On REIT returns and (un-)expected inflation: Empirical evidence based on Bayesian additive regression trees

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Abstract

We use Bayesian Additive Regression Trees (BART) to study the comovement of REIT returns with expected and unexpected inflation. Our findings show that the two inflation components are not among the leading predictors of REIT returns in terms of their relative importance, but also that the marginal effects of the two inflation components for REIT returns changed over time. REIT returns exhibit an asymmetric response to unexpected inflation, a phenomenon mainly concentrated in the Greenspan era.

1. Introduction

Building on the pioneering research by Fama and Schwert (1977), much research has been done to recover how returns on real-estate investments in general and REIT returns in particular are linked to (un-)expected inflation (Gyourko and Linneman, 1988; Park et al., 1990; Yobbaccio et al., 1995), among others). Some researchers find that REIT returns exhibit a positive comovement with expected inflation. Other researchers report that REIT returns do not comove or even are negatively linked to (un-)expected inflation.[1] Our contribution to this large body of research is that we use Bayesian Additive Regression Trees (Chipman et al., 1998; 2010) to reexamine the REIT returns-inflation nexus.

BART modeling is a natural candidate for studying how REIT returns comove with inflation because it has two advantages in comparison to other modeling techniques studied in earlier research.[2] First, BART modeling allows even complex nonlinearities in the links between REIT returns and inflation to be modeled. Modeling nonlinearities is important given that evidence has mounted that REIT returns are linked to macroeconomic variables in a nonlinear way (Chang, 2011; Chang et al., 2011; Chang, 2017). Second, BART modeling informs about the importance of (un-)expected inflation for REIT returns relative to other macroeconomic variables. Controlling for the impact of other macroeconomic variables is important because researchers have extensively studied the links between REIT returns and various macroeconomic variables (Ewing and Payne, 2005; Chang et al., 2011).

We study U.S. monthly data covering the sample period 1979 - 2016 and, like Park et al. (1990) and Yobbaccio et al. (1995), we use survey data to decompose inflation into an expected and unexpected component. Our findings show that expected and unexpected inflation are not among the leading determinants of REIT returns in terms of their relative importance. While expected inflation hardly affects REIT returns, marginal effects show that REIT returns significantly increase when unexpected inflation is positive. In contrast, REIT

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[1] The list of hypotheses to explain the comovement between asset returns and inflation includes the inflation-illusion hypothesis (Modigliani and Cohn, 1979) and the proxy hypothesis (Fama, 1981). See Hong and Lee (2013) for a useful review of the literature.

[2] For recent applications of BART modeling in economics, see Pierdzioch et al. (2016) and Gupta et al. (2016).

returns are insensitive to negative unexpected inflation, revealing an asymmetry in the link between REIT returns and unexpected inflation (Simpson et al., 2007). The asymmetric link between REIT returns and unexpected inflation is mainly concentrated during the period of time when Alan Greenspan served as Chairman of the Federal Reserve. The changing sensitivity of REIT returns with respect to unexpected inflation mirrors results in other recent contributions to the REIT literature demonstrating the importance of monetary policy for REIT returns (e.g., Chang et al., 2011). We further document the impact of the financial crisis of 2008/2009.

2. Bayesian additive regression trees

Bayesian regression trees are defined as a sum-of-tree ensemble that uses binary hierarchical recursive splits to partition the space of predictors into a set of rectangles. A single regression tree, T, consists of a root, interior nodes, and terminal nodes. Interior nodes are characterized by a decision rule taking the form $x_j < c$, where x_j is the splitting variable and c is the splitting value. Terminal nodes are synonymous with the leaves of a tree. Every leaf, i, is then dedicated to a real-valued parameter $\mu_i \in M = \{\mu_i, \ldots, \mu_b\}$ with b being the total number of leaves. After running through all decision rules, every x_j of the predictor space is assigned to a leave parameter μ_i. For a single tree, the model can be expressed as

$$y_t = f(x|T, M) + \epsilon_t, \qquad \epsilon \sim N(0, \sigma^2), \tag{1}$$

where y_t is the response variable, ϵ is a normally distributed disturbance term, and f equals the function that links x_j with μ_i.

Using a sum of trees rather than a single tree increases model flexibility and is expected to generally increase model performance because a single tree model may end up in too many leaves once the data structure is getting too complex. BART combines an ensemble of trees in an additive way:

$$y_t = \sum_{j=1}^{m} f(x|T_j, M_j) + \epsilon_t, \qquad \epsilon \sim N(0, \sigma^2). \tag{2}$$

The superscript j now denotes the leaf parameters of the jth regression tree that links the leave parameters to the predictor space.

To prevent large influences of a single trees, prior knowledge on the tree structure itself, the leaf parameters, and the residual error variance has to be specified to maintain regularization. The prior is of the form

$$p(\{T_j, M_j\}, \sigma^2|x) = p(\sigma^2) \prod_{j=1}^{m} p(\mu_{ij}|T_j) p(T_j|x), \tag{3}$$

which controls for the location of the interior nodes in a tree, and the residual variance σ^2. Upon letting $\alpha \in (0, 1)$ and $\beta \in [0, \infty)$, the absolute size of interior nodes (i.e., the depth of the tree, d) is controlled by $\alpha(1 + d)^{-\beta}$. A larger α leads to a deeper structure of the single tree, while a larger β reduces the number of interior nodes and makes the tree more shallow. We follow Chipman et al. (2010) and set α (β) to 0.95 (2).[3]

In order to sample from the posterior distribution, we assume μ_j to be normally and identically distributed with $\mu \sim N(\mu_\mu/m, \sigma_\mu^2)$, where μ_μ is the mean of y_{max} and y_{min} and σ^2 follow an Inverse Gamma (IG) distribution with $\sigma^2 \sim IG(\nu/2, \nu\lambda/2)$. The parameter λ is determined to achieve a q-percentage chance to reduce the root mean squared error. The IG distribution prevents σ^2 from becoming too small and reduces the probability of overfitting. σ_μ^2 is then chosen such that $y_{min} = m\mu_\mu - k\sqrt{m}\sigma_\mu$ and $y_{max} = m\mu_\mu + k\sqrt{m}\sigma_\mu$. The tightness of the prior is controlled by k, where a larger k leads to a stronger regularization of μ_μ.[4]

After setting up the priors, Chipman et al. (2010) recommend an iterative Bayesian MCMC backfitting algorithm[5] to sample from the posterior distribution

$$p(\{T_j, \mu_j\}_{j=1}^m, \sigma^2|y, x) \propto \ell(y|\{T_j, \mu_j\}_{j=1}^m, \sigma^2, x) p(\{T_j, \mu_j\}_{j=1}^m, \sigma^2|x), \tag{4}$$

where ℓ denotes the likelihood for the entire training data, with

$$\ell(y|(\{T_j, \mu_j\}_{j=1}^m, \sigma^2, x) = \prod_n \ell(y_n|\{T_j, \mu_j\}_{j=1}^m, \sigma^2, x_n). \tag{5}$$

3. Empirical analysis

We study monthly data from January 1979 to March 2016. We consider monthly index returns on the following three REIT indexes: the FTSE NAREIT All, Equity REITs index (an equity index), the FTSE NAREIT Mortgage REITs Index (a mortgage index), and the FTSE NAREIT Composite REIT Index (a composite index).[6] Earlier researchers have analyzed the sensitivities of REIT returns to a

[3] In this case, a regression tree with 2 or 3 interior nodes reaches the highest likelihood.

[4] As in Gupta et al. (2016), we choose $k = 5$, $q = 0.75$, and $\nu = 10$, which equals a conservative setup (see Chipman et al., 2010. The number of trees, m, is set to 50. We use the R programming environemnt (R Core Team 2017) and the add-on package "bartmachine" (Kapelner and Bleich, 2016) to compute our results.

[5] For details, see Kapelner and Bleich (2016). We use 7000 simulation runs and discard the first 2000 as burn-in runs.

[6] Datasource: https://www.reit.com/investing/index-data/monthly-index-values-returns. Results for the FTSE NAREIT All REITs Index are similar to the results for the FTSE NAREIT Composite REIT Index, and results for the FTSE NAREIT Equity Index resemble those for the FTSE NAREIT All Equity REITs Index. Results for these two other indexes are not reported, but are available from the authors upon request.

Table 1
The data.

Predictors	Explanations	Source
Dividend yield	Dividend yield of the REIT index	www.reit.com
Commodity Index	Month-on-month rate of change of the log GSCI commodity index (spot)	DATASTREAM
Industrial Production	Year-on-year rate of change of the log industrial production index	FRED
House-price growth	Year-on-year rate of change of Robert Shiller's log House-price index	SHILLER
Stock Market	Month-on-month rate of change of the log S&P500 Composite index	SHILLER
Exchange Rate	Year-on-year rate of change of the BIS log trade weighted exchange rate (broad)	FRED
CB spread	BAA corporate bond yield minus AAA corporate bond yield	FRED
Term spread	Three-month treasury bill minus ten-year treasury bond	FRED
Expected inflation	Expected inflation rate for period t, measured in $t-12$	FRED
Unexpected inflation	Actual inflation in t minus expected inflation for t	–

Notes: FRED - Federal Reserve Bank of St. Louis, https://fred.stlouisfed.org/ ; SHILLER - http://www.econ.yale.edu/~shiller/

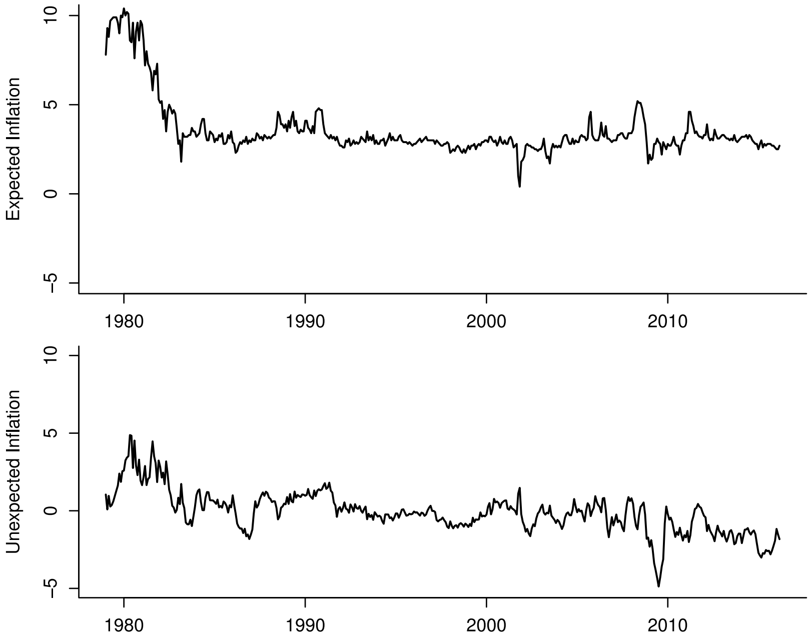

Fig. 1. Components of inflation.

large number of macroeconomic variables (Allen et al., 2000; Clayton and Mac Kinnon, 2003, Ewing and Payne, 2005, Bredin et al., 2007; Glascock et al., 2002; Simpson et al., 2007 for a study of spillover effects, see Damian and Elsayed, 2018). Accordingly, we consider various macroeconomic variables as predictors of REIT returns (Table 1). We measure the expected rate of inflation as the median expected price change for the next 12 months published by the Surveys of Consumers, University of Michigan. We extract the unexpected component of the inflation rate by subtracting the expected inflation rate as of period $t-12$ from the actual inflation rate in period t. Fig. 1 shows both components.

The results that we summarize in Table 2 demonstrate that the BART model is superior to a standard linear model. The standard linear model included all predictors and is estimated by the ordinary-least-squares technique. While the result of an F-test show that the predictors are jointly significant in the linear model for all three of categories of REIT returns, the results of a RESET test for nonlinearity clearly indicate a misspecification of two out of the three linear models. A BART-based linearity test confirms the results of the RESET test. We implement the BART-based linearity test by estimating a BART model on the residuals of the linear model. We then use permutation tests to assess the explanatory power of the BART model. The null hypothesis is that the BART model does not have explanatory power for the residuals of the linear model. The results of the permutation tests clearly show that we can reject the null hypothesis for two REIT indexes. Fig. 2illustrates the convergence properties of the BART model.[7] The top-left subplot shows the dynamics of the error variance, the top-right subplot shows the acceptance rate given prior information, the lower-left subplot shows the number of leaves, and the lower-right subplot shows tree depth. The two upper subplots further show results for the burn-in period. The message to take home from Fig. 2 is that the BART model produces a stable evolution of the three parameters and the

[7] Convergence results for the Mortgage REIT and the Composite REIT index are similar and are not reported (but available from the authors upon request).

Table 2
Specification tests for a linear model.

Dependent variable	F-test	R^2_{OLS}	RESET	BART-LT	R^2_{BART}
All Equity REIT	0.0000	0.2953	0.0000	0.0014	0.1989
Mortgage REIT	0.0000	0.1692	0.5875	0.2196	0.1536
Composite REIT	0.0000	0.3023	0.0000	0.0579	0.1800

Notes: This table reports diagnostic tests for a standard linear model estimated by the ordinary-least-squares technique. The linear model includes all predictors. The column entitled *F*-test reports the *p*-value of an F-test for the joint significance of the predictors. The column entitled R^2_{OLS} reports the unadjusted coefficient of determination for the linear model. The column entitled RESET reports the p-value of a RESET test that uses the second and third powers of the fitted values of the linear model. The column entitled BART-LT reports the p-value of a BART-based linearity test. This test is implemented by estimating a BART model on the residuals of the linear model and then using a permutation test (500 simulation runs) to assess the explanatory power of the BART model. The column entitled R^2_{BART} reports the explanatory power of the BART model for the residuals of the linear model.

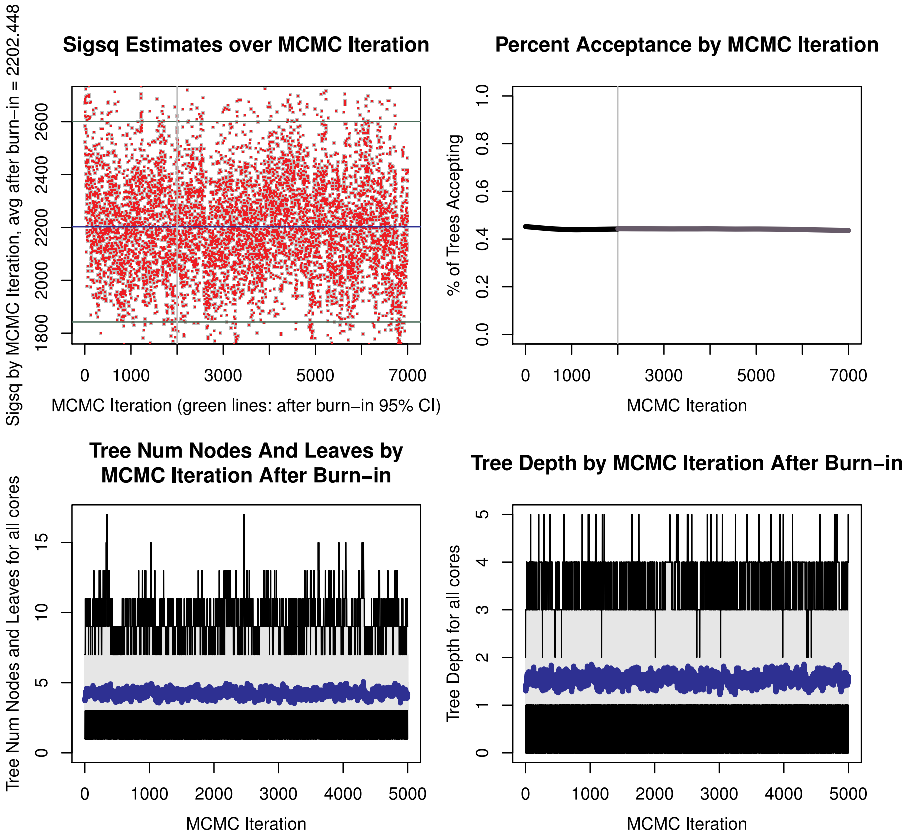

Fig. 2. Convergence statistics (All Equity REIT). Upper-left subplot: Sigsq denotes the error variance, σ^2. Burn-in results are shown in the region on the left-hand side of the vertical line. Upper-right subplot: Acceptance (in %) of the proposals across the *m* trees. Burn-in results are shown in the region on the left-hand side of the left vertical line. Lower-left subplot: Mean after-burn-in number of leaves across the *m* trees. Lower-right subplot: Mean after-burn-in tree depth across the *m* trees.

acceptance rate across iterations. The relatively small size of individual trees (lower plots) is a result of our choice of hyperparameters.

Fig. 3 shows the relative importance (in percent) of the predictors for REIT returns. Relative importance of a predictor informs about its average use as a splitting variable defined as the mean of the average use calculated across all posterior samples (Chipman et al., 2010, Kapelner and Bleich, 2016). For the returns on the equity and composite indexes, the returns on the S&P500 index clearly are the most important predictor. For the mortgage index, the S&P500 index is also the leading predictor, but to a lesser extent than for the other two REIT indexes. Expected and unexpected inflation are not among the leading predictors, with both having a relative importance below 10% for all three indexes.

Table 3 summarize the results of permutation tests (full sample period). The null hypothesis is that the predictors have no ex-planatory power for REIT returns. A joint permutation test for all predictors yields highly significant results. Individual permutation tests show that lagged REIT returns are a significant predictor in cases of the equity and the composite indexes. The

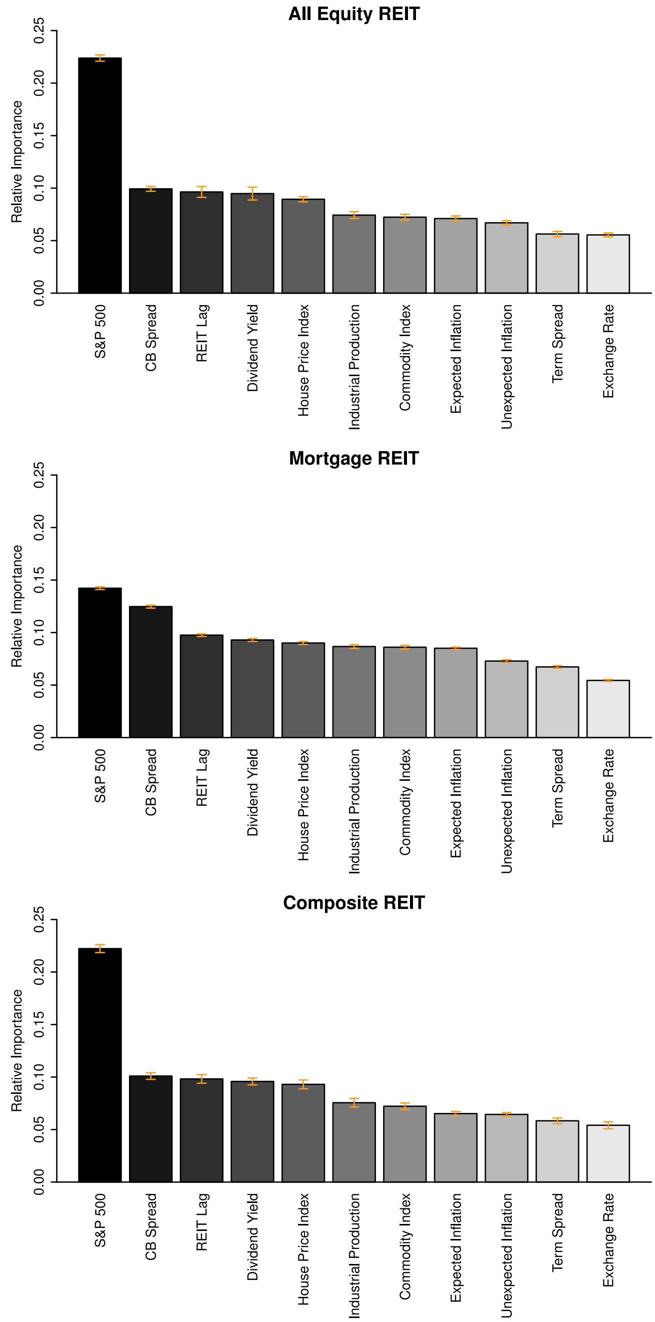

Fig. 3. Relative importance of predictors.

returns on the S&P500 index have predictive power for the returns of all three REIT indexes. The dividend yield has predictive power mainly in case of the mortgage index. Unexpected inflation is weakly significant only in case of the mortgage index. The Pseudo-R^2 shows that the overall fit of the fitted BART model is better for the equity and composite indexes than for the mortgage index.

Table 4 summarizes results of additional permutation tests for expected/unexpected inflation, where we use an AR(12) model rather than survey data to decompose the inflation rate into its expected/unexpected components. Results are similar to those reported in Table 3.

Table 5 summarizes results of permutation tests for the Volcker (1979/09–1987/08), Greenspan (1987/09–2006/01), and Ber-nanke (2006/02–2014/01) eras. The test results for expected inflation are insignificant in all three subsample periods. While the test results for unexpected inflation are significant at the 10% level for the mortgage index during all three subsample periods, the test results are strongest for the Greenspan era. The joint permutation tests for all predictors are highly significant for all three subsample periods.

Table 3
Significance of predictors and model fit (*p*-values).

Regressor	All equity REIT	Mortgage REIT	Composite REIT
Lagged REIT	0.0204	0.8898	0.0076
House-price index	0.0870	0.2659	0.1118
S&P-500 index	0.0000	0.0004	0.0000
Industrial production	0.5206	0.5752	0.5293
Exchange rate	0.5150	0.1070	0.6603
Commodity index	0.2762	0.6263	0.4124
Dividend yield	0.1082	0.0000	0.0834
CB spread	0.3529	0.1054	0.3749
Term spread	0.6100	0.0587	0.6890
Expected inflation	0.5497	0.8128	0.6467
Unexpected inflation	0.3489	0.0842	0.4571
Expected + Unexpected Inflation	0.5086	0.1309	0.3864
Overall significance	0.0000	0.0000	0.0000
Pseudo-R^2	0.5202	0.2815	0.5201

Notes: For the BART algorithm, *p*-values are computed by averaging over the results from permuting the data five times using different seeds 500 times. Overall significance summarizes the result of a joint permutation test for all predictors. The pseudo-R^2 is computed as $1-\sum_{t=1}^{T}(y_t-\hat{y}_t)^2/\sum_{t=1}^{T}(y_t-\bar{y}_t)^2$, where $\hat{y}_t$ is the predicted response and $\bar{y}_t$ the historical mean.

Table 4
Results based on an alternative inflation model.

Period	Expected	Unexpected	Both	All	Pseudo-R^2
All Equity REIT	0.3210	0.4555	0.3353	0.0000	0.5333
Mortgage REIT	0.1756	0.0902	0.0559	0.0000	0.2914
Composite REIT	0.3796	0.4583	0.3453	0.0000	0.5275

Notes: For the BART algorithm, *p*-values are computed by averaging over the results from permuting the data five times using different seeds 500 times. The pseudo-R^2 is computed as $1-\sum_{t=1}^{T}(y_t-\hat{y}_t)^2/\sum_{t=1}^{T}(y_t-\bar{y}_t)^2$, where $\hat{y}_t$ is the predicted response and $\bar{y}_t$ the historical mean. The BART models used to set up the permutation tests for expected/unexpected inflation also include all other (not permuted) predictors. The column entitled "All" summarizes the result of permutation tests for all predictors. An AR(12) model is used to decompose inflation into its expected/unexpected components.

Table 5
Expected vs. unexpected inflation rate.

Period	Expected	Unexpected	Both	All	Pseudo-R^2
			All Equity REIT		
Volcker	0.5457	0.3733	0.4559	0.0000	0.5216
Greenspan	0.5792	0.4116	0.5086	0.0000	0.5202
Bernanke	0.7018	0.5078	0.5681	0.0000	0.5175
			Mortgage REIT		
Volcker	0.7110	0.0527	0.1637	0.0000	0.2802
Greenspan	0.5848	0.0395	0.1309	0.0000	0.2815
Bernanke	0.7872	0.0651	0.1772	0.0000	0.2794
			Composite REIT		
Volcker	0.5780	0.4200	0.4531	0.0000	0.5177
Greenspan	0.4914	0.3421	0.3864	0.0000	0.5201
Bernanke	0.7409	0.5613	0.5916	0.0000	0.5135

Notes: For the BART algorithm, *p*-values are computed by averaging over the results from permuting the data five times using different seeds 500 times. The pseudo-R^2 is computed as $1-\sum_{t=1}^{T}(y_t-\hat{y}_t)^2/\sum_{t=1}^{T}(y_t-\bar{y}_t)^2$, where $\hat{y}_t$ is the predicted response and $\bar{y}_t$ the historical mean. The BART models used to set up the permutation tests for expected/unexpected inflation also include all other (not permuted) predictors. The column entitled "All" summarizes the result of permutation tests for all predictors.

Fig. 4 plots the marginal effect of (un-)expected inflation on REIT returns holding all other predictors fixed (the gray areas are the posterior 90% and 95% confidence intervals). We report marginal effects for the full sample period and for the Volcker, Greenspan, and Bernanke eras. As for the full sample period, the marginal effects for expected inflation is more or less a flat function that slightly increases in expected inflation in case of the equity and the composite index. In contrast, REIT returns significantly increase when unexpected inflation is positive. A negative unexpected inflation, in contrast, hardly affects REIT returns. We observe the asymmetric

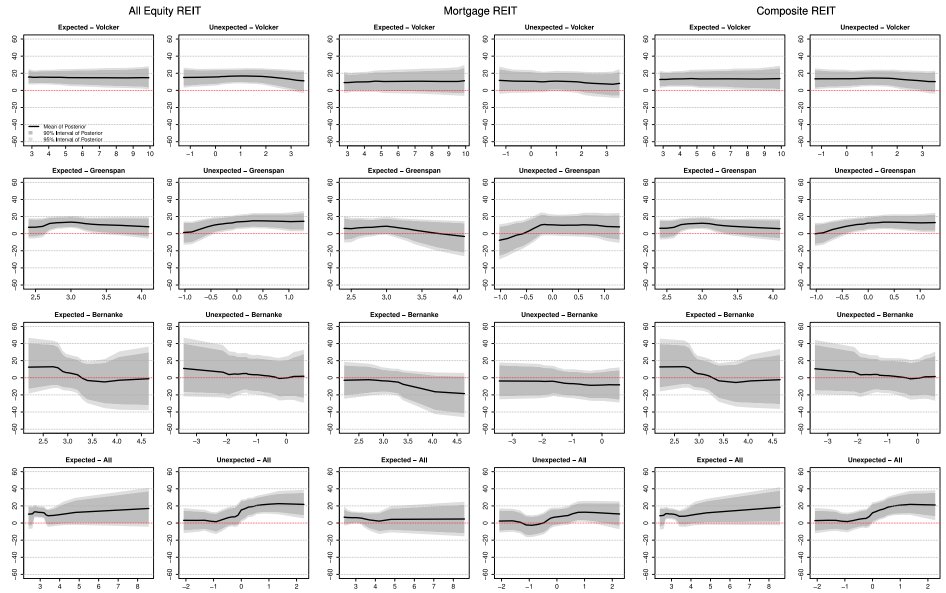

Fig. 4. Marginal effects.

response of REIT returns to unexpected inflation for all three REIT indexes. The strength of the asymmetric response is stronger in terms of significance for the equity and composite indexes than for the mortgage index. Turning to the subsample periods, we observe that the asymmetric response of REIT returns to unexpected inflation mainly was a phenomenon of the Greenspan era, especially for the equity and composite indexes.

Results on the relationship between REITs and both expected and unexpected inflation rates reported in earlier research are in general mixed. In other words, the evidence provided in favor or against whether REITs act as an inflation hedge is ambiguous, with results depending on model specification, variables under consideration, and also sample periods. Our BART-based analysis can be considered as an extension of earlier studies since we consider a more general model which allows for many possible predictors of REIT returns besides expected or unexpected inflation. Hence, our framework is a more robust one, unlike standard bivariate frameworks often used in earlier research to analyze the inflation-hedging properties of REITs, involving inflation rates and REITs returns only. In addition, our approach also controls for nonlinearities and, hence, avoids model misspecification in a linear framework. Given the superiority of our framework, our results are more reliable than those reported in earlier research using linear models and suffering from an omitted variable bias.

In sum, while (un-)expected inflation is not among the top predictors of REIT returns, the marginal effects show that the markets tend to act as an inflation hedge primarily for expected increases of the inflation rate rather than expected ones. To put it differently, the markets tend to price risks associated with expected movements of the inflation rate (so that REIT returns are largely invariant to changes in expected inflation), but REITs can indeed serve as a hedge, albeit an incomplete one, against unexpected inflation risks, especially if the latter are associated with an increase in the inflation rate. This result is in line with those reported by Chang (2017), whose results are based on a bivariate Markov-switching copula model. Hence, by using a modeling framework that avoids the misspecification of linear models, omitted variable bias, and also based on an extended data sample that includes the pre-, during- and post- financial-crisis periods (which, in the first place, originated from the U.S. real estate sector), we conclude that unexpected inflation (especially increases of the same) matter more than expected inflation for predicting REIT returns, where monetary policy evidently matters a lot for the strength of this effect.

The positive relationship between increases in unexpected inflation rates and REIT returns provides support to the Gordon (1962) growth model (and not necessarily the models postulating a negative relationship as in Modigliani and Cohn (1979), Feldstein (1980), and Fama (1981), which shows that asset prices are directly related to current and expected growth rates of dividend returns and inversely related to the required rate of return on the equity. Given this, unexpected inflation has a positive impact on REIT prices through two channels: First, monetary easing that stimulates the economy along with inflation would have a positive impact on the growth rate of dividends. Second, a monetary expansion that depresses bond returns would result in an increased demand for equities, including REITs, which in turn, would cause the average investor to lower expected rate of returns of REITs. Whether it is increased dividend returns or decreased expected returns on investment, both serve to raise REITs prices.

Fig. 5 shows that the wider confidence bands of the marginal effects that we observe for the Bernanke era transmit onto a more dispersed density of expected REIT returns. We compute the density estimates using a scaled Gaussian kernel and quantile predictions of the posterior sampling distribution averaged over all observations for the three different subsample periods. The estimated mean expected returns are larger for the Volcker than for the Greenspan era. For the Bernanke era, mean returns shrink further, and they become even negative in the case of the mortgage index. It is also evident that the estimated standard deviation is larger for the Bernanke era than for the other two subsample periods.

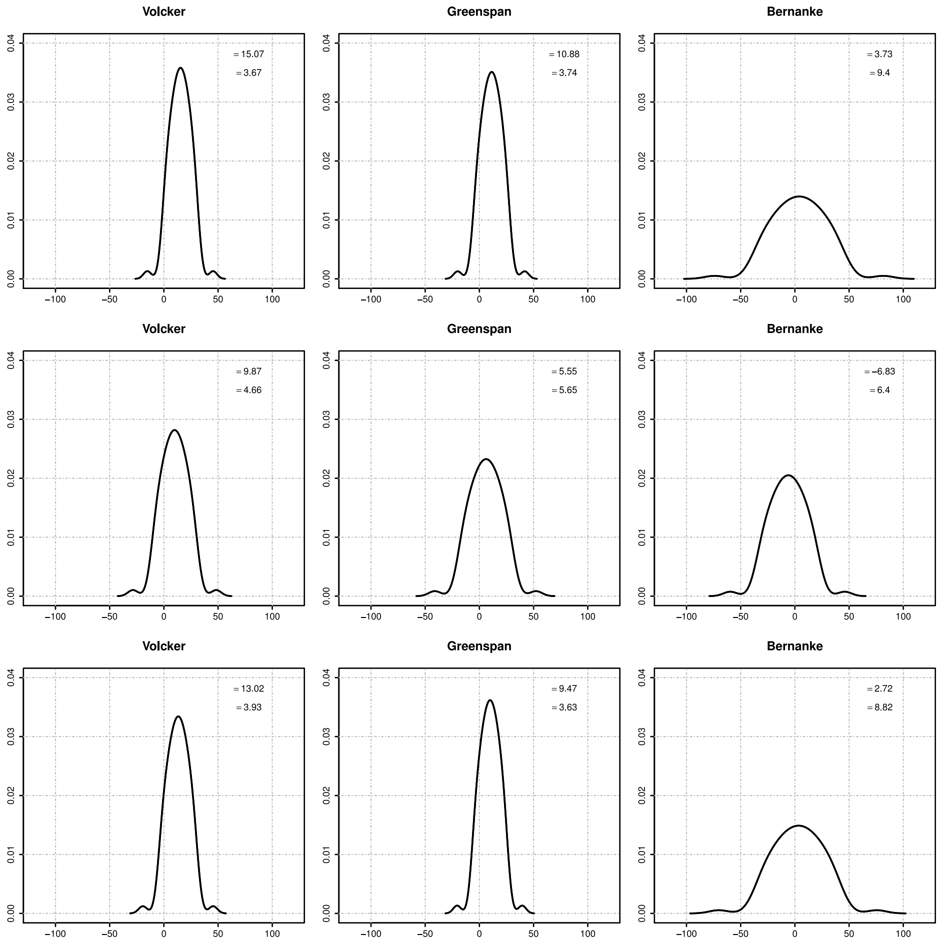

Fig. 5. Time-varying density of expected returns. Note: This figure shows the density plots of expected returns for the All Equity REIT index (top panel), the Mortgage REIT index (middle panel), and the Composite REIT index (lower panel) for the subsample periods when Volcker, Greenspan, and Bernanke served as chairman of the Federal Reserve. Density estimates are computed using a scaled Gaussian kernel and quantile predictions of the posterior sampling distribution averaged over all observations for the three different subsample periods μ: density mean, σ: kernel standard deviation (bandwidth).

Fig. 6 summarizes the effects of the financial crisis. The figure plots the mean width (computed across quantiles) of the confidence bands around the marginal effects of (un-)expected inflation for a BART model that we recursively estimated (beginning in September 1997) for every third month. The width of the confidence bands sharply increases for the equity and the composite indexes in September 2008 when Lehman Brothers collapsed, implying that the link between (un-)expected inflation and REIT returns can be estimated with less precision after the financial crisis than before. The confidence bands estimated for the mortgage index are relatively wide before the financial crisis, implying that the financial crisis had a comparatively small impact. Interestingly, in the case of the mortgage index, the width of the confidence band started increasing gradually several months before Lehman Brothers collapsed.

4. Concluding remarks

Our findings show that (un-)expected inflation is not among the top predictors in terms of relative importance. REIT returns exhibit an asymmetric response in terms of marginal effects to unexpected inflation, but this asymmetry was mainly a phenomenon of the Greenspan era. The asymmetric and time-varying sensitivity of REIT returns with respect to unexpected inflation implies that investors may find it difficult to use REIT investments to protect against inflation risk. Our findings further shed light on the effect of the financial crisis of 2008/2009 on the link between (un-)expected inflation and REIT returns. In future research, it is interesting to trace out in more detail how the financial crisis affected the REIT returns-inflation nexus. Moreover, given that our findings show that monetary policy matters for the comovement of REIT returns with (un-)expected inflation, it is interesting to study more closely the dynamics of REIT returns in an era of very low interest rates.

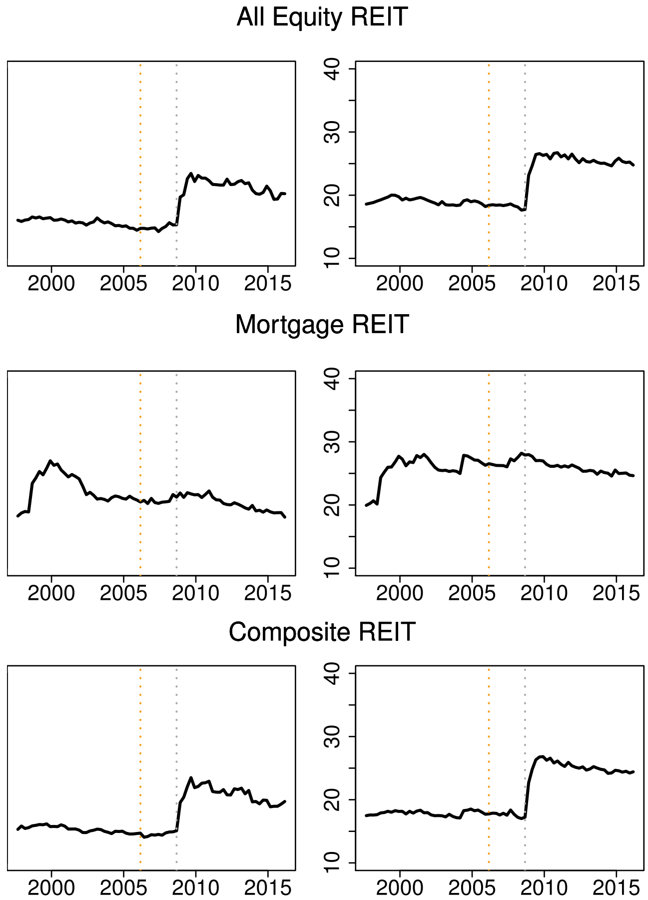

Fig. 6. Stability of confidence bands. Note: This figure shows the mean of the distance between the 0.975 quantile and the 0.025 quantile over time. The red dotted vertical line marks the beginning of Bernanke's first term as chairman of the Federal Reserve. The gray dotted line marks the collapse of Lehman Brothers in September 2008. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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References

Allen, M.T., Madura, J., Springer, T.M., 2000. REIT characteristics and the sensitivity of REIT returns. J. Real Estate Finance Econ. 21, 141–152.
Bredin, D., O'Reilly, G., Stevenson, S., 2007. Monetary shocks and REIT returns. J. Real Estate Finance Econ. 35, 315–331.
Chang, K.L., 2011. The nonlinear effects of expected and unexpected components of monetary policy on the dynamics of REIT returns. Econ. Model. 28, 911–920.
Chang, K.L., 2017. Does REIT index hedge inflation risk? new evidence from the tail quantile dependences of the markov-switching GRG copula. North Am. J. Econ. Finance 39, 56–67.
Chang, K.L., Chen, N.K., Leung, K.Y., 2011. Monetary policy, term structure and asset return: comparing REIT, housing and stock. J. Real Estate Finance Econ. 43, 221–257.
Chipman, H.A., George, E.I., Mc Culloch, R.E., 1998. Bayesian CART model search. J. Am. Stat. Assoc. 93, 935–960.
Chipman, H.A., George, E.I., Mc Culloch, R.E., 2010. BART: Bayesian additive regression trees. Ann. Appl. Stat. 4, 266–298.
Clayton, J., Mac Kinnon, G., 2003. The relative importance of stock, bond and real estate factors in explaining REIT returns. J. Real Estate Finance Econ. 27, 39–60.
Damian, S.D., Elsayed, A.H., 2018. On the transmission of spillover risks between the housing market, the mortgage and equity REITs markets, and the stock market. Finance Res. Lett. Forthcoming
Ewing, B., Payne, J., 2005. The response of real estate investment trust returns to macroeconomic shocks. J. Bus. Res. 58, 293–300.
Fama, E., Schwert, G., 1977. Asset returns and inflation. J. Financ. Econ. 5, 115–146.
Fama, E.F., 1981. Stock returns, real activity, inflation and money. Am. Econ. Rev. 71, 545–565.
Feldstein, M., 1980. Inflation and the stock market. Am. Econ. Rev. 70, 839–847.
Glascock, J.L., Lu, C., So, R., 2002. REIT returns and inflation: Perverse or reverse causality effects? J. Real Estate Finance Econ. 24, 301–317.
Gordon, M.J., 1962. The investment. Financing and Valuation of the Corporation. Homewood, III., R.D. Irwin.
Gupta, R., Pierdzioch, C., Risse, M., 2016. On international uncertainty links: BART-based empirical evidence for canada. Econ. Lett. 143, 24–27.

Gyourko, J., Linneman, P., 1988. Owner-occupied homes, income-producing real property, and REITs as inflation hedges. J. Real Estate Finance Econ. 143, 347–372.
Hong, G., Lee, B.S., 2013. Does inflation illusion explain the relation between REITs and inflation? J. Real Estate Finance Econ. 47, 123–151.
Kapelner, A., Bleich, J., 2016. bartMachine: Machine Learning with Bayesian Additive Regression Trees. Journal of Statistical Software 70, 1–40.
Modigliani, F., Cohn, R., 1979. Inflation, rational valuation, and the market. Financ. Anal. J. 35, 24–44.
Park, J., Mullineaux, D., Chew, I., 1990. Are REITs inflation hedges? J. Real Estate Finance Econ. 3, 91–103.
Pierdzioch, C., Risse, M., Rohloff, S., 2016. Are precious metals a hedge against exchange-rate movements? an empirical exploration using bayesian additive regression trees. North Am. J. Econ. Finance 38, 27–38.
Simpson, M.W., Ramchander, S., Webb, J.R., 2007. The asymmetric response of equity REIT returns to inflation. J. Real Estate Finance Econ. 34, 513–529.
R Core Team, 2017. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org/
Yobbaccio, E., Rubens, J.H., Ketcham, D.C., 1995. The inflation-hedging properties of risk assets: the case of REITs. J. Real Estate Res. 10, 279–298.