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What can commercial property performance reveal about bank valuations?[1]

Emanuel Kohlscheen[2] and Előd Takáts[3]

Abstract

We test whether commercial property performance, proxied by real estate investment trust (REIT) prices, can inform us about bank equity prices. Using data from the United States, the euro area and Japan, we show that REIT prices can predict bank equity prices. Furthermore, a "commercial property factor" adds significant explanatory power to both the CAPM and the 3-factor Fama-French model. At the same time, quantile regressions show that this factor becomes particularly prominent during downturns. It accounts for around half of the drop in average bank valuations during the great financial crisis and, again, during the Covid-19 pandemic.

JEL classification: E44; G12; G21

Key words: asset prices; banks; commercial property; financial stability; real estate

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1. Introduction

Understanding bank valuations is critical, particularly during crises. Regulators and markets cannot easily assess banks' resilience, especially when a large economic shock hits the value of bank assets. Banks themselves are unwilling or unable to provide timely information: they tend to recognize losses on their books only slowly (Laeven and Majnoni (2003)). Therefore, bank disclosures alone might not provide sufficiently clear guidance for markets and regulators, particularly during crises such as the Great Financial Crisis (GFC) a decade ago or the Covid-19 pandemic now. This raises the question: can we use additional market data to understand bank valuations better?

We propose and test a hypothesis: commercial property performance, as proxied by real estate investment trust (REIT) prices, can inform us about bank equity prices - particularly during downturns. Our hypothesis rests on three main building blocks: First, banks have large exposure to commercial property, both directly through their loan books (Davies and Zhu (2011)) and indirectly through, for instance, construction lending (ESRB (2015)). Second, REIT prices add information to bank disclosures. On the one hand, banks are slow to recognize losses, particularly, as the GFC shows, on hard-to-value real estate assets (see Huizinga and Laeven (2012)). On the other hand, REIT prices provide timely market assessment on commercial property values and return prospects. These might matter for bank exposures as REIT prices reflect more real estate prices than overall stock market performance (see Hoesli and Oikarinen (2012) and Miyakoshi et al (2016) for confirmation of this). Third and finally, commercial property performance matters more in downturns than in upswings because of the loan contracts structure. The fixed interest structure limits banks' profit from commercial property appreciation, while the principal exposes banks to losses from depreciation. Taken together, these three building blocks suggest that commercial property performance might help us understand bank valuations better. [4]

We find that commercial property performance indeed adds significant new information on bank equity performance in major economies. To the best of our knowledge, we are the first to document this. We obtain three main results: First, the evolution of the REIT index in a given economy is a significant predictor of bank index returns in the following month. This is unexpected, as it suggests that markets do not fully price in available public information. Yet, at the same time, this does not necessarily imply a widespread or large market efficiency failure. The coefficient estimate is statistically significant, but the projected effects are small compared to the noise of the model. Therefore, the deviation would

[4] Following Annaert et al (2012), CDS spreads could also be used instead of equity prices to assess banks' resilience. The main advantage of using share prices however is their much wider availability and far greater liquidity when compared to CDS instruments. Sarin and Summers (2016) also use a wide range of market indicators.

not enable profitable arbitrage during normal times. However, our quantile estimates show that the prediction becomes much more meaningful in crises. For instance, during the Covid-19 pandemic, REIT indices fell by 21% in March 2020, which would in itself predict on average an additional 6% drop in bank equity prices in April.

Second, we turn from prediction to explanation and show that the "commercial property risk factor" enhances the performance of standard asset pricing models significantly. Including excess REIT returns improves on both the capital asset price model (CAPM) dating back to Sharpe (1964) and Lintner (1965); and the well-known 3-factor model of Fama and French (1992, 1993, 1996, 2004). Commercial property information loads differently from standard bank equity pricing factors, which might explain why markets seem to ignore it in the short run.

Third and finally, to shed light on the working of the commercial property risk factor during downturns, we examine non-linearities through quantile regressions. We find that the effect of our commercial property factor is roughly three-times as strong during downturns than during tranquil times, both in the CAPM and the Fama-French 3-factor model. Indeed, during the sharpest downturns, such as the 2008 Q4 (GFC) or the 2020 Q1 (Covid-19 pandemic), our commercial property factor can explain more than half of the drop in average bank valuations.

Our results are robust to various changes in the specification. Outliers do not materially affect them: winsorizing our sample yields essentially the same results. Neither does the GFC drive the results: our main estimates remain robust in post-GFC samples. We also control for bank balance sheet characteristics, such as total assets and capital adequacy ratios following Cooper et al (2003). Including additional controls for potential common drivers, such as interest rates, the slope of the yield curve or corporate bond spreads, does not materially change our results either. Throughout, the commercial property coefficients, both their size and the pattern of the quantile distribution, remain robust.

Our findings are policy relevant. They suggest that the commercial property price factor is a significant driver of bank equity prices that markets do not fully price in immediately. Therefore, REIT prices can usefully complement supervisory monitoring of real estate exposures. In particular, regulators might use the commercial property factor to identify overheating risks – and fine-tune the application of macroprudential tools.

The remainder of the paper is organized as follows. Section 2 displays our data. Section 3 details our analysis and our three main results. Section 4 shows economic significance during crises. Section 5 provides robustness checks and section 6 concludes.

2. Data

The overwhelming majority of REITs operate in commercial property markets, by acquiring estates and distributing net rent proceeds as dividends to investors. Though individual REITs have been traded as shares for over three decades, representative aggregate indices only became available in late 2002. The Dow Jones REIT index is based on the performance of the largest and most liquid REITs in the U.S. market, the Euronext IEIF REIT in the European market and the Tokyo SX REIT in the Japanese market.

Figure 1a – Evolution of stock indices: United States
Jan 2020 = 100

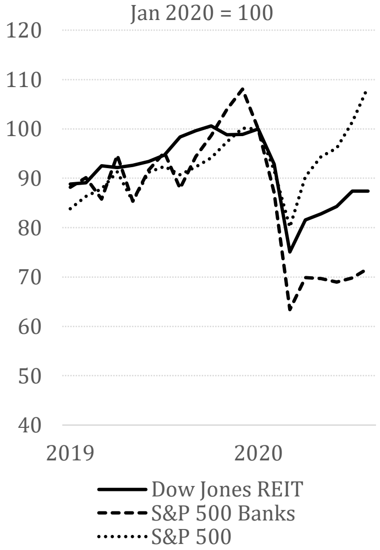


Figure 1b – Evolution of stock indices: Euro area
Jan 2020 = 100

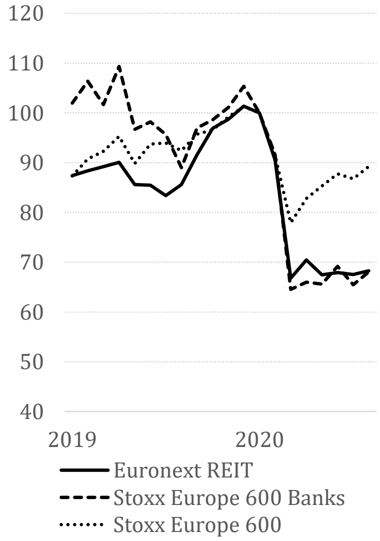
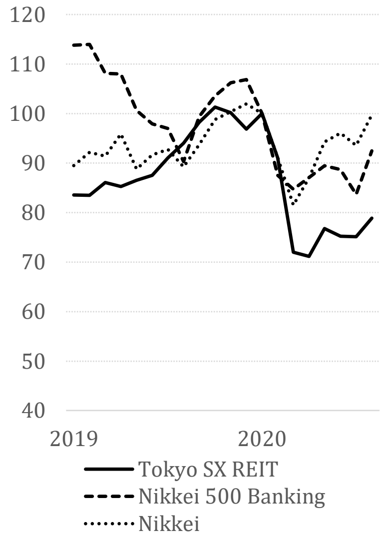


Figure 1c – Evolution of stock indices: Japan
Jan 2020 = 100



The performance of REIT, bank and general market indices show a peculiar pattern during the Covid-19 pandemic (Figure 1). All three indices declined sharply and in tandem during the initial stage of the pandemic in the three major economies. Yet, they diverged sharply during the recovery. While the general market indices recovered relatively quickly in all three economies, both bank and REIT indices remained depressed. The pattern was most pronounced in Europe (centre panel), but also visible in the US (where REITs recovered slightly more than banks, left-hand panel) and Japan (where banks recovered slightly more than REITs, right-hand panel). This is broadly consistent with our initial hypothesis and motivates our inquiry.

In our analysis, we use share prices and balance sheet data for 34 large banks (listed in Table A1 in the Appendix) for the above economies to analyse drivers of individual bank stocks. We collect data from January 2003 to August 2020 at monthly and at quarterly frequency.

The monthly index data shows that aside from a small difference in means, REIT and bank indices have broadly similar distributions (Table 1a). The quarterly frequency data shows the descriptive statistics of the Fama-French model (excess returns and factors) and balance sheet data (log assets and total capital ratio) as well (Table 1b). We use the money market rate for risk-free rates.

Table 1a: Summary statistics of aggregate data (monthly frequency)

variable	observations	mean	std. dev.	min	max
return of bank stock index	674	-0.002	0.070	-0.458	0.303
return of REIT index	674	0.002	0.057	-0.383	0.266

Table 1b: Summary statistics of data used for panel of banks (quarterly frequency)

variable	observations	mean	std. dev.	min	max
excess return of bank stock$_i$	2,432	-0.014	0.192	-0.728	0.483
excess return of market	2,432	0.007	0.090	-0.261	0.176
excess return of REIT	2,432	0.003	0.114	-0.512	0.388
money market rate	2,432	0.99	1.55	-0.36	6.52
SMB (size) factor	2,432	0.0058	0.0230	-0.0516	0.0610
HML (value) factor	2,432	0.0006	0.0292	-0.1412	0.0671
ln (total assets in mn USD)	2,058	13.31	0.99	10.67	14.85
total capital ratio	1,781	14.99	4.31	2.76	43.07

We obtain market data from Bloomberg and the IMF IFS database and quarterly bank balance sheet data from Bankscope/Bureau van Dijk. The selection of banks for our analysis is based purely on data availability.

3. Analysis

3.1 REIT indices predict bank indices

We first analyze whether changes in the respective REIT indices add value to the prediction of bank stock indices in the U.S., the euro area and Japan. We pool monthly observations from the three economies and estimate the impact of one-month lagged REIT indices on bank indices. We control for lagged bank indices throughout. Formally, we run regression on several versions of equation (1) below:

$$bankindex_{j,t} = \alpha + \beta bankindex_{j,t-1} + \gamma REITindex_{j,t-1} + FE_j + \varepsilon_{j,t} \qquad (1)$$

where $bankindex_{j,t}$ stands for the bank index in economy j in month t, $REITindex_{j,t-1}$ stands for the REIT index in economy j in month $t-1$, and FE stands for economy specific fixed effects.

Table 2
Drivers of bank index returns

D.V.: log change in bank index	(I)	(II)	(III)	(IV)	(V)	(VI)
Return equation						
log change in bank index (t-1)	0.115***		0.064	0.114		0.063
	0.038		0.046	0.040		0.028
log change in REIT index (t-1)		0.156***	0.112**		0.155***	0.112**
		0.047	0.057		0.047	0.025
fixed effects	no	no	no	yes	yes	yes
observations	674	674	674	674	674	674
Log-likelihood	-2264.4	-2263.5	-2262.5	-2264.3	-2263.3	-2262.3

Note: Estimated on monthly data for the United States, the euro area and Japan. Cluster-robust standard errors are shown below coefficients. ***/** denote statistical significance at 1/5% confidence level.

As one would expect based on the efficient market hypothesis, lagged bank indices are only significant predictors of current bank indices in one of the four specifications – precisely in the specification without any fixed effects and when the lagged REIT index is not included (Table 2, model I).

In clear contrast, the REIT index return of the past month adds significant value to predicting current bank stock index returns in all cases where it is included (i.e. models II, III, V and VI). The coefficient varies between 0.11 and 0.16, depending on the specification, indicating that a 10% higher return in REITs translates into 1.1–1.6% higher bank stock prices in the following month.[5] The log-likelihood statistic indicates that model (VI), with both lagged bank and REIT indices and fixed effects, is the superior model.

As our hypothesis suggests larger effects during bank equity price downturns, we turn to examine our prediction model under different quantiles (Table 3). We re-estimate our preferred specification (model VI of Table 2) at the 25th, 50th and 75th quantile. The results confirm that the linear prediction model masks stronger predicted changes during market downturns. The estimated impact of the REIT index increases for the lower quantiles. At the 25th quantile, the estimated coefficient is

[5] Note that the p-values of the coefficients are determined using a t-distribution where the degrees of freedom are equal to the number of clusters (three) The values would only have been similar to those obtained with a normal distribution if the number of clusters would be larger.

almost three times as large as the coefficient estimate from the linear model (0.283 in Table 3 vs 0.112 in Table 2).

Table 3
Drivers of bank index returns - Quantile Regressions

D.V.: log change in bank index

	percentile		
	25th	50th	75th
log change in bank index (t-1)	0.078	-0.044	-0.141**
	0.066	0.075	0.063
log change in REIT index (t-1)	0.283***	0.191**	0.111
	0.070	0.082	0.068
model	quantile reg.	quantile reg.	quantile reg.
observations	674	674	674
pseudo R2	0.031	0.008	0.008

Note: Estimated on monthly data for the United States, the euro area and Japan. Standard errors of the quantile regressions were obtained via bootstrapping (1,000 replications). ***/** denote statistical significance at 1/5% confidence level.

To gauge the predictive power of the REIT index for bank indices we undertake a thought experiment. We apply our quantile regression model from Table 3, and estimate the coefficients using data up to February 2020. In other words, we use only the information that was available at the onset of the Covid-19 epidemic. The coefficient estimate for the 25^{th} quantiles is 0.298 in this sample. If one would have applied this coefficient on the March 2020 REIT prices decline (21.2%), that information alone would have predicted an ex ante 6.3% average loss for bank equity prices for the following month, April.

The results should not be interpreted as providing a case for or against market efficiency. Indeed, they suggest some deviation from strict market efficiency: though bank prices incorporate their own past, they do not incorporate all past available information, most notably from REIT indices. However, this does not necessarily imply large profit opportunities. Not only is the coefficient estimate modest in the linear model, the explanatory power of the model is also low (as captured by R2s of less than 5%). In this respect, the tranquil times predictive results seem to be similar to that found for the relation between oil futures markets and the general stock market in Chiang and Hughen (2017). In contrast, the quantile regressions reveal much larger effects during market downturns. Yet, this would not necessarily imply arbitrage profits either: in crises arbitrage becomes inherently difficult.

In sum, our results suggest that REIT prices are useful to predict bank equity prices in downturns, but less so during tranquil times.

3.2 REIT prices explain bank excess returns in CAPM and Fama-French model

Next, we turn from prediction of bank indices to examine in more detail the drivers of individual bank valuations. In this context, we demonstrate that commercial property performance can add significant value to more standard drivers of bank equity prices. In other words, we demonstrate that REIT indices add value to standard equity price drivers, such as excess market returns. Doing so, we rely on two benchmark models to explain excess returns of individual bank stocks: (i) the CAPM dating back to Sharpe (1964) and Lintner (1965); and (ii) the 3-factor model of Fama and French (1992, 1993, 1996, 2004). For this analysis, we use an unbalanced sample of 34 banks with quarterly data over the 2003-2020 period.

First, we estimate the standard one-factor capital asset pricing model (CAPM). Formally, we estimate equation (2):

$$R_{Bi,t} - R_{fj,t} = \alpha + \beta \left(R_{Mj,t} - R_{fj,t}\right) + \varepsilon_{it} \tag{2}$$

The dependent variable ($R_{Bi,t} - R_{fj,t}$), is the excess return of bank stock i ($R_{Bi,t}$) over the risk-free return (i.e. money market return) of economy j at quarter t ($R_{fj,t}$). The right hand side contains, besides the constant, a single factor: the excess market return in economy j $(R_{Mj,t} - R_{fj,t})$.

We find that the β coefficient, which captures the sensitivity of individual bank stock prices to excess market return, is around 1.4 (Table 3, model I). This implies that in our sample banks are more volatile than average firms of the index: when the index moves one percentage point, bank stocks move on average around 1.4 percentage points. The results are similar to those obtained in other CAPM models applied to international samples of larges banks (see, for instance, King (2009)).

We then proceed to estimate the Fama-French (1992, 1993) 3-factor model. Formally, we estimate equation (3):

$$R_{Bi,t} - R_{f,t} = \alpha + \beta \left(R_{Mj,t} - R_{f,t}\right) + \gamma\, SMB_{\,t} + \theta\, HML_{\,t} + \varepsilon_{it} \tag{3}$$

where the dependent variable and the excess market return variable is the same as in the CAPM model of equation (2). SMB denotes the size factor, i.e. the small minus big market capitalization firm excess return. HML denotes the value factor, i.e. the high minus the low book-to-market ratio excess return.

Table 4
Drivers of bank specific stock returns

D.V.: log change in bank stock price	(I)	(II)	(III)	(IV)	(V)	(VI)
	CAPM model	F-F 3 factor model	CAPM plus ΔREIT	F-F 3 factor plus ΔREIT	CAPM plus ⊥ ΔREIT	F-F 3 factor plus ⊥ ΔREIT
excess market return (Rm - r)	1.428***	1.381***	1.117***	1.129***	1.428***	1.395***
	0.044	0.045	0.054	0.054	0.042	0.044
SMB (size) factor		0.133		0.066		0.066
		0.116		0.114		0.114
HML (value) factor		0.743***		0.551***		0.551***
		0.127		0.131		0.131
excess REIT return			0.343***	0.294***		
			0.048	0.050		
orthogonal comp. excess REIT ret.					0.343***	0.293***
					0.048	0.050
observations	2432	2432	2432	2432	2432	2432
log-likelihood	940.7	962.1	974.5	985.7	974.5	985.7
R2	0.382	0.393	0.399	0.405	0.399	0.405
RMSE	0.164	0.163	0.162	0.162	0.162	0.162

Note: Estimated on quarterly data for banks from the United States, the euro area and Japan. Robust standard errors are shown below coefficients. ***/**/* denote statistical significance at 1/5/10% confidence level.

The Fama-French model shows a β coefficient of around 1.4 (Table 3, models I and II). This is essentially the same coefficient that we obtained in the CAPM specification. Yet, our coefficient estimates on the size factor do not show statistically significantly higher returns for smaller banks.[6] Individual bank returns, however, do load positively on the Fama-French value factor (i.e. price-to-book ratio). The results are similar to the results obtained on other international samples of larges banks (see, for instance, Yang and Tsatsaronis (2012)).

We follow our hypothesis and add excess REIT returns, i.e. our commercial property risk factor, to our estimations (models III to IV on Table 3). The results confirm our main conjecture. Excess REIT returns in themselves are significant, both in the CAPM and in the Fama-French model. The coefficient estimate on this "commercial property factor" is around 0.3. This implies that a 3 percentage point change in excess bank stock return for every 10 percentage point change in the excess REIT index.

3.3 Quantile regressions: REITs matter particularly in downturns

Based on our hypothesis, we would expect our "commercial property risk factor" to have the largest impact during market downturns. Commercial property performance matters more in downturns than in upswings because of the loan contracts structure. The fixed interest limits banks'

[6] The estimated excess REIT return coefficients remain essentially the same when we include time fixed effects and estimate coefficients from the series of cross-sections. In this case, however, we also observe higher returns for smaller banks as one could expect (see Robustness section for details).

profit from commercial property appreciation, while the principal exposes banks to losses from rising credit risk.

To examine this asymmetry, we turn to quantile regressions which reflect differing degrees of pressure of bank stocks (see Koenker and Basset (1978), Koenker and Hallock (2001) and Koenker (2005)). More precisely, we re-estimate the CAPM model (model III in Table 3) and the Fama-French 3-factor models (model IV of Table 3) at the 5th, 50th and 95th percentile of conditional bank returns (Table 5).

Table 5
Drivers of bank specific stock returns: by quantile

D.V.: log change in bank stock price

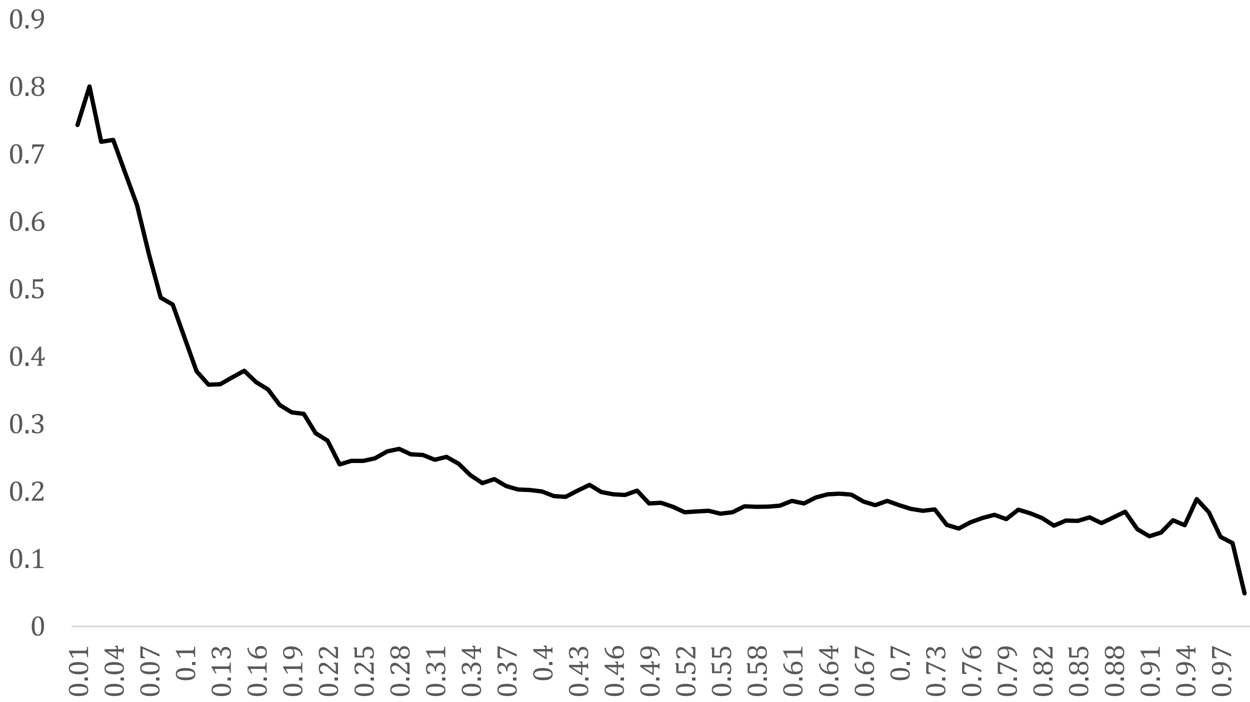
	CAPM model plus ΔREIT			F-F 3 factor model plus ΔREIT		
	percentile			percentile		
	5th	50th	95th	5th	50th	95th
excess market return (Rm - r)	1.031***	1.067***	1.143***	1.039***	1.090***	1.146***
	0.108	0.058	0.072	0.123	0.040	0.082
SMB (size) factor				-0.160	0.042	0.299
				0.277	0.105	0.277
HML (value) factor				0.021	0.810***	0.928***
				0.184	0.105	0.292
excess REIT return	0.664***	0.237***	0.207***	0.673***	0.183***	0.188**
	0.083	0.041	0.080	0.088	0.036	0.077
observations	2432	2432	2432	2432	2432	2432
R2	0.303	0.250	0.214	0.304	0.261	0.224

Note: Estimated on quarterly data for banks from the United States, the euro area and Japan. Standard errors of the quantile regressions were obtained via bootstrapping (1,000 replications). ***/**/* denote statistical significance at 1/5/10% confidence level.

Tellingly, the quantile regressions for the CAPM model show substantial non-linearity in the excess REIT return (our "commercial property factor"), but not in the market factor (Table 5, left-hand columns). The estimate of the market factor, β, varies very little across conditional quantiles. In fact, a standard test cannot reject the null hypothesis that the coefficients are the same. This confirms again the linear CAPM specification. However, this is clearly not the case for the coefficient on excess REIT returns. At the 5th quantile of bank stock returns, the effect of REIT performance is about three times as strong as at the 95th quantile of bank stock returns. The difference is also statistically significant.

We obtain similar results also for the Fama-French 3-factor model (Table 5, right-hand columns). The market and size factor remains virtually unchanged across the quantile regressions (the latter being insignificant). The value factor, i.e. the price-to-book ratio, however, displays some non-linearity and becomes insignificant during periods of low bank returns (5th percentile). Similarly to the CAPM model, the effect of REIT excess return is about three times stronger at the 5th quantile than at the 95th quantile of conditional bank stock returns. The difference is again statistically significant. In other words, REIT returns matter much more when market conditions deteriorate, than during normal times.

Figure 2 – Excess REIT return coefficient by quantile



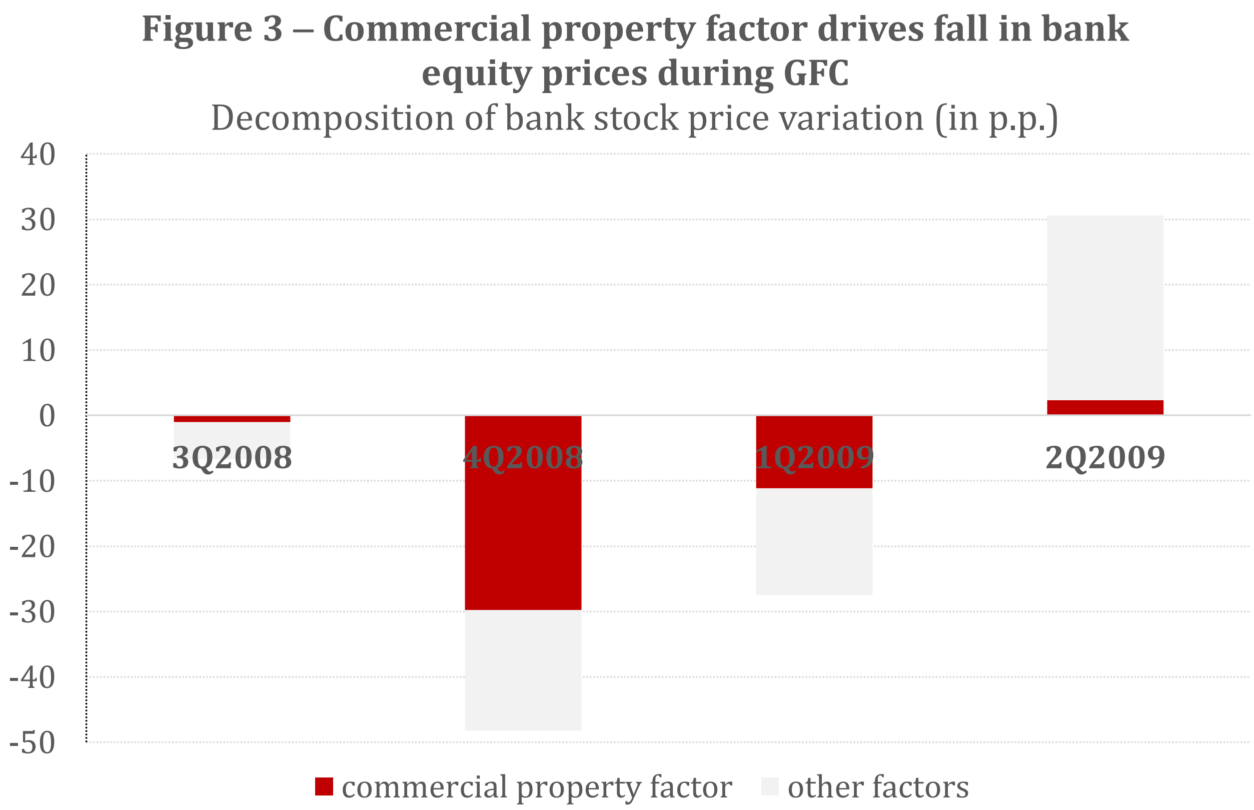
The coefficients for each quantile show clear non-linearity (Figure 2). Throughout most of the distribution, roughly between the 20th and the 95th percentile, the estimates remain stable around 0.2 (or around the median estimate). However, in downturns the coefficient estimates become larger: they start to increase from the 20th to the 10th percentile – and shoot up sharply in the lowest return decile.

4. Economic significance in crises

Our results display strong non-linearities. In crises, not only the larger REIT price decline affects bank prices, but the coefficient estimates increases too. Therefore, it is not straightforward to visualize the economic significance solely based on the coefficient estimates. To illustrate this we asses to which degree our commercial property factor drove bank equity prices during the GFC and the Covid-19 crisis.

First, we examine the impact of the commercial property factor during the GFC (Figure 3). We use the estimations from the "Fama-French plus commercial property factor" model. In line with the econometric model, we focus on quarterly returns. The commercial property factor (red column) always plays a role. Most of the time, however, its impact is moderate. During tranquil quarters (see, for instance, Q2 2009) it contributes to bank equity prices only marginally. In contrast, during the downturn

(Q4 2008 and to a lesser degree in Q1 2009) the commercial property factor becomes a key driver of bank equity prices.

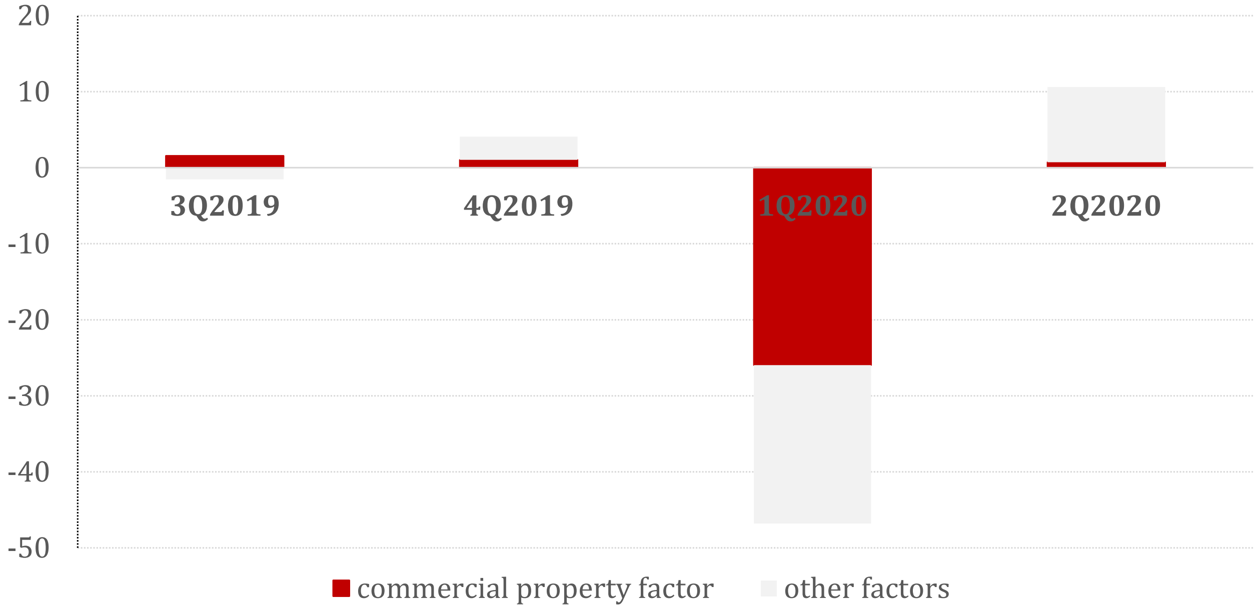


Second, we decompose the average change in bank equity price during the onset of the Covid-19 pandemic (Figure 4). We obtain very similar results. During tranquil quarters (see, for instance, Q3 and Q4 2019) the commercial property factor contributes to bank equity prices only marginally (red columns). In contrast, during the downturn, the commercial property factor becomes a key driver of bank equity prices. In Q1 2020 bank stocks retreated on average 46.8%: the REIT index decline alone explains around 26 percentage points of this.[7] In other words, during the crisis the commercial property factor explains more than half of the decline in bank equity prices.

[7] We obtain the average 26 percentage point commercial property impact in Q1 2020, by multiplying the average REIT index decline in the three economies (36.2%) with the coefficient estimate associated with the crisis (0.718).

Figure 4 – Commercial property factor drives fall in bank equity prices during Covid-19 shock

Decomposition of bank stock price variation (in p.p.)



The decompositions show three main features of economic significance. First, the commercial property factor is a highly economically significant driver of bank equity prices during crises. It is close to being dominant, as it explains around one-half of the total crisis-time fall in bank equity prices. Second, the economic impact tends to be marginal during tranquil times. Third, this economic impact pattern (high in crisis-times – low in tranquil-times) is present in both the GFC and the Covid-19 crisis.

5. Robustness

We investigate the robustness of our three main results in three separate subsections.

5.1 Robustness of prediction results

We first check whether the result that REIT returns predict future bank index returns are not just an artefact of the GFC. For this, we re-estimate our main results (from Table 2) on the post-crisis sample starting in Q3 2009. We find that REIT returns continue to predict bank indices one month in advance in the post-GFC sample too (Table A2 in the appendix).

In the next step, we examine how fast REIT prices are incorporated into bank prices. To do so, we add a second lag to the main specifications (results available upon request). While the first lags of

REIT returns remain significant throughout, the second lags never become significant, as the standard errors grow. This suggests that REIT price information does not provide additional information for bank equity prices beyond a one-month horizon. Further, this exercise also confirms the appropriateness of our one-lag specification (Table 2).

5.2 Robustness of CAPM and Fama-French model results

First, we address potential multicollinearity: the potential correlation between excess REIT returns and excess bank returns. To this end, we calculate the component of the excess REIT returns for each economy, which is orthogonal to the excess market return in that economy – and repeat our analysis with this "orthogonal" excess REIT return (Table 4, models V and VI). More specifically, we take the residual of a first stage regression of REIT returns on market returns as our orthogonal REIT excess return. This design ensures that the orthogonal excess returns are uncorrelated with excess market return. Remarkably, our coefficient estimates for REIT returns remain virtually unchanged both for the CAPM (model V) and 3-factor Fama-French model (model VI).

Table 6
Factor models with time fixed effects

D.V.: log change in bank stock price

	(I)	(II)	(III)	(IV)
	CAPM model	F-F 3 factor	CAPM plus ΔREIT	F-F 3 factor plus ΔREIT
excess market return (Rm - r)	1.615***	1.615***	1.417***	1.417***
	0.110	0.110	0.119	0.119
SMB (size) factor		7.326**		7.429**
		3.039		3.038
HML (value) factor		-5.101**		-5.595**
		2.218		2.217
excess REIT return			0.317***	0.317***
			0.079	0.079
time fixed effects	yes	yes	yes	yes
observations	2432	2432	2432	2432
log-likelihood	1188.9	1188.9	1200.1	1200.1
R2	0.496	0.496	0.501	0.501
RMSE	0.151	0.151	0.150	0.150

Note: Estimated on quarterly data for banks from the United States, the euro area and Japan. Robust standard errors are shown below coefficients. ***/**/* denote statistical significance at 1/5/10% confidence level.

Next, we also re-estimate our main results (from Table 5) on the post-crisis sample starting in Q3 2009. Again, we find that the commercial property factor coefficient estimates remain robustly significant in the post-GFC sample (detailed results available upon request).

Third, we examine that our results carry-over to an alternative specification that derives the factors solely from the cross-sectional variation. To do so, we add time fixed effects to the benchmark models (Table 6). The coefficient of the commercial property factor remains strongly significant, with a value that continues to be around 0.3. Additionally, the cross-sectional focus renders the size factor statistically significant and positive as expected.

Last, we check systematically that outlier observations do not drive our findings. To do so, we repeat the estimations after winsorizing all variables at the 1st and the 99th percentiles. That is, for observations in the bottom percentile of the distribution, we attribute the value of the 1st percentile instead. Similarly, for observations in the top percentile, we attribute the value of the 99th percentile. The winsorized estimates are similar to our main results (Table A3). We confirm robustness also when winsorisation was done at the 2nd and 98th percentiles (detailed results available upon request). Therefore, outliers do not seem to drive our results.

5.3 Robustness of the quantile regressions

We examine first the effects of excess REIT returns across different bank performance percentiles after controlling for bank balance sheet characteristics (see Cooper et al (2003)). We control for the size of the bank (as measured by total assets) and for capitalization (as measured by the total capital adequacy ratio under the Basel rules).[8] Formally, we estimate equation (4):

$$R_{Bi,t} = \alpha + \beta A_{\ i,t} + \gamma CAR_{\ i,t} + \theta R_{\ f,t} + \ (R_{REIT\,j,t} - \ R_{f\,j,t}) + \ \varepsilon_{it} \qquad (4)$$

where the dependent variable is the log change in bank stock price. The explanatory variables are log total assets in USD million at quarter t ($A_{\ i,t}$), the total capital adequacy ratio of bank i ($CAR\ i,_t$), the money market rate ($R_{\ f,t}$) and excess REIT return in economy j ($R_{REIT\,j,t} - \ R_{f\,j,t}$), i.e. our commercial property factor.

The results show that REIT index excess returns generally explain bank stock returns (Table 7). The standard regression approach already captures this (7th column, mean). Furthermore, as in the previous specification, the REIT coefficients remain clearly much larger for the lowest percentiles of the

[8] In addition, one could add the leverage ratio as an additional, traditional control. However, in our case this diminishes the sample size by about 70%. Since the leverage ratio variable is not significant in any of these estimates (detailed results available upon request), we focus on the results which exclude it.

dependent variable. In the most stressed condition, i.e. in the lowest percentile, the importance of excess REIT returns is roughly three times as large as during a boom (i.e. the 90^{th} percentile). The difference between the REIT coefficient at the 10^{th} and at the 90^{th} quantile is 0.407 (with a 95% confidence interval of 0.201–0.614). The p-value for equality of the coefficients is below 0.0005.

Remarkably, our commercial property factor estimates in the balance sheet model remain very similar in size as in the CAPM and 3-factor Fama-French model estimates. Furthermore, the factor three difference between crisis and tranquil time observations also remains essentially the same that we have obtained in the extended CAPM and 3-factor Fama-French models (Table 4).

Table 7
Quantile regressions of bank specific returns

D.V.: log change in bank stock price				percentile			
	1st	2nd	5th	10th	50th	90th	mean
ln (total assets in mn USD)	0.202***	0.068	0.019**	0.004	-0.002	-0.014	0.001
	0.058	0.047	0.009	0.008	0.004	0.006	0.004
total capital / assets (ratio)	0.013	0.003	0.006*	0.004**	0.001	-0.001	0.001
	0.015	0.010	0.003	0.002	0.001	0.002	0.001
money market rate	0.049**	0.028	0.021***	0.017***	0.005**	-0.002	0.009***
	0.022	0.017	0.006	0.005	0.003	0.006	0.003
REIT index excess return	0.776***	0.801***	0.728***	0.670***	0.288***	0.263***	0.442***
	0.111	0.083	0.053	0.086	0.043	0.072	0.042
model	quantile reg.	quantile reg.	quantile reg.	quantile reg.	quantile reg.	quantile reg.	std. reg.
observations	1780	1780	1780	1780	1780	1780	1780
r2	0.144	0.122	0.132	0.095	0.028	0.027	0.083

Note: Estimated on quarterly data for banks from the United States, the euro area and Japan. Standard errors are shown below coefficients. For quantile regressions these are based on bootstraping with 1,000 replications. ***/**/* denote statistical significance at 1/5/10% confidence level.

Next, we re-estimate the balance sheet model by adding the overall market excess return variable. Note, that this is equivalent to adding the balance sheet characteristics to the CAPM model. Again, the augmented results, particularly on the commercial property factor, remain robust (Table A4). Therefore, it seems that our results do not critically depend on whether or not we control for excess market returns and/or bank balance sheet variables.

Finally, we address further the role of potential common drivers, i.e. those factors that simultaneously drive REIT and bank equity prices. Note, that our approach to evaluate the commercial property factor in the framework of the standard equity pricing models (CAPM, Fama-French) already controls for one of the strongest candidates for such common drivers: equity market prices. The robust results when using orthogonal REIT excess returns provide further evidence against equity market movements as a common factor.

We examine two additional potential common drivers here. First, the interest rate yield curve, that is the difference between the 10-year and the money market rate, could drive both REIT and bank equity prices. The effect could work as follows: On the bank' side, a steeper yield curve increases profits. Directly, a steeper yield curve increases banks' intermediation margins. Indirectly, it is usually associated with stronger expected economic growth, which is also profit positive. On the REIT side, better economic prospects signaled by a steeper yield curve might lift REIT valuations. However, for both banks and REITs the steeper yield curve can also imply a higher discount factor on their dividends, which would hurt valuations. To exclude this potential common driver, we add a control for the slope of the yield curve (10-year sovereign bond yields minus money market rates) to our baseline specification. The slope of the yield curve does not materially affect our commercial property factor estimates throughout the quantiles (Table A5). Yet, it has a positive and significant effect on bank valuations in some downturn quantiles – but not consistently.

A similar potential common driver may be the credit risk spread. Both banks and REITs are highly levered and thereby might benefit from cheaper funding costs. Therefore, lower credit spread might boost bank and REIT valuations. Again, this impact is also debatable: lower risk spreads tend to coincide with low-risk mode on markets, i.e. with times when market prices rise generally. Yet, our baseline setup (CAPM, 3-factor Fama-French model) already controls for the impact of market prices. To shed light on this question, we include a control for credit risk, as captured by Moody's BAA corporate bond spread (Table A6). Once more, the inclusion of credit risk does not materially affect our commercial property factor estimates throughout the quantiles. Having said that we observe some positive effects of lower credit risk spread on bank valuations in some downturn quantiles. However, the effect is not present across all quantiles.

6. Conclusion

We posit a hypothesis that commercial property performance can inform us about bank valuations, particularly during downturns. We find evidence that this is indeed the case. For our analysis we proxied commercial property performance by REIT price indices. We confirm our hypothesis for both, aggregate bank indices and for a representative panel of bank-specific returns.

Our three main results are as follows. First, the evolution of the REIT index in a given economy is a significant predictor of bank index returns in that economy during the following month. This prediction is economically significant during downturns. Second, we find that the "commercial property factor", i.e. excess REIT return, enhances the performance both of the CAPM and of the Fama-French 3-factor model for bank equity prices. Third, quantile regressions show that excess REIT returns are particularly important for bank equity prices during downturns. They explain around one-half of the drop in average bank equity prices during both the GFC and the Covid-19 crisis.

Our findings are relevant for market practitioners, central bankers and regulators. They suggest that the commercial property price factor is a relevant driver of bank equity prices. The findings can help market practitioners to fine-tune their valuation models. Central bankers and regulators might find that REIT prices can usefully complement their monitoring of real estate exposures. While our predictive results are the strongest in crisis times, policy makers might benefit more from using the identified commercial property factor during boom times. Identifying overheating in commercial property markets may allow regulators to strengthen bank resilience in a timely manner. For instance, using REIT prices might help the timely application of macroprudential tools in good times – so that banks would be better positioned to weather the shock of an eventual commercial property price correction.

Summing up, our work is the first attempt to analyse the "commercial property factor". As such, it focuses on aggregates and on major economies. This leaves many avenues open for future research. Exploring if our results carry over to smaller and to emerging economies would be a direct extension. Similarly, exploring the heterogeneity across banks and types of commercial property could also add further value. We hope that our work paves the way for such efforts.

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Appendix tables

Table A1

List of banks

NL	ABN AMRO Group N.V.
ES	Banco de Sabadell, S.A.
ES	Banco Santander, S.A.
US	Bank of America Corporation
ES	Bankia S.A.
DE	BBVA, S.A.
FR	BNP Paribas S.A.
ES	CaixaBank S.A.
DE	Commerzbank AG
FR	Credit Agricole
DK	Danske Bank A/S
DE	Deutsche Bank AG
BE	Dexia S.A.
AT	Erste Group Bank AG
NL	ING Groep N.V.
IT	Intesa Sanpaolo S.p.A.
DK	Jyske Bank A/S
BE	KBC Group NV
JP	Mitsubishi UFJ Financial Group, Inc.
JP	Mizuho Financial Group, Inc.
IT	Monte dei Paschi di Siena S.p.A.
US	Morgan Stanley
JP	Nomura Holdings, Inc.
FI	Nordea Bank
US	Regions Financial Corporation
JP	Resona Holdings, Inc.
JP	Shinkin Central Bank
FR	Societe Generale S.A.
JP	Sumitomo Mitsui Financial Group, Inc.
JP	Sumitomo Mitsui Trust Holdings, Inc.
US	SunTrust Banks Inc.
US	Truist Financial Corporation
IT	Unicredit S.p.A.
US	Wells Fargo & Company

Table A2

Drivers of bank index returns: post-GFC only

D.V.: log change in bank index						
	(I)	(II)	(III)	(IV)	(V)	(VI)
Return equation						
log change in bank index (t-1)	0.040		-0.025	0.035		-0.030
	0.048		0.058	0.020		0.007
log change in REIT index (t-1)		0.132**	0.151**		0.128**	0.150**
		0.062	0.076		0.025	0.031
fixed effects	no	no	no	yes	yes	yes
observations	408	408	408	408	408	408
Log-likelihood	-1348.4	-1346.5	-1346.4	-1347.3	-1345.5	-1345.3

Note: Estimated on monthly data for the United States, the euro area and Japan, excluding all observations up to the first half of 2009. Cluster-robust standard errors are shown below coefficients. ***/**/* denote statistical significance at 1/5/10% confidence level.

Table A3

Drivers of bank specific stock returns: with winsorized data (at 1st and 99th percentiles)

D.V.: log change in bank stock price				
	(I)	(II)	(III)	(IV)
	CAPM model	F-F 3 factor model	CAPM plus ΔREIT	F-F 3 factor plus ΔREIT
excess market return (Rm - r)	1.393***	1.345***	1.091***	1.105***
	0.040	0.040	0.050	0.050
SMB (size) factor		0.111		0.054
		0.126		0.123
HML (value) factor		0.775***		0.592***
		0.121		0.124
excess REIT return			0.339***	0.284***
			0.044	0.046
observations	2432	2432	2432	2432
log-likelihood	1239.0	1268.9	1279.5	1296.1
R2	0.428	0.442	0.447	0.455
RMSE	0.145	0.144	0.143	0.142

Note: Estimated on quarterly data for banks from the United States, the euro area and Japan. Robust standard errors are shown below coefficients. ***/**/* denote statistical significance at 1/5/10% confidence level.

Table A4
Quantile regressions of bank specific returns: including market return

D.V.: log change in bank stock price

	percentile						
	1st	2nd	5th	10th	50th	90th	mean
ln (total assets in mn USD)	0.203***	0.075	0.020**	0.008	-0.002	-0.016**	0.001
	0.064	0.049	0.010	0.007	0.004	0.007	0.004
total capital / assets (ratio)	0.014	0.002	0.006	0.004**	0.001	-0.001	0.001
	0.017	0.009	0.004	0.002	0.001	0.002	0.001
money market rate	0.042*	0.027	0.020***	0.018***	0.005*	-0.002	0.009***
	0.026	0.017	0.007	0.004	0.003	0.007	0.003
market excess return	0.287	0.326	-0.015	0.291*	0.091	0.048	0.122*
	0.495	0.391	0.143	0.157	0.071	0.099	0.073
REIT index excess return	0.576**	0.655***	0.736***	0.498***	0.234***	0.220**	0.372***
	0.262	0.236	0.098	0.125	0.061	0.106	0.060
model	quantile reg.	quantile reg.	quantile reg.	quantile reg.	quantile reg.	quantile reg.	std. reg.
observations	1780	1780	1780	1780	1780	1780	1780
r2	0.147	0.124	0.132	0.098	0.029	0.028	0.085

Note: Estimated on quarterly data for banks from the United States, the euro area and Japan. Standard errors are shown below coefficients. For quantile regressions these are based on bootstraping with 1,000 replications. ***/**/* denote statistical significance at 1/5/10% confidence level.

Table A5
Quantile regressions of bank specific returns: adding the slope of the yield curve

D.V.: log change in bank stock price

	percentile					
	1st	2nd	5th	10th	50th	90th
ln (total assets in mn USD)	0.188***	0.058	0.018**	0.012*	-0.001	-0.014**
	0.065	0.048	0.008	0.007	0.004	0.007
total capital / assets (ratio)	0.010	0.000	0.004	0.002	0.001	0.000
	0.014	0.008	0.005	0.002	0.001	0.001
money market rate	0.016	0.010	0.014*	0.007	0.007*	0.001
	0.030	0.017	0.007	0.005	0.004	0.006
(10-year bond yield rate – mmr)	-0.066	-0.047**	-0.028**	-0.026***	0.003	0.012**
	0.058	0.021	0.012	0.008	0.003	0.006
REIT index excess return	0.649***	0.770***	0.707***	0.582***	0.275***	0.228***
	0.134	0.074	0.070	0.102	0.036	0.071
model	quantile reg.	quantile reg.	quantile reg.	quantile reg.	quantile reg.	quantile reg.
observations	1757	1757	1757	1757	1757	1757
r2	0.153	0.136	0.124	0.084	0.022	0.049

Note: Estimated on quarterly data for banks from the United States, the euro area and Japan. Standard errors are shown below coefficients. For quantile regressions these are based on bootstraping with 1,000 replications. ***/**/* denote statistical significance at 1/5/10% confidence level.

Table A6
Quantile regressions of bank specific returns: adding corporate bond spreads

D.V.: log change in bank stock price

	percentile					
	1st	2nd	5th	10th	50th	90th
ln (total assets in mn USD)	0.191***	0.052	0.024**	0.005	-0.003	-0.007
	0.058	0.051	0.009	0.007	0.004	0.005
total capital / assets (ratio)	0.016	0.004	0.003	0.002	0.001	0.001
	0.014	0.008	0.004	0.002	0.001	0.001
money market rate	0.046	0.015	0.014	0.008	0.008*	0.009
	0.021	0.013	0.007	0.004	0.003	0.005
BAA corporate bond spread	-0.030	-0.037***	-0.020***	-0.020***	0.003	0.021***
	0.020	0.012	0.007	0.004	0.003	0.004
REIT index excess return	0.593***	0.551***	0.666***	0.561***	0.314***	0.319***
	0.177	0.114	0.053	0.051	0.042	0.056
model	quantile reg.	quantile reg.	quantile reg.	quantile reg.	quantile reg.	quantile reg.
observations	1780	1780	1780	1780	1780	1780
r2	0.151	0.146	0.143	0.110	0.029	0.049

Note: Estimated on quarterly data for banks from the United States, the euro area and Japan. Standard errors are shown below coefficients. For quantile regressions these are based on bootstraping with 1,000 replications. ***/**/* denote statistical significance at 1/5/10% confidence level.

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