dV_t = \mu V_t^- dt + \sigma V_t^- dW_t + V_t^- (J_{ETO} - 1)\, dC_t \tag{G.4}$$

In this case, the structure remains the same as in Scenario 1 but with a smaller calibrated jump component, J_{ETO}, reflecting the lower but still elevated termination risk faced by properties that are eligible but not formally notified.

[9]Setting $\lambda = 0.15$ implies that the average waiting time for the next lease cancellation shock is 1/0.15 = 6.67 years. This exceeds the median soft term length of five years.

Scenario 3: Private-Tenant Spillovers

$$dV_t = \mu V_t^- dt + \sigma V_t^- dW_t + V_t^- (J_{SPILL} - 1)\, dC_t \tag{G.5}$$

Spillover properties are not directly subject to federal termination (private lease) but may experience correlated losses through demand reductions, diminished local activity, and adverse market signaling. We show in our empirical results that the jump component J_{SPILL} is likely driven by a combination of adverse market signaling and production externalities to the nearby tenants which provide services to the government agencies notified by DOGE. This jump-diffusion process thus captures the indirect yet economically meaningful disruptions that diffuse into nearby private leases.

In all cases, we define losses as the difference between a property's simulated terminal value with group-specific jumps and the terminal value from an otherwise identical no-jump diffusion path. For each property i with baseline value $V_{i,0}$ and horizon T, we first draw the number of shocks $N_T \sim \text{Poisson}(\lambda T)$ and simulate the no-jump counterfactual

$$V_{i,T}^{(0)} = V_{i,0} \exp\big((\mu - \sigma^2/2)T + \sigma W_T\big)$$

We then apply the group-specific jump multiplier impact β_g, yielding the jump-affected terminal value

$$V_{i,T}^{(g)} = V_{i,T}^{(0)} \exp\big(J_g\, N_T\big) = V_{i,T}^{(0)} (1 - \beta_g)^{N_T}$$

The property-level loss is defined as the difference between these two terminal values,

$$L_{i,T} = V_{i,T}^{(0)} - V_{i,T}^{(g)}$$

and the corresponding portfolio loss for group g at horizon T is the cross-sectional sum

$$L_{g,T} = \sum_{i \in \mathcal{I}_g} L_{i,T}$$

where $\mathcal{I}_g$ denotes the set of properties in three mutually exclusive groups g. Repeating this procedure over $N = 50{,}000$ Monte Carlo draws for each $T \in \{1, 2, 3, 4, 5\}$ yields empirical loss distributions used to compute tail-risk measures.

Table G.4 reports the VaR and expected shortfall at various confidence levels $\alpha \in \{20\%, 50\%, 75\%, 95\%\}$ and for each persistence parameter $T \in \{1, 2, 3, 4, 5\}$ years. Expected shortfalls nearly quadruple in tail-risk scenarios as we increase the simulation horizon from one year to five years. Figures G.1 and G.2 show how the distribution of losses evolves over time and by confidence level.

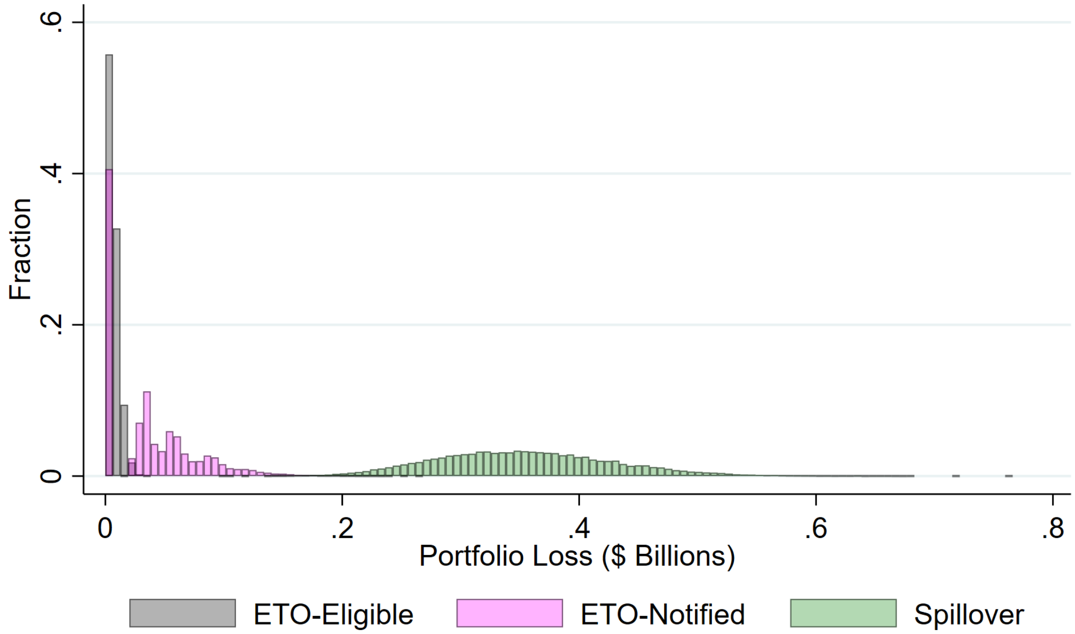
TABLE G.4. Value at Risk & Expected Shortfall by Group and Shock Horizon

	Value at Risk (VaR)				Expected Shortfall (ES)			
Group	20%	50%	75%	95%	20%	50%	75%	95%
Panel A: Horizon $T = 1$ year								
ETO-eligible	0.002	0.006	0.009	0.016	0.008	0.010	0.013	0.019
ETO-notified	0.000	0.032	0.058	0.111	0.036	0.066	0.090	0.136
Spillover	0.288	0.351	0.405	0.487	0.380	0.416	0.456	0.527
Panel B: Horizon $T = 2$ years								
ETO-eligible	0.007	0.012	0.018	0.026	0.015	0.019	0.023	0.031
ETO-notified	0.028	0.064	0.105	0.172	0.089	0.115	0.146	0.203
Spillover	0.623	0.712	0.788	0.903	0.753	0.803	0.859	0.956
Panel C: Horizon $T = 3$ years								
ETO-eligible	0.012	0.019	0.026	0.037	0.023	0.027	0.032	0.042
ETO-notified	0.048	0.102	0.150	0.231	0.130	0.162	0.199	0.266
Spillover	0.970	1.083	1.177	1.318	1.133	1.195	1.263	1.380
Panel D: Horizon $T = 4$ years								
ETO-eligible	0.018	0.026	0.034	0.047	0.031	0.036	0.042	0.053
ETO-notified	0.077	0.138	0.194	0.281	0.170	0.206	0.248	0.321
Spillover	1.333	1.460	1.571	1.740	1.521	1.594	1.675	1.818
Panel E: Horizon $T = 5$ years								
ETO-eligible	0.024	0.033	0.042	0.057	0.039	0.045	0.051	0.064
ETO-notified	0.107	0.176	0.236	0.333	0.210	0.251	0.296	0.378
Spillover	1.700	1.849	1.971	2.158	1.915	1.996	2.085	2.240

Notes: The table reports Value at Risk (VaR) and Expected Shortfall (ES) for simulated positive losses (in billions of dollars) at tail probabilities $1 - \alpha \in \{20\%, 50\%, 75\%, 95\%\}$ for each group and shock persistence horizon $T \in \{1, 2, 3, 4, 5\}$ years for Panel A, B, C, D, and E respectively.

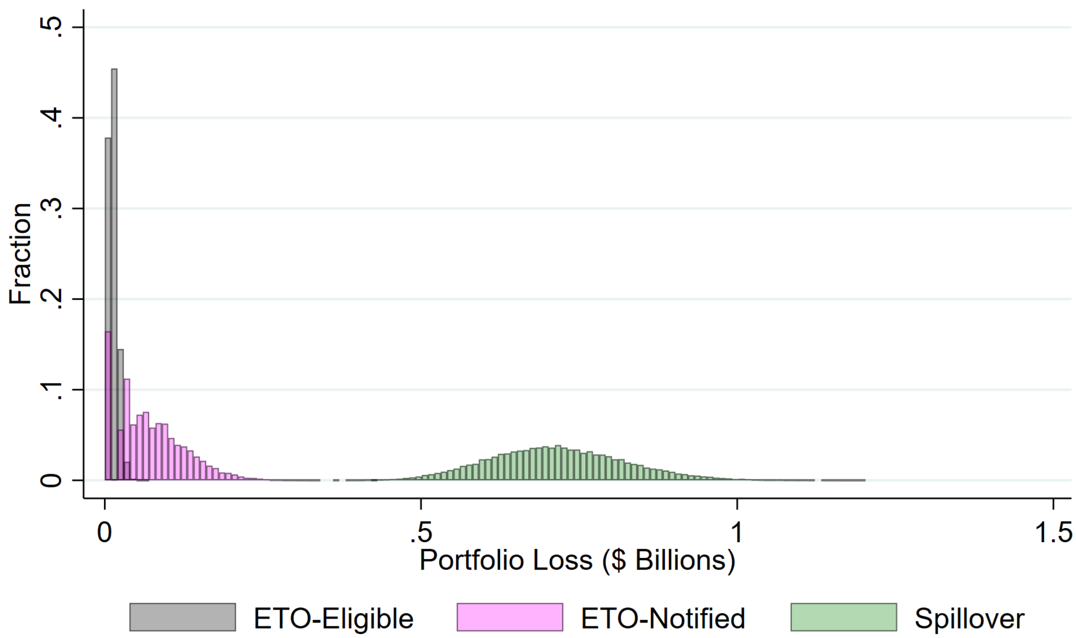
FIGURE G.1. Simulated Loss Distributions over 1 & 2-Year Shock Horizons
ETO-Eligible (Non-Exercised) vs. ETO-Notified (Exercised) vs. Private Tenant

A. Shock Horizon: 1 Years



VaR (20/50/75/95) in USD Billions
ETO-Eligible (0.003/ 0.006/ 0.010/ 0.016) ETO-Notified (0.033/ 0.053/ 0.077/ 0.124) Spillover (0.288/ 0.351/ 0.405/ 0.487)

B. Shock Horizon: 2 Years

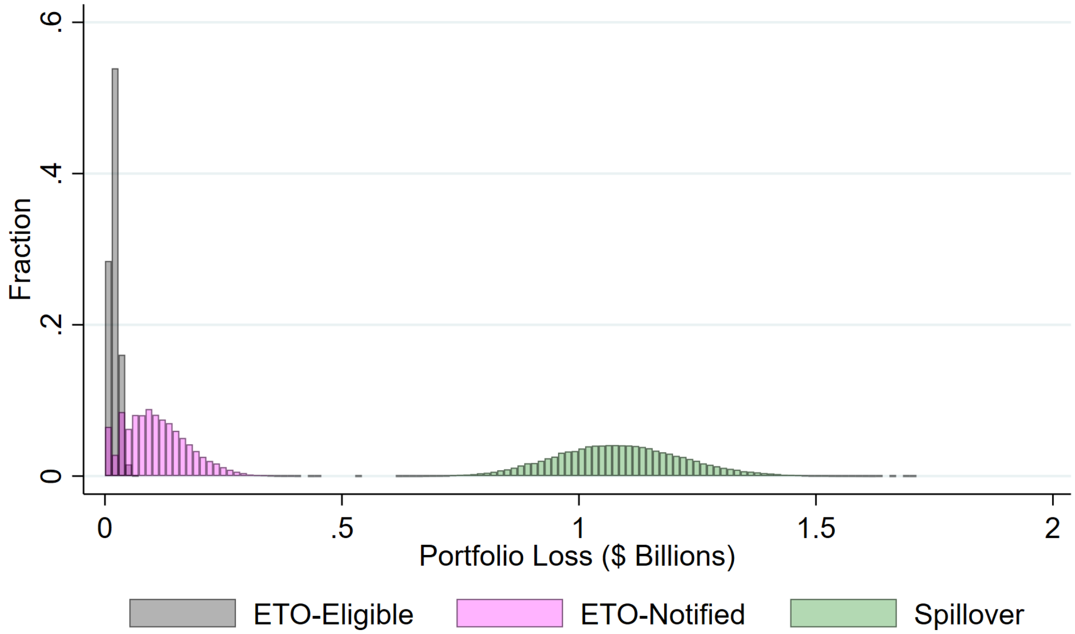


VaR (20/50/75/95) in USD Billions
ETO-Eligible (0.007/ 0.012/ 0.018/ 0.026) ETO-Notified (0.040/ 0.077/ 0.115/ 0.178) Spillover (0.623/ 0.712/ 0.788/ 0.903)

Notes: The figure plots the simulated portfolio loss distributions under early termination option (ETO) risk for three groups of properties: those that are eligible for ETO exercise but not notified (gray), those that have received formal ETO notifications (pink), and private-lease properties within a 5-mile radius of terminated leases which are indirectly affected through spatial spillovers (green). Panel A and B represent 1-year and 2-year horizons respectively.

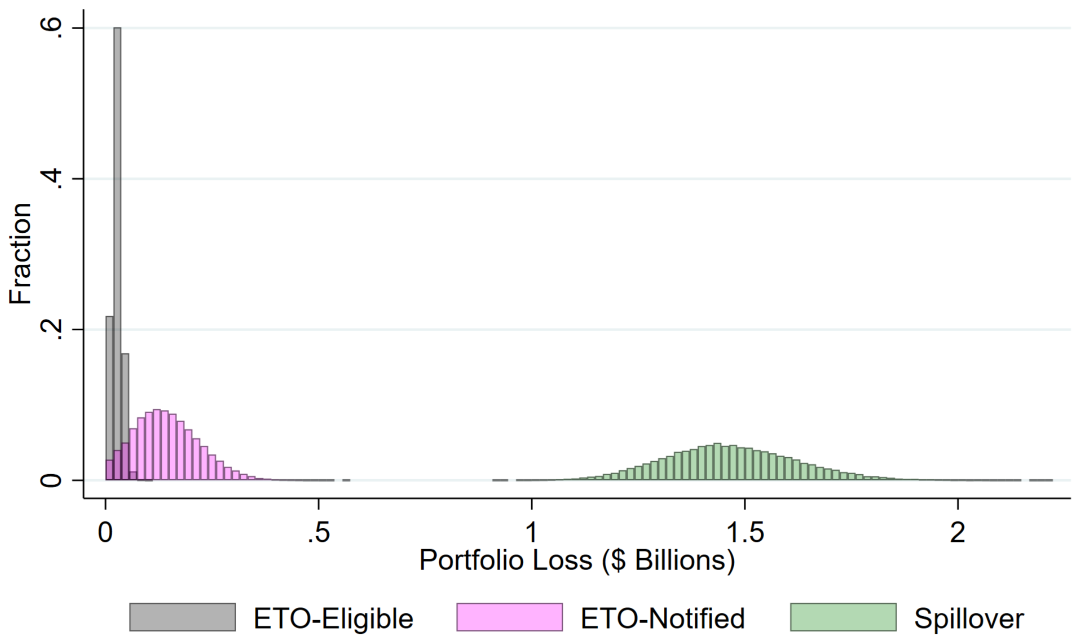
FIGURE G.2. Simulated Loss Distributions over 3 & 4-Year Shock Horizons
ETO-Eligible (Non-Exercised) vs. ETO-Notified (Exercised) vs. Private Tenant

A. Shock Horizon: 3 Years



VaR (20/50/75/95) in USD Billions
ETO-Eligible (0.012/ 0.019/ 0.026/ 0.037) ETO-Notified (0.059/ 0.107/ 0.154/ 0.233) Spillover (0.970/ 1.083/ 1.177/ 1.318)

B. Shock Horizon: 4 Years



VaR (20/50/75/95) in USD Billions
ETO-Eligible (0.018/ 0.026/ 0.034/ 0.047) ETO-Notified (0.082/ 0.141/ 0.196/ 0.282) Spillover (1.333/ 1.460/ 1.571/ 1.740)

Notes: The figure plots the simulated portfolio loss distributions under early termination option (ETO) risk for three groups of properties: those that are eligible for ETO exercise but not notified (gray), those that have received formal ETO notifications (pink), and private-lease properties within a 5-mile radius of terminated leases which are indirectly affected through spatial spillovers (green). Panel A and B represent 3-year and 4-year horizons respectively.