Tower Building and Stock Market Returns

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Abstract

This papers shows that construction starts of record-breaking skyscrapers predict subsequent US stock returns. In the three to five years after the construction of a record-breaking new skyscraper began, per annum stock market returns are around 10 percentage points lower than in other years. The predictive ability is significant and relatively stable. It exceeds that of alternatives such as the prevailing historical mean, predictions based on dividend ratios, and recently suggested combination forecasts. The findings are robust against a wide range of specifications. Further analyses show that tower building also predicts international stock market returns. One explanation for these patterns is that tower building is indicative of over-optimism. Widespread over-optimism could lead not only to tower-building, but also to overvalued stock markets. The rational asset pricing explanation is that in periods of low risk aversion, financing of large-scale projects such as record-breaking towers is easier, and expected returns are lower. The explanations are difficult to separate empirically. There is no significant influence of financing conditions or sentiment on tower building. However, unlike in other models studied in the literature, imposing a non-negativity constraint on return forecasts does not increase predictive accuracy. This provides indirect evidence that the predictive content of tower building is at least partly related to overvaluation.

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1 Introduction

Ever since the story of the tower of Babel was recorded, the construction of tall towers has been associated with human hubris. From a profane finance theory perspective, towers are large-scale projects with uncertain future cash flows and large funding requirements. These observations suggest two ways why tower building might predict low future stock market returns. Either it indicates periods in which over-optimism has led to overvalued stock markets, or it helps to identify times of low risk aversion. (With low risk premia, funding costs for large-scale projects are lower, while future stock market returns are expected to be relatively low as well.) An example that illustrates the two opposite interpretations is the Chicago Spire, which has a planned height of 609 meters, exceeding existing buildings in the US as well as the planned height of the One World Trade Center. Construction of the Chicago Spire began in June 2007, a time in which (i) risk premia – as exemplified by low credit spreads – were low, and (ii) valuation levels appear to have been relatively high.

In this paper, I therefore examine whether tower building is associated with lower subsequent stock market returns. Using US data from 1871 to 2009, I document significant predictability. In the three to five years after the construction of a record-breaking new skyscraper began, per annum stock market returns are around 10 percentage points lower than in other years. The analysis shows that the predictive ability of tower building is significant and stable over time. This contrasts with the fragile predictive power of variables that have been studied extensively in the literature, such as the dividend price ratio (e.g. Welch and Goyal, 2008). Further analyses show that tower building also predicts international stock market returns.

The two possible explanations for the predictive content of tower building are difficult to separate empirically. Financing conditions or sentiment variables do not have a significant influence on tower building. However, unlike in other models studied in the literature, imposing a non-negativity constraint on return forecasts does not increase predictive accuracy. This provides indirect evidence that the predictive content of tower building is at least partly related to overvaluation.

The perception that tower building could be linked to economic as well as stock market performance is frequently voiced in the media.[1] Often, news articles cite the research report of Lawrence (1999). The only academic paper I am aware of is Thornton (2005), who discusses the relation between tower building, business cycles, and economic crises but does not conduct a statistical analysis. Barr (2010) empirically examines the determinants of skyscraper height and concludes that status plays a role, leading to heights that exceed the profit maximizing height.

There is a large body of literature on predicting stock markets with dividend ratios and other variables. Classical references are Campbell and Shiller (1988) and Fama and French (1988). Recent contributions include Goyal and Welch (2003), Boudoukh, Richardson and Whitelaw (2008), Campbell and Thompson (2008), Cochrane (2008), Lettau, Ludvigson and Wachter (2008), Welch and Goyal (2008), and Rapach, Strauss and Zhou (2010). Whether stock market returns are predictable remains controversial. While the evidence for in-sample predictability appears strong, out-of-sample evidence is much weaker. In the present paper, I compare the predictive ability of tower building to that of variables suggested in this literature, and find that the former is mostly larger.

The remainder of the paper is structured as follows. In Section 2, I describe the data and the methodology. Section 3 analyzes the predictive ability of regression models that include information on tower building. Section 4 examines robustness, and Section 5 concludes.

2 Data and methodology

Data on towers is obtained from the research database of Emporis, a private information provider focusing on building-related information. The database also contains information on planned projects and construction status.[2] This allows us to identify buildings began to be built but were never finished, thereby avoiding possible selection biases that might arise when only finished buildings are studied. The measure of height used is the elevation from the building's base to its

[1] Examples include a 2005 article in Fortune (http://money.cnn.com/magazines/fortune/fortune_archive/2005/09/05/8271392/index.htm) and a 2009 article in the Telegraph http://www.telegraph.co.uk/news/worldnews/middleeast/dubai/6934603/Burj-Dubai-The-new-pinnacle-of-vanity.html)

[2] The quality of the database was confirmed through cross-checks with Landau and Condit (1996) as well as official websites of existing buildings.

highest architectural element.[3] I focus on towers with either residential or office use, for which the term "skyscraper" is commonly used, and neglect telecommunications towers and other high-rise structures. Skyscrapers are often viewed as being in a class of their own. For example, the Sears (now Willis) tower is often described to have held the record for the world's tallest building until the building of the Petronas Towers,[4] even though it was exceeded by the CN telecommunications tower in Toronto in 1976. Furthermore, skyscrapers are more expensive to build than telecommunications towers. The Sears tower, finished in 1974, had construction costs of USD 160 million; the CN tower, finished in 1976, cost CDN 63 million.[5] In the US, skyscrapers are so tall relative to other structures that including the latter in the analysis would not change the constructed series of record-breaking buildings. Note that in the following, I will use the words *towers* and *skyscrapers* interchangeably.

To measure tower building activity, I identify the years in which a tower that would break the current US height record began to be built, or in which construction was finished. (In a sensitivity analysis, this is also done based on buildings that break the international record.) The information is recorded in the following two dummy variables:

$RecordStart_t$ One if construction of a tower breaking the current US record was begun in year t, zero otherwise.

$RecordFinish_t$: One if construction of a tower breaking the current US record was finished in year t, zero otherwise.

As a general measure of US building activity, I examine the number of towers exceeding a height of 100 meters. Since the number of towers above that size is trending upward in long cycles, I examine logarithms relative to their 20-year trailing average. Specifically, I construct the following variables:

[3] "Architectural elements include everything which is integral to the design, including sculptures, spires, screens, parapets, and decorative features." (Source: http://standards.emporis.com).
[4] E.g. http://www.willistower.com/propertyprofile.html, or emporis.com.
[5] Source: emporis.com. The 1976 average CAN/USD exchange rate was 0.9863 as reported in http://research.stlouisfed.org/fred2/data/.

100_Start_t:

$$\ln\left(\frac{1+\text{Number of } US \text{ towers taller than 100 meters } \textit{begun} \text{ in year t}}{1+\text{Average } n\text{umber of } US \text{ towers taller than 100 meters } \textit{begun} \text{ in t - 1, t - 20}}\right)$$

100_Finish_t:

$$\ln\left(\frac{1+\text{Number of } US \text{ towers taller than 100 meters } \textit{finished} \text{ in year t}}{1+\text{Average } n\text{umber of } US \text{ towers taller than 100 meters } \textit{finished} \text{ in t - 1, t - 20}}\right)$$

Table 1 lists the record-breaking buildings that enter the construction of the *Record* variables. International towers breaking the world record are also listed in the table. Note that there is no year in which two or more record-breaking towers were either started or finished. Therefore, there is no need to decide how multiple starts or completions should be treated in the analysis. Figure 1 shows the building activity as measured by the variables 100_Start and 100_Finish.

Stock market data is obtained from different sources. Annual US stock market returns, associated dividend information, and risk-free returns for the time period 1871 – 2009 are obtained from Robert Shiller's website.[6] For the 1926-2009 subperiod, annual data on the value-weighted market portfolio and dividend information are from CRSP, made available by Michael Roberts;[7] the risk-free rate that is used for the CRSP data is the one-month Treasury bill rate taken from Ken French's website.[8] In the literature on stock market predictability, dividend-based ratios are the most widely studied predictors for long-horizon stock market returns. I follow the literature and use the dividend price ratio, defined as the logarithm of dividends paid over the last year divided by the current index value; it will be denoted *dp*. Other predictors, including combination forecasts, as suggested by Rapach, Strauss, and Zhou (2010), will be studied in the sensitivity analysis of Section 4.

Stock market returns enter the analysis as logarithmic excess returns over the risk-free rate, denoted by $r_{t,t+k}$. In using log returns, I follow e.g. Fama and French (1988) and Welch and

[6] http://www.econ.yale.edu/~shiller/data.htm
[7] http://finance.wharton.upenn.edu/~mrrobert/data_code.htm
[8] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/

Goyal (2008). One justification is the fact that log returns are closer to being normally distributed, which should increase the reliability of regression analysis.[9]

In line with the extant literature, predictability is analyzed through linear regressions. As the information contained in tower building activities may be reflected with a time lag, I also include one-year lags of the tower variables. When studying the effects of record-breaking tower starts, for example, I would run the following regression:

$$r_{t,t+k} = b_0 + b_1 dp_t + b_2 RecordStart_t + b_3 RecordStart_{t-1} + u_{t,t+k} \quad (1)$$

For return horizons larger than one year (k>1), the return observations are overlapping, which induces correlations in the error terms. While ordinary least squares regression continues to yield consistent estimates of the coefficients *b*, standard errors are no longer reliable. Until recently, the common academic response was to use Newey and West's (1987) standard errors. Ang and Bekaert (2007), however, have shown that the Newey and West procedure is sensitive to time persistence in the explanatory variables. Through simulations, Ang and Bekaert (2007) show that Hodrick's (1992) standard errors are much more reliable in regressions such as (1). With k>1, I therefore use Hodrick's (1992) standard errors. With one-year returns, the standard heteroscedasticity-robust estimator of White (1980) is used.

I will also explore the out-of-sample performance of predictions based on regressions such as (1). One of the metrics examined is the out-of-sample R^2 suggested by Campbell and Thompson (2008), which compares the mean squared error of a prediction model to the errors one would incur when using the historical mean prevailing at time t as a predictor. Let $\bar{r}_{t,t+k}$ denote the prediction derived from the historical mean prevailing at time t, and let $\hat{r}_{t,t+k}$ denote an out-of-sample regression-based prediction. The out-of-sample R^2 is then computed as follows:

$$R^2_{OS} = 1 - \frac{\sum_{t=m}^{T} \left(r_{t,t+k} - \hat{r}_{t,t+k}\right)^2}{\sum_{t=m}^{T} \left(r_{t,t+k} - \bar{r}_{t,t+k}\right)^2} \quad (2)$$

where *m* is the starting year of the out-of-sample analysis. If the R^2_{OS} is positive, the prediction model outperforms the prevailing mean, which serves as a natural benchmark for evaluating

[9] For the 1871-2009 data, regressing 5-year log returns on the dividend price ratio leads to residuals whose normality is not rejected by a skewness/kurtosis test (p-value = 0.608); with simple returns, normality of residuals is rejected (p-value=0.012).

predictive performance. To assess the statistical significance of the out-of-sample R^2, I follow Rapach, Strauss, and Zhou (2010) and favor the Clark and West (2007) MSPE-adjusted statistic over the Diebold-Mariano (1995) test, which can have low power when applied to nested models.[10] To compute the MSPE-adjusted statistic, define

$$f_{t,t+k} = \left(r_{t,t+k} - \bar{r}_t\right)^2 - \left(\left(r_{t,t+k} - \hat{r}_{t,t+k}\right)^2 - \left(\bar{r}_{t,t+k} - \hat{r}_{t,t+k}\right)^2\right), \quad (3)$$

and regress $f_{t,t+k}$ on a constant. The p-value for a one-sided test is obtained by applying the standard normal distribution to the t-statistic of the constant. For $k>1$, I use the Newey and West standard errors with lag k.[11]

3 Tower building and stock market returns

3.1 In-sample analysis

I start the analysis with a regression in which future stock market returns are predicted with the logarithm of the dividend price ratio (*dp*) and the variables capturing tower construction starts. Results for prediction horizons of one, three, and five years are reported in Table 2, separately for the 1871-2009 and 1926-2009 samples. As is familiar from the literature, high dividend price ratios are associated with high future returns. However, the coefficients are not significant at a level of 10%, which is in line with the findings of Ang and Bekaert (2007).[12] The dummy variables capturing the construction start of record-breaking towers are consistently negative. For horizons of three and five years, the t-statistics for the lagged construction start $RecordStart_{t-1}$ range between -2.14 and -3.57; the construction start $RecordStart_t$ is significant on the 5% level in one regression. The scaled number of building starts (with height above 100 meters) does not show a strong association with future returns. In the two cases in which coefficients are significant at the 10% level, though, they are also negative.

[10] See the discussion in Rapach, Strauss, and Zhou (2010). The prevailing mean is nested in regression models of type (1) because it would result from restricting coefficients other than b_0 to be zero.
[11] Note that the doubts about the reliability of Newey and West (1987) discussed in conjunction with regression (1) arise from the persistence of the predictors, and therefore do not carry over to the regression that is run for the MSPE-adjusted statistic.
[12] With the Newey and West estimator, the coefficient on the dividend yield has a t-statistic of 2.84 in the five-year regression.

Coefficients of RecordStart_{t-1} are not only statistically, but also economically significant. The coefficient of -.305 in the three-year regression, for example, implies that the three-year return from year 2 to year 4 after a record-breaking tower was begun is, on average, 30.5 percentage points lower than in years not preceded by tower building activities. This translates into a per annum return difference of around 10 percentage points.

The predictability literature (cf. Cochrane, 2005, ch. 20) has shown that one should be careful to interpret coefficients or R^2's that increase with the horizon as evidence that forecasting ability increases with a longer horizon. This observation, however, applies to persistent predictors such as the dividend price ratio. The *RecordStart* variables are not persistent. Their first-order autocorrelation is 0.11, while the first-order autocorrelation of the dividend price ratio is 0.87. It is, therefore, appropriate to say that the predictive power of tower starts increases with the horizon. This seems compatible with both explanations of a link between tower building and stock returns. If tower starts are indicative of overvaluation, predictive power should increase with the horizon, provided that periods of overvaluation persist for more than one year. In this case, tower starts will not necessarily be observed at the end of the overvaluation period. To see why the risk premium explanation can be compatible, consider a situation where risk premia fall over an extended period. If the building of a tower begins in the middle of such a period, the short-term returns after the building start will be positive as the fall of risk premia continues to push up prices for a while. In the one-year regressions, such effects could be captured by including additional lags of the tower variables. Indeed, with two further lags of *RecordStart,* the R^2 of the 1871-2009 regression of one-year returns increases from to 0.025 to 0.136. $\textit{RecordStart}_{t-3}$ is most significant with a coefficient of -0.178 (t-stat: -3.17).

The regressions on Table 3 also examine whether the completion of towers predicts future returns. The answer is in the negative. None of the variables capturing the completion of towers has a significant coefficient. This conforms to expectations. Construction starts should provide a better measure of the current situation – be it overvaluation or low risk premia – than construction completions. Several record-breaking towers like the Chrysler Building and the Sears Tower have been completed despite the fact that economic conditions worsened significantly after their start.

Summarizing the results from Tables 2 and 3, it appears that tower building is associated with mid-term future stock returns, and that these effects can be captured well through information about the start of record-breaking towers in the two years prior to the prediction horizon. This suggests a parsimonious model, in which tower building is represented through the variables $RecordStart_t$ and $RecordStart_{t-1}$. In the following, I will therefore concentrate on three simplified models. For purposes of comparison, I first examine the standard dividend model without tower information:

Dividend model: $$r_{t,t+k} = b_0 + b_1 dp_t + u_{t,t+k} \qquad (4)$$

In addition, I either explain future returns with tower information only, or add the tower information to the dividend model:

Tower model: $$r_{t,t+k} = b_0 + b_1 RecordStart_t + b_2 RecordStart_{t-1} + u_{t,t+k} \qquad (5)$$

Dividend + tower model: $$r_{t,t+k} = b_0 + b_1 dp_t + b_2 RecordStart_t + b_3 RecordStart_{t-1} + u_{t,t+k} \qquad (6)$$

Table 4 compares the in-sample fit of these models. None of the models is able to significantly predict one-year returns. On the three-year horizon, the tower model leads to an R^2 of 22.3% over the 1926-2009 sample; the corresponding R^2 of the dividend model is 9.7%. On the five-year horizon, the two models have R^2's that are very close. Combining dividend and tower information further increases the in-sample fit, suggesting that the two variables capture different information. This is confirmed by the low correlation of the predictive variables used in the regressions. Over the 1871-2009 period, the correlation of the dividend price ratio variable with $RecordStart_t$ and $RecordStart_{t-1}$ is -0.047 and 0.027, respectively. I further examine whether the results are sensitive to defining *RecordStart* with US or non-US towers breaking the current world record, rather than defining it with US towers breaking the US record. Results (not reported) do not change conspicuously. Over the three-year horizon, for example, the lagged tower starts continue to be significant on a 1% level in each regression. The next section will examine whether the in-sample predictability documented here carries over to out-of-sample predictability.

3.2 **Out-of-sample analysis**

An out-of-sample analysis mimics the situation of market participants who tried to use the information in predictive variables at a certain point τ in the past. To predict *k*-year returns starting at the end of year τ, one would run the regression (when using the dividend+tower model)

$$r_{t,t+k} = b_0 + b_1 \mathrm{dp_t} + \mathrm{b_2 RecordStart}_t + b_3 \mathrm{RecordStart}_{t-1} + u_{t,t+k}, \quad t = 1,...,\tau - k, \quad (7)$$

derive coefficient estimates $\hat{b}$, and compute the prediction

$$\hat{r}_{\tau,\tau+k} = \hat{b}_0 + \hat{b}_1 \mathrm{dp}_\tau + \hat{b}_2 \mathrm{RecordStart}_\tau + \hat{b}_3 \mathrm{RecordStart}_{\tau-1}. \quad (8)$$

By running regressions of type (7) or (8) for each τ considered in the analysis, one obtains a series of out-of-sample predictions. Following the suggestion of Campbell and Thompson (2008), I also examine the effects of imposing a non-negativity constraint on the prediction. The motivation is that expected excess returns on an asset exposed to systematic risk should be non-negative if the average investor is risk-averse. Since the returns $r_{t.t+1}$ are log returns, negative forecasts can be consistent with rationality as the relevant simple returns also depend on volatility. Assuming normally distributed log returns and estimating future volatilities with the standard errors of the predictive regressions leads to the following predictor that constrains predicted simple returns to be non-negative:

$$\hat{r}_{\tau,\tau+k}(constrained) = \max\left(-\hat{\sigma}_\tau^2(u_{t,t+k})/2, \hat{r}_{\tau,\tau+k}\right), \quad (9)$$

where $\hat{\sigma}_\tau(u_{t,t+k})$ denotes the estimated standard error of a regression that is run to make a prediction from time τ on.

For the sake of brevity, I limit the presentation to the three-year horizon because the analysis of the previous section has shown that the in-sample predictability is strongest over the three-year horizon. The first date τ on which a prediction is made is chosen to be 1915. By then, the three construction starts of 1906-1910 have fully entered the three-year return regressions.

Out-of-sample performance will suffer if coefficient estimates are unstable. It is, therefore, illustrative to examine how coefficients change over time. Figure 2 shows the time series of coefficients for the dividend plus tower model. The coefficient on lagged construction starts is consistently negative. It decreases following the building activity from 1926-1930, but it is largely unaffected by the subsequent construction starts.[13] The coefficient on the non-lagged $RecordStart_t$ is more volatile at the start, but also quite stable afterwards. The coefficient on the dividend variable shows a larger volatility than the tower variable coefficients.

In accordance with prior literature, the benchmark for assessing the predictive performance of a regression model is the prevailing historical mean, which predicts the return from t to $t+k$ as follows:

$$\bar{r}_{\tau,\tau+k} = \frac{1}{\tau - k} \sum_{t=1}^{\tau-k} r_{\tau,\tau+k} \ . \tag{10}$$

Separately for each of the three regression models, Figure 3 shows how the sum of squared prediction errors of a given regression model compares to the sum of squared prediction errors of the historical mean. Specifically, for a given year T, the cumulative relative squared prediction errors are determined through:

$$\text{Cumulative relative SSE} \ = \sum_{\tau=t(1915)}^{T} \left(r_{t,t+k} - \bar{r}_{t,t+k} \right)^2 - \sum_{\tau=t(1915)}^{T} \left(r_{t,t+k} - \hat{r}_{t,t+k} \right)^2 \tag{11}$$

If the cumulative relative SSE is positive, the regression predictions perform better than the simple prediction based on the historical mean. As is evident from Figure 3, the in-sample performance of the tower variables carries over to the out-of-sample analysis. Including the tower variables in the predictive regressions leads to squared errors that are lower than the ones of the historical mean; squared errors are also lower than those arising from the dividend model, in which the dividend price ratio is the sole predictor. Furthermore, results do not critically depend on whether the non-negativity constraint is imposed or not. Regarding stability, it is noteworthy that the performance gains of the tower model are steadier than those of models that include the dividend price ratio. Finally, note that the performance advantage of the tower model also increases during periods with no tower building activity. From 1934 to 1966, for example, the cumulative relative SSE of the unconstrained tower model more than doubles. The fact that the construction of record-breaking towers is a rare event does not mean that one can rarely

[13] It should be noted that the 2006 and 2007 construction starts only partially enter the regressions as the last three-year horizon considered is from 2007-2009.

benefit from regression models that use tower starts as a predictor. In periods with no building activity, these models can be useful if they correctly predict that returns are higher than average.

Table 5 provides a battery of statistics on the prediction errors. Results are presented both for the entire 1915-2009 period and for two subperiods, 1915-1945 and 1945-2009. In each case, the estimation sample starts in 1871, and the Shiller data are used throughout.

All predictors tend to underestimate returns on average, leading to a positive mean prediction error. Compared to the dividend model, however, including information on tower building reduces the bias; the bias of the tower model is not significantly different from zero. (To assess significance, the prediction errors are regressed on a constant; standard errors are based on Newey and West (1987) with a lag length of k=3.)

As is evident from the out-of-sample R^2, which is based on the root mean squared errors, models with tower information consistently outperform the historical mean. With the exception of the constrained dividend+tower model in the 1945-2009 subperiod (significance of 10%), the performance difference is significant on a level of 5% or better. Note that the out-of-sample R^2's of the tower-model are also mostly larger than those of the dividend model. An examination of the mean absolute error MAE shows that the superiority of the models with tower information continues to hold when moving from squared prediction errors to mean absolute errors.

The differences between the errors of unconstrained and constrained predictors are interesting because they could help to differentiate between the two possible explanations for why tower building predicts returns. The constraint is motivated by an equilibrium approach. Even if risk-aversion is very low, one would not expect risk premia to be negative since the stock market is not only risky, but also positively correlated with consumption risk. If tower building is indicative of overvaluation, by contrast, there is no reason for ruling out non-negative expected returns. In the tower and dividend plus tower models, errors increase if the constraint is imposed. As is evident from Figure 3, the difference is largely due to the tower building activity in the 1960s and 1970s. Using the MSPE-adjusted test to examine whether there is a difference between the unconstrained model and the corresponding, constrained model yields t-statistics of 1.32 (tower model) and 1.38 (dividend plus tower model). Therefore, there is some, albeit weak, indication that the predictive ability of tower building is partly related to overvaluation. Note that in the dividend model, the opposite is true. There, imposing the constraint increases the predictive performance. Of course, one should bear in mind that it is generally difficult to distinguish between overvaluation and risk premia explanations in long-horizon returns (see Cochrane (2005) for a general discussion). Together with the low significance levels and the dependence on relatively few events, this justifies caution when giving an interpretation in favor of overvaluation.

In order to assess the economic significance of superior predictive performance, one can examine the performance of portfolio strategies. To facilitate the interpretation and to avoid problems from estimating the variance of multi-period returns, I examine annual portfolio returns.[14] With respect to tower-related information, I examine the following strategy that is easy to implement: At the end of year t, invest 100% in the stock market as long as no record-breaking tower began to be built in years t-4 to t; if there was building activity in the preceding years, invest 100% in short-term bonds. The strategy thus captures the basic insight from the three-year regressions, in which both current and lagged tower building activity predicted returns over the subsequent three years. Its performance is compared to a 100% percent investment in the stock market and an optimized strategy based on the prevailing historical mean. Assuming that an investor has mean-variance preferences of the form

$$Utillity = \mathrm{E}[Return] - \frac{\gamma}{2}\,\mathrm{Var}[Return], \tag{12}$$

today's optimal equity investment is obtained through:

$$\max_{w} \quad Utility = R^{f}_{\tau,\tau+1} + w\hat{R}_{\tau,\tau+1} - \frac{\gamma}{2} w^2 \hat{\sigma}^2_{\tau,\tau+1} \quad \Rightarrow \quad w^* = \frac{1}{\gamma}\frac{\hat{R}_{\tau,\tau+1}}{\hat{\sigma}^2_{\tau,\tau+1}} \tag{13}$$

where R^f denotes the simple risk-free rate. $\hat{R}_{\tau,\tau+1}$ is the predicted simple stock market return, which is set here to the average excess return observed until year τ. The stock return variance is estimated through the variance of the 60 monthly S&P 500 returns ending in December of year

[14] I also examined an optimized strategy based on three-year return forecasts from regressions (8). Assuming log normality and estimating volatility with the standard error of the regression, the log equity premium forecasts were converted into simple forecasts. As with the mean-based strategy, γ was set to 3 and portfolio weights constrained to [0, 1.5]. The resulting three-year Sharpe ratios were 0.469 (stock market), 0.475 (optimized based on historical mean), and 0.616 (optimized based on tower model).

τ.[15] As in Campbell and Thompson (2008) and Rapach, Strauss, and Zhou (2010), portfolio weights are constrained to lie between 0 and 1.5, and the risk aversion parameter γ is set to 3.

Table 6 summarizes the results. Over the 1915-2009 period, the tower-based strategy leads to a Sharpe ratio of 0.474, significantly higher (p-value = 0.025) than the Sharpe ratio of the market, which is 0.354.[16] The measure *Δreturn*, when added to the market return, would equate the market's Sharpe ratio with that of the strategy under analysis. It can be interpreted as an annual management fee that an investor would be willing to pay to gain access to the strategy. For the tower-based strategy, Δreturn is 0.023, which appears economically significant. At 0.008, the Δreturn of the strategy based on historical returns is considerably smaller, and its performance advantage relative to the market is not statistically significant. These patterns prevail in both subperiods, but are stronger during the 1945-2009 subperiod, despite the fact that there were only four construction starts in the 1945-2009 period, compared to eleven starts from 1871-1945.

3.2 Determinants of tower building

Two possible reasons for the predictive power of tower building are that (i) it captures credit market conditions, and therefore, risk aversion, and (ii) it proxies for market sentiment, and therefore, overvaluation. The analysis of the previous section produced weak evidence that overvaluation might play a role. In this section, the question shall be addressed from a different angle. Examining whether tower building is related to credit market conditions or sentiment could shed light on the validity of the different explanations.

I use the following variables to capture credit market conditions:

- The annual change in the volume of real estate loans at all commercial banks, deflated with the US consumer price index (CPI). CPI as well as loan data after 1947 are from *Federal Reserve Economic Data* (Fred).[17] Loan data before 1947 are from the US All Bank Statistics.[18]

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[15] The variance of monthly returns is annualized by multiplication with 12. Data is obtained from Robert Shiller's website.
[16] To test the difference, I use the Jobson and Korkie test corrected by Memmel (2003).
[17] http://research.stlouisfed.org/fred2/data/.
[18] http://fraser.stlouisfed.org/publications/allbkstat/

- The credit spread is defined as yield on Baa-rated bonds minus yield on Aaa-rated bonds. Data are from Fred.

To capture sentiment, I use the component of the sentiment index of Baker and Wurgler (2006) with the longest data history, which is the equity share in new issues. The data from Jeff Wurgler's website is updated with data from the Federal Reserve.[19] Loan and spread data start in 1919; the equity issue data begin in 1927.

Table 7 presents logit regressions in which the building of a record-breaking tower in year *t* is explained through the lagged loan growth, the lagged credit spread, and the equity share in new issues. As is evident from the absence of significant t-statistics and the insignificance of the entire regressions, the proxies for credit market conditions and sentiment do not explain the building of record-breaking towers. Further analysis shows that this is unlikely to be due to an inadequacy of the chosen proxies. As is shown in linear regressions also reported in Table 7, these variables are able to predict the construction of large towers as measured by the variable 100_Start_t introduced above, which is the number of building starts with a height above 100 meters relative to the average number of such starts over the preceding 20 years. The regressions are highly significant (p-values below 0.001), and the coefficients have the expected sign: Building activity is higher after periods of high loan growth, low credit spreads, and high sentiment as proxied by the equity share in new issues.

An additional logit regression in Table 7, in which 100_Start_t is used as an additional predictor for the start of record-breaking towers, shows that the latter is predictable by building activity as a whole, but that it is not particularly sensitive to either credit market conditions or sentiment.

The building of record-breaking towers thus seems to capture information about expected returns that is not easily captured by standard variables. Sensitivity analyses show that this conclusion is not affected if credit spreads are defined differently (Baa yield minus long-term treasury yield, Aaa yield minus long-term treasury yield), if the sentiment index of Baker and Wurgler (2006) is used, or if contemporaneous values of the predictive variables are included in the regression.

Therefore, the results are of little help when trying to distinguish between rational and irrational explanations for the predictive power of tower building. However, they show that there is no

[19] http://pages.stern.nyu.edu/~jwurgler/ and http://www.federalreserve.gov/econresdata/releases/statisticsdata.htm.

support for possible explanations such as ‘tower building merely reflects low financing costs or high sentiment as measured by standard variables.’

4 Robustness

To check robustness of the results from Section 3, I start by examining alternative variable definitions and predictors. Subsequently, I perform a simulation study to gauge the reliability of out-of-sample test statistics, and present results for international stock markets.

4.1 Variable selection and definition

I explore the following variations:

Variations of additional predictors

1) Instead of using the log dividend price ratio as an additional predictor, I use the log 10-year price-earnings ratio computed by Robert Shiller.

2) I replace the log dividend price ratio by the log dividend *yield*, defined as log of dividends minus log of *lagged* index values.

3) A recent paper by Rapach, Strauss, and Zhou (2010) shows that a simple average of return predictions from individual regressions models produces superior out-of-sample performance. I consider the full set of 15 variables studied by Rapach, Strauss, and Zhou (2010):

   Dividend–price ratio; dividend yield; earnings–price ratio; dividend–payout ratio; historical S&P 500 volatility; book-to-market ratio of the Dow Jones Industrial Average; net NYSE equity issues scaled by NYSE market capitalization; three-month treasury bill rate; long-term government bond yield; lagged return on long-term government bonds; term spread, default yield spread (Baa minus Aaa); difference between long-term corporate bond and long-term government bond returns; inflation rate; investment-to-capital ratio (ratio of aggregate investment to aggregate capital for the entire economy.

   Rapach, Strauss, and Zhou (2010) start their out-of-sample analysis in 1965, as some variables are only available from 1947 on. To apply their combination approach to the 1915-2009 period, I suggest the following procedure: At time *t*, use any individual prediction that is based on a regression with ten observations or more. The number of variables that enter the prediction increases from 5 in 1915 and 10 in 1933 to 15 in 1960.[20] In Rapach, Strauss, and Zhou (2010), the arithmetic mean performs best over their full sample period. Therefore, I also take the simple average of the individual predictions.

Variations of tower variables

4) The first building in the list of record-breaking towers, the Philadelphia City Hall, stands out from the others because it is a public building, and because it reaches its height largely through a clock tower rather than office floors. One could surmise that its linkages to the stock market differ from those of later buildings. Therefore, using the Emporis database and information in Landau and Condit (1996), I construct a new list of record-breaking towers after removing Philadelphia City Hall as well as other public buildings. The list has five new buildings whose construction started between 1872 and 1896.[21] As in the base case, I include a dummy for construction starts in the year of prediction as well as in the year before.

5) In the in-sample regressions of Table 2, the dummy variable capturing construction starts during the year in which a prediction is made was only marginally significant in most cases. The predictive power of lagged construction was much stronger. As this could induce modelers to consider only lagged construction starts for predictions, I examine the performance of such a simplified model.

Variations of return variables

6) Instead of using the Shiller data from 1871-2009, I link the Shiller data from 1871 to the end of 1926 with the CRSP data from the end of 1926 to 2009.

7) Rather than using log returns for the predictive regressions and the computation of out-of-sample performance statistics, I use simple returns.

Table 8 summarizes the results of the robustness checks by presenting the out-of-sample R^2. They are shown for both the full 1871-2009 period and the 1915-145 and 1945-2009 subperiods.

Over the entire sample, the price-earnings ratio leads to a better performance than the dividend price ratio, but conclusions are not affected. The out-of-sample R^2 of the unconstrained tower

[20] Requiring a minimum of 20 observations does not affect conclusions. The out-of-sample R^2 for the entire sample decreases to −0.065, while the 1945-2009 subperiod sees a modest improvement from 0.066 to 0.074.

[21] These are (construction starts in parentheses): Western Union Building (1872), New York Tribune Building (1873), World Building (1889), Manhattan Life Building (1893), and Park Row Building (1896).

model (0.106) still exceeds that of a model including only the price-earnings ratio (0.086). Between 1915 and 1945, the price-earnings ratio leads to a superior performance, but the performance after 1945 is disappointing. Using the dividend yield instead of the dividend price ratio strongly reduces performance. The combination forecast of Rapach, Strauss, and Zhou (2010) makes use of a wide range of variables and represents the best choice for out-of-sample prediction based on the predictability literature. It performs well after 1945, but its out-of-sample R^2 remains below that of the tower model. Before 1945, the relative performance is negative. This corroborates the strength of the results. The performance of predictions based on tower building activity is not only statistically significant, but they also win the race against a large number of models that have been intensively studied in the literature.

Excluding public buildings from the list of record-breaking towers does not strongly affect the results. In most cases, the results are slightly better, which is what one would expect given that private building activity may provide more information about the stock market than public building activity. Capturing tower building activity only through construction starts in year t-2 reduces the performance, but it is still significant for the tower model.

Linking the Shiller data from 1871 to the end of 1926 with the CRSP data from the end of 1926 to 2009 does not greatly change the results relative to using the Shiller data for 1871-2009. In a further variant that is not reported in the table, I conduct the 1945-2009 analysis with the CRSP data only, i.e. the estimation starts in 1926 rather than 1871. Conclusions are not affected. The out-of-sample R^2 of the unconstrained tower model changes from 0.151 to 0.154. Finally, using simple rather than logarithmic returns does not lead to conspicuous changes in the results.

The predictive power of tower building activity that was documented in the previous section is therefore robust to variations in model specification. The following simulation exercise shall demonstrate that the statistical tests can also be trusted.

4.2 Exploring the reliability of test statistics

Using a bootstrap procedure, I generate many datasets with actual returns but hypothetical tower building activity. With each of these datasets, I run the tower model and compute its out-of-sample R^2. As building activity is clustered in time, I draw blocks of three years from the historical experience. Specifically, the simulation exercise has the following structure:

1) For each year $t \in \{1871, 1874, 1877, \ldots, 2006\}$ randomly draw with replacement a year *n(t)* from the period 1871 – 2007. Assign the values of *RecordStart* values from the year *n(t)* to year *t*. For each *t*+1 and *t*+2, assign the values of *RecordStart* values from the years *n(t)* + 1 and *n(t)* + 2.
2) Determine the out-of-sample R^2 using actual return data and the tower building information bootstrapped in 1).
3) Repeat 1) to 2) 10.000 times.

With the actual data, the out-of-sample R^2 was 0.106. In the bootstrapped data, this value was exceeded in only 0.18% of all runs, showing that it is highly unlikely that the high R^2 is a product of chance. The finding that the unconstrained model is better than the constrained one is also corroborated in the simulation. The difference between the unconstrained out-of-sample R^2 and the constrained one is only as large as the empirical one in 0.48% of all simulations.

4.3 International evidence

Finally, I examine whether there is international evidence for the predictive power of tower building activities. I examine Datastream country stock market indices denominated in US dollars, including all countries for which such indices are available. (The countries are listed in the Appendix.) Again, using the Emporis database, I define the following two tower-related variables on a country-by-country basis:

$RecordStart_{it}$	One if construction of a tower breaking the current record in country i was begun in year t, zero else.
100_Start_{it}	$\ln\left(\frac{1+\text{Number of towers taller than 100 meters } \textit{begun} \text{ in country i in year t}}{1+\text{Average number of towers taller than 100 meters } \textit{begun} \text{ in country i in t-1, t-20}}\right)$

As above, I study logarithmic *k*-year excess returns over the US short-term, risk-free rate. They are denoted by $r_{i,t,t+k}$ The following control variables are used to control for other sources of differences in expected returns: the country beta (estimated with weekly returns of year *t* and using the Datastream world index as the market portfolio); the dividend-price ratio *dp* (log of

Datastream item *dy*); *size*, defined as the logarithm of the relative market value (log of Datastream item *mv* divided by the cross-sectional sum of the market values); and the return over the previous year ($r_{i,t-1,t}$) to control for possible momentum or reversal effects. As in the regressions in Table 2, the tower-related variables enter both with their values from t and t-1. This leads to the following regression equation:

$$\begin{aligned} r_{i,t,t+k} &= b_0 + b_1 beta_{it} + b_2 dp_{it} + b_3 size_{it} + b_4 r_{i,t-1,t} \\ &+ b_5 RecordStart_{it} + b_6 RecordStart_{i,t-1} + b_7 100\_Start_{it} + b_8 100\_Start_{i,t-1} + u_{i,t,t+k} \end{aligned} \tag{14}$$

The regression equation (14) is estimated with the procedure of Fama and MacBeth (1973), i.e., I run cross-sectional regressions for each *t* and then report mean coefficients and test statistics based on the time series of estimated coefficients. To capture serial correlation in coefficients, I estimate standard errors with the Newey and West (1987) procedure and a lag length of k - 1. Since the length of the data is fairly short, and small-sample biases of Newey and West are known (cf. Gow, Ormazabal, and Taylor, 2010), I run a simulation study to derive critical t-values. The simulation is structured as follows:

1) Randomly reshuffle the countries, i.e. for each country i, randomly draw a country without replacement from the entire set of countries, j=1,…,37.
2) For country i, determine the two tower-related variables by using the corresponding values of country j. If country j was chosen for country i, for example, the value of $RecordStart_{it}$ is replaced by the value of $RecordStart_{jt}$ for each t.
3) Run regression (14) with the reshuffled variables and determine the t-statistics of the tower-related variables.
4) Repeat 1) to 3) 10.000 times.

Since we expect negative coefficients for the tower-related variables, I report the 2.5% quantiles of the simulated t-statistics.

Results are presented in Table 9. The only tower-related variable that is significant on a level better than 5% is the lagged tower start dummy for the 5-year horizon. Its t-statistic of -2.82 is above the simulated one of -2.35. Although the predictive power of tower building is less pronounced than in the US regression, the patterns are quite similar. First, the building of record-breaking towers is found to have an influence, while general tower building activity as measured through the variable 100_Start_{it} is not. Second, the lagged tower start dummy has a stronger influence than the one from the year in which the prediction horizon starts. Finally, the effects are more visible over longer horizons.

For the following two reasons, it does not come as a surprise that the international evidence is weaker than in the US. The time period is relatively short. Moreover, the average height of the record-breaking towers in the international sample is only 235 meters, which is considerably smaller than the average height of record-breaking US towers in the 1970-2009 period (531 meters). The typical record-breaking tower in the international sample is, therefore, less prominent than in the US data. The fact that there is, nevertheless, a significant relationship over long horizons corroborates the findings for the US market.

5 Conclusion

In this paper, I have shown that construction starts of record-breaking skyscrapers in the United States predict subsequent US stock returns. The predictive ability appears to be stable. It exceeds the one of alternatives such as the prevailing historical mean, predictions based on dividend price ratios, and recently suggested combination forecasts (Rapach, Strauss, and Zhou, 2010). One could be concerned about reliability and significance because there are few tower building episodes. Here, it is important to note that other, frequently used predictive variables such as the dividend price ratio are slowly moving. Their high persistence leads to situations in which a regression is heavily affected by a few regime shifts even though it uses decades of continuous data (cf. the discussion in Cochrane, 2005, Ch. 20). Persistence also leads to problems in assessing statistical significance (Ang and Bekaert, 2007). Viewed in this light, it is not obvious that statistical tests (which, by construction, take the number of observations into account) should be less reliable when applied to tower building, as compared to tests applied to dividend price ratios or other variables. In addition, the analysis has shown that prediction models based on tower building can be useful even during times in which no tower is built. In the years 1934-1966, for example, the tower-based model correctly predicted that stock market returns were above average, and therefore yielded better forecasts than the historical average.

One explanation for the documented patterns is that tower building is indicative of over-optimism. Widespread over-optimism could lead not only to tower building, but also to overvalued stock markets. The rational asset pricing explanation is that in periods of low risk aversion, financing of large-scale projects such as record-breaking towers is easier, and expected returns are lower. It is generally difficult to disentangle rational and irrational explanations for patterns in long-run returns. In this paper, I provide indirect evidence that is consistent with the overvaluation view. Given its weakness, it should not be over-interpreted. In any case, the results suggest that a small number of episodes can have a significant impact on the long-run returns earned by investors. They also show that non-financial information like tower building may help investors to identify periods of low future expected returns.

Appendix: Datastream country indices used in the international analysis

Country	First data in	Country	First data in
ARGENTINA	1993	MALAYSIA	1986
AUSTRALIA	1973	MEXICO	1989
AUSTRIA	1973	NETHERLANDS	1973
BELGIUM	1973	NEW ZEALAND	1988
BRAZIL	1994	NORWAY	1980
CANADA	1973	PHILIPPINES	1988
CHILE	1989	POLAND	1994
CHINA A	1994	PORTUGAL	1990
DENMARK	1973	SINGAPORE	1973
FINLAND	1988	SOUTH AFRICA	1973
FRANCE	1973	SPAIN	1987
GERMANY	1973	SWEDEN	1982
GREECE	1990	SWITZ.	1973
HONG KONG	1973	TAIWAN	1988
INDONESIA	1990	THAILAND	1987
IRELAND	1973	TURKEY	1989
ITALY	1973	UK	1969
JAPAN	1973	VENEZUELA	1990
KOREA	1987		

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Table 1: List of towers that were expected to break the US or world record at the time when construction began

Data from Emporis. The measure of height used is the elevation from the building's base to its highest architectural element.

Name	Height	Start	Finished
US buildings			
Philadelphia City Hall	167.03	1871	1901
Singer Building	186.57	1906	1908
Metropolitan Life Tower	213.36	1907	1909
Woolworth Building	241.4	1910	1913
Church Missionary Building	243.84	1926	
Chrysler Building	318.92	1928	1930
Empire State Building	381	1930	1931
One World Trade Center	417	1966	1972
Willis Tower (Sears Tower)	442.14	1970	1974
One World Trade Center	541.33	2006	
Chicago Spire	609.61	2007	
Non-US buildings			
Petronas Tower	451.9	1992	1998
Shanghai World Financial Center	492 (460 planned at start)	1997	2008
Taipei 101	509.2	1999	2004
Burj Khalifa	827.99	2004	2010

Table 2: Explaining returns on the US stock market with information related to the start of large towers

The log excess return on the US stock market from t to t+k is regressed on the log dividend price ratio (dp) and variables containing information about the building starts of large towers in the US. $RecordStart_t$ equals 1 when a record-breaking tower was started to be built in year t. 100_Start_t relates the number of towers larger than 100 meters started in year t to the number of such starts in the 20 years before t. Data from 1871 – 2009 is constructed by Robert Shiller based on the S&P 500 and other series; data from 1926-2009 is for the CRSP value-weighted market portfolio. T-statistics are based on White (1980) for the one-year horizon, and on Hodrick (1992) for horizons larger than one. Stars flag significance at the 1% (***), 5% (**) or 10% (*) levels.

	1-year horizon (k=1)		3-year horizon (k=3)		5-year horizon (k=5)	
	1871-2009	1926-2009	1871-2009	1926-2009	1871-2009	1926-2009
dp	0.030	0.045	0.149	0.253	0.273	0.388
	(0.75)	(0.81)	(1.22)	(1.46)	(1.40)	(1.55)
$RecordStart_t$	-0.095	-0.192	-0.177	-0.514*	-0.282	-0.502**
	(-1.06)	(-1.40)	(-1.09)	(-1.78)	(-1.47)	(-2.23)
$RecordStart_{t-1}$	-0.006	-0.077	-0.305***	-0.658***	-0.294**	-0.526***
	(-0.07)	(-0.71)	(-2.72)	(-3.57)	(-2.14)	(-3.35)
100_Start_t	-0.025	-0.067*	-0.052	-0.108	-0.093	-0.133*
	(-0.80)	(-1.77)	(-1.01)	(-1.49)	(-1.21)	(-1.64)
100_Start_{t-1}	-0.001	0.044	0.001	0.085	0.005	0.069
	(-0.04)	(1.02)	(0.02)	(1.33)	(0.08)	(0.91)
Constant	0.142	0.224	0.619	1.085*	1.097*	1.651*
	(1.09)	(1.18)	(1.59)	(1.83)	(1.75)	(1.95)
Adj. R^2	0.025	0.094	0.146	0.400	0.211	0.398
N	138	82	136	80	134	78

Table 3: Explaining returns on the US stock market with information related to the completion of large towers

The log excess return on the US stock market from t to t+k is regressed on the log dividend price ratio (dp) and variables containing information about the building starts of large towers in the US. $RecordFinish_t$ equals 1 when a record-breaking tower was completed in year t. 100_Finish_t relates the number of towers larger than 100 meters completed in year t to the number of such completions in the 20 years before t. Data from 1871 – 2009 is constructed by Robert Shiller based on the S&P 500 and other series; Data from 1926-2009 is for the CRSP value-weighted market portfolio. T-statistics are based on White (1980) for the one-year horizon, and on Hodrick (1992) for horizons larger than one. Stars flag significance at the 1% (***), 5% (**) or 10% (*) levels.

	1-year horizon (k=1)		3-year horizon (k=3)		5-year horizon (k=5)	
	1871-2009	1926-2009	1871-2009	1926-2009	1871-2009	1926-2009
dp	0.054	0.109**	0.150	0.229	0.270	0.349
	(1.45)	(2.13)	(1.26)	(1.37)	(1.40)	(1.37)
$RecordFinish_t$	-0.123	-0.268	-0.095	-0.161	-0.037	0.054
	(-1.29)	(-1.52)	(-0.65)	(-0.58)	(-0.22)	(0.20)
$RecordFinish_{t-1}$	-0.030	-0.039	0.059	0.200	0.043	0.193
	(-0.33)	(-0.23)	(0.46)	(0.80)	(0.25)	(0.73)
100_Finish_t	-0.026	-0.068	-0.046	-0.107	-0.096	-0.147
	(-0.80)	(-1.59)	(-0.75)	(-1.38)	(-1.02)	(-1.29)
100_Finish_{t-1}	0.003	0.050	-0.036	0.013	-0.045	0.016
	(0.09)	(1.15)	(-0.61)	(0.18)	(-0.53)	(0.14)
constant	0.218*	0.436***	0.593	0.922	1.051*	1.442*
	(1.81)	(2.47)	(1.57)	(1.61)	(1.71)	(1.68)
Adj. R^2	0.032	0.100	0.085	0.183	0.184	0.297
N	138	82	136	80	134	78

Table 4: Parsimonious models for explaining returns on the US stock market

The log excess return on the US stock market from t to t+k is regressed on the log dividend price ratio (dp) and variables containing information about the building starts of large towers in the US. $RecordStart_t$ equals 1 when a record-breaking tower was started to be built in year t. Data from 1871 – 2009 is constructed by Robert Shiller based on the S&P 500 and other series; Data from 1926-2009 is for the CRSP value-weighted market portfolio. T-statistics are based on White (1980) for the one-year horizon, and on Hodrick (1992) for horizons larger than one. Stars flag significance at the 1% (***), 5% (**) or 10% (*) levels. Coefficients of regression constants are not reported.

	1-year horizon (k=1)		3-year horizon (k=3)		5-year horizon (k=5)	
	1871-2009	1926-2009	1871-2009	1926-2009	1871-2009	1926-2009
Panel A: Dividend price ratio as predictor – Dividend Model						
dp	0.050	0.087	0.163	0.265*	0.296	0.418*
	(1.30)	(1.59)	(1.39)	(1.69)	(1.57)	(1.73)
Adj. R^2	0.006	0.022	0.039	0.097	0.086	0.186
N	138	82	136	80	134	78
Panel B: Tower building as predictor – Tower Model						
$RecordStart_t$	-0.125	-0.167	-0.234	-0.438	-0.351	-0.629*
	(-1.43)	(-1.38)	(-1.35)	(-1.63)	(-1.60)	(-1.92)
$RecordStart_{t-1}$	-0.018	-0.080	-0.303***	-0.581***	-0.292*	-0.475**
	(-0.24)	(-0.79)	(-2.66)	(-3.03)	(-1.93)	(-2.14)
Adj. R^2	0.021	0.040	0.087	0.223	0.077	0.174
N	138	83	136	81	134	79
Panel C: Dividend price ratio and tower building as predictors – Dividend+Tower Model						
dp	0.047	0.078	0.183	0.298*	0.329*	0.469*
	(1.24)	(1.56)	(1.57)	(1.89)	(1.75)	(1.94)
$RecordStart_t$	-0.122	-0.215	-0.233	-0.538*	-0.378*	-0.591***
	(-1.39)	(-1.60)	(-1.35)	(-1.78)	(-1.74)	(-2.54)
$RecordStart_{t-1}$	-0.020	-0.076	-0.333***	-0.645***	-0.341**	-0.571***
	(-0.27)	(-0.75)	(-2.91)	(-3.50)	(-2.25)	(-3.49)
Adj. R^2	0.026	0.086	0.140	0.390	0.186	0.374
N	138	82	136	80	134	78

Table 5: Analysis of prediction errors for the three-year horizon

Out-of-sample forecasts of three-year stock returns are generated with (i) a model including only the dividend price ratio (dividend model); (ii) a model including record tower building and lagged record tower building (tower model) and (iii) a model combining the variables from (i) and (ii), denoted as dividend+tower model Constrained forecasts are forced to be non-negative. Stock market data is constructed by Robert Shiller based on the S&P 500 and other series. Statistical significance of mean errors is assessed through a regression of forecast errors on a constant, using Newey and West (1987) standard errors. Statistical significance of the R^2_{os} statistic (out-of-sample R^2 relative to the historical mean) is based on the Clark and West (2007) MSPE-adjusted statistic, again computed with Newey and West (1987) standard errors. RMSE is root mean squared error, MAE mean absolute error. Stars flag significance at the 1% (***), 5% (**) or 10% (*) levels.

	Hist. mean	Dividend model		Tower model		Dividend+Tower model	
		unconstr.	constrained	unconstr.	constrained	unconstr.	constrained
Panel A: 1915-2009							
Mean	0.059	0.110**	0.108**	0.036	0.035	0.097**	0.087**
st.dev	0.344	0.329	0.328	0.328	0.329	0.311	0.317
R^2_{os}	-	0.008	0.018*	0.106***	0.099***	0.127***	0.111***
RMSE	0.347	0.345	0.344	0.328	0.329	0.324	0.327
MAE	0.263	0.271	0.270	0.243	0.245	0.252	0.253
Panel B: 1915-1945							
Mean	0.086	0.076	0.076	0.066	0.066	0.062	0.062
st.dev	0.433	0.421	0.421	0.422	0.422	0.407	0.407
R^2_{os}	-	0.062***	0.062***	0.066**	0.066**	0.132***	0.132***
RMSE	0.435	0.421	0.421	0.420	0.420	0.405	0.405
MAE	0.325	0.312	0.311	0.321	0.321	0.305	0.305
Panel C: 1945-2009							
Mean	0.045	0.126***	0.123***	0.020	0.017	0.114***	0.099**
st.dev	0.285	0.268	0.266	0.265	0.267	0.245	0.257
R^2_{os}	-	-0.054	-0.034	0.151***	0.138***	0.122**	0.089*
RMSE	0.286	0.294	0.291	0.264	0.266	0.268	0.273
MAE	0.227	0.245	0.243	0.200	0.202	0.219	0.222

Table 6: Performance of investment strategies

The table presents Sharpe ratios of annual simple returns on (i) the US stock market, (ii) a trading strategy that invests 100% in the stock market as long as no record-breaking tower was started to be built in years t-4 to t; and 100% in short-term bonds else, (iii) a mean-variance optimized strategy which uses the prevailing historical mean to estimate the expected stock market return.. The p-values are for the null hypothesis that the returns of a strategy have the same Sharpe ratio as the return on the market, based on the Jobson and Korkie test corrected by Memmel (2003). Δ return, if added to the market return, would equate the market Sharpe ratio with the strategy Sharpe ratio.

	Sharpe Ratio (SR)	p-value (SR = SR of market)	Δ return
Panel A: 1915-2009			
Market index	0.354	-	-
Tower-based strategy	0.474	0.025	0.023
Optimized with historical mean	0.393	0.424	0.008
Panel B: 1915-1945			
Market index	0.279	-	-
Tower-based strategy	0.349	0.366	0.017
Optimized with historical mean	0.287	0.319	0.002
Panel C: 1945-2009			
Market index	0.434	-	-
Tower-based strategy	0.568	0.035	0.023
Optimized with historical mean	0.455	0.736	0.003

Table 7: Determinants of tower building

The table shows whether loan growth, credit spreads and the equity share in new issues explain the building starts of large towers in the US. $RecordStart_t$ equals 1 when a record-breaking tower was started to be built in year t. 100_Start_t relates the number of towers larger than 100 meters started in year t to the number of such starts in the 20 years before t. T-statistics in parentheses. For the linear regression, they are based on Newey and West (1987) with a lag length of three. Stars flag significance at the 1% (***), 5% (**) or 10% (*) levels.

	Logit analysis Depvar: $RecordStart_t$			Linear regression analysis Depvar: 100_Start_t	
Real estate loan growth (real, t-1)	1.49	2.23	-10.73	5.909***	5.930**
	(0.21)	(0.26)	(-0.49)	(2.45)	(2.02)
Baa-Aaa spread (t-1)	-88.62	-111.99	-235.07	-30.552**	-34.041*
	(-1.03)	(-0.95)	(-0.88)	(-2.00)	(-1.93)
Equity share in new issues (t-1)		4.90	0.27		2.207*
		(1.52)	(0.07)		(1.74)
100_Start_{t-1}			4.66***		
			(2.37)		
constant	-3.10	-4.86	6.57	-5.833**	-6.313**
	(-0.40)	(-0.50)	(0.27)	(-2.23)	(-1.97)
p(regression)	0.404	0.294	0.000***	0.000***	0.003***
Pseudo R^2	0.037	0.087	0.468		
Adj. R^2				0.211	0.260
N	90	82	82	90	82

Table 8: Out-of-sample R²s from sensitivity analyses

In the base case, out-of-sample forecasts of three-year stock returns are generated as in Table 5. Constrained forecasts are forced to be non-negative. This table presents out-of-sample R^2 statistics (R^2_{os}) relative to the historical mean for several variations. Combination forecast are obtained as in Rapach, Strauss and Zhou (RSZ) (2010) and their performance is evaluated directly without using them as a predictor in a regression. Statistical significance of the R^2_{os} statistic is based on the Clark and West (2007) MSPE-adjusted statistic, computed with Newey and West (1987) standard errors. Stars flag significance at the 1% (***), 5% (**) or 10% (*) levels.

Variation relative to base case	Evaluation period	Non-tower predictor only		Tower predictors only		Tower + other predictors	
		unconstr.	constrained	unconstr.	constrained	unconstr.	constrained
Base case – for comparative purposes							
-	1915-2009	0.008	0.018*	0.106***	0.099***	0.127***	0.111***
	1915-1945	0.062***	0.062***	0.066**	0.066**	0.132***	0.132***
	1945-2009	-0.054	-0.034	0.151***	0.138***	0.122**	0.089*
Variations of non-tower predictors							
PE ratio instead of dp ratio	1915-2009	0.086**	0.092***	0.106***	0.099***	0.160***	0.136***
	1915-1945	0.191***	0.183***	0.066**	0.066**	0.211***	0.193***
	1945-2009	-0.035*	-0.010*	0.151***	0.138***	0.104**	0.071**
Dividend yield instead of dp ratio	1915-2009	-0.013	0.007	0.106***	0.099***	0.100**	0.083**
	1915-1945	0.044	0.045	0.066**	0.066**	0.096**	0.092**
	1945-2009	-0.078	-0.035	0.151***	0.138***	0.105**	0.074*
Combination forecast as in RSZ	1915-2009	0.011	0.011				
	1915-1945	-0.122	-0.122				
	1945-2009	0.066**	0.066**				
Variations of tower predictors							
Public buildings ignored	1915-2009	0.008	0.018*	0.110***	0.109***	0.146***	0.133***
	1915-1945	0.062***	0.062***	0.080**	0.080**	0.149***	0.149***
	1945-2009	-0.054	-0.034	0.145***	0.142***	0.144**	0.116*
Only lagged tower building dummy	1915-2009	0.008	0.018*	0.072***	0.064***	0.090**	0.082**
	1915-1945	0.062***	0.062***	0.050**	0.050**	0.119***	0.119***
	1945-2009	-0.054	-0.034	0.098**	0.081**	0.058*	0.040
Variatons of return definitions							
Shiller data until 1926, then CRSP	1915-2009	-0.012	-0.004	0.113***	0.107***	0.113***	0.102**
	1915-1945	0.049**	0.057**	0.069***	0.069***	0.126***	0.128***
	1945-2009	-0.097	-0.088	0.172***	0.159***	0.097*	0.069*
Discrete returns instead of log returns	1915-2009	0.011	0.014	0.085***	0.085***	0.106**	0.097**
	1915-1945	0.065***	0.065***	0.055**	0.055**	0.121***	0.121***
	1945-2009	-0.043	-0.036	0.114***	0.114***	0.093*	0.075*

Table 9: Explaining international stock market returns with information related to the start of large towers

The log excess return of country i from t to t+k is regressed on the country's beta estimated with 52 weekly returns, the log dividend price ratio (dp), size as measured by the relative market capitalization, the stock market performance in year t, and variables containing information about the building starts of large towers. $RecordStart_{it}$ equals 1 when a tower breaking the record of country *i* was started to be built in year t. 100_Start_{it} relates the number of towers larger than 100 meters started in country *i* in year *t* to the number of such starts in the 20 years before t. Data is obtained from Datastream and Emporis. Regressions are estimated with the procedure of Fama and MacBeth (1973), using Newey-and-West t-statistics to determine standard errors (lag length k-1). Simulated t-statistics are 2.5% critical values from a simulation experiment in which values for the tower-building related variables are randomly reshuffled across countries.

	1-year horizon(k=1)	3-year horizon(k=3)	5-year horizon(k=5)
Beta	-0.055	-0.002	0.138
	(-1.54)	(-0.04)	(1.38)
DP	0.078	0.168	0.213
	(2.80)	(3.33)	(3.12)
Size	-0.007	-0.042	-0.051
	(-0.85)	(-2.69)	(-2.61)
Prior 1-year return	-0.005	-0.176	-0.399
	(-0.09)	(-2.27)	(-4.66)
$RecordStart_t$	-0.034	-0.050	-0.070
	(-0.73)	(-0.83)	(-1.51)
simulated t-statistic	*-1.94*	*-2.07*	*-2.39*
$RecordStart_{t-1}$	0.028	-0.068	-0.194
	(0.57)	(-0.99)	(-2.82)
simulated t-statistic	*-2.01*	*-2.09*	*-2.35*
100_Start_t	-0.016	-0.081	-0.080
	(-0.47)	(-0.97)	(-0.85)
simulated t-statistic	*-1.86*	*-1.93*	*-2.22*
100_Start_{t-1}	0.049	-0.055	0.013
	(1.32)	(-0.85)	(0.20)
simulated t-statistic	*-1.91*	*-1.84*	*-2.10*
constant	-0.005	-0.161	-0.202
	(-0.09)	(-1.21)	(-1.05)
Average adj. R^2	0.136	0.164	0.154
N	952	878	804

Figure 1: US building activity in towers above a height of 100 meters.

The start of tower above 100 meters is measured by the variable $100Start_{t,}$ defined through.

$$\ln\left(\frac{1+\text{Number of } US \text{ towers taller than 100 meters } \textit{begun} \text{ in year t}}{1+\text{Average } n\text{umber of } US \text{ towers taller than 100 meters } \textit{begun} \text{ in t - 1, t - 20}}\right)$$

The variable $100Finish_{t,}$ is defined analogously for buildings finished in *t*.

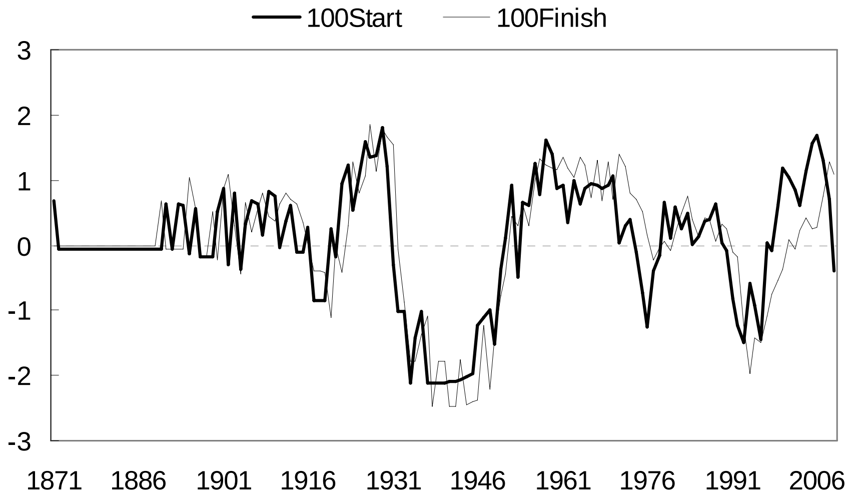

Figure 2: Recursive coefficient updates

The figure shows the coefficients estimates from the recursive regression

$$r_{t,t+3} = b_0 + b_1 \mathrm{dp}_t + b_2 \mathrm{RecordStart}_t + b_3 \mathrm{RecordStart}_{t-1} + u_{t,t+3}, \quad t = 1,\ldots,\tau - 3$$

where $r_{t,t+3}$ is the log excess return on the US stock market from year t to t+3.; dp is the log dividend price ratio;. $\mathrm{RecordStart}_t$ equals 1 when a record-breaking tower was started in year t. Data from 1871 – 2009 is constructed by Robert Shiller based on the S&P 500 and other series

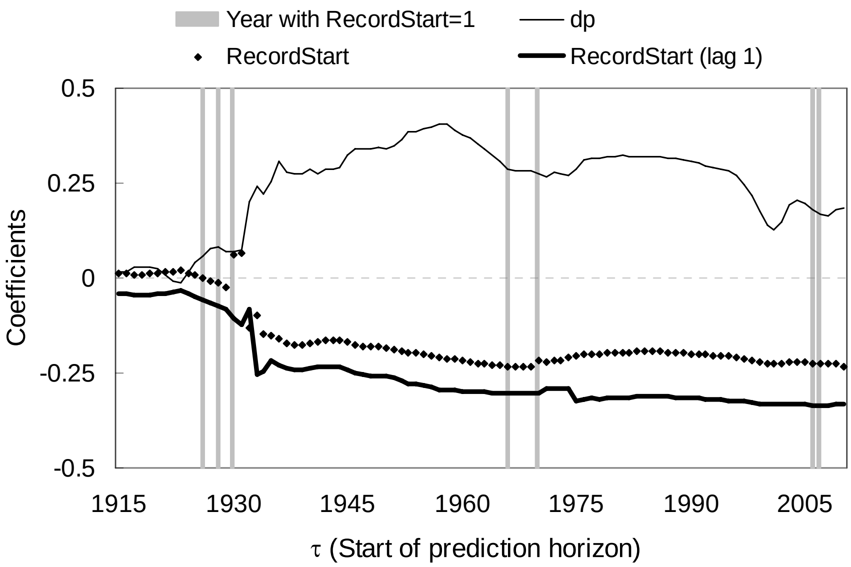

Figure 3: Cumulative out-of-sample performance relative to the prevailing mean

Based on one of the following regressions:

Dividend model: $r_{t,t+k} = b_0 + b_1 dy_t + u_{t,t+k}$

Tower model: $r_{t,t+k} = b_0 + b_1 RecordStart_t + b_2 RecordStart_{t-1} + u_{t,t+k}$

Dividend + tower model: $r_{t,t+k} = b_0 + b_1 dy_t + b_2 RecordStart_t + b_3 RecordStart_{t-1} + u_{t,t+k}$

Recursive out-of-sample predictions for the stock market return over the next three years (k=3) are made with information available at time t. Variables are defined as in Figure 2. The predictions are denoted by $\hat{r}_{t,t+k}$. The figure plots the relative sum of squared predictions errors

$$\text{Cumulative relative SSE} = \sum_{\tau=t(1915)}^{T} \left(r_{t,t+k} - \bar{r}_{t,t+k} \right)^2 - \sum_{\tau=t(1915)}^{T} \left(r_{t,t+k} - \hat{r}_{t,t+k} \right)^2$$

where the test starts in t= 1925 or 1945, and the prevailing historical three-year mean return over years 1871 to t is denoted by $\bar{r}_{t,t+k}$. A positive cumulative relative SSE shows that the regression model performed better than the historical mean.