Corporate Real Estate Usage and Firm Valuation: Evidence from a Dynamic Partial Adjustment Model

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The trade-off between the potential benefits and costs of using corporate real estate (CorRE) in the production process creates an optimal level of CorRE that varies over time and across firms. We document the importance of conditioning on a firm's optimal CorRE usage when analyzing the influences of CorRE on firm valuations. Using a dynamic partial adjustment model, we estimate differences in firms' actual CorRE usage from predicted levels and the speed at which firms move toward their predicted CorRE usage. We find that investors tend to punish the valuation of companies that deviate from predicted CorRE usage, probably through the channel that large deviations from predicted CorRE usage hurt firm profitability.

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1 Introduction

The National Association of Real Estate Investment Trusts estimates that the market value of real estate in the U.S. held primarily as an investment by various public and private entities is approximately $16 trillion.[1] Real estate is also an important component of the production processes of many non-real estate firms; therefore, a substantial amount of real estate is owned or leased by corporations, nonprofit institutions, and other entities not primarily in the business of investing in real estate. This includes production facilities, but also office buildings, warehouses, and retail properties. The Federal Reserve estimates the market value of U.S. corporate real estate (CorRE) held by these entities was an additional $24.6 trillion in the first quarter of 2021.[2] Nevertheless, there is significant variation across industries and firms in the use of real estate in the production process relative to equipment, vehicles, and other capital goods, as well as labor, management, and intellectual property (copyrights, patents, and trademarks),

The existing literature discusses the potential benefits associated with CorRE usage, beyond its use in a firm's production process, including its value as loan collateral, its long-term price appreciation potential, and its value as a diversifier of corporate investment risk (Smith and Wakeman 1985, Liow and Nappi-Choulet 2008, Yu and Liow 2009, Chaney, Sraer and Thesmar 2012, Zhao and Sing 2016, Ambrose, Diop and Yoshida 2017). The potential negative effects of CorRE usage, such as higher risk due to its price procyclicality (Tuzel and Zhang 2017), higher adjustment costs in the face of declining demand for the firm's products and services (Tuzel 2010), and the potential for companies to sub-optimally utilize real estate (Coles, Daniel and Naveen 2006), have also been examined. Several studies have sought to infer the net effect of CorRE usage by examining the relation between the *level* of CorRE usage and firms' risk and/or stock returns (Deng and Gyourko 1999, Seiler, Chatrath and Webb 2001, Brounen and Eichholtz 2005, Yu and Liow 2009, Ling, Naranjo and Ryngaert 2012, Diop 2018). Others have focused on the stock price effects of large CorRE sales or corporate breakups (Rodriquez and Sirmans 1996) to infer the effects of CorRE usage on firm values. Overall, the literature has produced mixed results on the impact of CorRE on firm values.

[1] https://www.reit.com/news/blog/market-commentary/total-size-of-us-commercial-real-estate-estimated-between-14-and-17-trillion

[2] *Flow of Funds Accounts of the United States Federal Reserve*, June 10, 2021, Tables B.101, B.103, and B.104.

The trade-off between the potential benefits and costs of CorRE creates an optimal level of CorRE that varies over time and across firms. We do not present a formal model of optimal CorRE; rather, we regress CorRE usage for a large sample of firms on a set of lagged firm characteristics as well as time and industry fixed effects. This reduced form regression allows us to predict each firm's CorRE usage under the assumption that it varies in line with observationally equivalent firms. We posit that firm valuations should be driven by *differences* in actual CorRE usage from predicted levels and the speed at which investors expect the firm to move toward its predicted level. We therefore empirically investigate the effects of *deviations* from firm-specific predicted CorRE usage, rather than the usage level or usage relative to a sample or industry mean, on firm valuations. Using a dynamic partial adjustment model, we estimate firm-level deviations over time based on a set of lagged firm characteristics.

We obtain CorRE usage data for all U.S. listed firms from COMPUSTAT and define a firm's real estate usage as the sum of buildings, capitalized leases, land, and construction in process. The average *RER* across our 71,303 firm-year observations is 13.4%; however, this ratio varies significantly across firms and industries. We estimate our dynamic partial adjustment model for 1993 to 2018 and find an average annual speed of adjustment toward predicted *RER*s of 11.5% per year, which implies it takes approximately six years to close the gap between actual *RER*s and predicted *RER*s by 50 percent. This slow adjustment speed supports the notion that the cost of adjusting CorRE usage is high.

We next investigate the extent to which deviations from predicted CorRE usage (*DEV*s) are predictive of firm valuations and find that the market tends to punish the valuation of firms whose use of real estate deviates from predicted. We test for asymmetric valuation responses to positive and negative deviations and find that investors tend to drive down the valuation of companies that have excess CorRE as well as firms that have too little. The estimation of our valuation regressions using data prior to the recent financial crisis (1993-2006), during the crisis (2007-2009), and post crisis (2010-2018) reveals that our results are robust to the use of alternative time periods.

We conclude by examining the effects of deviations from the predicted use of CorRE on firm profitability and find evidence that profitability tends to increase as firms move from large negative deviations toward their predicted use of CorRE; in contrast, profitability declines as firms move well beyond their predicted use of CorRE. These results support our contention that the effects of CorRE usage on profitability are an important channel through which a deeper understanding of the effects of real estate on firm valuations can be obtained.

Our study extends the literature in several ways. First, we study *deviations* from predicted CorRE usage, rather than the *level* of CorRE usage or an industry-adjusted CorRE level. We find that conditioning on firm's predicted CorRE usage is necessary to understand the benefits and risks associated with CorRE usage. Second, we examine the impact of CorRE deviations on firm valuations. Third, we test for the asymmetric effects of CorRE usage by separating positive deviations from predicted usage from negative deviations. This separation is critical to understanding the effects of CorRE on valuations. Finally, we provide evidence that reduced profitability is a potential channel through which too much or too little CorRE usage is harmful to valuations.

The article proceeds as follows. Section 2 provides a conceptual framework for our empirical analysis. Section 3 describes our sample selection process, data, and provides a discussion of key summary statistics. Section 4 presents the regression model used to estimate predicted levels of CorRE usage and the speed at which firms adjust toward their predicted CorRE usage. We then examine in section 5 the relation between deviations from predicted CorRE usage and firm values. Our analysis of the effects of CorRE usage on profitability is contained in section 6. The article is concluded in section 7.

2 Conceptual Framework

Beyond its role in a firm's production process, the usage of CorRE can benefit firms in several ways. Corporate-owned real estate is generally a better form of loan collateral than equipment and intangible assets. Thus, an increase in the usage of CorRE can enhance overall borrowing capacity (Campello et al. 2021) that, in turn, leads to more investment (Chaney, Sraer, and Thesmar 2012). Benmelech, Garmaise, and Moskowitz (2005) document that collateral assets that are more "redeployable" can be financed with loans of longer maturities, which can reduce refinancing risk. Benmelech and Bergman (2009) find that more deployable collateral is associated with lower credit spreads, higher credit ratings, and higher loan-to-value ratios. Thus, a firm's cost of capital is tightly linked to its use of real estate in the production process. CorRE usage may also help diversify a firm's asset portfolio because it has a relatively low correlation with the broad common stock market (Seiler, Chatrath and Webb 2001, Yu and Liow 2009). This is especially true for firms with high betas or whose returns have a low correlation with real estate markets.

The usage of CorRE has potential disadvantages. Real estate is typically relatively expensive. These high costs could mean that less capital is available to invest in the firm's core business activities or in research and development (Shi et al. 2016), especially if required CorRE is purchased instead of leased. If a firm uses too much real estate in its production process, its marginal benefit declines, including its collateral value, and it becomes increasingly difficult to quickly dispose of these assets when downward adjustments in CorRE usage are required. This increased adjustment risk, and the *ex ante* return premia that must be offered to investors as compensation for bearing this risk, contribute to a rising marginal cost of CorRE usage. This is typically true for leased, as well as owned, real estate unless the leases have short average durations.

If the mixture of real estate, equipment, and other factors of production could be costlessly adjusted, firms would always own or lease the optimal amount of real estate for a desired level of output. That is, the marginal benefit of an additional unit of owned or leased real estate would always equal its marginal cost. However, adjustments to the level and mix of a firm's capital stock are often costly and time-consuming, and the long economic life of real estate (land and structures) exacerbates adjustment costs. Bokhari and Geltner (2018) find an overall average depreciation rate of just 1.5% per year for income-producing real estate, ranging from 1.82% per year for properties with new buildings to 1.12% per year for properties with 50-year-old buildings. This slow depreciation rate relative to equipment increases adjustment costs and reduces flexibility in the face of both positive and negative demand shocks, causing firms to operate with too little (much) real estate when demand for its goods/services is increasing (decreasing).

The existing literature tends to use the level of a firm's CorRE usage as the primary test variable in analyzing the relation between CorRE and returns. Tuzel (2010) uses industry-adjusted real estate ratio (*RER*), defined as the ratio of the firm's CorRE usage to total assets in excess of the average ratio for the industry in which the firm competes. However, even within industry groups, we observe substantial variation in the use of real estate relative to the total assets of the firm. This cross-sectional variation may be explained, at least in part, by differences in firms' optimal real estate usage that cannot be adequately controlled for by subtracting an industry average from a firm's real estate usage.

Implications for Firm Valuations

The benefit-cost trade-off of CorRE produces a usage level at which firm value is maximized. We posit that the valuation benefit of owning or leasing CorRE (on a long-term basis) is a concave function of *RER* (see Figure 1). The intuition is as follows. First, at low usage levels, adding real estate to the firm's production process is likely to increase production efficiency with attendant declines in average production costs. However, the marginal efficiency benefit of increasing the use of CorRE in the production process will begin to decline at some level of *RER*. Second, because a firm's debt capacity has an upper limit, the marginal collateral benefit of increasing the *RER* will also decline at some level of *RER*. Third, real estate's marginal diversification benefit also has an upper limit because a non-real estate firm can only stay "diversified" if it has both real estate and other assets.

In contrast, we posit that the cost of CorRE usage is a convex function of *RER*. As firms increase their real estate usage, investors expect it faces more difficulties in disposing of these assets in response to negative demand shocks. This drives up the required *ex ante* risk premium and therefore the marginal cost of CorRE usage. Similarly, as a firm increases its *RER*, the extent to which capital is deployed to its core business functions may decrease, with potential negative ramifications for production efficiency and profitability.

If a firm has a low *RER*, the marginal benefit to the firm's production efficiency is increasing with additional CorRE usage; moreover, required increases in the cost of CorRE usage are likely modest, although they do work to reduce valuations and thereby partially offset the benefits of gains in production efficiency. Therefore, the marginal benefit of increasing its use of CorRE likely exceeds the marginal cost, and hence the firm's market value should rise with increases in *RER*. CorRE additions to the production process will continue to be value-increasing until investors perceive that the marginal benefit of additional *RER* equals its marginal cost; i.e., where the distance between the benefit of more *RER* investment and its cost is the largest. This inflection point is the firm's optimal *RER*. We use a firm's predicted *RER* as a proxy for its optimal CorRE usage.

Additions to *RER* beyond the optimal (predicted) level are expected to reduce firm valuations. This is because the disadvantages of increased CorRE usage, including declines in the marginal efficiency, collateral value, and diversification benefits, begin to affect valuations. The effects of increases in CorRE usage on firm valuations, up to and beyond optimal levels, are summarized in Figure 2. To what extent this relationship holds is an empirical question we seek to answer in this research.

Because the shapes and locations of the marginal CorRE benefits and costs curves in Figure 1 are dynamic and can change quickly, a firm's predicted CorRE usage must be estimated frequently. We address this issue using a dynamic partial adjustment model in section 4. We test the relation between *RER* deviations and firm values in section 5.

3 Sample Selection and Descriptive Statistics

We obtain real estate usage data for all U.S. listed firms from COMPUSTAT. These data are measured at historical cost and available beginning in 1984.[3] We exclude real estate operating companies (REOCs) and real estate investment trusts (REITs) from the analysis.[4] Tuzel's (2010) measure of CorRE usage includes buildings (*Buildings*) and capital leases (*Leases*). In contrast, Chaney, Sraer, and Thesmar's (2012) measure excludes capital leases but includes buildings, land and improvements (*Land*), and construction in progress (*Construction*). We combine these two measures and include *Buildings*, *Leases*, *Land*, and *Construction* in our measure of CorRE usage.[5] In our preferred specification, we estimate the magnitude of CorRE usage, *RER*, by dividing CorRE usage by a firm's total assets rather than total property, plant, and equipment. This initial screening process produces a sample of 296,846 firm-year observations over the period 1984-2018. The total historical cost of owned CorRE in our sample is about $953 billion in 2018.

To formally measure deviations from predicted CorRE usage (*DEV*), we estimate rolling regressions using 10-year windows. The rolling-window approach has been widely used in finance studies, such as Kacperczyk, Nieuwerburgh, and Veldkamp (2014) and Petkova and Zhang (2005), to avoid look-ahead bias. We use 10-year windows; for example,

[3] COMPUSTAT also provides CorRE usage data measured at the net (of depreciation) level; however, these data are not available after 1997.

[4] REOCs include publicly traded construction and development firms as well as brokerage and real estate advisory firms. A "qualified" equity REIT may deduct dividends paid from corporate taxable income if it satisfies a set of restrictive conditions on an ongoing basis. Among other things, these requirements ensure that REITs invest primarily in real estate.

[5] The variable names in COMPUSTAT for our real estate ratio components are: *Buildings*, FATB; *Leases*, FATL; *Land*, FATP; and *Construction*, FATC.

DEV in 1993 is equal to the firms' *RER* in 1993 minus the predicted *RER* estimated with data from 1984 to 1993. This approach eliminates 1984 to 1992 from our formal analysis, thereby reducing our sample size to 91,968 firm-year observations over the period of 1993-2018. We delete observations if other financial or accounting information required for our regressions is unavailable in the COMPUSTAT database. This leaves us with a final sample of 9,661 firms and 71,303 firm-year observations.

3.1 Real Estate Ratio

Table 1 displays summary statistics for our regression sample. All continuous variables are winsorized at the 1% level for both tails of the distribution. The average ratio of total CorRE usage to total assets (*RER*) across our 71,303 firm-year observations is 13.4%. The largest component of *RER* is *Buildings* (6.7%), followed by *Leases* (4.7%), *Land* (1.5%), and *Construction* (0.8%). The mean ratio of *RER* at the 25th percentile is 1.3%; the mean at the 75th percentile is 17.7%.

To examine how CorRE usage varies across industries, we sort firms into 12 industries based on the classifications developed and maintained by Eugene Fama and Ken French.[6] Summary statistics for these 12 industries are presented in Table 2. With a mean *RER* of 27.9%, wholesale, retail, and select service firms make the greatest use of real estate in their production processes. The utility industry is the second, with a mean *RER* of 23.6%. Firms focused on consumer durables, chemicals, manufacturing, and "other" products have mean *RER*s of 16 to 17%. With a mean *RER* of 3.8%, the finance industry uses the least amount of real estate.

3.2 Financial and Accounting Variables

The financial and accounting data required to estimate our speed of adjustment and firm value regressions are obtained from COMPUSTAT. We measure firm values using Tobin's Q (*TobinQ*), defined as the market value of assets scaled by the book value of assets, where the market value is calculated as the sum of the book value of assets and the market value of common stock, less the book value of common stock and deferred taxes. Firm stock

[6] See: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12_ind_port.html. Fama and French assign each NYSE, AMEX, and NASDAQ stock to an industry portfolio at the end of June of year *t* based on its four-digit SIC code at that time. COMPUSTAT SIC codes for the fiscal year ending in calendar year *t*-1 are used. If COMPUSTAT SIC codes are not available, CRSP SIC codes for June of year *t* are used.

market values are obtained from CRSP. The mean *TobinQ* in our sample is 3.68 with a standard deviation of 9.94 (Table 1).

Leverage is defined as the ratio of long-term debt to total assets. *Size* is equal to the log of the total book value of assets. *Profit* is equal to income before extraordinary items divided by total revenue. *Age* is the log of one plus the number of years since the firm first appeared in COMPUSTAT or CRSP, whichever came first. *Capx* is defined as the ratio of capital expenditures to total assets and *Capx_dum* is a dichotomous variable set equal to one if *Capx* information is missing, otherwise zero. *R&D* is equal to research and development expenditures normalized by total assets and *R&D_dum* is a dichotomous variable set equal to one if *R&D* information is missing. *Dividend_dum* is a dichotomous variable set equal to one if dividends paid is positive, otherwise zero. *Sale_grow* is the annual growth rate of revenue and *Cash* is defined as the sum of cash and short-term investments normalized by total assets. Finally, *Prod_risk* is defined as the standard deviation of the ratio of total cash flow to total assets (Zhao and Sing 2016), where total cash flow is calculated as income before extraordinary items plus depreciation and amortization.

Leverage averages 16.0% in our sample. Profitability has a median of 1.5% but a mean of -1.64% and a standard deviation of 7.53, implying a substantial variation of profitability in our sample. Capital expenditures and R&D expenses average 4.7% and 8.4%, respectively, of total assets. Sale growth has an average of 33.4% with significant variation across firms. Cash and short-term investments average 23.6% of total assets, and *Prod_risk* has a mean of 41.6%.[7]

4 Speed of Adjustment in Real Estate Ratio

In this section, we introduce our measure of deviations of a firm's actual *RER* from its predicted *RER* based on a partial adjustment model. As discussed in section 2, the cost-benefit trade-off associated with CorRE creates an optimal (predicted) *RER* that varies across firms and over time. We therefore estimate the following partial adjustment model of CorRE usage:

[7] These summary statistics are generally comparable with previous studies that use COMPUSTAT, such as Cremers and Ferrell (2014) and Duchin (2010).

$RER_{i,t+1} - RER_{i,t} = \lambda(RER^*_{i,t+1} - RER_{i,t}) + \varepsilon_{i,t+1}$, (1)

where $RER^*_{i,t+1} = \beta X_{i,t}$ is the predicted *RER* that is determined by a set of lagged factors, including leverage, size, profitability, productivity risk, and year and industry fixed effects (Chaney, Sraer, and Thesmar 2012, Zhao and Sing 2016).[8] The coefficient λ is the estimated annual speed at which firms adjust toward their predicted *RERs*. Although our measure of *RER* includes four components (buildings, capital leases, land, and construction in process), our results are robust to alternative *RER* measures.[9]

We replace $RER^*_{i,t+1}$ in equation (1) with $\beta X_{i,t}$ and estimate the following reduced-form regression:

$RER_{i,t+1} = (\lambda\beta)X_{i,t} + (1-\lambda)RER_{i,t} + \varepsilon_{i,t+1}$. (2)

After estimating equation (2), we calculate the deviation from the predicted *RER* as follows:

$DEV_{i,t} = RER_{i,t} - RER^*_{i,t+1} = RER_{i,t} - \boldsymbol{\beta X}_{i,t} = \frac{RER_{i,t} - Predict\_RER_{i,t+1}}{\boldsymbol{\lambda}}$. (3)

Positive (negative) values of *DEV* indicate that a firm's *RER* is greater (less) than its predicted ratio, and a downward (upward) adjustment is required.[10]

To compute deviations using equation (3), we assume a firm's *RER* is a function of the lagged values of *Leverage*, *Size*, *Profit*, *Prod_risk*, and *RER*. Our 10-year rolling-window approach to estimating equation (3) ensures that $DEV_{i,t}$ only captures information through year *t*, following the mutual fund literature (e.g., Kacperczyk, Nieuwerburgh, and Veldkamp 2014) and the asset pricing literature (e.g., Petkova and Zhang 2005).[11] For each 10-year rolling window from 1993 to 2018, we regress $RER_{i,t+1}$ on $RER_{i,t}$ and a set of control variables in year *t*. We then calculate *DEV* based on equation (3) and keep the *DEV* in the last year of the rolling window. Our deviation measure controls for factors not captured by an industry-adjusted measure. These factors include firm-specific variables shown to be related to CorRE usage, as well as unobserved time and industry factors. Moreover, our model enables us to

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[8] In our main analysis, we control for industry fixed effects based on SIC 2-digit industry classification, but our results hold for other fixed effects as well. Using SIC 2-digit industries instead of Fama-French's 12 industries allows us to capture the effects of more time invariant unobserved factors.

[9] To test if our results are robust to different *RER* measures, we replace our four component *RER* measure with Tuzel (2010)'s two component measure (buildings and capital leases) and Chaney, Sraer, and Thesmar's (2012)'s three component measure (buildings, land, and construction in progress) and find similar results.

[10] Yu and Liow (2009) use iterative three-stage least squares to estimate a firm's predictive real estate ratio that is then used as an explanatory variable in their regressions of stock market returns on real estate usage.

[11] Our results are robust to different window lengths.

examine how fast firms move toward their predicted CorRE usage and allows for the speed of adjustment toward predicted *RER* to vary over time.[12]

We estimate our speed of adjustment model for 26 years: 1993-2018. The average coefficient estimate on lagged *RER* across the 26 years is 0.885, which implies an average annual speed of adjustment toward predicted *RER*s of 11.5% per year.[13] Adjustment speeds increased from 9.7% in 1993 to 13.9% in 2005 before declining. They averaged approximately 9% per year during the final four years of our sample. These slow adjustment speeds imply that the difficulty and costs of adjusting CorRE usage, in either direction, are high.

5 Deviations from Predicted Real Estate Usage and Firm Value

To investigate the extent to which deviations from predicted CorRE usage (*DEV*s) are predictive of firm valuations, we estimate the following panel regression model:

$$TobinQ_{i,t+1} = \beta_0 + \beta_1 DEV\_POSABS_{it} + \beta_2 DEV\_NEGABS_{it} + \beta_3 X_{it} + \varepsilon_{it}. \quad (4)$$

To test for asymmetric valuation responses to positive and negative deviations, we construct the following two variables: *DEV_POSABS* is set equal to the absolute value of *DEV* if *DEV* is positive, and zero otherwise; *DEV_NEGABS* equals the absolute value of *DEV* if *DEV* is negative, and zero otherwise. The vector X_{it} includes a set of lagged explanatory variables commonly used to explain cross-sectional variation in firm valuations (e.g., Palia 2001, Fang, Noe, and Tice 2009, Roll, Schwartz, and Subrahmanyam 2009, Cremers and Ferrell 2014). These variables, which are measured at the end of fiscal year *t*, include *Leverage*, *Size*, *Profit*, *Age*, *R&D*, *Capx*, *Div_dum*, *Sale_grow*, *Prod_risk*, and *Cash*. Dichotomous variables that indicate missing data on R&D expenses and capital expenditure are also included. Year fixed effects and industry fixed effects are included in select specifications.

To provide a baseline, Model (1) of Table 3 displays results from estimating equation (4) without year fixed effects or industry fixed effects. T-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The

[12] We use leverage, size, profitability, risk and year and industry fixed effects to explain each firm's real estate ratio. However, a firm's real estate ratio may partially determine variables such as leverage, profitability, and risk. To the extent these variables are persistent, using their lagged values may not solve the potential endogeneity problem. We are experimenting with alternative models for predicting firm-level RERs.

[13] This 11.5% speed of adjustment per year can be translated to a half-life time of 5.7 years, calculated as ln(0.5)/ln(1-0.115) (e.g., Ogden and Wu 2013). In other words, it takes 5.7 years for a firm to close the gap between actual and predicted *RER* by 50 percent.

estimated coefficients on *DEV_POSABS* and *DEV_NEGABS* are negative and highly significant, which indicates that firm valuations decline as CorRE usage deviates from predicted in either a positive or negative direction. Firm valuations are positively and significantly related to *Leverage*, *Age*, *Capx*, *Cash*, and *Prod_risk*. *Size*, *Profit*, and *R&D* are negatively and significantly related to firm valuations. The results are little altered when year fixed effects are included (Model (2)). With the inclusion of industry fixed effects based on two-digit SIC codes (Model (3)), the magnitude and significance of the negative coefficient on *DEV_NEGABS* declines but is still significant at the 5% level. The magnitudes and significance of the control variables are largely unaltered by the addition of year and industry fixed effects. Based on Model (3), a one standard deviation increase in *DEV_POSABS* (*DEV_NEGABS*) is associated with a 10.6% (4.4%) percent decrease in firm value relative to its sample average.[14]

It is possible that small deviations from predicted CorRE usage have little effect on firm valuations. To examine this potential non-linearity, we sort the absolute values of positive and negative *DEV*s into quintiles. *DUM_POS(Q345)* equals one if the absolute value of a positive *DEV* belongs to the largest three positive quintiles, and zero otherwise. *DUM_NEG(Q345)* equals one if the absolute value of a negative *DEV* belongs to the largest three negative quintiles, and zero otherwise. Without industry fixed effects (Models (4) and (5)), the estimated coefficients on *DUM_POS(Q345)* and *DUM_NEG(Q345)* are significantly negative and larger in magnitude than the corresponding results reported for Models (1) and (2). For instance, when the deviation from a firm's predicted CorRE moves to the largest positive (or negative) three quintiles, firm value declines by 18.6% (or 13.2%) according to Model (5).[15] With the inclusion of industry fixed effects, both coefficient estimates remain negative and significant at the 1% level. Overall, the results reported in Table 3 suggest the market punishes the valuation of firms whose use of CorRE deviates from the predicted amount in their production process.[16]

[14] If not otherwise specified, economic significance is calculated as the coefficient estimate times the standard deviation of the independent variable of interest scaled by the sample average of the dependent variable. For example, -10.6% = -2.547 * 0.153 / 3.68.

[15] -18.6% = -0.684 / 3.68; -13.2% = -0.484 / 3.68.

[16] Our valuation results and conclusions are not altered if we delete extremely small firms with less than $10 million in total assets.

Panel A of Table 4 presents results obtained from estimating our valuation equations using only data from 1993-2006 (prior to the financial crisis). Model (1) displays results from estimating equation (4) without year fixed effects or industry fixed effects. Although somewhat smaller in magnitude than the results reported in Table 3, the estimated coefficients on *DEV_POSABS* and *DEV_NEGABS* are negative and highly significant. The results are similar when year fixed effects are included (Model (2)). With the inclusion of industry fixed effects based on two-digit SIC codes (Model (3)), the coefficient estimate on *DEV_NEGABS* cannot be distinguished from zero. Without industry fixed effects (Models (4) and (5)), the estimated coefficients on *DUM_POS(Q345)* and *DUM_NEG(Q345)* are, with one exception, significantly negative and larger in magnitude than the corresponding results for the full sample presented in Table 3.

Panel B of Table 4 presents results obtained from estimating our valuation equations using data from 2007-2009 (during the financial crisis). With or without year fixed effects the estimated coefficients on *DEV_POSABS* and *DEV_NEGABS* are negative and highly significant. However, the inclusion of industry fixed effects reduces significance. Once again, the estimated coefficients on *DUM_POS(Q345)* and *DUM_NEG(Q345)* are significantly negative. Similar results are found for the post crisis (2010-2018) period. Overall, these subperiod analyses reveal that our results are robust to the use of alternative time periods.

6 Examining the Profitability Channel

Our regression results in previous section indicate that the effects of CorRE usage on production efficiency, collateral value, and potential diversification benefits should be considered in any analysis of the effects of CorRE usage on valuations. We use three measures to further examine the potential profitability channel. *EBITDA/SALE* is equal to earnings before interest, taxes, depreciation, and amortization in year $t+1$ divided by sales in year t. *EBIT/SALE* is equal to earnings before interest and taxes in year $t+1$ scaled by sales in year t. Finally, *IB/SALE* is equal to income before extraordinary items in year $t+1$ divided by sales in year t.

We then conduct a set of univariate tests to examine the effects of deviations from the predicted use of CorRE on these measures of profitability. We first sort firms into positive and negative deviations. We then sort both the positive and negative deviations into five quintiles based on the deviations of CorRE usage from predicted levels. These portfolios are rebalanced annually. We then calculate the equal-weighted profitability for the portfolios in each quintile of negative and positive deviations. Panel A of Table 5 contains the results for *EBITDA/SALE*. The average equal-weighted *EBITDA/SALE* for firms with the most negative *RER* deviations is -0.06; the corresponding ratio for firms with the least negative *RER* deviations is 0.01. The difference of 0.07 is economically large and significant at the 1% level. Thus, at levels of CorRE usage below predicted, profitability increases as firms move toward the predicted level of CorRE.

EBITDA/SALE for firms with positive *RER* deviations are presented next. The average equal-weighted profitability for firms with the least positive *RER* deviations is -0.03; the corresponding average for firms with the most positive *RER* deviations is -0.12. The difference between the average *EBITDA/SALE* of portfolios with the most positive deviations and those with the least positive is -0.08, which is highly significant. Thus, firms that increase their usage of CorRE far beyond their predicted levels are less profitable.

In Panel B of Table 5, we use *EBIT/SALE* as our measure of profitability. We again find that profitability tends to increase as firms adjust their use of CorRE toward predicted levels. The average equal-weighted *EBIT/SALE* for firms with the most negative *RER* deviations is -0.14; the corresponding ratio for firms with the least negative *RER* deviations is -0.07. The difference of 0.08 is economically large and significant at the 1% level. The average equal-weighted profitability for firms with the least positive *RER* deviations is -0.10; the corresponding average for firms with the most positive *RER* deviations is -0.22. The difference between the average *EBITDA/SALE* of portfolios with the most positive deviations and those with the least positive is -0.10, which is highly significant. The results are very similar if we use *IB/SALE* (Panel C) to measure profitability.

The results presented in Table 5 provide evidence that profitability tends to increase as firms move from large negative deviations toward their predicted use of CorRE and decline as firms move well beyond their predicted use of CorRE. To check the robustness of these univariate results, we estimate several regressions with different controls or fixed effects as follows:

$$IB/SALE_{i,t+1} = \beta_0 + \beta_1 DEV\_POSABS_{it} + \beta_2 DEV\_NEGABS_{it} + \beta_3 X_{it} + \varepsilon_{it}. \quad (5)$$

We use *IB/SALE* at year *t*+1 as a representative measure of profitability.[17] The vector X_{it} includes *Leverage*, *Size*, *Profit*, *Age*, *Capx*, *R&D*, *Capx_dum*, *R&D_dum*, *Div_dum*, *Sale_grow*, and *Prod_risk*; we also add year fixed effects and 2-digit SIC-industry fixed effects in select specifications. The main independent variables of interest are *DEV_POSABS* and *DEV_NEGABS*. We also replace the above two variables with two dummies, *DUM_POS(Q345)* and *DUM_NEG(Q345)*, that equal one if the absolute value of positive and negative *DEV*s belongs to the largest three quintiles, respectively, and zero otherwise.

Table 6 presents the results based on equation (5) and provides additional support for our finding that large deviations from predicted CorRE usage are associated with lower profitability. The only exception is that positive deviations from predicted CorRE usage are not significantly related to profitability. Overall, these results in Tables 5 and 6 support our contention that the effects of CorRE usage on profitability are an important channel through CorRE usage affects valuations.

As robustness check, we re-estimate profitability regressions after splitting our sample into three periods: pre-crisis period from 1993 to 2006; crisis period from 2007 to 2009; post-crisis period from 2010-2018. We present the corresponding results in Table 7. As shown, large positive deviations as associated with lower profitability only in the post-crisis period, although negative deviations seem to be always related to reduced profitability. Overall, these subsample results suggest that our results in Table 6 are generally robust to different periods, although with some variation in terms of statistical significance.

7 Conclusion

The trade-off between the potential benefits and costs of corporate real estate (CorRE) in the production process creates an optimal level of CorRE usage that varies over time and across firms. We regress CorRE usage for a large sample of firms on a set of lagged firm characteristics as well as time and industry fixed effects. This reduced form regression allows us to predict each firm's CorRE usage under the assumption that it varies in line with observationally equivalent firms. We posit that firm valuations and returns should be driven

[17] The results are similar if we use *EBITDA/SALE* or *EBIT/SALE* as our proxy for profitability. Moreover, the sample used for profitability regressions excludes extremely small firms with total assets below $10 million to mitigate potential bias of coefficient estimates driven by profitability outliers (Huang and Ritter 2009).

by differences in actual CorRE usage from predicted levels and the speed at which investors expect the firm to move toward its predicted level. We therefore empirically investigate the effects on firm valuations of deviations from predicted CorRE usage, rather than relative to a sample or industry mean. Using a dynamic partial adjustment model, we estimate firm-level deviations in CorRE usage over time based on a set of firm characteristics. We also investigate the determinants of firms' real estate usage and the speed at which firms tend to adjust toward predicted CorRE levels.

We find that the market tends to punish the valuation of firms whose use of CorRE deviates from the predicted amount, no matter whether firms use too much or too little CorRE. This result is also supported by the evidence that profitability tends to increase as firms move toward their predicted use of CorRE.

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Figure 1: Benefit and Cost of Real Estate Usage
This figure depicts the benefit and cost of CorRE usage, denoted by real estate ratio (*RER*), and the level of CorRE usage that maximizes the firm value.

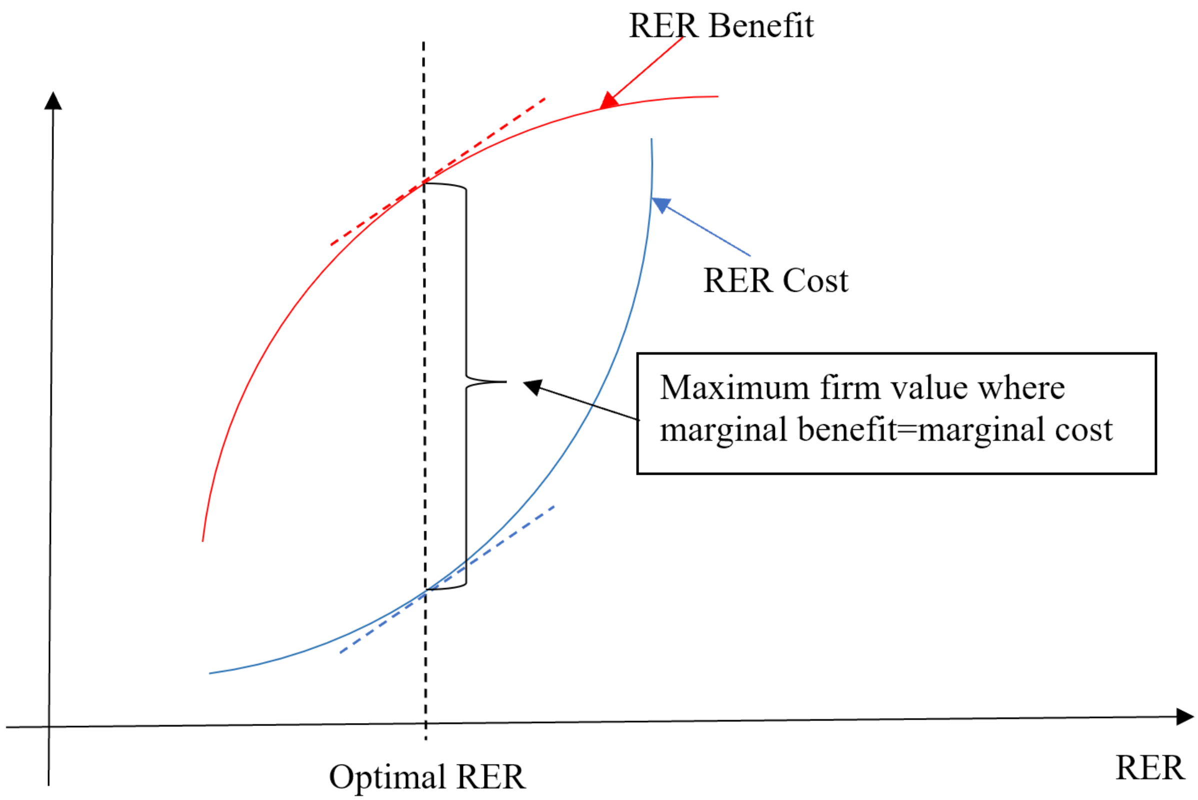

Figure 2: Asymmetric Impacts of CorRE Usage on Firm Value

Effects of increases in CorRE on Valuations

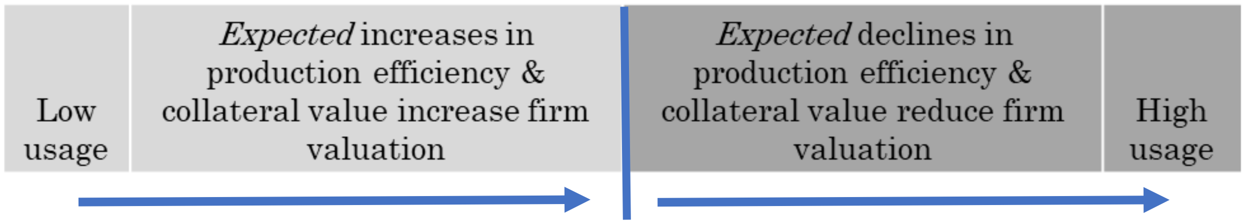

Table 1: Summary Statistics

This table presents the descriptions and summary statistics of the main dependent and independent variables in our empirical analysis. The sample period is from 1993 to 2018, after applying the rolling-window approach and excluding those observations with missing values. All variables are winsorized at 1% and 99%.

Variable	Description	mean	sd	0.25	median	0.75
firm-level annual data 1993-2018 (N=71,303)						
RER	(fatb+fatl+fatc+fatp)/at	0.134	0.185	0.013	0.064	0.177
Buildings	Buildings at cost divided by total assets	0.067	0.132	0	0	0.091
Construction	Construction in progress at cost divided by total assets	0.008	0.030	0	0	0.001
Leases	Capital leases at cost divided by total assets	0.047	0.129	0	0.009	0.038
Land	Land and improvements at cost divided by total assets	0.015	0.054	0	0	0.012
DEV	Deviation from predicted real estate usage ratio	-0.009	0.153	-0.086	-0.030	0.038
TobinQ	Market value of assets divided by book value of assets=(csho*prcc_f+at-ceq-txdb)/at	3.679	9.940	1.108	1.626	2.842
Leverage	Long term debt divided by total assets	0.160	0.238	0.000	0.051	0.244
Size	log of total book value of assets	4.558	2.356	3.000	4.550	6.135
Profit	Income before extraordinary items divided by total revenue	-1.636	7.527	-0.191	0.015	0.067
Age	ln(firm age+1)	2.305	0.685	1.792	2.398	2.833
Capx	Capital expenditures scaled by total assets	0.047	0.058	0.011	0.029	0.059
R&D	Research and development expense scaled by total assets	0.084	0.171	0	0.004	0.093
Capx_dum	Capx_dum=1 if missing(capx)	0.011	0.104	0	0	0
R&D_dum	R&D_dum=1 if missing(xrd)	0.357	0.479	0	0	1
Div_dum	Div_dum=1 if dvt>0	0.319	0.466	0	0	1
Sale_grow	Revenue growth rate	0.334	1.127	-0.041	0.091	0.300
Cash	Cash and short-term investments scaled by total assets	0.236	0.249	0.037	0.140	0.368
Prod_risk	Standard deviation of total cash flow (IB+DP) to total assets	0.416	0.818	0.058	0.126	0.322

Table 2: Real Estate Usage by Fama-French 12 Industries

This table presents the average real estate ratio (*RER*) for a given industry following the Fama-French 12 industrial classification. Real estate ratio (*RER*) is defined as the summation of buildings, construction in progress, capital leases, and land divided by total assets, following the description in Table 1.

FF12	Description	Mean	Std. Dev.	Freq.
1	Consumer Nondurables -- Food, Tobacco, Textiles, Apparel, Leather, Toys	0.165	0.157	4074
2	Consumer Durables -- Cars, TVs, Furniture, Household Appliances	0.132	0.118	1988
3	Manufacturing -- Machinery, Trucks, Planes, Off Furn, Paper, Com Printing	0.158	0.135	7584
4	Oil, Gas, and Coal Extraction and Products	0.121	0.182	659
5	Chemicals and Allied Products	0.162	0.169	1903
6	Business Equipment -- Computers, Software, and Electronic Equipment	0.073	0.109	18817
7	Telephone and Television Transmission	0.093	0.133	1605
8	Utilities	0.236	0.091	12
9	Wholesale, Retail, and Some Services (Laundries, Repair Shops)	0.279	0.264	8380
10	Healthcare, Medical Equipment, and Drugs	0.117	0.159	11383
11	Finance	0.038	0.103	5218
12	Other	0.170	0.248	9680
Total		0.134	0.185	71303

Table 3: Absolute Value of Real Estate Deviation and Firm Value

This table examines the asymmetric effects of real estate deviation on firm value. The dependent variable is Tobin's Q in year *t*+1; all independent variables are measured in year *t*. In Models (1) to (3), *DEV_POSABS* (*DEV_NEGABS*) equals the absolute value of *DEV* if *DEV* is positive (negative), and zero otherwise. To construct *DUM_POS(Q345)* and *DUM_NEG(Q345)* used in Models (4) to (6), we first sort the absolute values of positive and negative *DEV*s into quintiles. *DUM_POS(Q345)* (*DUM_NEG(Q345)*) equals one if the absolute value of positive (negative) *DEV*s belongs to the largest three quintiles, and zero otherwise. Other controls include *Leverage*, *Size*, *Profit*, *Age*, *Capx*, *R&D*, *Capx_dum*, *R&D_dum*, *Div_dum*, *Sale_grow*, *Prod_risk*, and *Cash*. Models (2) and (4) include year fixed effects. Models (3) and (6) include year fixed effects and 2-digit SIC-industry fixed effects. The descriptions of all variables are in Table 1. Robust t-statistics are shown in the parentheses. ***, **, and * represent the significance level at 1%, 5%, and 10%, respectively.

	$TobinQ_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
DEV_POSABS	-2.796***	-2.928***	-2.547***			
	(-6.50)	(-6.83)	(-5.75)			
DEV_NEGABS	-2.482***	-2.082***	-1.068**			
	(-5.60)	(-4.61)	(-2.20)			
DUM_POSABS(Q345)				-0.685***	-0.684***	-0.518***
				(-7.46)	(-7.50)	(-5.51)
DUM_NEGABS(Q345)				-0.588***	-0.484***	-0.235***
				(-8.18)	(-6.52)	(-3.02)
Leverage	3.537***	3.423***	3.623***	3.453***	3.341***	3.566***
	(11.82)	(11.42)	(11.62)	(11.61)	(11.21)	(11.49)
Size	-0.681***	-0.759***	-0.766***	-0.666***	-0.745***	-0.755***
	(-28.38)	(-29.34)	(-29.11)	(-28.07)	(-29.07)	(-28.88)
Profit	-0.127***	-0.121***	-0.127***	-0.127***	-0.121***	-0.127***
	(-9.30)	(-8.95)	(-9.28)	(-9.32)	(-8.96)	(-9.27)
Age	0.567***	0.230***	0.313***	0.559***	0.224***	0.302***
	(9.13)	(3.50)	(4.62)	(8.99)	(3.41)	(4.48)
Capx	4.108***	5.732***	6.250***	3.916***	5.540***	6.140***
	(4.52)	(6.21)	(6.05)	(4.29)	(5.98)	(5.98)
R&D	2.374***	2.244***	2.780***	2.365***	2.228***	2.745***
	(4.27)	(4.04)	(4.84)	(4.26)	(4.02)	(4.77)
Capx_dum	8.421***	8.703***	7.510***	8.407***	8.686***	7.526***
	(9.68)	(10.05)	(9.58)	(9.68)	(10.04)	(9.60)
R&D_dum	0.477***	0.427***	0.267***	0.452***	0.402***	0.258***
	(6.32)	(5.69)	(2.76)	(6.00)	(5.37)	(2.67)
Div_dum	0.958***	1.061***	0.945***	0.949***	1.056***	0.943***
	(14.48)	(15.82)	(14.55)	(14.41)	(15.80)	(14.55)
Sale_grow	-0.135***	-0.128**	-0.109**	-0.132**	-0.125**	-0.108**
	(-2.60)	(-2.45)	(-2.11)	(-2.53)	(-2.40)	(-2.07)
Cash	1.274***	0.902***	1.102***	1.341***	0.970***	1.168***
	(4.56)	(3.22)	(3.93)	(4.78)	(3.45)	(4.14)

Prod_risk	4.125***	3.976***	4.001***	4.127***	3.978***	4.006***
	(29.29)	(28.44)	(28.56)	(29.26)	(28.40)	(28.56)
Constant	2.034***	2.456***	2.736***	2.113***	2.510***	2.653***
	(9.74)	(10.50)	(3.17)	(10.22)	(10.88)	(3.02)
Year FE	N	Y	Y	N	Y	Y
SIC FE	N	N	Y	N	N	Y
Observations	71,303	71,303	71,303	71,303	71,303	71,303
R-squared	0.257	0.262	0.268	0.257	0.262	0.268

Table 4: Subsample Firm Value Regression

This table re-estimates firm value regressions in Table 3 by splitting the whole sample into three periods: 1993-2006 in Panel A, 2007-2009 in Panel B, and 2010-2018 in Panel C. The descriptions of all variables are in Table 1. Robust t-statistics are shown in the parentheses. ***, **, and * represent the significance level at 1%, 5%, and 10%, respectively.

Panel A: 1993-2006	$TobinQ_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
DEV_POSABS	-2.262***	-2.293***	-2.163***			
	(-5.35)	(-5.43)	(-4.99)			
DEV_NEGABS	-2.477***	-1.596***	-0.570			
	(-4.60)	(-2.98)	(-0.96)			
DUM_POSABS(Q345)				-0.392***	-0.394***	-0.309***
				(-3.83)	(-3.87)	(-2.96)
DUM_NEGABS(Q345)				-0.492***	-0.324***	-0.136
				(-6.42)	(-4.26)	(-1.63)
Controls	Y	Y	Y	Y	Y	Y
Year FE	N	Y	Y	N	Y	Y
SIC FE	N	N	Y	N	N	Y
Observations	46,664	46,664	46,664	46,664	46,664	46,664
R-squared	0.218	0.222	0.229	0.218	0.222	0.229
Panel B: 2007-2009	$TobinQ_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
DEV_POSABS	-4.020**	-4.142**	-3.655*			
	(-2.22)	(-2.30)	(-1.86)			
DEV_NEGABS	-4.185***	-2.849**	-2.274			
	(-3.17)	(-2.06)	(-1.42)			
DUM_POSABS(Q345)				-1.447***	-1.461***	-1.274***
				(-4.31)	(-4.35)	(-3.65)
DUM_NEGABS(Q345)				-0.943***	-0.703**	-0.521*
				(-3.37)	(-2.37)	(-1.71)
Controls	Y	Y	Y	Y	Y	Y
Year FE	N	Y	Y	N	Y	Y
SIC FE	N	N	Y	N	N	Y
Observations	7,527	7,527	7,527	7,527	7,527	7,527
R-squared	0.328	0.329	0.338	0.329	0.330	0.339
Panel C: 2010-2018	$TobinQ_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
DEV_POSABS	-3.334***	-3.355***	-2.516**			
	(-3.02)	(-3.04)	(-2.16)			
DEV_NEGABS	-3.122***	-2.926***	-1.523			
	(-3.21)	(-2.97)	(-1.42)			
DUM_POSABS(Q345)				-0.985***	-0.979***	-0.538**
				(-4.56)	(-4.53)	(-2.36)
DUM_NEGABS(Q345)				-0.860***	-0.820***	-0.260
				(-4.99)	(-4.52)	(-1.37)
Controls	Y	Y	Y	Y	Y	Y
Year FE	N	Y	Y	N	Y	Y
SIC FE	N	N	Y	N	N	Y
Observations	17,112	17,112	17,112	17,112	17,112	17,112
R-squared	0.326	0.327	0.338	0.327	0.327	0.338

Table 5: Profitability and Deviations from Predicted *RER*: Portfolios Sorts

This table presents equal-weighted average profitability for portfolios constructed by sorting firms into quintiles based on positive or negative *RER* deviations in year *t*. The last column in each panel is the average profitability of quintile 5 (the least negative or most positive quintile) minus the average profitability of quintile 1. Panels A through C present the results for three profitability measures. *EBITDA/SALE* is equal to earnings before interests, taxes, depreciation, and amortization in year *t*+1 divided by sales in year *t*. *EBIT/SALE* is equal to earnings before interests and taxes in year *t+1* scaled by sales in year *t*. *IB/SALE* is equal to income before extraordinary items in year *t+1* divided by sales in year *t*. Robust t-statistics are shown in the parentheses. ***, **, and * represent the significance level at 1%, 5%, and 10%, respectively.

			Panel A: EBITDA/SALE			
Dev quintile	1 (Most Negative)	2	3	4	5 (Least Negative)	5-1
	-0.06	-0.07	-0.03	0.04	0.01	0.07***
	(-5.80)	(-5.54)	(-2.34)	(2.86)	(0.98)	(7.61)
Dev quintile	1 (Least Positive)	2	3	4	5 (Most Positive)	5-1
	-0.03	-0.05	-0.04	-0.02	-0.12	-0.08***
	(-1.82)	(-2.05)	(-3.66)	(-1.24)	(-5.84)	(-9.49)
			Panel B: EBIT/SALE			
Dev quintile	1 (Most Negative)	2	3	4	5 (Least Negative)	5-1
	-0.14	-0.16	-0.12	-0.04	-0.07	0.08***
	(-12.29)	(-9.88)	(-6.98)	(-2.82)	(-5.89)	(7.95)
Dev quintile	1 (Least Positive)	2	3	4	5 (Most Positive)	5-1
	-0.10	-0.13	-0.12	-0.10	-0.22	-0.10***
	(-6.05)	(-4.58)	(-9.02)	(-6.22)	(-9.64)	(-11.23)
			Panel C: IB/SALE			
Dev quintile	1 (Most Negative)	2	3	4	5 (Least Negative)	5-1
	-0.22	-0.24	-0.19	-0.12	-0.14	0.08***
	(-16.67)	(-13.56)	(-12.07)	(-8.66)	(-11.77)	(7.69)
Dev quintile	1 (Least Positive)	2	3	4	5 (Most Positive)	5-1
	-0.17	-0.19	-0.18	-0.16	-0.27	-0.10***
	(-9.19)	(-6.70)	(-11.05)	(-9.93)	(-12.53)	(-10.54)

Table 6: Profitability and Deviations from Predicted *RER*: Regressions

This table examines the asymmetric effects of real estate deviation on firm profitability, measured by *IB/SALE* in year *t*+1. All independent variables are measured in year *t*. In Models (1) to (3), *DEV_POSABS* (*DEV_NEGABS*) equals the absolute value of *DEV* if *DEV* is positive (negative), and zero otherwise. To construct *DUM_POS(Q345)* and *DUM_NEG(Q345)* used in Models (4) to (6), we first sort the absolute values of positive and negative *DEV*s into quintiles. *DUM_POS(Q345)* (*DUM_NEG(Q345)*) equals one if the absolute value of positive (negative) *DEV*s belongs to the largest three quintiles, and zero otherwise. Other controls include *Leverage*, *Size*, *Age*, *Capx*, *R&D*, *Capx_dum*, *R&D_dum*, *Div_dum*, *Sale_grow*, and *Prod_risk*. Models (2) and (4) include year fixed effects. Models (3) and (6) include year fixed effects and 2-digit SIC-industry fixed effects. The descriptions of all variables are in Table 1. Robust t-statistics are shown in the parentheses. ***, **, and * represent the significance level at 1%, 5%, and 10%, respectively.

	$IB/SALE_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
DEV_POSABS	-0.730**	-0.755***	-0.116			
	(-2.52)	(-2.62)	(-0.39)			
DEV_NEGABS	-4.287***	-4.116***	-2.982***			
	(-12.84)	(-12.30)	(-8.65)			
DUM_POSABS(Q345)				-0.212***	-0.236***	-0.013
				(-3.77)	(-4.17)	(-0.23)
DUM_NEGABS(Q345)				-0.863***	-0.872***	-0.561***
				(-16.11)	(-15.72)	(-9.76)
Leverage	-0.283**	-0.266**	-0.044	-0.355***	-0.338**	-0.062
	(-2.14)	(-2.01)	(-0.31)	(-2.70)	(-2.56)	(-0.44)
Size	0.026**	0.072***	0.095***	0.039***	0.085***	0.104***
	(1.99)	(5.22)	(6.66)	(2.99)	(6.18)	(7.24)
Age	0.251***	0.431***	0.484***	0.242***	0.421***	0.474***
	(6.20)	(9.72)	(10.69)	(5.98)	(9.52)	(10.49)
Capx	2.075***	1.178**	0.531	1.694***	0.779	0.422
	(3.96)	(2.23)	(0.89)	(3.23)	(1.47)	(0.71)
R&D	-9.673***	-9.446***	-7.870***	-9.577***	-9.357***	-7.857***
	(-25.01)	(-24.47)	(-20.20)	(-24.84)	(-24.32)	(-20.17)
Capx_dum	0.210	0.078	0.007	0.201	0.061	0.024
	(1.00)	(0.37)	(0.03)	(0.96)	(0.29)	(0.10)
R&D_dum	-0.242***	-0.230***	-0.347***	-0.260***	-0.248***	-0.351***
	(-5.44)	(-5.16)	(-6.38)	(-5.83)	(-5.57)	(-6.45)
Div_dum	-0.063	-0.127***	-0.064	-0.077*	-0.142***	-0.074
	(-1.37)	(-2.77)	(-1.37)	(-1.70)	(-3.09)	(-1.57)
Sale_grow	0.089**	0.096**	0.142***	0.094**	0.101**	0.145***
	(2.05)	(2.21)	(3.31)	(2.17)	(2.33)	(3.36)
Prod_risk	-2.665***	-2.569***	-2.565***	-2.656***	-2.559***	-2.558***
	(-31.59)	(-30.46)	(-30.27)	(-31.51)	(-30.36)	(-30.19)
Constant	-0.018	-0.243	1.042***	0.076	-0.124	0.982***
	(-0.14)	(-1.56)	(3.31)	(0.59)	(-0.81)	(3.39)
Year FE	N	Y	Y	N	Y	Y
SIC FE	N	N	Y	N	N	Y
Observations	76,119	76,119	76,119	76,119	76,119	76,119
R-squared	0.186	0.190	0.211	0.187	0.191	0.211

Table 7: Subsample Profitability Regression

This table re-estimates profitability regressions in Table 6 by splitting the whole sample into three periods: 1993-2006 in Panel A, 2007-2009 in Panel B, and 2010-2018 in Panel C. The descriptions of all variables are in Table 1. Robust t-statistics are shown in the parentheses. ***, **, and * represent the significance level at 1%, 5%, and 10%, respectively.

Panel A: 1993-2006			IB/SALE$_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)
DEV_POSABS	-0.066	-0.128	0.399			
	(-0.24)	(-0.46)	(1.41)			
DEV_NEGABS	-3.207***	-3.297***	-2.104***			
	(-8.20)	(-8.38)	(-5.28)			
DUM_POSABS(Q345)				-0.084	-0.101	0.065
				(-1.34)	(-1.60)	(1.03)
DUM_NEGABS(Q345)				-0.634***	-0.657***	-0.351***
				(-10.32)	(-10.35)	(-5.34)
Controls	Y	Y	Y	Y	Y	Y
Year FE	N	Y	Y	N	Y	Y
SIC FE	N	N	Y	N	N	Y
Observations	49,773	49,773	49,773	49,773	49,773	49,773
R-squared	0.162	0.164	0.183	0.162	0.164	0.183
Panel B: 2007-2009			IB/SALE$_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)
DEV_POSABS	-0.637	-0.674	-0.332			
	(-0.79)	(-0.83)	(-0.40)			
DEV_NEGABS	-4.963***	-4.544***	-4.073***			
	(-5.45)	(-5.03)	(-4.07)			
DUM_POSABS(Q345)				-0.500**	-0.502**	-0.346*
				(-2.49)	(-2.50)	(-1.67)
DUM_NEGABS(Q345)				-0.982***	-0.919***	-0.782***
				(-6.31)	(-5.42)	(-4.52)
Controls	Y	Y	Y	Y	Y	Y
Year FE	N	Y	Y	N	Y	Y
SIC FE	N	N	Y	N	N	Y
Observations	8,064	8,064	8,064	8,064	8,064	8,064
R-squared	0.235	0.235	0.252	0.236	0.236	0.252
Panel C: 2010-2018			IB/SALE$_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)
DEV_POSABS	-2.446***	-2.456***	-1.796**			
	(-2.95)	(-2.95)	(-2.06)			
DEV_NEGABS	-6.604***	-6.444***	-7.196***			
	(-8.87)	(-8.62)	(-8.07)			
DUM_POSABS(Q345)				-0.515***	-0.522***	-0.150
				(-3.67)	(-3.71)	(-1.01)
DUM_NEGABS(Q345)				-1.405***	-1.433***	-1.259***
				(-10.84)	(-10.85)	(-8.56)
Controls	Y	Y	Y	Y	Y	Y
Year FE	N	Y	Y	N	Y	Y
SIC FE	N	N	Y	N	N	Y
Observations	18,282	18,282	18,282	18,282	18,282	18,282
R-squared	0.226	0.227	0.255	0.228	0.229	0.256