Do Stock Prices Move too Much to be Justified by Changes in Cash Flows? New Evidence from Parallel Asset Markets *

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Abstract

We take advantage of two parallel markets for a set of cash flows to show that better measurement of cash flows improves the performance of a dividend discount model. Unlike previous literature, we use out-of-sample estimation. We use a unique data set of commercial real estate and augment REIT dividends with cash flow information from this parallel market. The results improve dramatically when information from direct property cash flows is added. These findings suggest that the performance of dividend pricing models improves greatly with better measurement of cash flows, and thus contribute to the resolution of the excess volatility puzzle.

Keywords: Dividend Pricing Models, Excess Volatility, Cash Flows, Vector Autoregression, Real Estate Investment Trusts. JEL Classifications: G12

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1 Introduction

Understanding the variation of asset returns presents an important challenge to economists. Every model of variation in asset returns tells a story about the exogenous shocks that are ultimately responsible for changes in the prices of risky assets. The characterization of these ultimate sources of variability is of fundamental interest, in order to better understand what drives asset returns.

Economic reasoning tells us that financial assets should be priced by investors according to a Discounted Cash Flow (DCF) or Net Present Value (NPV) methodology, an idea that has been tested in the literature since its early days (for example, Gordon (1959)). This fundamental understanding yields a natural decomposition of asset returns into sources of variation related to the cash flows associated with these assets, and sources of variation related to changes in the discount factor. There exists an important puzzle in this literature, stemming from the result that in this context cash-flow variation does not play an important role in determining the returns of publicly traded equity, in that asset prices are too volatile to be driven by this source of variation (this is known as the *excess volatility puzzle*, first formulated by Shiller (1981) and LeRoy and Porter (1981)). In contrast to these results, studies such as Evans (1998), Goetzmann and Jorion (1993, 1995), or Hall (2001b) find evidence in favor of the importance of cash flow information in the stock price formation process.[1] The consequence of the excess volatility result is that either investors do not use the NPV framework to price these assets, or that the discount factor itself is extremely variable, in order to impart such overall volatility to asset prices. Both implications are economically troubling.

[1]This debate is still very active in the literature today. For example, Hall (2001a), Robertson and Wright (2006), or Larrain and Yogo (2008) also find evidence in favor of the importance of cash flows or generally fundamentals in asset pricing. DeJong and Ripoll (2007) show the difficulty of constructing a set of investor preferences that would yield excess volatility. Cochrane (1992, 2001, 2008), and van Binsbergen and Koijen (2009), among others discusses excess volatility, its causes, and its implications.

Our contribution is to show to what extent the excess volatility puzzle is resolved in a setting where better information on cash flows is available. One of the empirical problems associated with tests of the NPV model for stocks is that it is often difficult to find variables that accurately reflect changes in the two fundamental sources of variability; doing so effectively is necessary to correctly attribute price variability to a respective source. Chen and Zhao (2009), for example, discuss this point in great detail, and Chen (2009) further highlights its importance. Our study focuses on the empirical challenge of appropriately capturing changes in cash flows. While basic economic rationale posits that for equity securities, actual payments to investors (i.e. primarily dividends) should be the relevant metric for the cash flows associated with the security, empirical tests have failed to show that changes in information related to dividends hold the expected level of importance in determining asset returns. We argue that this result could be due to a measurement problem of the cash flow stream associated with securities. This is due to the fact that dividends (and even earnings) are not accurate representations for the stream of cash flows which investors perceive underlies the equity securities in question, because they can be smoothed, managed, or otherwise manipulated by the firm, and firm management has incentive to do this.[2] If it were possible for an econometrician to observe the true (un-smoothed) cash flow information that underlies a security, it would be possible to make better attributions of sources of variation.[3]

We contribute to the literature by exposing the role that the accuracy with which cash flows are measured plays in findings of excess volatility. Specifically, we examine the improvements to the performance of dynamic Net-Present-Value models that can be achieved by using more complete cash-flow information. We are in the unique position to measure

[2]Boudoukh, Michaely, Richardson and Roberts (2007), for example, document this and investigate in detail the implications for asset pricing of this recognition. See also, e.g. Bergstresser, Desai and Rauh (2006), and Ackert and Hunter (1999), who document the management of cash flow measures by firms in great detail.

[3]Robertson and Wright (2006) argue along the same lines. In a related approach, Larrain and Yogo (2008) model overall firm value using total firm payouts, and also find no excess volatility under this approach.

cash flows that enter the firm rather than payouts. Assuming money is not systematically wasted, investors should perceive that their security entitles them to all these cash flows and should therefore price them in.[4] We find that using a more complete cash flow measure, vastly improves the predictive ability of such models. The improved performance of our model comes despite the fact that, unlike previous literature, we conduct all estimation out of sample and thus avoid look-ahead bias.[5]

We are able to construct such cash flow proxies by taking advantage of the unique features of commercial property markets, as a natural laboratory. The market for commercial property cash flows is unique, in that these cash flows are traded independently in two parallel asset markets. One is the direct property market, in which these cash flows are traded privately through purchases and sales of buildings and land. The other is the market for Real Estate Investment Trusts (REITs), which is a subset of the larger publicly traded US equity market. This latter market becomes our natural laboratory: REIT share prices are subject to all of the normal influences of stock prices in general, and yet we have additional insights into REIT cash flows by measuring cash flows derived from the direct property market.[6]

More precisely, REITs present at least two important advantages, when compared to ordinary equity securities. First, due to the fact that REITs derive their cash flows from the operation of commercial property, these firms should offer a higher level of transparency

[4]These will eventually be paid out through anticipated dividends, currently unannounced future dividends, or even through a payout of terminal value upon the firm's liquidation.

[5]Our rolling out-of-sample estimation further constitutes a similar paradigm to that of Evans (1998), who allows for the possibility that aggregate dividends and discount rates do not follow stable time series processes; investors rationally account for instability in the dividend and discount rate processes. Relatedly, Barsky and De Long (1993) argue that investors re-estimate dividend growth rates every period and their paradigm pivots on the informativeness of current dividend levels for forecasting future dividend growth rates. Relatedly, Brennan and Xia (2001) argue that learning by investors generates increased volatility in asset prices. Our work is consistent with these views, and we show the improvements that result from being better able to capture dividend (or cash flow) information that exists in the market at a given time.

[6]Our analysis is different from that of Plazzi, Torous and Valkanov (2010). They examine this question in the other of the two parallel asset markets (i.e. the direct property market), while we study prices of publicly traded securities where the excess volatility puzzle has been observed. In the privately-traded asset market, Plazzi et al. (2010) find that cash flow information plays a more important role in the price formation process than changes in the discount factor.

than other firms, since commercial real estate (held and operated by REITs) is more straightforward to price than more complex assets held by ordinary companies (e.g. a production line for rivets). Thus, there is less incentive and necessity for firm management to manage traditional cash flow measures in order to signal information about the firm to the market, as the informational asymmetry is lower.[7] Second, it is possible to directly observe commercial property income returns from the primary (or direct) real estate market, in which REITs trade, but which of course has its own readily observable dynamics, since REITs only constitute a part of this asset market.[8] Thus, we as econometricians are better able to understand the investor's information set as it pertains to cash flows, since in this way we can proxy for the cash flows that enter the firm. Securities for which one can observe this type of cash flow information are extremely rare. However, if one can find these, they do constitute a more appropriate empirical framework to use in testing the Present-Value paradigm. Correspondingly, we are in the unique position to show that the paradigm actually functions (exactly as formulated, for example in Shiller (1992)) at the security level,[9] for an important part of the US equity market, in which cash flow information can be captured more fully.[10]

The approach of Pontiff (1997) resembles ours in spirit, in that this study too uses a subset of public equity markets better suited to test this question, as a natural laboratory. Pontiff uses equity closed-end funds. At the end of 2010, the market capitalization of equity closed end funds equaled $101 billion, while the market capitalization of equity REITs (which

[7]See, for example, Wang, Erickson and Gau (1993). In addition to this, REITs are mandated to pay out at least 90% of their taxable income as dividends. While this removes some discretion from dividend policy, it is a less binding constraint than it seems, due to the high amounts of depreciation which REITs can claim. See Kallberg, Liu and Srinivasan (2003), who also use REITs in the context of testing NPV models. We discuss important differences between their work and our approach later. Section 2 also presents further elaboration of this issue.

[8]It should be noted that we never use direct property prices, but only cash flow information from this market.

[9]This qualification is often referred to as the *portfolio approach*, to be distinguished from the *macro approach* which examines overall firm value. Larrain and Yogo (2008) show that the paradigm works at the overall firm level.

[10]There are several settings in which Real Estate data has proven useful in helping to solve general economic puzzles. See for example Davis and Heathcote (2007), Hryshko, Luengo-Prado and Sorensen (2010).

we use as a natural laboratory) at the same time equaled \$359 billion.[11] Economically also, our study differs markedly from that of Pontiff (1997), in that REITs allow us to better examine *cash flow* data and how this information is incorporated in price formation, while Pontiff focuses on *prices* of funds relative to the *prices* of the underlying securities (not cash flows). We study the economics of the relationship between asset prices and their underlying cash flows. An important difference is that we work with a richer data set which fully incorporates the parallel asset markets at work in real estate. Thus, our setup examines more closely the formation of prices placed on streams of cash flows. Closed-end funds yield a better insight into already-formed underlying *asset values* and allow the author to test whether additional volatility is imposed on these. In his context, Pontiff finds in favor of excess volatility, while in our context we find that cash flows actually play an important role when more fully captured by an empirical measure.

We first validate the use of our natural laboratory, by comparing the R^2 from a Fama and French (1993) three-factor model for our REIT industry portfolio to that obtained for each of the Fama-French 49 industries and show that, at .54 this lies right at the center of the distribution of industry R^2s. This means that systematic risk plays as important a role for these securities as it does across the rest of the stock market, and that therefore REITs are as difficult to price as any other portfolio of securities.[12]

Our main approach works within the established framework for testing sources of price variability within the context of an NPV model. We rely on the methodology of Shiller (1992) and Campbell and Shiller (1988a,b). We impose a structural model on asset price dynamics, which is based on an empirically estimable version of a dynamic (i.e. time-varying)

[11] Sources: Investment Company Institute and National Association of Real Estate Investment Trusts, respectively.

[12] This finding also fundamentally differentiates our results from those of studies such as Vuolteenaho (2002), who finds that cash flow information is important at the firm level but only constitutes idiosyncratic risk in a portfolio setting. Given that we use a diversified portfolio and the variation of returns in our setting is dominated by systematic risk, the results we present are therefore of a different nature than those of this earlier study.

Net Present Value Model, that is, a *dividend ratio model*. We use this to model the dividend yield based on variables relating to cash flow- and interest-rate information, and test what fraction of the overall variation in dividend yields this information explains.

We first use REIT dividends alone as a cash flow variable. As stated above, REIT dividends should contain more information and be less smoothed than the dividends of ordinary equities.[13] This study's most important contribution in this respect, however, lies in exploiting the relationship between the two parallel asset markets, by adding direct-property returns data (instead of earnings data, like for example in Campbell and Shiller (1988b)) to the cash flow information set on which a dividend pricing model is tested. The data we use for this purpose comes from properties held by entities which are not continuously publicly traded, and it is collected privately and only published in aggregate by its provider. Therefore, it seems that the participants who provide this data have little to no incentive for manipulation or management thereof, and so this data should provide us as econometricians with reliable information on the true cash flows produced by the commercial property market, to measure the dynamics of cash flows that enter REITs. In this study we demonstrate the improvement that this information content gives to traditional dividend pricing models. Further, by more fully capturing cash flow-related information, we should also come closer to isolating that component of dividend yields which is driven by changes in the discount factor.

We follow the methodology of Campbell and Shiller (1988a,b), which consists of using a vector of state variables containing the dividend yield as well as variables pertaining to certain sources of variation in a VAR estimation, in order to construct predicted dividend

[13] Kallberg, Liu and Srinivasan (2003) test the dividend-yield models of Campbell and Shiller (1988a) on a sample of REITs, using not just dividends but all distributions, and find that the dividend pricing model is not rejected for REITs. They also rerun these tests on the S&P 500 Index, where they do reject the dividend pricing model. Our benchmark results confirm these findings qualitatively, but our analysis is conducted out of sample. Our study differs fundamentally from that of Kallberg et al. (2003), however, in that we capture cash flows at the level at which they enter the firm, and do not merely limit ourselves to payouts.

yields based on these variables. Economically, these predicted dividend yields constitute that component of the variation in dividend yields which is driven by the variables in this state vector. It is then possible to draw statistical comparisons between the predicted dividend yields and the actual observed ex-post dividend yields, in order to determine how much of the overall variation in dividend yields is captured by the state variables included. The figures we produce in order to make this comparison are the ratio of the standard deviation of the predicted dividend yields from each VAR specification over the standard deviation of the ex-post observed dividend yields, as well as the correlation between the two series of dividend yields. If this ratio is high, and at the same time the two series of dividend yields are highly correlated, the predicted dividend yields constructed solely from a particular information set closely mirror those actually applied to asset prices in the market, and therefore this set of variables has a large influence on the overall variation in dividend yields and ultimately asset prices. It is important to note once again that our empirical approach differs from that of Campbell and Shiller (1988a,b)[14], in that while these studies estimate their VARs over their entire data sample and compute the predicted dividend yields just as fitted values from the VAR estimation, we conduct our VAR estimations on which we base our predictions using a 40-quarter rolling window, and construct the predictions out of sample. This should more cleanly capture the true information content available to market participants at a particular point in time, while also allowing for the relationships described within this VAR system to be time-varying.

We also conduct our estimation in sample, exactly as is done in previous literature, and construct "predicted" dividend yields out of fitted values from the full-sample VAR. We find that our results are qualitatively unaltered in such a setting.

Using quarterly data from 1980 through 2007, we begin by estimating a benchmark VAR system, consisting of the logs of REIT dividend yields, the logs of REIT dividend

[14] As well as much of the rest of the literature, including Kallberg et al. (2003).

growth rates, and the logs of the long-term interest rate. We find that with two lags, where this system seems to generate the best forecast dividend yields, the ratio of the standard deviations of the predicted over the actual dividend yield is .7108, while the correlation between the two yield series is .4528.[15] When we add the logs of NOI yields (quarterly net operating income to our direct property portfolio, divided by end-of-quarter REIT prices) to this system, the ratio of the standard deviations increases to .9563, while the correlation coefficient increases to .6847. These numbers increase further to .9813 and .7323, respectively, when we add the logs of quarterly direct-property NOI growth to this system and do not decrease much (.9291 and .7313), if we exclude the logs of quarterly REIT dividend growth and only use the logs of dividend yield, NOI yield, NOI growth, and the long-term rate. We further compute an out-of-sample R^2 measure for each model.[16] The dividend-only specification yields an out-of-sample R^2 of .30, while this is nearly doubled (.59) in the best-performing specification which includes property-based cash flows.[17] This presents strong evidence that our direct property cash flow variables constitute important information for the pricing of REITs. More generally, however, this suggests that, if cash flow information is more fully captured empirically (at the level at which cash flows enter the firm), such information does constitute a very important component in the determination of asset prices, yielding generally strong support to the Present-Value paradigm.

We then estimate OLS regressions with the log-difference between the observed dividend yields and the predicted dividend yields from each rolling VAR estimation as a dependent variable, and log quarterly volatility of daily total REIT returns as an independent variable. The idea behind this specification is that, after having accounted for variation in the dividend yield that is due to cash flow and interest-rate information, we should have approximately

[15]This ratio of standard deviations is close to that found in Kallberg et al. (2003), who use similar variables in their VAR setup, while Campbell and Shiller (1988a) in the model specification that resembles ours but uses regular stocks, find the ratio of standard deviations to be .186 and the correlation coefficient .253.

[16]See Welch and Goyal (2008).

[17]Figure 2 shows ex-post realized and predicted dividend yields for our best specification.

isolated a component of variation that should be related to time-varying risk premia, which in turn should be driven at least in part by a measure of risk. If, on the other hand, we have not isolated this component to enough of an extent (namely by subtracting from actual dividend yields a component of variation in the dividend yield that does not satisfactorily capture cash flow- and interest-related parts of variation), we should see other sources of variation potentially overpower that component related to time-varying risk premia, and thus obtain a model that is only noise. Further, this test should show whether our direct-market cash flow variables inadvertently capture sources of variation related to time-varying risk-premia, as these would also disappear from the VAR residuals if this were the case, yielding a noise relationship.

In these regressions we do not find a significantly positive effect of log REIT return volatility on either the overall log dividend yield itself (we run this model for calibration purposes), or on observed dividend yield minus the predicted dividend yield generated with REIT-dividend variables and interest rate only. We do find, on the other hand, that log REIT return volatility has a significantly positive effect on both the log differences computed with dividend yields predicted using our additional cash flow measures. While we must approach these results with caution, as the coefficients are only significant at the ten-percent level and the R-squareds are only .0482 and .0434, these results do seem to lend additional support to our hypothesis that direct property cash flow information plays an important role in determining REIT prices, and more generally that cash flow information, when captured more fully, constitutes an important determinant of asset prices in general. This applies especially if one considers that realized quarterly volatility only incompletely accounts for risk-related pricing information (which must be forward looking).

The rest of this study proceeds as follows. Section 2 presents the empirical methodology and results for the dividend yield models using our natural laboratory. Section 3 concludes.

2 Taking Advantage of the Parallel Asset Markets to Assess the Performance of Dividend Pricing Models

2.1 Modeling the Dividend Yield

We employ dividend pricing models, as a useful approach in attributing the variability of asset returns. This approach has been taken frequently in the asset pricing literature (see for example Shiller (1987), Campbell and Shiller (1988a,b), Campbell (1991), and Kallberg et al. (2003) who test this approach for REITs). This framework can be summarized as follows.

In a basic view, a financial asset can be seen as simply a claim to all future cash flows this asset offers, and thus can be priced as the present discounted value of all these cash flows. With equity, these cash flows will consist of dividends paid out by a firm, and so a share of stock should be priced as the present discounted value of all future dividends, or

$$P_t = \sum_{k=1}^{\infty} \gamma_{t+k}^{k} D_{t+k} \tag{1}$$

In this formulation, the stock price today, P_t, is the sum of all future dividends (assuming an infinite life time for the firm), discounted by a possibly time-varying discount factor $\gamma_\tau < 1$, and thus this formulation is called a dividend pricing model. Since the right-hand side of equation (1) concerns future cash flows, the stock price P_t will in reality be based on expectations of future dividends ($E[D_{t+k}]$), and (assuming a time-varying discount factor) also on expectations of future discount factors ($E[\gamma_{t+k}]$).

A further modification in the approach to equation (1) will allow an additional insight. The stream of expected future dividends, $E[D_{t+1}], E[D_{t+2}], E[D_{t+3}], \ldots$, given the current observed dividend, D_t, can be seen as a product of the current dividend and an expectation of the dividend growth rate $E[\Delta D_{t+k}]$, which means that, given today's dividend, asset prices depend solely on the market's expectations of future discount factors and dividend growth rates.

$$P_t = D_t \, E\left[\sum_{k=1}^{\infty} \gamma_{t+k}^{k} \Delta D_{t+k}\right] \qquad (2)$$

It is therefore intuitively appealing to examine the dynamics of asset prices *conditional* on the current dividend, in that this provides insight into the component of variation in asset prices that is due to the market's processing of current cash flow and discount rate information, by making predictions of both discount rates and dividend growth rates into the indefinite future. This provides an intuitive explanation for why a high degree of attention has been devoted to modeling dividend-price ratios or *dividend yields*[18] (in the above notation D_t/P_t), and why we now turn our attention to this measure.

2.2 Why REITs?

Real Estate Investment Trusts (REITs) offer distinct advantages in applying dividend pricing models in several respects. First, REITs are mandated by law to pay out at least 90% of their taxable income as dividends (this figure was 95% before 2000). However, while this regulation is in place in order to make REITs more like pass-through investment vehicles, in reality this is not a particularly binding constraint, in that a REIT's taxable income is generally low in comparison with its overall cash flows, due to the high amounts of depreciation a REIT can deduct, due to its property holdings. Thus, while to some extent, there is a constraint placed on REITs' dividend policy and these firms' ability to manage dividends (thus apparently making their dividend stream a better proxy for their true underlying

[18]This is a vast literature which we do not attempt to summarize here. A useful overview of this line of literature is given in Brown (2008), or Campbell, Lo and MacKinlay (1997).

cash flows than that of other firms), there is still a large heterogeneity of dividend payout ratios, indicating that a large amount of discretion exists on the part of management in determining dividends. Kallberg et al. (2003), for example, find that out of the 50 largest REITs in 1999, only three paid out the required 95%, while the median payout ratio lies at 111%, and the distribution of REITs' payout ratios extends well above this number. Due to the misleading nature of the taxable income figure with respect to REITs, the industry uses Funds From Operation (FFO) as a cash flow measure, which adjusts, among other things, for depreciation.[19] While there is less dispersion in the percentage of FFO that REITs pay out as dividends (the median figure here lies at 85%, according to Kallberg et al. (2003)), there is still some dispersion (the authors find that 84% of firms pay between 70 and 105% of FFO), which may indicate some degree of dividend management by REITs, and therefore even for REITs, dividends remain a noisy proxy of the firm's underlying cash flows, and thus of the cash flows investors perceive equity ownership entitles them to. However, it does seem to be the case that the dividend payout constraint (or perhaps the custom of paying out a large percentage of cash flows as dividends) does add at least somewhat more information content to REIT dividends than what one finds in the dividend of other firms.

A second factor which should increase the overall informativeness of REIT dividends lies in these firms' relative transparency, which may make signaling through dividends less of a motivation for dividend management, since there is generally less informational asymmetry, and therefore less necessity for this. Wang et al. (1993), for example, document that while REIT prices tend to exhibit abnormal returns upon dividend announcements, the magnitude of these returns is only about 40% that of ordinary equities. Thus, while one must approach both of these points with some degree of caution, it does seem to be the case that dividends themselves offer a greater information content about the cash flows of the firm in the case of

[19] Further adjustments include amortization as well as revenues from unconsolidated partnerships and joint ventures.

REITs, when compared to other equities. This explains the results of Kallberg et al. (2003).

There exists a second important advantage in using REITs to determine the relative importance of cash flows versus market predictions on discount factors, in the dynamics of price formation. Because REITs generate their cash flows by holding and operating commercial real estate, and commercial real estate returns themselves are generally observable, it is possible to use returns data directly from the commercial property market, to proxy for data on REIT cash flows and supplement the information content of dividends. For example, the cash flows a REIT earns by holding a property of a particular type (say, an office building) in a particular city (say, New York City) should be closely related to the overall rental cash flows that the market for New York office buildings gives at that time. Similarly, in aggregate, the dynamics of the cash flows earned by the REIT industry as a whole, should be closely related to those of the cash flows a broad nationally diversified portfolio of commercial properties of the same type generates. This study's contribution in this respect lies in exploiting this relationship between the two asset markets, by adding direct-property returns data to the cash flow information set on which a dividend pricing model is tested.

While REITs present the above advantages in terms of granting us as econometricians insight into the investor base's cash flow information set, at the same time the general nature of the stock returns to this industry very much resembles that of other industries within the US publicly traded equity market. In order to demonstrate this, we run regressions of excess returns to our REIT portfolio on the three factors from a Fama and French (1993) three-factor model. We also perform these regressions for each of the Fama-French 49 industries for comparison. Figure 1 shows the histogram of $\overline{R}^2$ obtained in these regressions. For REITs the $\overline{R}^2$ equals 0.54, while the median $\overline{R}^2$ from the 49 industries equals 0.60 and the mean is 0.56. These results indicate that the traditional factors play a similar role in pricing REITs as they do in pricing other industries. Further, these results indicate that REIT returns contain a significant amount of systematic shocks.

This fact also constitutes a key distinction between our experimental setup and that of Vuolteenaho (2002), who examines this question on an individual firm level and finds that cash flows are an important driver of returns in that setting. Vuolteenaho's finding is reconciled with excess volatility, by arguing that cash-flow related variation accounts for idiosyncratic risk, but is then diversified away at a larger portfolio level.[20] The above results show that systematic variation accounts for more than half the total variation of returns in our setting (at least four times as much as one would find on any individual firm in the market). Thus, our finding that cash flow information constitutes an important driver in the price formation process for a portfolio this diversified, simply will not allow for the same reconciliation to be made between our findings and market-wide excess volatility, as can be made for those of Vuolteenaho (2002). Thus, we offer important new insights into this topic, beyond those of this earlier study. The power of our study to do this pivots crucially on the availability of a more reliable cash flow measure within our natural laboratory, which has not been the case for any study in the past.

These results thus indicate that the price formation for REITs should follow a similar process to that for other industries in publicly traded US equity markets, and that systematic risk factors play as important a role for pricing these stocks, as they do for the stocks of other industries. Yet at the same time, with REITs we have unique insight into the investor's information set regarding cash flows. Therefore, REITs constitute an ideal natural laboratory to shed new light on the role of cash-flow information within a dynamic net-present-value model, applied to stocks.

[20] To our knowledge, no economic explanation has so far been found for why this should happen, and, for example Chen and Zhao (2009) show specific empirical evidence against this.

2.3 The Empirical Approach

In the Campbell and Shiller (1988a,b) framework, dividend pricing models are tested by attributing a component of the variation in the dividend yield to a part of the investor's information set which is linked to the dynamics of dividends. If this component does not constitute a sufficiently high fraction of the overall observed variation in the dividend yield, the dividend pricing model is rejected. In order to model the dividend yield based on this information set, Campbell and Shiller employ a Vector Autoregression (VAR), and we follow their technique, and for the purpose of this exposition largely borrow their notation.

It is clear from equation (2), that while the dividend yield (D_t/P_t) is a function of expected dividend growth rates and discount rates, this relationship is non-linear, and it would therefore not be possible to model this variable within the linear framework of a VAR. In order to remedy this, Campbell and Shiller re-write this equation in terms of natural logarithms of variables. In the limit as the prediction window becomes arbitrarily large, and assuming constant excess returns, Campbell and Shiller obtain what they term the *dividend-ratio model*, or the *dynamic Gordon Model*, a dynamic version of the Gordon Growth Model[21] in which expected dividend growth rates, as well as, to a certain extent, discount factors can vary through time:

$$\delta_t = \sum_{j=1}^{\infty} \rho^j E_t \left[r_{t+j} - \Delta d_{t+j} \right] + C \tag{3}$$

This version of the dividend ratio model assumes that, while the risk-free interest rate can vary through time, the excess return is constant. In this representation, δ is the log of the dividend yield, r_{t+j} is the return to an alternative asset (a proxy for the risk-free rate)

[21] In the Gordon Growth Model, both the discount rate and the dividend growth rate are assumed to be constant through time, and so the dividend yield becomes an exact linear function of the discount rate (r) and growth rate (g), or $D_t/P_t = r - g$.

during the time period ending j periods from now, Δd_{t+j} is the dividend growth rate during this time period, ρ is the ex-post observed discount factor, and C is a constant relating the observable discount rate to the actual, unobservable discount rate.

It is now possible to model the time-series dynamics of the dividend-ratio model through a VAR consisting of the variables δ_t and $r_t - \Delta d_t$, the growth-adjusted interest rate. Since this is just a restricted form of a three variables VAR system, modeling δ_t, Δd_t and r_t separately, we elect to use this latter specification. The above restriction would force the coefficient on r_t to be exactly the negative version of the coefficient on Δd_t. This is not necessary in order for the present-value relationship to hold: all that is needed is that the two coefficients have opposite signs, which we find is the case in our model. On the contrary, since all time series are only specified up to a constant, including this restriction might actually lead to incorrect inferences.

Thus, with only one lag, the basic VAR we estimate becomes:

$$\begin{bmatrix} \delta_t \\ \Delta d_t \\ r_t \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \delta_{t-1} \\ \Delta d_{t-1} \\ r_{t-1} \end{bmatrix} + \begin{bmatrix} u_{1,t} \\ u_{2,t} \\ u_{3,t} \end{bmatrix} \tag{4}$$

In this representation, a_{ij} are the regression coefficients and $u_{i,\tau}$ are error terms, while all other variables are as defined above. We also estimate augmented versions of this system which include direct-property cash flow variables, creating systems of up to five variables and including up to two lags.[22] We de-mean all data, in order to be able to specify these systems without a constant.

[22] For details on the exact regressions we estimate as well as variable definitions, please see section 2.4.

The system in equation (4) can be written more compactly in matrix form as

$$z_t = Az_{t-1} + v_t \tag{5}$$

where z_τ is the observed vector of state variables at time τ, A is the matrix of coefficients, and v_t is the vector of error terms. Economically, it can be argued that the vector of state variables z_t contains all present and past information concerning the variables in this vector. Therefore, in order to construct a forecast of this vector k periods ahead, conditioned upon this information set, one simply needs to multiply z_t by the matrix of VAR coefficients A raised to the k power. In other words, forecasts are computed as

$$E[z_{t+k}] = A^k z_t \tag{6}$$

We proceed by estimating various specifications of this VAR system over a 40-period rolling window (i.e. at any time t we use observations from $t-39$ to t, to generate $A_{t,t-39}$) and creating a one-period out-of-sample forecast δ'_{t+1}, which economically represents the portion of the dividend yield that is entirely based on the information contained in the state vector used. We then draw statistical comparisons between the series of forecast dividend yields based on only cash flow and interest rate information, and the ex-post realized dividend yield for the same period (δ_{t+1}), in order to determine how well the overall dynamics of the dividend yield are explained by these state variables. Since none of our state variables concern time-varying risk premia, we posit that the portion of dividend yields that is not forecast by our VAR will be largely due to this component, and conduct basic tests for this hypothesis, using the difference between forecast and observed dividend yields.

Note that our empirical approach differs from that of Campbell and Shiller (1988a,b) and other studies in this literature, in that earlier studies estimate the matrix of coefficients A

over the entire sample, and generate their predicted values δ' as essentially just fitted values from the VAR. Our approach seems advantageous in this respect, in that by predicting δ' out of sample, we use only information about state variables that truly was available to market participants at that particular time. Further, by doing this, we allow the nature of the cash flow and interest rate processes to vary through time, which these previous studies do not do. Our technique also demonstrates that even with a relatively short estimation period upon which A is estimated, ex-post reasonable estimates can be generated from this data. Finally, by using only one-quarter forecasts and not a sum of infinite-horizon forecasts, we do not need to pick an exogenous discount factor ρ, since we do not need to produce a bounded sum of future growth rates. The implication here would simply be that the VAR coefficients we estimate differ from the true weightings the market places on these sources of information by a cross-sectionally consistent multiplicative constant. Since we do not place much interest on the size of the coefficients we obtain, this does not matter to our analysis.

2.4 Data and Methodology

The innovation of this study within the framework of modeling the dividend yield lies in adding information related directly to the underlying property market to the traditional REIT dividend information. This allows us to more closely proxy for the overall cash flow information, with which an investor or analyst is able to make forecasts. This information is derived from the data provided by the National Council of Real Estate Fiduciaries (NCREIF). NCREIF collects data on Net Operating Income (NOI), as well as appraisals from a large portfolio of institutional-grade commercial properties. Table 1 shows the total appraised value of the portfolio NCREIF follows, in comparison with the total estimated market capitalization of publicly-traded REITs at the end of each year since 1980. It is apparent from this comparison that the size of the portfolio followed by NCREIF is similar to that of the overall REIT industry. The properties on which NCREIF collects data are held by private institutions such as commingled real estate funds. It is widely documented that the appraisal values used in this data are somewhat problematic, in that they suffer from various types of appraisal bias. However, in this part of the study, we only use Net Operating Income (NOI), which is simply the quarterly operating cash flow for each property, reported to NCREIF directly, and which therefore does not suffer from these problems.[23] The types of commercial property covered by NCREIF are Apartment, Hotel, Industrial, Retail, and Office. When we construct the REIT data we only retain equity REITs which invest in these types of properties in our sample.[24] This data is of quarterly frequency, and this is the frequency we use throughout this study. We obtain NOI per square foot values from this dataset, disaggregated by property type. We then use weights based on the relative market capitalization of the REITs that invest into this property type, in order to form a weighted average quarterly NOI per square foot, which becomes our basic direct property cash flow measure. Table 1 shows these weights as of the end of each year. Weights are computed quarterly, based on REITs' relative market capitalization at the end of the previous quarter.

The direct-property NOI variable has two very desirable properties in terms of the information content on direct property cash flows it provides. First, as mentioned above, the properties in the NCREIF dataset are held by institutions which are not publicly traded. Therefore, the managers of these property portfolios have no adverse market overreaction to fear, upon reporting lower-than-expected cash flows, a common explanation for the incentive to smooth dividends and even earnings for publicly traded firms. Second, the NOIs for each individual property are reported to NCREIF in private under a strict non-disclosure

[23] Net Operating Income consists of rental revenue (as well as other ancillary income, such as parking revenue, billboard space, etc.) minus operating expenses. Capital Expenditures made on the property are not part of NOI, as these are not considered part of the property's normal operations. While we also have data on CapEx, we elect to exclude this quantity from our direct-property cash flow measure, as economically this should not constitute an industry-wide systematic expenditure, to which REITs would necessarily also be exposed.

[24] Further, until 1983 the NCREIF portfolio does not contain any Hotel properties, and thus we eliminate Hotel REITs from our sample before this time.

agreement, and NCREIF then only publishes these returns in aggregate. This should further mitigate the incentive for managers to smooth or mask low cash flows for a particular quarter.

Our data on REITs comes from the Center for Research in Securities Prices (CRSP). We identify and use all equity REITs which invest in the five types of property that NCREIF covers, and form a value-weighted portfolio, using market capitalizations from the end of the previous quarter (quarter $t-1$) to compute weights for quarter t. This procedure makes this portfolio tradeable. Further, at the end of each quarter, we record the market capitalization of all the firms we identified as investing into the NCREIF property types as a fraction of total REIT market capitalization that quarter (end-of-year snapshots are reported under **Fraction Matched** in Table 1), as well as the market capitalization associated with each of our five property types, as a fraction of all firms we were able to match (end of year snapshots are reported under each property type heading in Table 1).[25] These fractions serve as weights to construct the weighted-average NOI per square foot coming from NCREIF. Our data starts in 1980.

The basic variables we then construct for this portfolio are a series of quarterly weighted-average total returns (variable RET in CRSP), which includes dividends and other distributions, and a series of quarterly weighted average price returns (variable $RETX$ in CRSP), which consists of quarterly price movements only. We then construct a series of weighted average dividend yields, which at time t is defined as the total weighted average distributions during quarter t divided by the price at the end of quarter t. We also construct a series of quarterly weighted-average dividends for the REIT portfolio. Both series are constructed as functions of the total return and price return series, and (as is customary with index-type construction) are defined up to an arbitrary multiplier, which is consistent through time.

[25] Once again, since NCREIF does not cover any hotel properties until 1983, we exclude these REITs from our sample until then.

For details on the construction of these series, see Appendix A. We also construct a REIT price index, which we set to a value of 100 in the last quarter of 1979, and we then compute as 100 times the geometrically compounded price returns. The REIT variables we use in our analysis are the natural logarithm of the dividend yield ($div.yield$), and the log of the quarterly dividend growth rate ($\Delta dividend$), which is defined as the difference of the logs of the dividends paid in quarter t and in quarter $t-1$.

We further define the variable ($noi.yield$), as the natural log of the ratio of weighted-average NOI per square foot over the end-of-quarter level of the REIT price index mentioned above. Once again, this variable is defined only up to an arbitrary multiplier which is constant through time.[26] The other direct-property cash flow variable we use is Δnoi which is the first difference in the natural logs of quarterly weighted-average NOI per square foot figures, and represents the quarterly growth rate of direct property cash flows.

The final variable we use for our analysis is $lt.rate$ which is defined as the natural log of the long-term interest rate as of the end of quarter t. We use the 30-year US Treasury Bond rate where available, and otherwise the 20-year US Treasury Bond rate. Note that Campbell and Shiller (1988a,b) use the short-term interest rate for their analysis. We elect to use the long-term interest rate, because this variable offers a better idea of the market's indefinite forecast of future risk-free rates. While we only construct one-quarter forecasts of the dividend yield from our VAR, economically these should still constitute the market's best forecast of the combination of dividend growth rate, cash flow growth, and the risk-free rate, over the indefinite future, and so the choice of a long-term interest seems warranted.

[26]Because we de-mean all data in our VAR analysis, the size of these multipliers is irrelevant for all variables, even those that are not defined as a log difference.

2.5 Results and Implications

Before proceeding to a discussion of the results from our VAR procedure, we present a simple and preliminary test designed to illustrate that the time-series dynamics of our *noi.yield* measure behave as we would expect those of a dividend yield to behave. This in turn should constitute preliminary evidence that direct property NOIs give useful information for the cash flow-related portion of REIT price movements. Specifically, we run a simple OLS regression of the first difference in *noi.yield* on the change in *lt.rate*. Note that both variables are logs of their raw data series, and so these first differences approximate fractional changes in these series. Economically, since the dividend yield consists in part of the risk-free rate, a change in the latter should cause a change in the former, with the two changes being positively related. Conversely, if *noi.yield* does not resemble a dividend yield at all (most likely because NOIs do not yield useful information about REIT cash flows and therefore REIT prices), fluctuations in NOI yield would be less likely to be explained by fluctuations in the long term rate.

To save space, we do not show the results from this regression in a table, but report them here. The intercept in this regression is insignificant, while the coefficient for the interest rate is 0.2393, and statistically significant at the 10% level, with a t-statistic of 1.73. The R^2 from the model is .027 and the joint model F statistic is 2.995, significant at the 5% level. It is congruous with economic intuition that the risk-free interest rate alone should explain a part of the dynamics of a cash-flow yield, yet not a very important one. Therefore, these results establish preliminary evidence that direct-property NOI yields contain economically meaningful cash flow yield information, in that the time-series dynamics of our NOI yield do resemble those of a dividend yield.

Table 2 presents the matrix of coefficients for the one-lag version of the most complete VAR system we estimate, estimated on the entire 1980-2007 sample, in order to illustrate some of the dynamics and interlinkages between our data series. In the first line of Table 2, we see that the dividend growth rate from the previous period negatively affects dividend yield, and that this effect is significant at the 5% level (coefficient of -0.2027 and t-statistic of -1.8463). Further, we can see that *noi.yield* the previous period significantly positively affects *div.yield* (coefficient of 0.2675, t-statistic of 2.1631). This can be contrasted with the earnings yield used in Campbell and Shiller (1988b), which, while helping the VAR system as a whole, does not show a significant effect on the dividend yield next period. In this equation, the coefficient on the risk-free rate is positive and very significant. Together with the negative and significant coefficient on the dividend growth rate, this does coincide with the basic formulation of the Dynamic Gordon Model (equation 3), which models the dividend yield as a function of the growth-adjusted interest rate. One more issue of note about this equation is that its $\overline{R^2}$ is 0.5843, while that of the equivalent equation in Campbell and Shiller (1988b) is 0.503, so we do explain a slightly higher fraction of the dividend yield with our direct-property cash flow measures than Campbell and Shiller do with earnings.

Of note in the second line of Table 2, is the significantly positive coefficient on *noi.yield* (coefficient 0.2735, t-statistic 2.4031, which makes this coefficient 5% significant). This suggests that direct property cash flow information is relevant in predicting not just REIT dividend yields, but also REIT dividend growth rates. Besides this, the coefficient on $\Delta dividend$ may be of note, in that it is negative, while Campbell and Shiller (1988b) find this to be significantly positive. This may be due to intra-year autocorrelation patterns in dividends which are apparent in our quarterly data, but get smoothed out of the annual data Campbell and Shiller use.

We can also see from Table 2 that the three remaining variables are strongly autocorrelated, *noi.yield* and *lt.rate* positively, and Δnoi negatively.[27] Besides this, $\Delta dividend_{t-1}$ seems to have a significantly negative effect on Δnoi_t. Economically this effect is difficult

[27] The persistence of these variables is not problematic in the VAR setting, given our focus on predicted values rather than significance of coefficients.

to rationalize, and we can perhaps ascribe it to different seasonality patterns in what is otherwise a pair of series that describe very similar information.

Table 3 presents the primary results from this section. For each quarter $t > 40$, we estimate eight different VARs, over a rolling 40-quarter (10-year) time window and with the estimated coefficient matrix generate a predicted log dividend yield for the next quarter $t + 1$ ($pred.div.yield_{t,t+1}$). As mentioned before, intuitively this should be a dividend yield that only contains the information included in the VAR. We draw statistical comparisons between this predicted dividend yield and the ex-post realized dividend yield for quarter $t + 1$. The reason we include only two lags in this table is because the full VAR system that contains both dividend and NOI growth rates becomes near rank-deficient at greater lags. While this prevents us from investigating higher-order lags,[28] this is also quite informative, in that this shows that the dividend growth rate and the NOI growth rate contain very similar information. The table reports for each VAR specification, the ratio of the standard deviations of the predicted and the realized dividend yield, as well as the correlation between the two, together with a test statistic of the hypothesis that the true correlation between the two series is 0. While, ideally, we should be pleased with the ratio of the standard deviations being as close to 1 as possible, in that this would presumably show that the VAR system is explaining a large fraction of the variation in realized dividend yields, one must approach this statistic with caution, since another reason why this statistic is high could simply be the fact that the predicted dividend yield is constructed very imprecisely, for example from noisy, unstable VAR coefficient matrices. Only in conjunction with a high correlation coefficient can we infer that the variation in the predicted dividend yield actually resembles that of the realized dividend yield.

VAR System 1 contains the benchmark model specification without direct-property cash

[28] For the sake of consistency we only use one and two lags for each of the other specifications, where this would not be the case. Using one or two lags is also standard in this literature.

flow measures, making this a specification that is comparable to that of Campbell and Shiller (1988a) and Kallberg et al. (2003). For one lag, we obtain a ratio of standard deviations of 0.6941 and a correlation coefficient of 0.4593 and this is nearly unchanged if we extend the VAR specification to two lags. This closely resembles results of Kallberg et al. (2003), who obtain standard deviation ratios of 0.5970 and 0.7575 respectively, without conducting a rolling window VAR estimation.[29] In the model estimated by Campbell and Shiller (1988a) that is closest to this specification, the ratios of standard deviations are 0.186 and 0.253 respectively, while the correlation coefficients are 0.395 and 0.383. Thus despite the fact that we as well as Kallberg et al. (2003) use a quarterly frequency while Campbell and Shiller (1988a) use an annual frequency, it seems to be the case that REIT dividends themselves offer more pertinent information for forecasting dividend yields, than the dividends of other companies. For REITs we manage to explain a higher fraction of the variation in dividend yields, and due to the higher correlation coefficient we can infer that this is not just due to more estimation noise, but that the variation in these predicted dividend yields really does follow that of actual yields more closely.

As is visible in the next panels of Table 3, these results improve dramatically when direct-property cash flow variables are added to the rolling VAR system. When adding the $noi.yield$ in System 2, we find that the ratio of standard deviations increases to 0.9298 for one lag and 0.9563 for two lags, with the correlations at 0.6086 and 0.6847, respectively. Adding the NOI growth rate, further improves these values to 0.9765 for one lag and 0.9813 for two, with correlations of 0.6503 and 0.7323, respectively. Once again, while the increase in the ratio of standard deviations alone would not necessarily indicate better performance of these specifications over the benchmark model, the strongly increased correlations yield strong credibility to the idea that direct-property cash flows do proxy for important information in REIT price formation.

[29] Kallberg et al. (2003) do not report correlation coefficients of predicted and actual dividend yields.

System 4 omits REIT dividend growth rate, and retains the two direct-market cash flow variables. This system performs especially well with two lags, where the ratio of the standard deviations is reduced to 0.9291, while the correlation figure is only reduced to 0.7313 (from 0.7323 in the full specification). The inference we draw from this is twofold. First, it is probably the case that the reduction in the ratio of the standard deviations is due in large part to a reduction in estimation noise, since the correlation is almost unchanged. Second, and more importantly, however, it seems to be the case that the quarterly direct-property NOI growth rate contains more relevant information to generating predictions about the future value to be derived from REITs, than the REIT dividend growth rate itself. This highlights the importance of the information contained in this measure in pricing REITs.

Figure 2 shows a plot of the predicted dividend yield (the red dashed line) and the ex-post realized dividend yield (the black solid line). Notice how closely the predicted dividend yield tracks many of the movements of the ex-post realized yield. This plot, together with the results in Table 3 presents strong evidence that cash flow information, when completely accounted for, does constitute a very important part of price dynamics. The problem with previous studies has simply been that it is very difficult to measure the true underlying cash flows of a firm. With the unique opportunity that REITs offer, in that the direct property market yields an informative view of the firm's true cash flows, we are in fact able to show that a strong dependency exists between cash flows and security prices.

We supplement these results by computing an out-of-sample R^2 measure along the lines of Welch and Goyal (2008). The measure is defined as follows:

$$R^2_{OOS} = 1 - \frac{\sum_{t=40}^{T}(\delta'_{t,t+1} - \delta_{t+1})^2}{\sum_{t=40}^{T}(\overline{\delta_t} - \delta_{t+1})^2} \tag{7}$$

In this expression δ_{t+1} is the ex-post realized dividend yield at time $t+1$, $\delta'_{t,t+1}$ is the predicted dividend yield for time $t+1$ generated at time t from the 40-quarter rolling VAR, and $\overline{\delta_t}$ is the historical average dividend yield over the 40-quarter rolling window ending at time t. This figure compares the sum-squared prediction error from the VAR to the prediction error that would be obtained by using the historical mean as the best predicted dividend yield. The more of an improvement the VAR offers over the historical mean, the closer to 1 this statistic gets. If the VAR does no better than the historical mean, the statistic is zero, and if it does worse, the statistic is negative. We calculate this measure for the two-lag version of each VAR system in Table 3.

As is shown in Table 3, for System 1, which contains only REIT dividends and growth rate, we obtain an out-of-sample R^2 of 0.3113. This measure increases to 0.4987 for VAR System 2 which includes NOI yield in addition to the previous measures and to 0.5702 for VAR System 3, which also includes NOI growth. For VAR System 4, we obtain an out-of-sample R^2 of 0.5884, which supports our earlier conjecture that by removing REIT dividend growth, we obtain a VAR system that contains largely the same explanatory power, but less estimation noise. These results further strengthen our overall picture that a large portion of dividend yield variation can be explained by cash flow information, when such information is measured more fully.

We perform two robustness tests for this setup. First, we estimate a set of single VAR systems over the entire sample, one for each specification shown in Table 3, and then produce "predicted" dividend yields as fitted values from each VAR. Of course, it should be clear that such a procedure cannot possibly model the true price formation process of investors in the market, as, for example, observations of state variable levels in 2007 were not available to investors in 1990. Thus, doing this introduces look-ahead bias to the empirical methodology. However, this type of in-sample "prediction" is common in this literature, and we therefore test this alternate empirical setup, for consistency. The second robustness test we undertake is to specify the VAR models shown in Table 3 with the inclusion of quarter dummies, to account for possible seasonality effects. In both cases, our results remain qualitatively unaltered.[30]

The final test we conduct in this section constitutes a preliminary attempt to model the nature of the residual variation in dividend yields, that is not explained by a state vector containing reliable cash flow proxies, and the risk-free rate. Economically, this variation should be brought about by time-varying risk premia, which determine a security's required outperformance over the risk-free rate. From basic intuition, these should be a product of the market-price of risk, and forecast volatility. If using logs, once again we should have a linear relationship here. Specifically, we run an OLS regression with as dependent variables the difference between the ex-post realized log dividend yield and the predicted log dividend yields from our VARs, and as an independent variable the log of realized volatility (variance) of daily total returns to the value-weighted REIT portfolio over the same quarter. While the risk measure that should enter into a dividend yield would need to forecast the entire expected term-structure of volatility, it would seem that the most recent realized volatility would feature prominently in the information set used to conduct such a forecast, and that therefore it should help explain at least some of the residual variation in dividend yields. Additionally, if the dividend yield still has too much other variation left in it (i.e. we have not isolated the risk-related component in its variation enough) this other variation, especially if not completely orthogonal to risk-related variation, might mask the component of variation that is due to volatility, yielding a noise relationship in this regression.

Table 6 shows the results from this regression. Note, first of all, that in the first column, where the dependent variable is the entire log dividend yield, the coefficient for volatility is indistinguishable from zero. As mentioned above, while presumably the overall dividend yield should at least in part be driven by volatility, it seems to be the case that the variation related to this variable is masked by other sources of dividend yield variation, leading to

[30] The results are not reported here to save space, but are available from the authors upon request.

no significance in the regression. Following in this line of argument, we find practically no improvement over this in the second column, where we use the difference between realized dividend yields and the dividend yields predicted by VAR System 1, which has only dividend and interest rate variables, but no direct-property cash flow variables. It still seems to be the case that this predicted dividend yield does not account for enough of the cash flow-related variation in dividend yields, in order to isolate in a clean enough way, the component related to risk.

This situation, however, changes in the third column, where we use as a dependent variable the difference between the realized dividend yield and the predicted yield from VAR System 3, which adds NOI yield to the REIT dividend and interest rate variables. In this model, we find a positive coefficient of 0.0509, with a t-statistic of 1.8298, making this coefficient significant at the 10% level. From basic intuition, we would in fact expect a risk measure to have a positive effect on the dividend yield, as higher risk should increase the overall discount factor, and therefore lower prices relative to dividends. A similar situation can be found in the fifth column, where as a dependent variable we use the difference between the realized dividend yield and the predicted dividend yield from VAR System 4, which contains no REIT dividend growth, but only REIT dividend yield, NOI yield, NOI growth, and the risk-free rate. In this model we also have a positive significant coefficient of 0.0441, with a t-statistic of 1.7311, also making this coefficient significant at the 10% level. The R^2 for the two models are similar, at 0.0482 and 0.0434, respectively. The model based on predicted dividend yields from System 3, does not exhibit a positively significant coefficient; however, the coefficient value for volatility, its t-statistic, as well as the model's R^2 are more comparable with the other models that contain predicted dividend yields based on direct property cash flow information, than with those that do not. It may be the case here, that the estimation error argument raised above becomes relevant in this case, in that the predictions from System 3 seem to be more noisy. These results also show that our direct-market cash flow variables do not inadvertently capture sources of variation related to time-varying risk-premia. If this were the case these would disappear from the VAR residuals, yielding a noise relationship.

These results further validate the usefulness of reliable cash flow measures in modeling dividend yields. It seems that by modeling the cash flow-related portion of the variation in dividend yield more accurately, we are not only able to demonstrate the relative importance of true cash flow information in asset price formation, but we are also able to more cleanly isolate components of the dividend yield that are driven by time-varying risk premia.

3 Conclusion

In this study we examine sources of variability in asset returns within a framework of a dividend pricing model. We use data on two parallel asset markets – Real Estate Investment Trusts (REITs) and on directly owned real estate. Thus, we supplement information on REIT cash flows with information on cash flows derived from the direct property market. We find that this fuller view of cash flow information significantly improves the performance of the dividend discount asset pricing model.

We analyze the connection between cash flows and asset returns within the structural framework of the dividend pricing model, and more specifically by modeling the dividend yield. We find in basic tests that the time-series dynamics of our direct-property NOI-based yield resemble those of a dividend yield, and that therefore direct-property NOIs do seem to contain useful information for REIT prices. Further, we are able to generate predicted dividend yields (based on information from REIT dividends and cash flow information from the direct property market) which closely resemble ex-post observed dividend yields. We are thus able to show that a strong dependency exists between cash flows and security prices, if this cash flow information is captured fully enough. Further, we demonstrate that by modeling the cash flow-related portion of the variation in dividend yield more accurately, we are also able to more cleanly isolate components of the dividend yield that are driven by time-varying risk premia.

Taken together, these findings suggest that better measurement of cash flows (dividends) can significantly improve the performance of dynamic dividend pricing models, and thus contribute to the resolution of the excess volatility puzzle.

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A Appendix: Computation of Weighted-Average Dividend and Dividend Yield Series

This section illustrates the method we use to compute the weighted-average dividend and dividend yield series for the value-weighted REIT portfolio. CRSP has two return figures: RET and $RETX$. RET is total holding period return, and $RETX$ is holding period return excluding distributions. While both of these contain factors to adjust for stock splits, conceptually, we have:

$$
\begin{aligned}
RET_t &= \frac{P_t + D_t}{P_{t-1}} - 1 & (8) \\
RETX_t &= \frac{P_t}{P_{t-1}} - 1 & (9)
\end{aligned}
$$

Thus, the dividend yield $y_t = D_t/P_t$ for our weighted portfolio is constructed as

$$
y_t = (ret_t - retx_t) \times (retx_t + 1)^{-1} \qquad (10)
$$

This is because

$$
\begin{aligned}
(ret_t - retx_t) \times (retx_t + 1)^{-1} &= \left[\frac{P_t + D_t}{P_{t-1}} - 1 - \frac{P_t}{P_{t-1}} + 1 \right] \times \frac{P_{t-1}}{P_t} & (11) \\
&= \frac{D_t}{P_{t-1}} \times \frac{P_{t-1}}{P_t} \\
&= D_t/P_t
\end{aligned}
$$

Here ret_t and $retx_t$ are the total returns and price returns respectively, to our value-weighted portfolio of REITs over quarter t. P_t is the price at the end of quarter t, and D_t the total dividend paid out over quarter t, to someone holding one share of the value-weighted index.

Subsequently, the dividend for quarter t (D_t) is computed as the dividend yield above, multiplied by the level of our REIT price index. This figure is once again only correct up to an arbitrary multiplier that is consistent over time. However, since we use log-differences of this dividend series for our study, this is irrelevant.

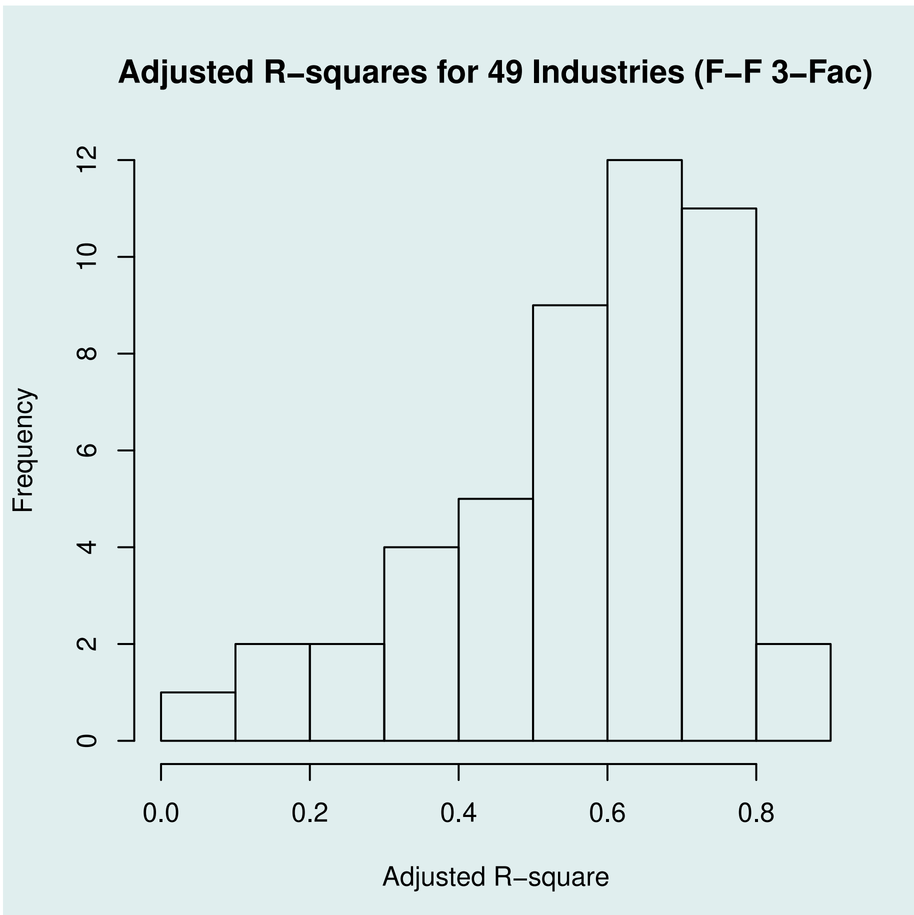

Figure 1: This figure shows the distribution of adjusted R^2 obtained by regressing each of the Fama-French 49 industries on a Fama-French three-factor model.

Note: Mean: .565. Median: .602.
$\overline{R^2}$ for REITs: .537.

Table 1: Summary Statistics for REIT and Property Portfolios.

This table presents summary statistics for the REIT– and Direct Property data, as of the end of each year in our sample. The statistics presented are the total market capitalization of the REIT industry (in millions of Dollars), the fraction of market capitalization that we matched against NCREIF's property types (Apartment, Hotel, Industrial, Office Retail), the fraction of the matched portfolio market capitalization that is made up by each property sector, and the total appraised value of all properties in NCREIF's property universe (also in millions of Dollars).

Year	**Total Industry Capitalization**	**Fraction Matched**	**Apartment**	**Hotel**	**Industrial**	**Office**	**Retail**	**Total NCREIF Portfolio Value**
1980	3,365	0.361	0.305	0	0.069	0.048	0.579	1,770
1981	3,115	0.307	0.384	0	0.091	0.049	0.477	3,351
1982	4,451	0.301	0.456	0	0.121	0.033	0.39	4,603
1983	5,554	0.411	0.395	0.095	0.054	0.025	0.43	8,427
1984	5,901	0.436	0.408	0.107	0.048	0.041	0.396	10,828
1985	7,673	0.362	0.305	0.128	0.095	0.049	0.422	14,575
1986	10,438	0.325	0.326	0.091	0.102	0.037	0.444	17,214
1987	9,890	0.334	0.264	0.093	0.118	0.046	0.48	21,025
1988	11,140	0.343	0.235	0.063	0.107	0.106	0.488	26,472
1989	11,889	0.372	0.196	0.034	0.082	0.106	0.581	30,801
1990	9,302	0.343	0.187	0.018	0.065	0.108	0.622	37,066
1991	13,289	0.336	0.219	0.008	0.043	0.104	0.626	37,423
1992	16,903	0.394	0.229	0.004	0.027	0.069	0.671	39,289
1993	33,336	0.532	0.3	0.006	0.048	0.081	0.565	39,872
1994	44,429	0.665	0.313	0.024	0.105	0.089	0.469	38,919
1995	59,305	0.661	0.281	0.073	0.1	0.118	0.429	45,896
1996	82,171	0.68	0.275	0.096	0.123	0.163	0.342	51,817
1997	137,833	0.769	0.213	0.132	0.127	0.276	0.252	61,744
1998	146,105	0.78	0.198	0.167	0.132	0.247	0.257	63,344
1999	126,649	0.779	0.227	0.118	0.141	0.242	0.271	77,024
2000	137,756	0.819	0.234	0.124	0.149	0.265	0.227	89,383
2001	162,026	0.758	0.231	0.106	0.145	0.248	0.27	105,175
2002	170,319	0.741	0.219	0.104	0.141	0.231	0.305	110,797
2003	229,935	0.727	0.211	0.101	0.133	0.215	0.34	119,999
2004	321,050	0.691	0.198	0.12	0.158	0.2	0.323	127,365
2005	363,112	0.708	0.194	0.132	0.136	0.206	0.332	155,700
2006	494,965	0.701	0.195	0.163	0.117	0.23	0.296	195,663
2007	375,748	0.679	0.163	0.163	0.152	0.177	0.345	246,209

Note that NCREIF's data contains hotels only from 1983 onwards.

Table 2: Matrix of Results from First-Order Vector Autoregression

This table presents coefficient estimates from a first-order Vector Autoregression (VAR). The system consist of the natural logarithm of the dividend yield to the value-weighted REIT portfolio ($div.yield$), the quarterly dividend growth rate to this portfolio ($\Delta dividend$), the NOI Yield, defined as the ratio of the quarterly Net Operating Income (NOI) to the direct property portfolio over the weighted average price of the REIT portfolio, the quarterly NOI growth rate for the direct property portfolio (Δnoi), and the long-term interest rate ($lt.rate$). All variables are computed as the natural logarithm of their respective raw series, and all change variables are computed as the first difference of the natural logarithms. All variables are de-meaned. The F-statistic included is the joint significance test that all variables are different from zero, for each equation of the system. (T-statistics in parentheses).

	$div.yield_{t-1}$	$\Delta dividend_{t-1}$	$noi.yield_{t-1}$	Δnoi_{t-1}	$lt.rate_{t-1}$	$\overline{R^2}$	F
$div.yield_t$	0.209896	−0.202704	0.267465	−0.031055	0.545732	0.5843	31.09***
	(1.456)	(−1.8463)*	(2.1631)**	(−0.1083)	(4.6335)***		
$\Delta dividend_t$	−0.723462	−0.252806	0.273537	−0.133077	0.507927	0.4554	18.89***
	(−5.4518)***	(−2.5014)**	(2.4031)**	(−0.5044)	(4.6848)***		
$noi.yield_t$	−0.047148	−0.025606	0.91043	−0.146612	0.055685	0.789485	81.255584
	(−0.6958)	(−0.4962)	(15.6647)***	(−1.0882)	(1.0059)		
Δnoi_t	0.017875	−0.076058	−0.082448	−0.24949	0.019283	0.1558	4.95***
	(0.3805)	(−2.1261)**	(−2.0463)**	(−2.6713)***	(0.5024)		
$lt.rate_t$	0.083709	−0.038882	−0.064341	0.108815	0.917549	0.9500	407.43***
	(1.7457)*	(−1.0647)	(−1.5643)	(1.1413)	(23.42)***		

Number of observations: 108

*: $p < 10\%$; **: $p < 5\%$; ***: $p < 1\%$.

Table 3: Results from Rolling Vector Autoregressions.

This table presents statistics comparing the predicted dividend yield for quarter $t+1$ (generated by a VAR using 40 quarters' worth of data, ending at t), $pred.div.yield_{t,t+1}$, with the ex-post realized dividend yield at quarter $t+1$, $div.yield_{t+1}$. Specifically, the table presents, for each VAR specification, the ratio of the standard deviations between the predicted and the realized series, as well as their correlation coefficient. In parentheses there is the value of a t-statistic testing the hypothesis that the actual correlation between the two series is 0. Below, the out-of-sample R^2 for each model is also presented. For VAR Systems 2, 3, and 4, we present a DM statistic for a Diebold-Mariano test (with a Harvey, Leybourne, and Newbold correction for small samples), testing the hypothesis that the prediction error from the system in question is statistically equal to that from VAR System 1, against the one-sided alternative, that the prediction error is less. The set of candidate variables for the VAR consists of $div.yield_t$, the dividend yield to the value-weighted REIT portfolio, $\Delta dividend_t$, the quarterly growth in the weighted-average REIT dividend, $noi.yield_t$ the ratio of the quarterly weighted-average net operating income (NOI) per square foot to the property portfolio, over the weighted-average end-of-quarter price to the REIT portfolio, Δnoi_t the quarterly NOI growth, and $lt.rate_t$, the long-term interest rate. All variables are computed as the natural logarithm of their respective raw series, and all change variables are computed as the first difference of the natural logarithms. All variables are de-meaned.

VAR System 1: $[div.yield_t,\ \Delta dividend_t,\ lt.rate_t]'$		
Lags:	1	2
$\sigma(pred.div.yield_{t,t+1})/\sigma(div.yield_{t+1})$	0.6941	0.7108
$cor(pred.div.yield_{t,t+1},\ div.yield_{t+1})$	0.4593	0.4528
	(4.201)***	(4.126)***
R^2_{OOS}	0.3013	0.3113
VAR System 2: $[div.yield_t,\ \Delta dividend_t,\ noi.yield_t,\ lt.rate_t]'$		
Lags:	1	2
$\sigma(pred.div.yield_{t,t+1})/\sigma(div.yield_{t+1})$	0.9298	0.9563
$cor(pred.div.yield_{t,t+1},\ div.yield_{t+1})$	0.6086	0.6847
	(6.232)***	(7.631)***
R^2_{OOS}	0.3836	0.4987
DM	-1.4913°	-2.6063^{**}
VAR System 3: $[div.yield_t,\ \Delta dividend_t,\ noi.yield_t,\ \Delta noi_t,\ lt.rate_t]'$		
Lags:	1	2
$\sigma(pred.div.yield_{t,t+1})/\sigma(div.yield_{t+1})$	0.9765	0.9813
$cor(pred.div.yield_{t,t+1},\ div.yield_{t+1})$	0.6503	0.7323
	(6.955)***	(8.736)***
R^2_{OOS}	0.4268	0.5702
DM	-2.2968^{*}	-1.8722^{*}
VAR System 4: $[div.yield_t,\ noi.yield_t,\ \Delta noi_t,\ lt.rate_t]'$		
Lags:	1	2
$\sigma(pred.div.yield_{t,t+1})/\sigma(div.yield_{t+1})$	0.9464	0.9291
$cor(pred.div.yield_{t,t+1},\ div.yield_{t+1})$	0.5949	0.7313
	(6.012)***	(8.712)***
R^2_{OOS}	0.3778	0.5884
DM	-0.851	-2.9189^{**}

VARs are computed on a rolling 40-quarter window. Statistics are computed on the remaining 68 observations.

*: $p < 5\%$; **: $p < 1\%$, ***: $p < .1\%$

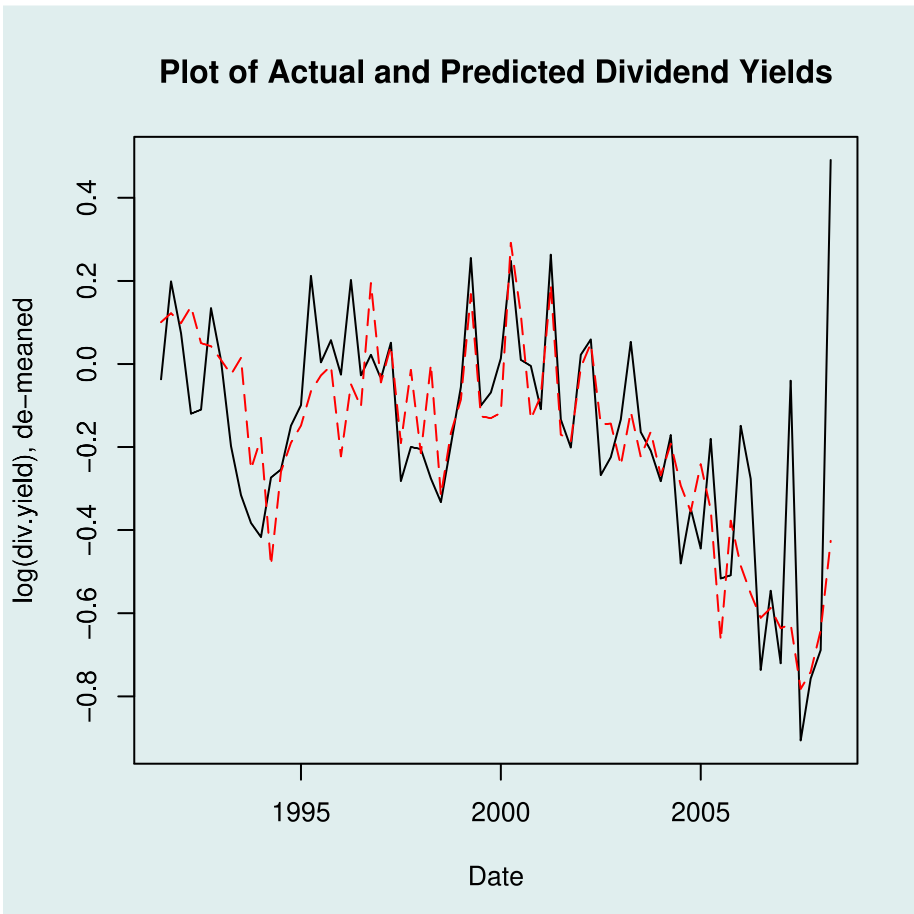

Figure 2: This figure shows a plot of the log of realized dividend yields (the black continuous line) and predicted dividend yields from VAR System 4 (Table 3) for the same quarter (the red dashed line).

Table 4: Results from Rolling Vector Autoregressions: Cash-Flow Growth.

This table presents statistics comparing the predicted cash-flow growth variables for quarter $t+1$ (generated by a VAR using 40 quarters' worth of data, ending at t), $pred_{t,t+1}$, with the ex-post realization of that variable at quarter $t+1$, act_{t+1}. Specifically, the table presents, for each VAR specification and cash-flow growth variable, the ratio of the standard deviations between the predicted and the realized series, as well as their correlation coefficient. In parentheses there is the value of a t-statistic testing the hypothesis that the actual correlation between the two series is 0. Below, the out-of-sample R^2 for each model is also presented. For VAR Systems 2 and 3, we present a DM statistic for a Diebold-Mariano test (with a Harvey, Leybourne, and Newbold correction for small samples), testing the hypothesis that the prediction error from the system in question is statistically equal to that from VAR System 1, against the one-sided alternative, that the prediction error is less. The cash-flow variables are dividend growth ($\Delta dividend$) and noi growth (Δnoi), each predicted respectively by the VAR models that contain it as a state variable. The set of candidate variables for the VAR consists of $div.yield_t$, the dividend yield to the value-weighted REIT portfolio, $\Delta dividend_t$, the quarterly growth in the weighted-average REIT dividend, $noi.yield_t$ the ratio of the quarterly weighted-average net operating income (NOI) per square foot to the property portfolio, over the weighted-average end-of-quarter price to the REIT portfolio, Δnoi_t the quarterly NOI growth, and $lt.rate_t$, the long-term interest rate. All variables are computed as the natural logarithm of their respective raw series, and all change variables are computed as the first difference of the natural logarithms. All variables are de-meaned. Each VAR has two lags.

VAR System 1: $[div.yield_t,\ \Delta dividend_t,\ lt.rate_t]'$		
Variable:	$\Delta dividend$	Δnoi
$\sigma(pred_{t,t+1})/\sigma(act_{t+1})$	0.6972	
$cor(pred_{t,t+1},\ act_{t+1})$	0.4973	
	$(4.621)^{***}$	
R^2_{OOS}	0.2296	
VAR System 2: $[div.yield_t,\ \Delta dividend_t,\ noi.yield_t,\ lt.rate_t]'$		
Variable:	$\Delta dividend$	Δnoi
$\sigma(pred_{t,t+1})/\sigma(act_{t+1})$	0.7679	
$cor(pred_{t,t+1},\ act_{t+1})$	0.7025	
	$(7.957)^{***}$	
R^2_{OOS}	0.4808	
DM	-2.813^{**}	
VAR System 3: $[div.yield_t,\ \Delta dividend_t,\ noi.yield_t,\ \Delta noi_t,\ lt.rate_t]'$		
Variable:	$\Delta dividend$	Δnoi
$\sigma(pred_{t,t+1})/\sigma(act_{t+1})$	0.8112	0.8772
$cor(pred_{t,t+1},\ act_{t+1})$	0.7067	0.466
	$(8.053)^{***}$	$(4.246)^{***}$
R^2_{OOS}	0.4777	0.0602
DM	-2.6199^{**}	
VAR System 4: $[div.yield_t,\ noi.yield_t,\ \Delta noi_t,\ lt.rate_t]'$		
Variable:	$\Delta dividend$	Δnoi
$\sigma(pred_{t,t+1})/\sigma(act_{t+1})$		0.8356
$cor(pred_{t,t+1},\ act_{t+1})$		0.5234
		$(4.952)^{***}$
R^2_{OOS}		0.2028

VARs are computed on a rolling 40-quarter window. Statistics are computed on the remaining 68 observations.

Table 5: Results from Rolling Vector Autoregressions Including Returns.

This table presents statistics comparing predicted variables for quarter $t+1$ (generated by a VAR using 40 quarters' worth of data, ending at t), $pred_{t,t+1}$, with the ex-post realization of that variable at quarter $t+1$, act_{t+1}. Specifically, the table presents, for each VAR specification and cash-flow growth variable, the ratio of the standard deviations between the predicted and the realized series, as well as their correlation coefficient. In parentheses there is the value of a t-statistic testing the hypothesis that the actual correlation between the two series is 0. Below, the out-of-sample R^2 for each model is also presented. For VAR Systems 2, 3, and 4, we present a DM statistic for a Diebold-Mariano test (with a Harvey, Leybourne, and Newbold correction for small samples), testing the hypothesis that the prediction error from the system in question is statistically equal to that from VAR System 1, against the one-sided alternative, that the prediction error is less. The predicted variables are dividend yield ($div.yield$), dividend growth ($\Delta dividend$), NOI growth (Δnoi), and stock return (ret) each predicted respectively by the VAR models that contain it as a state variable. The set of candidate variables for the VAR consists of $div.yield_t$, the dividend yield to the value-weighted REIT portfolio, $\Delta dividend_t$, the quarterly growth in the weighted-average REIT dividend, $noi.yield_t$ the ratio of the quarterly weighted-average net operating income (NOI) per square foot to the property portfolio, over the weighted-average end-of-quarter price to the REIT portfolio, Δnoi_t the quarterly NOI growth, and $lt.rate_t$, the long-term interest rate. All variables are computed as the natural logarithm of their respective raw series, and all change variables are computed as the first difference of the natural logarithms. All variables are de-meaned. Each VAR has two lags.

VAR System 1: $[div.yield_t,\ \Delta dividend_t,\ lt.rate_t,\ ret_t]'$				
Variable:	$div.yield$	$\Delta dividend$	Δnoi	ret
$\sigma(pred_{t,t+1})/\sigma(act_{t+1})$	0.8602	0.6487		0.6261
$cor(pred_{t,t+1},\ act_{t+1})$	0.4798	0.4542		−0.1825
	(4.408)***	(4.11)***		(−1.496)
R^2_{OOS}	0.2624	0.1903		−0.5987
VAR System 2: $[div.yield_t,\ \Delta dividend_t,\ noi.yield_t,\ lt.rate_t,\ ret_t]'$				
Variable:	$div.yield$	$\Delta dividend$	Δnoi	ret
$\sigma(pred_{t,t+1})/\sigma(act_{t+1})$	1.067	0.7628		0.7036
$cor(pred_{t,t+1},\ act_{t+1})$	0.7495	0.7183		−0.2019
	(9.126)***	(8.323)***		(−1.662)
R^2_{OOS}	0.5499	0.5035		−0.7527
DM	−2.9095**	−3.0188**		1.7295
VAR System 3: $[div.yield_t,\ \Delta dividend_t,\ noi.yield_t,\ \Delta noi_t,\ lt.rate_t,\ ret_t]'$				
Variable:	$div.yield$	$\Delta dividend$	Δnoi	ret
$\sigma(pred_{t,t+1})/\sigma(act_{t+1})$	1.0274	0.7879	0.8225	0.8591
$cor(pred_{t,t+1},\ act_{t+1})$	0.7682	0.7151	0.4631	−0.1055
	(9.675)***	(8.248)***	(4.212)***	(−0.855)
R^2_{OOS}	0.5901	0.4941	0.11	−0.8882
DM	−3.3148***	−2.9864**		2.4118
VAR System 4: $[div.yield_t,\ noi.yield_t,\ \Delta noi_t,\ lt.rate_t,\ ret_t]'$				
Variable:	$div.yield$	$\Delta dividend$	Δnoi	ret
$\sigma(pred_{t,t+1})/\sigma(act_{t+1})$	0.924		0.8385	0.7717
$cor(pred_{t,t+1},\ act_{t+1})$	0.7596		0.484	−0.0804
	(9.416)***		(4.46)***	(−0.65)
R^2_{OOS}	0.5932		0.1358	−0.7054
DM	−3.3773***			0.6763

VARs are computed on a rolling 40-quarter window. Statistics are computed on the remaining 68

Table 6: Regression Results of Residual Dividend Yield on Realized Quarterly REIT Volatility.

This table presents results from an OLS regression of the difference between ex-post realized dividend yield on the REIT portfolio ($div.yield_{t+1}$) minus the predicted dividend yields, generated through a 40-quarter rolling window VAR in quarter t, and concerning quarter $t+1$. Each of the variables $pred.div.yield_{t,t+1,i}$ corresponds to the predicted dividend yields generated by VAR system i in Table 3. The independent variable is the logarithm of the volatility of daily returns on the value-weighted REIT portfolio for quarter $t+1$, minus its mean. (T-statistics in parentheses).

	$div.yield_{t+1}$	$div.yield_{t+1}-$ $pred.div.yield_{t,t+1,1}$	$div.yield_{t+1}-$ $pred.div.yield_{t,t+1,2}$	$div.yield_{t+1}-$ $pred.div.yield_{t,t+1,3}$	$div.yield_{t+1}-$ $pred.div.yield_{t,t+1,4}$
$(Intercept)$	0.00056	0.0043	0.0405	0.0523	0.0295
	(0.0173)	(0.1421)	(1.6213)	$(2.2286)^{**}$	(1.2912)
$reit.vol_{t+1}$	0.00702	0.0207	0.0509	0.0399	0.0441
	(0.1800)	(0.6111)	$(1.8298)^{*}$	(1.5273)	$(1.7311)^{*}$
R^2	0.0003	0.0056	0.0482	0.0341	0.0434
F	0.0324	0.3734	3.348^{*}	2.333	2.997
$N = 68$					

*: $p < 5\%$; **: $p < 1\%$, ***: $p < .1\%$

Table 7: Results from Rolling Vector Autoregressions, Crude Oil Producers.

This table presents statistics comparing the predicted dividend yield for quarter $t+1$ (generated by a VAR using 40 quarters' worth of data, ending at t), $pred.div.yield_{t,t+1}$, with the ex-post realized dividend yield at quarter $t+1$, $div.yield_{t+1}$, for Crude Oil Producers. Specifically, the table presents, for each VAR specification, the ratio of the standard deviations between the predicted and the realized series, as well as their correlation coefficient. In parentheses there is the value of a t-statistic testing the hypothesis that the actual correlation between the two series is 0. Below, the out-of-sample R^2 for each model is also presented. The set of candidate variables for the VAR consists of $div.yield_t$, the dividend yield to the value-weighted Oil-Producer portfolio, $\Delta dividend_t$, the quarterly growth in the weighted-average Oil-Producer dividend, $oil.price.yield_t$ the ratio of the end-of-quarter oil price, over the weighted-average end-of-quarter price to the Oil-Producer portfolio, $\Delta oil.price_t$ the quarterly oil-price growth, and $lt.rate_t$, the long-term interest rate. All variables are computed as the natural logarithm of their respective raw series, and all change variables are computed as the first difference of the natural logarithms. All variables are de-meaned.

VAR System 1: $[div.yield_t,\ \Delta dividend_t,\ lt.rate_t]'$	
Lags:	2
$\sigma(pred.div.yield_{t,t+1})/\sigma(div.yield_{t+1})$	0.9226
$cor(pred.div.yield_{t,t+1},\ div.yield_{t+1})$	0.2451 (2.038)*
R^2_{OOS}	0.1435
VAR System 2: $[div.yield_t,\ \Delta dividend_t,\ oil.price.yield_t,\ lt.rate_t]'$	
Lags:	2
$\sigma(pred.div.yield_{t,t+1})/\sigma(div.yield_{t+1})$	0.9753
$cor(pred.div.yield_{t,t+1},\ div.yield_{t+1})$	0.235 (1.949)°
R^2_{OOS}	0.0807
VAR System 3: $[div.yield_t,\ \Delta dividend_t,\ noi.yield_t,\ \Delta oil.price_t,\ lt.rate_t]'$	
Lags:	2
$\sigma(pred.div.yield_{t,t+1})/\sigma(div.yield_{t+1})$	1.0476
$cor(pred.div.yield_{t,t+1},\ div.yield_{t+1})$	0.4137 (3.663)***
R^2_{OOS}	0.2188

VARs are computed on a rolling 40-quarter window. Statistics are computed on the remaining 67 observations.

*: $p < 5\%$; **: $p < 1\%$, ***: $p < .1\%$