Beating a Random Walk

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Abstract

As a crucial input to many valuation models, earnings forecasts are important to many practitioners and academics. Unfortunately, analysts' earnings forecasts and popular earnings forecasts from panel models are less accurate than a random walk at long horizons. We present a simple and intuitive modification to these models – the use of quantile rather than OLS regressions in the prediction model – that produces earnings forecasts significantly better than a random walk. This simple modification produces earnings forecasts that better represent market expectations and lead to more accurate return forecasts.

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1 Introduction

As realized returns are a noisy proxy for expected returns (see e.g. Elton (1999)) and popular asset pricing models are imprecise (see e.g. Fama and French 1997), many practitioners and academics calculate a firm's implied cost of capital (ICC) to estimate expected returns. ICCs equate the firm's stock price to the present value of expected future cash flows.[2] Until recently, most studies used analyst earnings forecasts as an input for these models. Unfortunately, analyst forecasts are undesirable as many firms are not covered by analysts and analyst forecasts are less accurate than a random walk at long horizons. (Bradshaw et al., 2012)

Recent studies suggest the use of cross-sectional earnings prediction models in lieu of analyst forecasts. Hou, van Dijk and Zhang (2012) (hereafter, HVZ) build on models suggested by Fama and French [2000, 2006] to develop a cross-sectional earnings prediction model. They use market prices and these forecasts of earnings to estimate the implied cost of capital (ICC) for a large sample of firms. They show that earnings forecasts generated by their model are superior to analysts' forecasts in terms of coverage, forecast bias, and earnings response coefficients. Their model-based ICCs are a more reliable proxy for expected returns than ICCs based on analysts' forecasts. Several studies immediately adopted the HVZ model because of the obvious advantage that forecasts can be formed for a sample that is much greater than the sample covered by analysts. Subsequent models in Li and Mohanram (2014) improve upon the

[2] Perhaps the most popular ICCs are Gordon and Gordon (1997), Claus and Thomas (2001), Gebhardt, Lee and Swaminathan (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005).

HVZ model. Specifically, cross-sectional models based on the persistence in earnings and the residual income model from Feltham and Ohlson (1996) offer better earnings forecasts than those based on the HVZ model. Still, all these models offer forecasts of earnings that are less accurate than a random walk.

We propose a simple modification that is related to the work of Gu and Wu [2003] and Basu and Markov [2004]. They point out an inherent inconsistency in the use of ordinary least squares (OLS) to examine inefficiencies in analysts' forecasts and use of the mean absolute forecast error as the measure of their accuracy. A similar inconsistency exists in the use of OLS in the HVZ earnings prediction model and the use of the mean absolute forecast error as the measure of the accuracy of these predictions. Basu and Markov [2004] suggest a simple solution, which is use of regressions based on least absolute deviations rather than OLS. Similarly, we examine the improvements in forecast accuracy when we estimate cross-sectional earnings models using median regressions rather than OLS.

We show that the use of median regressions rather than OLS in the cross-sectional earnings forecasting models proposed by Hou, van Dijk, and Zhang (2012) and Li and Mohanram (2014) results in forecasts that are significantly more accurate. Importantly, our simple modification leads to forecasts of earnings that beat a random walk.

Similar to earlier work (see, Li and Mohanram [2013] and Gerakos and Gramacy [2017]), we show that forecasts based on the HVZ OLS prediction model have a mean absolute forecast error that is significantly larger than predictions based on a random walk in earnings. We also find that earnings forecasts from the earnings persistence model (hereafter, EP model) and residual income model (hereafter, RI model) of Li and Mohanram (2014) are significantly less accurate than a random walk. Using median regressions in the prediction model results in forecasts that are significantly more accurate than a random walk when we use the EP model or RI model.

Similar to Gu and Wu [2003] and Basu and Markov [2004], we argue that the loss function implicit in minimizing the mean absolute forecast error, which is the most-often used error metric, is perhaps the most valid. As Basu and Markov [2004] point out, this seems more reasonable than the use of a mean squared error metric, which would be a metric that arguably would be consistent with the use of OLS in the estimation of the earnings prediction model.[3] They argue that, *ceteris paribus*, analysts view a three cent forecast error as three times as costly as a one cent forecast error rather the nine times as costly. Part of the reason that analysts may use this loss function is that the market seemingly uses a similar loss function – Freeman and Tse (1992) show that ERCs are concave over positive surprises and convex over negative surprises.

There are several advantages to using median regressions in the prediction model. Again, and perhaps most importantly, a median regression methodology offers higher accuracy. Using this methodology not only improves the predictions of the HVZ, EP and RI models, but also offers predictions that are often more accurate than a random walk. Second, because median regressions build on ranks, median regression predictions are not influenced by the presence of outliers. Thus, our results do not change with winsorization or truncation of the

[3] We also find that the EP and RI models produce forecasts significantly more accurate than a random walk when the error function is mean squared error.

data rendering these *ad hoc* adjustments unnecessary. This allows for a more general approach than the OLS methodology. Since OLS regressions minimize squared deviations while median regressions minimize absolute deviations, OLS parameter estimates will tend to be more influenced by observations in the tails of the distribution. Thus, the parameter estimates are less stable. We show that the parameter estimates in our prediction models are far more stable over time and it follows that we can use shorter prediction windows and capture more short-term dynamics. This is particularly important if there is a limited time-series, as is often the case with international data, for example.[4] Fourth, our predictions are associated with higher earnings response coefficients (ERCs) - this suggests that they are a better measure of market expectations.[5] Finally, we find that the accuracy of the implied cost of capital (ICC), as it relates to ex-post returns, is much higher for ICCs that use earnings forecasts based on quantile regressions compared to ICCs that use earnings forecasts based on least squares regressions.

2 Data

Firm-level accounting data are obtained from the CRSP/Compustat merged data set. Firm-level price and returns data are obtained from CRSP and data on the risk-free rate of return are obtained from Kenneth French's website. We delete observations that are duplicates by permno and fiscal year. We exclude ADRs, closed-end funds, and REITs (i.e., we retain observations with share codes equal to 10 or 11). We only consider firms that have U.S. dollars

[4] See Chattopadhyay, Lyle and Wang [2016].

[5] See Brown, et al. [1987].

as their currency. Earnings is defined as income before extraordinary items minus special items.[6] We use data from 1960-2017.

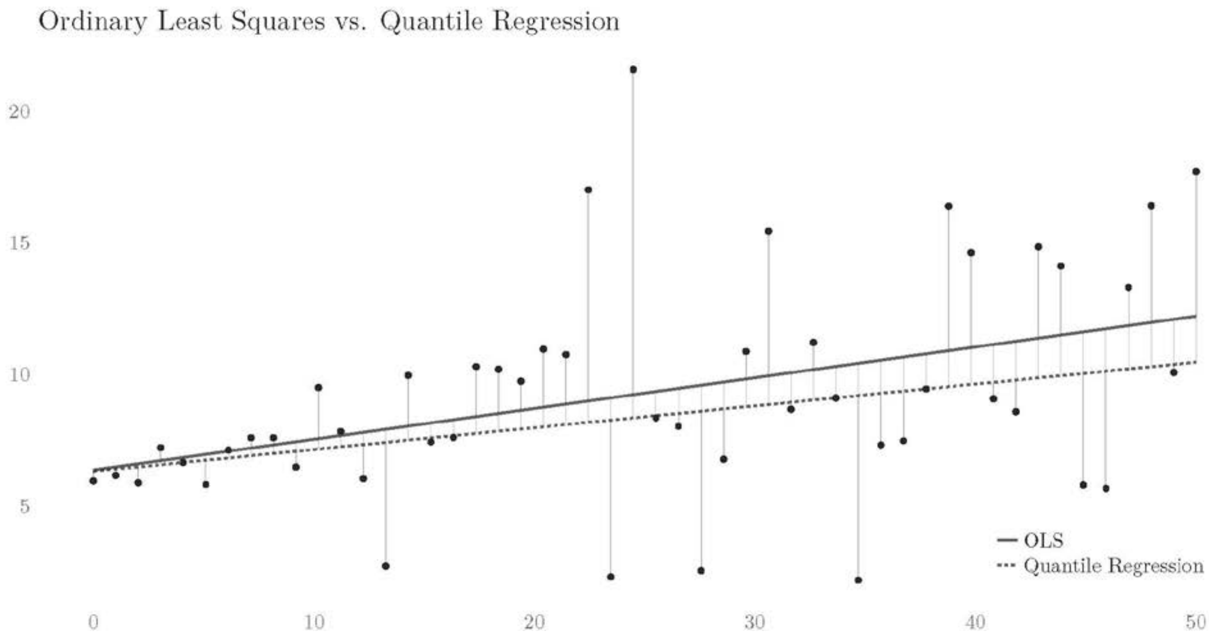
Following HVZ, we make earnings predictions based on a ten-year estimation window. To avoid a look-ahead bias, we only use data available as of year (t-1), to make predictions for year t. Across the three different earnings prediction models we consider, there are a number of regressors: *total assets* (compustat=at), *total dividends* (compustat=dvc), a *dividend dummy* equal to one if the firm paid dividends in the associated year (if total dividends is positive), *earnings*, a *negative earnings dummy* that equals one if the firm had negative earnings, *book value* (compustat= ceq), *accruals,* and *accruals_other. Accruals* is the accruals measure used in the HVZ model. Prior to 1988, we use the balance sheet method to define *accruals.* Specifically, *accruals* equal the change in non-cash current assets minus the change in current liabilities excluding the change in short-term debt and the change in taxes payable minus the depreciation and amortization expense. After 1988, we follow HVZ, who follow Collins and Hribar (2002), and use the statement of cash flows to determine accruals. Specifically, after 1988, *accruals* are defined as the negative of the sum of the change in accounts receivable (compustat=recch), the change in inventory (compustat=invch), the change in accounts payable (compustat=apalch), the change in taxes payable (compustat=txach), the net change in other current assets (compustat=aoloch), and the depreciation expense (compustat=dpc). *Accruals_other* is the accruals measure used in the EP and RI models. It follows the accruals calculation from Richardson et al. (2005). Specifically, *accruals_other* equals the change in

[6] This is a small departure from HVZ, who do not subtract off special items. We subtract special items as they are by definition unusual or infrequent. Using Compustat identifiers, we define earnings as ib-spi.

working capital (compustat: (act-che)-(lct-dlc)) plus the change in net non-current operating assets (compustat: (at-act-ivao)-(lt-lct-dltt)) plus the change in net financial assets (compustat: (ivst+ivao)-(dltt+dlc+pstk)). The coverage for the depreciation and amortization expense is limited – it is missing before fiscal year 1971. We replace missing values of the depreciation and amortization expense with one-tenth of net property plant and equipment. Again, due to limited coverage, we replace the change in taxes payable with zero when the value is missing.

3 Quantile Regression Methodology

Before advancing to a more formal discussion of quantile regressions, we briefly compare it to least squares regressions to build some intuition as to why it is an appropriate methodology to predict earnings. OLS regression minimizes the sum of squared deviations between an observed outcome and a within sample prediction – the prediction is modelled as a linear function of a set of observed predictors. A median regression (the special case of quantile regression, which we use), minimizes the sum of absolute deviations. The figure below illustrates the differences. The solid line is the least squares estimate and the dotted line is the median regression estimate.



Large deviations have a stronger influence on the slope of the solid line compared to the dotted line. If both methods of regression are readily available, which one should we use? It depends on the purpose and how the difference between the prediction and the observed outcome are evaluated, i.e., which loss function is used. OLS may be better in some circumstances, whereas median regression (or other quantiles) might be more desirable in other cases.

If we are interested in making predictions and are seeking to minimize expected square loss then least squares is indeed optimal.[7] More formally, we can state that if the goal is the minimization of the following loss function,

[7] Interestingly, we do not see evidence that OLS offers more accurate forecasts when mean square error is the loss function. If anything, we find evidence that median regressions offer more accurate forecasts when mean square error is the loss function. We present these results in the supplementary materials.

$$\min_g E[(y - g(x))^2],$$

where y is the response, or realized earnings, and x is a vector of the observed correlates, then choosing $g(x) = E[y|x]$ is the best choice. In the evaluation of earnings forecasts, however, the common practice (see Bradshaw (2011) for a summary) is to evaluate the quality of a prediction by looking at the mean absolute forecast error (MAFE). There are a number of motivations for this commonly used loss function over the mean squared error loss function. First, in terms of valuation, there is little reason to believe that the market cares more about large deviations. Freeman and Tse (1992) show that earnings response coefficients (ERCs) are non-linear. Namely, ERCs are S-shaped – concave over positive surprises and convex over negative surprises. In other words, the market seems to care proportionally less about large surprises. As such, there is little justification for a loss function that places proportionally larger weight on large surprises relative to small surprises. Further, Gu and Wu (2003) document that the market reacts positively to analyst earnings forecast errors, but reacts negatively to earnings skewness. Finally, Gu and Wu (2003) and Basu and Markov (2004) show that analysts are judged based on their mean absolute forecast error (MAFE). In summary, the standard practice, motivated by empirical evidence, is to look at averages (over firms and years) of

$$|Earnings - Predicted\ Earnings|.$$

In other words, the extant literature typically focuses on the mean (or median) absolute deviation between realized and predicted earnings. If minimizing the mean absolute forecast error is the objective, it seems natural to incorporate this into the prediction directly.

Therefore, it seems prudent to use a prediction model that directly minimizes expected mean absolute deviations. More formally, we should choose g to minimize:

$$\min_g E[|y - g(x)|].$$

That is, rather than minimizing expected squared deviations, we find a $g(x)$ that minimizes expected absolute deviations. The conditional median, $med(y|x)$, minimizes expected absolute deviations. Since our goal is to estimate the linear conditional mean and quantile functions, we aim to find α's to minimize:

$$\min_{\alpha 0,\, \alpha 1,\, \ldots,\, \alpha n} \sum_{i=1}^{i=N} |y_i - \alpha_0 - \alpha_1 * x_{i,1} - \alpha_2 * x_{i,2} - \ldots - \alpha_n * x_{i,n}|.$$

At first, this objective function may look somewhat clumsy because it is not differentiable everywhere, but the important property is its convexity which makes numerical solutions very efficient (the complexity of the computation is actually less for this regression than it is for OLS!).[8]

Since our objective is to obtain the best possible earnings forecast measured via the absolute deviation from realized earnings, it seems quite natural to make forecasts using a median regression model. Similar to OLS regression, inference for estimated parameters in the case of quantile regression is usually based on asymptotic approximation, i.e., an application of central limit theorem. In the case of linear quantile regression, we have the following result (Koenker (2005)):

[8] Standard statistical software packages such as R or Stata have readily available routines for quantile regression. In R, an implementation of estimation and inference for quantile regression is available in the "rq" package. Stata provides quantile regression functionality through the "qreg" command – one could run a simple quantile regression of y on x as "qreg y x".

$$\sqrt{N}(\widehat{\beta_\tau} - \beta_\tau) \rightarrow^{d} N(0, V_\tau)$$

where τ is the quartile, $V_\tau = \tau(1-\tau)(E(x_i x_i{'} f(0|x_i)))^{-1}(E(x_i x_i{'})(E(x_i x_i{'} f(0|x_i)))^{-1}$, and $f(e|x_i)$ is the conditional density of e_i given $x_i = x$. For the purposes of this paper, we consider the median, or when $\tau = 0.5$. In empirical work, V_τ has to be estimated. Koenker (2005) shows how to estimate this matrix directly. Alternatively, inference can also be obtained through an application of the bootstrap (Horowitz (1998)). Overall, statistical inference for the estimated parameters of a median regression model is readily available.

4 Empirical Results

In this section, we document how the use of median regressions in the prediction model when following the HVZ, EP, and RI methodology produces more desirable earnings estimates than the use of OLS in the estimation window when following the HVZ, EP and RI methodology.

4.1 Forecast Accuracy

In this subsection, we document how our modification to the HVZ, EP, and RI methodology produces more accurate earnings estimates. Specifically, the use of median regressions in the earnings prediction model produces earnings estimates that are more accurate than the ones produced using an OLS methodology.

4.1.1 Standard Estimation Window

We estimate the following regression models for firm i in year t over an estimation window of 10 years:

$$E_{i,t} = \alpha_0 + \alpha_1 A_{i,t-n} + \alpha_2 D_{i,t-n} + \alpha_3 DD_{i,t-n} + \alpha_4 E_{i,t-n}$$
$$+\alpha_5 NegE_{i,t-n} + \alpha_6 ACC_{i,t-n} + \epsilon_{i,t}, \qquad \text{(HVZ)}$$

$$E_{i,t} = \alpha_0 + \alpha_1 NegE_{i,t-n} + \alpha_2 E_{i,t-n} + \alpha_3 NegE_{i,t-n} * E_{i,t-n}$$
$$+\epsilon_{i,t}, \qquad \text{(EP)}$$

$$E_{i,t} = \alpha_0 + \alpha_1 NegE_{i,t-n} + \alpha_2 E_{i,t-n} + \alpha_3 NegE_{i,t-n} * E_{i,t-n}$$
$$+\alpha_4 B_{i,t-n} + \alpha_5 TACC_{i,t-n} + \epsilon_{i,t}, \qquad \text{(RI)}$$

where $E_{i,t}$ is the earnings of firm *i* during year *t, A* is total assets, *D* is total dividends, *DD* is a dividend dummy, *NegE* is a negative earnings dummy*, ACC* is accruals as measured in HVZ, *NegE*E* is an interaction term between the negative earnings dummy and earnings, *B* is book value, and *TACC* is total accruals as measured in Richardson et al. (2005). Since we make forecasts up to five years in advance, we consider *n* ranging from 1 to 5. To ensure that there will not be any forward looking bias, we only use information known at time *t* to develop coefficient estimates for our prediction in year *t+1*. For example, to form 1-year forecasts for 2001, we will use a sample from 1991-2000 in the earnings prediction model, and the regressors will span the years 1990-1999. To form 5 year forecasts for 2001, we will use a sample from 1986-2000, and the regressors will span the years 1986-1995. In other words, we use a sample that considers the most recent 10 years of regressors without incurring a forward-looking bias.[9] We choose ten years as the basis for our prediction model because HVZ run their regression using the previous ten years of data. We use unscaled earnings as the ICC literature exclusively uses dollar earnings forecasts to estimate the ICC.

In our initial analyses, we use the same model that HVZ, LM, and RI use, but estimate the model using median regressions while the standard was to estimate the model using OLS. We then examine the difference in forecast accuracy using a median regression methodology relative to an OLS methodology. We cluster standard errors in two-dimensions - by year and by firm. We cluster standard errors by firm because the error terms could be correlated within firm due to common accounting treatment across years. We cluster standard errors by year because earnings shocks could affect particular industries, which could lead to correlated error terms within year.

We present results in Table 1. Forecast accuracy is defined as the mean absolute forecast error, and, like Hou, van Dijk and Zhang (2012) and Li and Mohanram (2014), we scale the forecast error by market equity. We use market equity as of three months after the last fiscal year end. First, we see that the mean absolute forecast error for earnings forecasts based on the OLS prediction model are significantly less accurate than forecasts based on a random walk. Specifically, we find that when we estimate the models using OLS regressions, the mean absolute deviation for forecasts at the one-year horizon are about 3 (6) percent of market value less accurate than the mean absolute deviation for forecasts based on a random walk for the RI

[9] We make predictions for years 1973-2016. Since we begin our data set in 1960, there will not be ten years of regressor data for long-horizon forecasts in the first few years.

and EP models (HVZ model). In contrast, when we estimate the EP and RI models using median regressions, the mean absolute deviation for forecasts at the one-year horizon is about 1-percent *more* accurate than the mean absolute deviation for forecasts based on a random walk. The HVZ model does not significantly beat a random walk, but does not lose to a random walk at the one-year horizon when median regression is used for estimation. At the two and three-year forecast horizons, we also see that OLS forecasts for the EP and RI models are significantly worse than random walk forecasts while forecasts based on median regressions for the EP and RI models are about 1-percent more accurate than random walk forecasts in terms of forecast accuracy. Using median regressions substantially improves the accuracy of HVZ forecasts, but they still lose to a random walk at longer horizons.

Our approach offers an advantage over an approach that uses winsorization as it does not require ad-hoc specifications of when/how to cut the distribution and allows us to consider the entire sample. Still, it is interesting to see whether a median regression approach is superior to an OLS approach after winsorization. We follow the approach in HVZ and winsorize all levels variables each year at the 1 percent and 99 percent levels and we find significant evidence that a median regression approach is still superior to an OLS approach. The results are presented in Table 2. For all models, at all horizons, earnings forecasts from the OLS approach are significantly less accurate than random walk forecasts at the one-percent level.[10] Consequently,

[10] Again, this assumes a mean absolute forecast error as the loss function. Interestingly, when mean squared forecast error is the loss function, we find that median regressions still produce more accurate forecasts

the median regression methodology continues to offer significant improvement over the OLS methodology. We present 1-year forecast results for the OLS and median regression methodologies by year in Figure 1. At the 1-year horizon, the median regression approach produces forecasts that are more accurate by about 1.3 percent of market-equity, 2.1 percent of market-equity, and 1.4 percent of market-equity relative to OLS forecasts for the HVZ, EP, and RI models, respectively. At the 2-year horizon, the median regression approach produces forecasts that are more accurate by about 3.5 percent of market-equity, 4.8 percent of market-equity, and 2.3 percent of market-equity relative to OLS forecasts for the HVZ, EP, and RI models, respectively. At the 3-year horizon, the median regression approach produces forecasts that are more accurate by about 5.4 percent of market-equity, 7.5 percent of market-equity, and 3.7 percent of market-equity relative to OLS forecasts for the HVZ, EP, and RI models, respectively. From this point forward, we mean OLS regressions with winsorization when we refer to OLS regressions.

Following the standard in the earnings forecasting literature (e.g. Li and Mohanram, 2014), we also calculate the median absolute forecast error. We find that median regressions produce far more accurate forecasts than OLS regressions with all three models. Indeed, all three models produce forecasts that are significantly more accurate than a random walk when the median regression methodology is used for estimation, while all three models produce forecasts that are less accurate than a random walk when OLS methodology is used for

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than forecasts based on OLS regressions most of the time. We present those results in the Supplementary Materials section.

estimation. The median absolute forecast error difference between forecasts produced using a median regression methodology and forecasts produced using an OLS regression methodology is significant at the one-percent level at all horizons for all models. We calculate standard errors in 2-dimensions – by firm and by year – using cluster bootstrap standard errors.

4.1.2 Shorter Estimation Window

In this subsection, we document how our modification to the HVZ methodology works when we shorten the estimation window. There are two primary reasons why it might be desirable to have shorter estimation windows. First, there may not be enough data for long horizon estimation (this could be especially true in international markets). Second, we may want to generate coefficient estimates based on a possible new regime. There are a number of reasons for regime changes - e.g. there may be a lot of new listings or a significant accounting rule change.

The motivation for examining shorter estimation windows comes from the stability of the parameters. In Figure 2, we see that the estimated coefficients are far more stable when they are estimated via median regressions rather than via OLS. This suggests that shortening the estimation window may not affect the reliability of estimates produced using median regressions.

We analyze how shorter estimation windows affect the accuracy of our earnings predictions. When we use a median regression methodology, we see similar levels of accuracy for forecasts produced from a short estimation window and forecasts produced from a long estimation window. When we use an OLS regression methodology, we see that forecasts produced from a short estimation window are less accurate than forecasts produced from a long estimation window. We present the results in Table 4. The magnitude of the difference in accuracy is larger with shorter estimation windows. Specifically, at the 1-year horizon, the median regression approach produces forecasts that are more accurate by about 3.5 percent of market equity, 4 percent of market equity, and 3 percent of market equity relative to OLS forecasts for the HVZ model, EP model, and RI model, respectively. At the 2-year horizon, the median regression approach produces forecasts that are more accurate by over 6 percent of market equity, over 5 percent of market equity, and over 3 percent of market equity relative to OLS forecasts for the HVZ model, EP model, and RI model, respectively. At the 3-year horizon, the median regression approach produces forecasts that are more accurate by about 7.9 percent of market equity, 8 percent of market equity, and 5 percent of market equity relative to OLS forecasts for the HVZ model, EP model, and RI model, respectively.

4.1.2 Scaling

Like Hou, van Dijk, and Zhang (2012), we predict unscaled earnings as we want to directly predict the input for valuation models. This results in firms with large earnings having a big impact on the estimation of the regression model. Specifically, firms with large earnings will have a lot of influence on the model's estimation as their error terms will be relatively large. To examine whether this is driving our results, we also predict scaled variables. Of course, it is also of interest to see how our methodological modification works when we predict scaled variables as academics and practitioners are also interested in predicting scaled variables. In this subsection, we document how our modification to the HVZ, EP, and RI models works when we adjust our estimation model by scaling the level variables. Specifically, we document how median regressions work as a forecasting tool relative to OLS regressions when we predict the return on market equity and the return on assets.

First, we predict the return on market equity (ROE) by scaling all level variables in equations (HVZ), (EP), and (RI) by market equity as of year (t-n). We present the results in Table 5. We find significant evidence that median regressions produce more accurate forecasts than OLS regressions even after scaling by market equity. For example, at the 1-year horizon, relative to an OLS regression methodology, median regressions produce mean absolute forecast errors about .25 percent of market equity smaller, about .18 percent of market equity smaller, .20 percent of market equity smaller than OLS regressions for the HVZ, EP, and RI models, respectively. All of these differences are significant at the 1-percent level when we cluster standard errors by firm and by year.

Next, we alter equations (HVZ), (EP), and (RI) by scaling all level variables by total assets as of year (t-n) (Total assets is dropped as a regressor in the HVZ model). In other words, we predict the return on assets (ROA) – a common profitability measure. We present the results in Table 6. We find significant evidence that median regressions produce more accurate profitability forecasts than OLS regressions. For example, at the 1-year horizon, relative to an OLS regression methodology, median regressions produce mean absolute forecast errors about .13 percent of total assets smaller, about .11 percent of total assets smaller, .38 percent of total assets smaller than OLS regressions for the HVZ, EP, and RI models, respectively. All these differences are significant at the 5-percent level when we cluster standard errors by firm and by year.

4.3 Earnings Response Coefficients

In this subsection, we examine earnings response coefficients (ERCs), which are a measure of how the market responds to earnings surprises. As Brown et al. (1987) note, the measurement error associated with proxies for market expectations will bias ERCs towards zero. As such, a better measure of market expectations is associated with a larger ERC. We analyze the ERCs associated with forecasts produced using median regressions and compare them with the ERCs from forecasts produced using OLS regressions and random walk forecasts. We find evidence that suggests the forecasts produced using median regressions are a better proxy for market expectations than those produced using OLS regressions.

We calculate earnings response coefficients based on buy and hold returns. We only consider firm-years for which we have earnings announcement date information. To calculate buy and hold return ERCs we run a regression each year of the following form:

$$N - Year\ Excess\ Return_i = \alpha_0 + \alpha_1 Scaled\ UE_i + \epsilon_i\ (ERC)$$

where the *N-year excess return* is the future N year return starting at the end of the third month after the previous year's fiscal year-end minus the CRSP value-weighted return over the same period. *Scaled UE*, or the scaled unexpected earnings, equals actual earnings minus the earnings forecast divided by market equity. When we use the future 3-year return as the dependent variable, we use the sum of the three annual *Scaled UEs*. To ease interpretation, and compare magnitudes across regressions, we next follow Hou, van Dijk and Zhang (2012) and standardize the *Scaled UE*, and the sum of *Scaled UEs*, to have mean zero and a standard deviation of one. The ERC now equals the average of α_1 across all years. The analysis starts in

1983 and runs until 2016 for the 1-year regressions and 2014 for the 3-year regressions.[11] We calculate ERCs for forecasts based on the HVZ, EP, and RI models using OLS regressions, for forecasts based on the HVZ, EP, and RI models using median regressions, and for forecasts based on a random walk. We present the results in Table 8. We find strong evidence in favor of the median regression methodology at long-horizons. The median regression methodology produces forecasts that offer higher ERCs at the 3-year horizon than the ERCs associated with forecasts produced using the OLS methodology at the 3-year horizon for the HVZ, EP, and RI models. For example, at the 3-year horizon, the ERC associated with the OLS regression methodology and the EP model is 0.278, which implies that a one-standard deviation increase in the earnings surprise is associated with a 3-year buy-and-hold excess return about 28 percent higher. On the other hand, the ERC associated with the median regression methodology and the EP model is 0.349, which implies that a one-standard deviation increase in the earnings surprise is associated with a 3-year buy-and-hold excess return about 35 percent higher. Additionally, the ERCs associated with the median regression methodology produce higher ERCs than those associated with a random walk at the 3-year horizon for the EP and RI model, while the ERCs associated with the OLS regression methodology produce lower ERCs than those associated with a random walk at the 3-year horizon for all 3 models.[12]

We also compute ERCs without standardization. We estimate equation (ERC) across the entire sample. Following the literature, we winsorize *Scaled UE* at the 1-percent level. Again, we find evidence, especially at longer horizons, that the median regression methodology produces

[11] Coverage is extremely limited before 1983.

[12] There are different ERCs for the random walk models as we compute the ERCs for the random walk model for the HVZ sample, the EP sample and the RI sample. The sample changes depending on data availability.

forecasts associated with higher ERCs than the OLS regression methodology and forecasts based on a random walk. For example, at the 1-year horizon, we see that the ERCs associated with the median regression methodology are higher than the ERCs associated with the OLS methodology across all 3 models. At the 3-year horizon, we see that the ERCs associated with the median regression methodology are higher than the ERCs associated with the OLS regression methodology across all 3 models and are higher than the ERCs associated with forecasts based on a random walk. ERCs associated with an OLS regression methodology are lower than a random walk.

5 Implied Cost of Capital and Returns

Perhaps the key motivation behind the HVZ model, and the subsequent EP and RI models is to produce a better implied cost of capital (ICC). Analyst forecasts produce unreliable ICCs and there is no earnings growth, a component of some ICC models, with random walk forecasts. Hou, van Dijk and Zhang (2012) show that using forecasts from the HVZ model produces much better ICCs than analyst forecasts. In this section, we show that using median regressions to estimate the HVZ model instead of OLS regressions produces even more reliable earnings forecasts to use in ICC calculations.

Following the methods of Gordon and Gordon (1997), Claus and Thomas (2001), Gebhardt, Lee and Swaminathan (2001), Easton (2004), and Ohlson and Juettner-Nauroth

(2005), we calculate five different ICCs.[13] We use the price at the close of the third month after the fiscal-year end. As such, to have the timing of market equity agree with the timing of accounting information in our ICC calculations, we discount market equity by $(1+r)^{1/4}$, where r is the implied cost of capital. For ICC calculations that involve future dividends, we also impose a restriction that dividends cannot be negative. Following HVZ, we assume a dividend payout ratio equal to the current dividend payout ratio for firms with positive earnings, or the current dividend divided by 0.06 times total assets for firms with negative earnings. We then use this dividend payout ratio for future periods. However, if the future earnings forecast is negative, we do not use this dividend payout ratio. Instead, we use the dividend payout ratio times the quantity of 0.06 times total assets.[14]

We first follow the literature and form quintile portfolios based on the implied cost of capital. We define the composite ICC as the average of the five ICCs. Like HVZ, we require only one non-missing ICC value. We present the results in Table 9 for ICCs constructed using earnings forecasts based on OLS models and earnings forecasts based on median regression

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[13] We acknowledge that there are significant problems with ICC calculations (Easton and Monahan, 2016). Still, the lack of a better alternative, the importance of an accounting based measure of expected returns, and their wide popularity motivates our analysis in this section. We show that our simple modification – the use of median regressions instead of OLS regressions – produces more reliable ICCs for a number of commonly used ICC measures.

[14] We solve for the implied cost of capital using numerical methods in R. We assume a lower bound of 0 and an upper bound of 1 when solving numerically.

models. We see a very similar pattern in portfolio returns regardless of which earnings forecasts are used. Like Hou, van Dijk and Zhang (2012), we find a positive association between ICCs and ex-post returns. This is encouraging given the weak link between ICCs based on analyst forecasts and ex-post returns (Easton and Monahan (2016), Hou, van Dijk, and Zhang (2012)).

Of course, academics and practitioners use ICCs for more than portfolio creation. Many desire an accurate measure of expected returns. It is possible that, while these forecasts produce very similar portfolios, they differ in the accuracy of the ICCs they produce. As such, we also measure the accuracy of ICCs. Specifically, we examine how ICCs relate, in terms of accuracy, to returns starting at the end of the month in which the fiscal year starts. We compare ICCs to two different measures. The first is the 1-year return. To reduce noise, we also compare ICCs to the cubic root of the future 3-year return. We first use the mean absolute error as our loss function to evaluate accuracy. We, again, calculate ICCs based on the methods of Gordon and Gordon (1997), Claus and Thomas (2001), Gebhardt, Lee and Swaminathan (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005). Again, we define the composite ICC as the average of the five ICCs. We find significant evidence that the use of median regression earnings forecasts produces more reliable ICCs than the use of OLS earnings forecasts. We present the results in Table 10. When we compare ICCs to the future 1-year return, we see that ICCs generated using median regressions have a mean absolute forecast error smaller by about 0.9 percent, 0.8 percent, and 0.3 percent relative to ICCs generated using OLS regressions for the HVZ, EP, and RI models, respectively. The difference is significant at the 1-percent level for all 3 models when standard errors are clustered by firm and by year. Similarly, when we compare ICCs to the cubic root of the future 3-year return, we see that ICCs generated using median regressions have a mean absolute forecast error smaller by about 1.2 percent, 1.2 percent, and .4 percent relative to ICCs generated using OLS regressions for the HVZ, EP, and RI models, respectively. The difference is significant at the 1-percent level for all 3 models.

For completeness, we consider another popular loss function – mean squared error. We present these accuracy results in Table 11. We find evidence of a significant difference in accuracy between the ICCs that quantile regressions produce and the ICCs than OLS regressions produce when we use a mean square error loss function and compare to the cubic root of 3-year returns. Specifically, median regression forecasts produce a mean squared error smaller by about 0.9 percent for the HVZ model and the EP model relative to mean squared error produced with OLS forecasts. Median regressions offer a mean squared error smaller by about 25 basis points relative to the mean squared error produced using OLS regressions. All of these differences are significant at the one-percent level. In summary, these results suggest that using median regressions to produce earnings forecasts leads to more reliable ICCs.

6 Conclusion

In this paper, we document that a very simple modification to the HVZ methodology – specifically, the use of median regressions in the estimation model rather than OLS regressions – produces significantly better earnings forecasts. Future practitioners and academics should consider using this modification when valuing companies, determining an earnings benchmark as part of a future contract, or as a means of forming an expectation of future market earnings.

There is still significant room for future research. One natural direction is to systematically study which variables to use in forecasting models more systematically and incorporate possible nonlinearities.

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Table 1 Forecast Accuracy – No Winsorization

This table highlights how median regressions substantially improve the accuracy of earnings forecasts when used instead of OLS regressions. Accuracy is measured by mean absolute deviation of the forecast from the actual divided by market equity as of the end of the third month after the previous fiscal year-end. HVZ = the Hou, van Dijk and Zhang methodology, EP= Earnings Persistence model, RI=residual income model, and RW = Random walk. Earnings is defined as income before extraordinary items minus special items from Compustat. LS indicates the model is estimated using least squares. MR indicates that the model is estimated using a median regression. We cluster standard errors in two-dimensions - by firm and by year. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Earnings in year (t+1)	Earnings in year (t+2)	Earnings in year (t+3)
Accuracy of HVZ (LS) – Accuracy of RW	0.0591***	0.0809***	0.0998***
Accuracy of HVZ (MR) – Accuracy of RW	-0.0003	0.0011	0.0035**
Accuracy of HVZ (MR) – Accuracy of HVZ (LS)	-0.0594***	-0.0798***	-0.0963***
Number of observations	115,966	106,573	98,310
Accuracy of EP (LS) – Accuracy of RW	0.0313***	0.0734***	0.1104***
Accuracy of EP (MR) – Accuracy of RW	-0.0101***	-0.0116***	-0.0087***
Accuracy of EP (MR) – Accuracy of EP (LS)	-0.0414***	-0.0850***	-0.1191***
Number of observations	162,705	147,879	135,000
Accuracy of RI (LS) – Accuracy of RW	0.0306***	0.0395***	0.0538***
Accuracy of RI (MR) – Accuracy of RW	-0.0090***	-0.0120***	-0.0087***
Accuracy of RI (MR) – Accuracy of RI (LS)	-0.0396***	-0.0515***	-0.0625***
Number of observations	141,975	129,490	118,593

Table 2 Forecast Accuracy - Main Result

This table highlights how median regressions substantially improve the accuracy of earnings forecasts when used instead of OLS regressions. Accuracy is measured by mean absolute deviation of the forecast from the actual divided by market equity as of the end of the third month after the previous fiscal year-end. HVZ = the Hou, van Dijk and Zhang methodology, EP= Earnings Persistence model, RI=residual income model, and RW = Random walk. Earnings is defined as income before extraordinary items minus special items from Compustat. LS indicates the model is estimated using least squares. We winsorize all levels variables at the one-percent level for LS prediction models. MR indicates that the model is estimated using a median regression. We cluster standard errors in two-dimensions - by firm and by year. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Earnings in year (t+1)	Earnings in year (t+2)	Earnings in year (t+3)
Accuracy of HVZ (LS) – Accuracy of RW	0.0126***	0.0356***	0.0572***
Accuracy of HVZ (MR) – Accuracy of RW	-0.0003	0.0011	0.0035**
Accuracy of HVZ (MR) – Accuracy of HVZ (LS)	-0.0129***	-0.0345***	-0.0537***
Number of observations	115,966	106,573	98,310
Accuracy of EP (LS) – Accuracy of RW	0.0106***	0.0362***	0.0664***
Accuracy of EP (MR) – Accuracy of RW	-0.0101***	-0.0116***	-0.0087***
Accuracy of EP (MR) – Accuracy of EP (LS)	-0.0207***	-0.0477***	-0.0751***
Number of observations	162,705	147,879	135,000
Accuracy of RI (LS) – Accuracy of RW	0.0048***	0.0106***	0.0288***
Accuracy of RI (MR) – Accuracy of RW	-0.0090***	-0.0120***	-0.0087***
Accuracy of RI (MR) – Accuracy of RI (LS)	-0.0139***	-0.0226***	-0.0374***
Number of observations	141,975	129,490	118,593

Table 3 Forecast Accuracy – Median Absolute Forecast Error

This table highlights how median regressions substantially improve the accuracy of earnings forecasts when used instead of OLS regressions. Accuracy is measured by median absolute deviation of the forecast from the actual divided by market equity as of the end of the third month after the previous fiscal year-end. HVZ = the Hou, van Dijk and Zhang methodology, EP= Earnings Persistence model, RI=residual income model, and RW = Random walk. Earnings is defined as income before extraordinary items minus special items from Compustat. LS indicates the model is estimated using least squares. We winsorize all levels variables at the one-percent level for LS prediction models. MR indicates that the model is estimated using a median regression. We cluster our bootstrapped standard errors in two-dimensions - by firm and by year. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Earnings in year (t+1)	Earnings in year (t+2)	Earnings in year (t+3)
Accuracy of HVZ (LS) – Accuracy of RW	0.0010***	0.0015***	0.0025*
Accuracy of HVZ (MR) – Accuracy of RW	-0.0009***	-0.0010***	-0.0015**
Accuracy of HVZ (MR) – Accuracy of HVZ (LS)	-0.0020***	-0.0021***	-0.0028***
Number of observations	115,966	106,573	98,310
Accuracy of EP (LS) – Accuracy of RW	0.0006	0.0040**	0.0076***
Accuracy of EP (MR) – Accuracy of RW	-0.0016***	-0.0017***	-0.0021***
Accuracy of EP (MR) – Accuracy of EP (LS)	-0.0008***	-0.0018***	-0.0036***
Number of observations	162,705	147,879	135,000
Accuracy of RI (LS) – Accuracy of RW	0.0002	0.0007	0.0019
Accuracy of RI (MR) – Accuracy of RW	-0.0013***	-0.0016***	-0.0019***
Accuracy of RI (MR) – Accuracy of RI (LS)	-0.0009***	-0.0011***	-0.0020***
Number of observations	141,975	129,490	118,593

Table 4 Forecast Accuracy – 1 year Estimation Window

This table highlights how median regressions substantially improve the accuracy of earnings forecasts relative to forecasts based on OLS regressions when the estimation window is 1 year long. Accuracy is measured by mean absolute deviation of the forecast from the actual divided by market equity as of the end of the third month after the previous fiscal year-end. HVZ = the Hou, van Dijk and Zhang methodology, EP= Earnings Persistence model, RI=residual income model, and RW = Random walk. Earnings is defined as income before extraordinary items minus special items from Compustat. LS indicates the model is estimated using least squares. We winsorize all levels variables at the one-percent level for LS prediction models. MR indicates that the model is estimated using a median regression. We cluster standard errors in two-dimensions - by firm and by year. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Earnings in year (t+1)	Earnings in year (t+2)	Earnings in year (t+3)
Accuracy of HVZ (LS) – Accuracy of RW	0.0343***	0.0633***	0.0845***
Accuracy of HVZ (MR) – Accuracy of RW	-0.0006	0.0017	0.0056**
Accuracy of HVZ (MR) – Accuracy of HVZ (LS)	-0.0349***	-0.0615***	-0.0789***
Number of observations	115,966	106,573	98,310
Accuracy of EP (LS) – Accuracy of RW	0.0310***	0.0455***	0.0757***
Accuracy of EP (MR) – Accuracy of RW	-0.0064***	-0.0075***	-0.0050*
Accuracy of EP (MR) – Accuracy of EP (LS)	-0.0374***	-0.0529***	-0.0806***
Number of observations	162,705	147,879	135,000
Accuracy of RI (LS) – Accuracy of RW	0.0230***	0.0266***	0.0451***
Accuracy of RI (MR) – Accuracy of RW	-0.0057***	-0.0077***	-0.0046*
Accuracy of RI (MR) – Accuracy of RI (LS)	-0.0287***	-0.0343***	-0.0497***
Number of observations	141,975	129,490	118,593

Table 5 Forecast Accuracy – Scaling by Market Equity

This table highlights how median regressions improve the accuracy of earnings forecasts when one scales by market equity in the prediction model. Accuracy is measured by mean absolute deviation of the forecast from the actual. HVZ = the Hou, van Dijk and Zhang methodology, EP= Earnings Persistence model, RI=residual income model, and RW = Random walk. Earnings is defined as income before extraordinary items minus special items from Compustat. LS indicates the model is estimated using least squares. We winsorize all levels variables at the one-percent level for LS prediction models. MR indicates that the model is estimated using a median regression. We cluster standard errors in two-dimensions - by firm and by year. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Earnings in year (t+1)	Earnings in year (t+2)	Earnings in year (t+3)
Accuracy of HVZ (MR) – Accuracy of HVZ (LS)	-0.0025***	-0.0009***	-0.0015***
Number of observations	115,318	105,823	97,514
Accuracy of EP (MR) – Accuracy of EP (LS)	-0.0018***	-0.0003	-0.0012***
Number of observations	161,923	146,977	134,017
Accuracy of RI (MR) – Accuracy of RI (LS)	-0.0020***	-0.0006	-0.0011**
Number of observations	141,250	128,666	117,708

Table 6 Forecast Accuracy – Scaling by Total Assets

This table highlights how median regressions improve the accuracy of earnings forecasts when one scales by total assets in the prediction model. Accuracy is measured by mean absolute deviation of the forecast from the actual. HVZ = the Hou, van Dijk and Zhang methodology, EP= Earnings Persistence model, RI=residual income model, and RW = Random walk. Total assets is dropped as one of the predictors in the HVZ model. Earnings is defined as income before extraordinary items minus special items from Compustat. LS indicates the model is estimated using least squares. We winsorize all levels variables at the one-percent level for LS prediction models. MR indicates that the model is estimated using a median regression. We cluster standard errors in two-dimensions - by firm and by year. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Earnings in year (t+1)	Earnings in year (t+2)	Earnings in year (t+3)
Accuracy of HVZ (MR) – Accuracy of HVZ (LS)	-0.0013***	-0.0013***	-0.0018***
Number of observations	117,848	108,238	99,791
Accuracy of EP (MR) – Accuracy of EP (LS)	-0.0011***	-0.0012**	-0.0011*
Number of observations	164,466	149,451	136,391
Accuracy of RI (MR) – Accuracy of RI (LS)	-0.0038**	-0.0040*	0.0009
Number of observations	144,077	131,363	120,253

Table 7 Earnings Response Coefficient – Buy and Hold Returns (Standardized)

This table presents the results of regressions of long horizon excess returns on unexpected earnings scaled by market equity normalized to have mean zero and a standard deviation of one. The buy and hold returns start at the end of the third month after the previous fiscal year end. They continue for 3 years or 1 years – as indicated. We scale the forecast errors, or the sum of the next 3 or 1 annual forecast errors, by market equity at the end of the 3rd month after the previous fiscal year end. We then standardize the unexpected earnings to have mean zero and a standard deviation of one. LS indicates the use of earnings forecasts derived from using OLS in the prediction model. MR indicates the use of earnings forecasts derived from using median regressions in the prediction model. RW indicates the use of earnings forecasts based on a random walk. HVZ indicates the use of the Hou, van Dijk and Zhang (2012) model. EP indicates the use of the earnings persistence model and RI indicates the use of the residual income model. We consider years from 1983-2016. (We only consider years until 2014 if we are looking at the 3 year horizon) * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	1-year return	1-year return	1-year return	3-year return	3-year return	3-year return
RW-HVZ	0.164***			0.340***		
t-stat	(5.39)			(7.67)		
LS-HVZ		0.111***			0.265***	
t-stat		(9.77)			(7.54)	
MR-HVZ			0.116***			0.293***
t-stat			(9.11)			(8.81)
RW-EP	0.0986***			0.296***		
t-stat	(9.51)			(9.03)		
LS-EP		0.0920***			0.278***	
t-stat		(8.87)			(9.49)	
MR-EP			0.0987***			0.349***
t-stat			(9.86)			(10.61)
RW-RI	0.142***			0.333***		
t-stat	(5.21)			(9.47)		
LS-RI		0.111***			0.337***	
t-stat		(10.26)			(7.49)	
MR-RI			0.109***			0.346***
t-stat			(10.32)			(11.09)

Table 8 Earnings Response Coefficient – Buy and Hold Returns

This table presents the results of regressions of buy and hold excess returns on unexpected earnings divided by market equity. We winsorize the scaled unexpected earnings divided by market equity at the one-percent level. The buy and hold returns start at the end of the third month after the previous fiscal year end. They continue for 3 years or 1 year – as indicated. We scale the forecast errors, or the sum of the next 3 or 1 annual forecast errors, by market equity at the end of the 3rd month after the previous fiscal year end. LS indicates the use of earnings forecasts derived from using OLS in the prediction model. MR indicates the use of earnings forecasts derived from using median regressions in the prediction model. RW indicates the use of earnings forecasts based on a random walk. HVZ indicates the use of the Hou, van Dijk and Zhang (2012) model. EP indicates the use of the earnings persistence model and RI indicates the use of the residual income model. We cluster our standard errors by year and by firm. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	1-year return	1-year return	1-year return	3-year return	3-year return	3-year return
RW-HVZ	1.287***			1.218***		
t-stat	(8.82)			(12.63)		
LS-HVZ		1.155***			1.029***	
t-stat		(7.39)			(8.70)	
MR-HVZ			1.259***			1.275***
t-stat			(8.71)			(12.97)
N	70,427	70,427	70,427	55,266	55,266	55,266
RW-EP	1.175***			1.177***		
t-stat	(8.78)			(11.89)		
LS-EP		0.851***			0.732***	
t-stat		(8.22)			(7.71)	
MR-EP			1.062***			1.289***
t-stat			(8.67)			(10.80)
N	112,094	112,094	112,094	87,554	87,554	87,554
RW-RI	1.230***			1.214***		
t-stat	(8.57)			(13.10)		
LS-RI		1.062***			1.119***	
t-stat		(8.83)			(10.85)	
MR-RI			1.155***			1.360***
t-stat			(9.69)			(12.25)
N	92,962	92,962	92,962	72,571	72,571	72,571

Table 9 Quintile Portfolios

This table presents portfolio raw returns by quintile. We form portfolios at the end of each June from 1972-2015 based on the composite ICCs calculated in the previous year. We define the composite ICC as the average of the Gordon and Gordon (1997), Claus and Thomas (2001), Gebhardt, Lee and Swaminathan (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005) ICCs. We require one non-missing ICC value to calculate the composite ICC. We then examine the raw return over the following year for the different quintiles. HVZ indicates the use of the Hou, van Dijk and Zhang (2012) model. EP indicates the use of the earnings persistence model and RI indicates the use of the residual income model. The first column shows the portfolio results when quintiles are formed using the composite ICC based on median regression earnings forecasts. The second column document portfolio results when quintiles are formed using the composite ICC based on OLS earnings forecasts. *** indicates significance at the 1% level.

HVZ Model		
	Median Regression Forecasts	OLS Regression Forecasts
Bottom	0.117***	0.118***
2nd	0.166***	0.157***
3rd	0.178***	0.170***
4th	0.190***	0.189***
Top	0.226***	0.242***
EP Model		
Bottom	0.115***	0.123***
2nd	0.163***	0.158***
3rd	0.185***	0.172***
4th	0.189***	0.185***

Top	0.223***	0.236***
RI Model		
	Median Regression Forecasts	OLS Regression Forecasts
Bottom	0.120***	0.122***
2nd	0.162***	0.160***
3rd	0.184***	0.179***
4th	0.186***	0.189***
Top	0.228***	0.231***

Table 10 ICC Accuracy

This table highlights how median regressions substantially improve the accuracy of implied cost of capital (ICC) as measured by mean absolute deviation of the ICC from the actual ex-post return. We examine how ICCs relate to future 1-year returns and the cubic root of future 3-year returns. The return period starts at the end of the third month after the fiscal-year end. We define the composite ICC as the average of the Gordon and Gordon (1997), Claus and Thomas (2001), Gebhardt, Lee and Swaminathan (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005) ICCs. We require one non-missing ICC value to calculate the composite ICC. HVZ indicates the use of the Hou, van Dijk and Zhang (2012) model. EP indicates the use of the earnings persistence model and RI indicates the use of the residual income model. MR represents the use of earnings forecasts obtained from the associated model using median regressions and LS represents the use of earnings forecasts obtained from the associated model using OLS regressions. Standard errors are clustered by firm and by year. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	1-year	3-year
Accuracy of HVZ Composite ICC (MR) – Accuracy of HVZ Composite ICC (LS)	-0.0089***	-0.0119***
t-stat	(-6.65)	(-11.69)
N	102,660	91,100
Accuracy of EP Composite ICC (MR) – Accuracy of EP Composite ICC (LS)	-0.0081***	-0.0120***
t-stat	(-5.26)	(-8.63)
N	144,316	128,266
Accuracy of RI Composite ICC (MR) – Accuracy of RI Composite ICC (LS)	-0.0029***	-0.0039***
t-stat	(-3.62)	(-4.15)
N	119,751	107,193

Table 11 ICC Accuracy using MSE

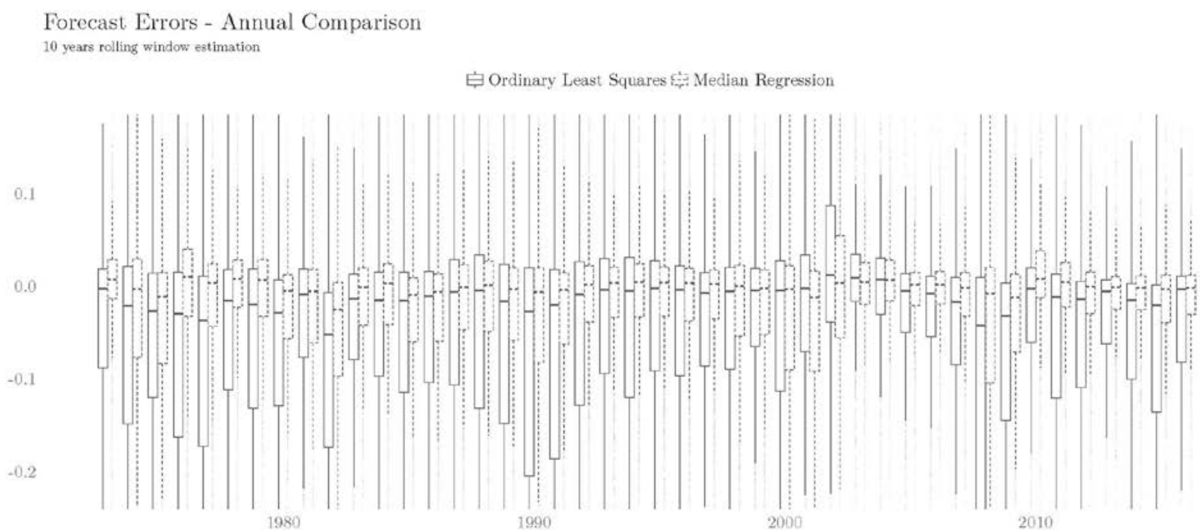
This table highlights how median regressions improve the accuracy of implied cost of capital (ICC) as measured by mean square error of the ICC from the actual ex-post return. We examine how ICCs relate to future 1-year returns and the cubic root of future 3-year returns. The return period starts at the end of the third month after the fiscal-year end. We define the composite ICC as the average of the Gordon and Gordon (1997), Claus and Thomas (2001), Gebhardt, Lee and Swaminathan (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005) ICCs. We require one non-missing ICC value to calculate the composite ICC. EP indicates the use of the earnings persistence model and RI indicates the use of the residual income model. MR represents the use of earnings forecasts obtained from the associated model using median regressions and LS represents the use of earnings forecasts obtained from the associated model using OLS regressions. Standard errors are clustered by firm and by year. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	1-year	3-year
Accuracy of HVZ Composite ICC (MR) – Accuracy of HVZ Composite ICC (LS)	0.0046	-0.0086***
t-stat	(1.18)	(-9.04)
N	102,660	91,100
Accuracy of EP Composite ICC (MR) – Accuracy of EP Composite ICC (LS)	0.0010	-0.0089***
t-stat	(0.32)	(-6.87)
N	144,316	128,266
Accuracy of RI Composite ICC (MR) – Accuracy of RI Composite ICC (LS)	0.0016	-0.0025***
t-stat	(0.92)	(-3.19)
N	119,751	107,193

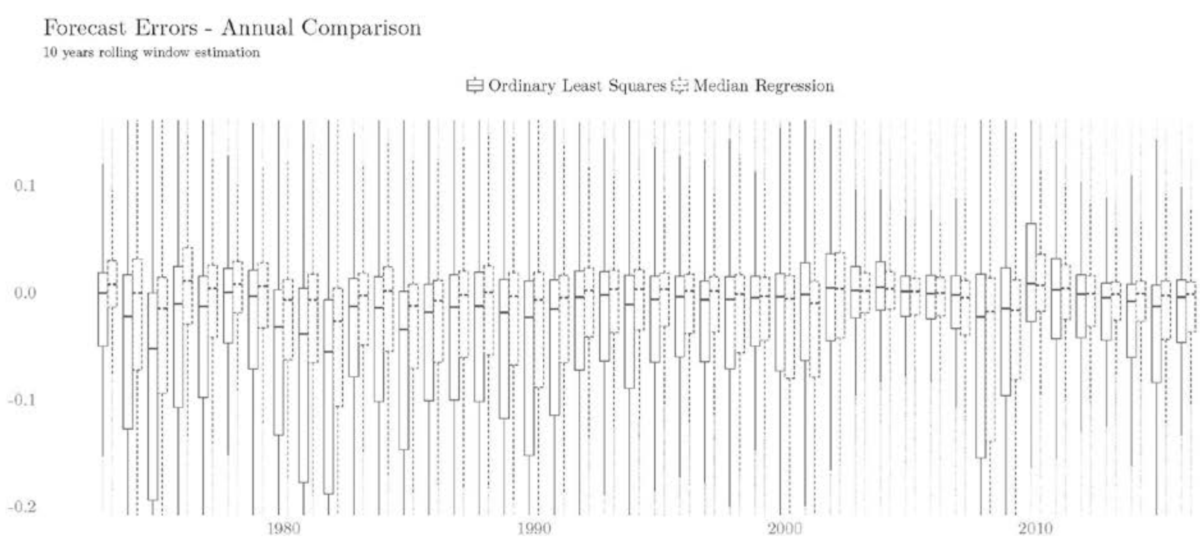
Figure 1

This figure presents forecast accuracy by year for the three cross-sectional models under consideration.

Hou, van Dijk and Zhang (2012) Model



Earnings Persistence Model



Residual Income Model

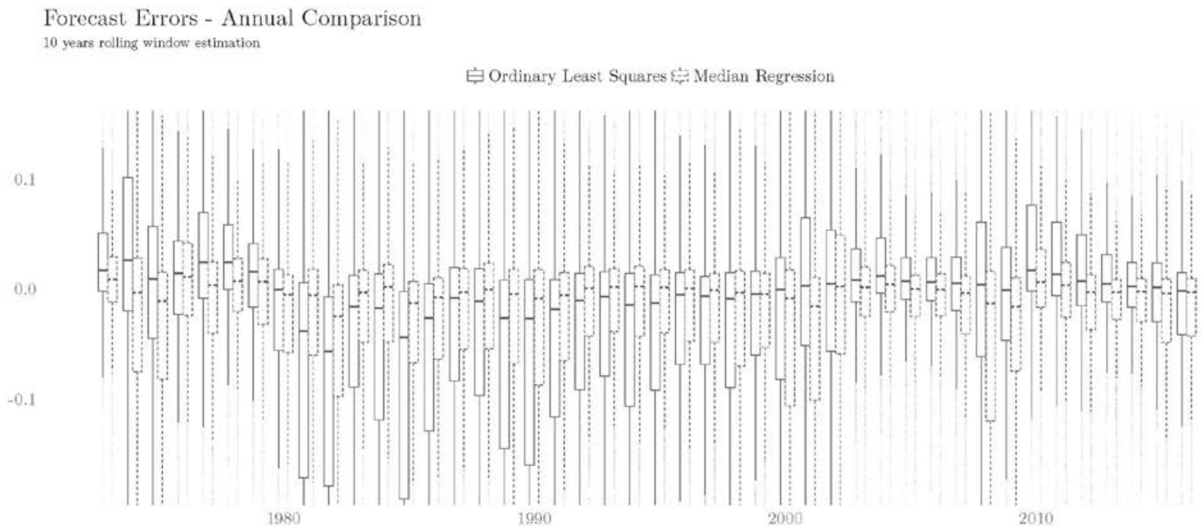
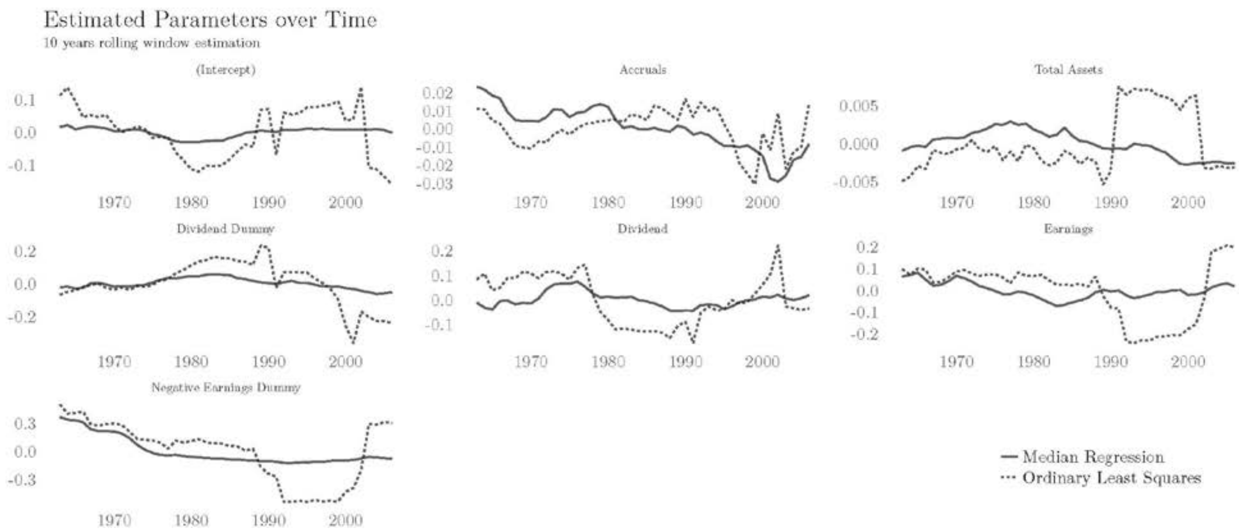
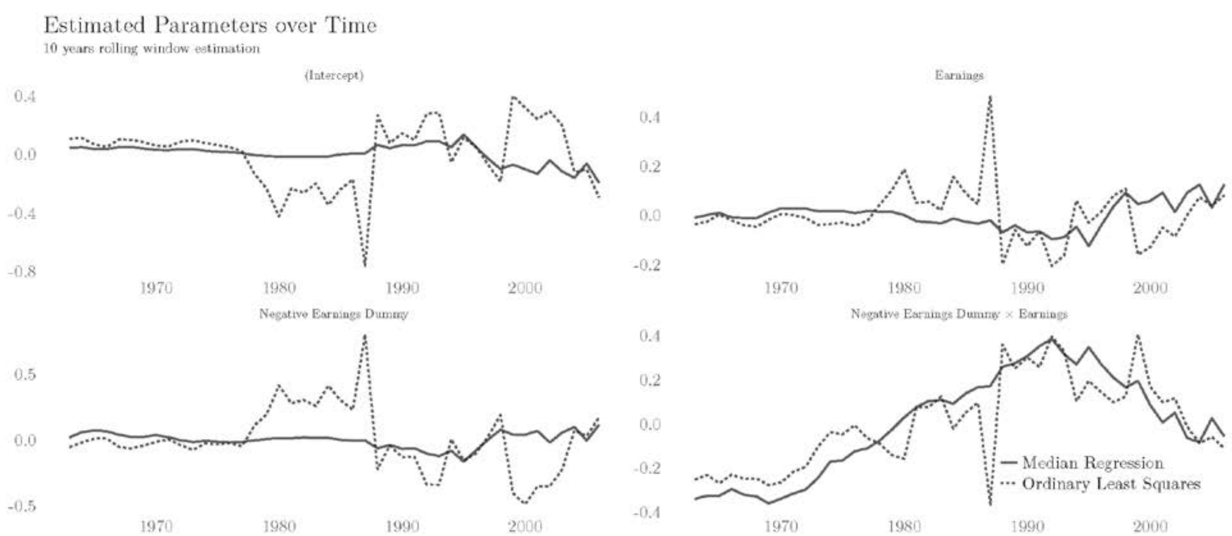


Figure 2

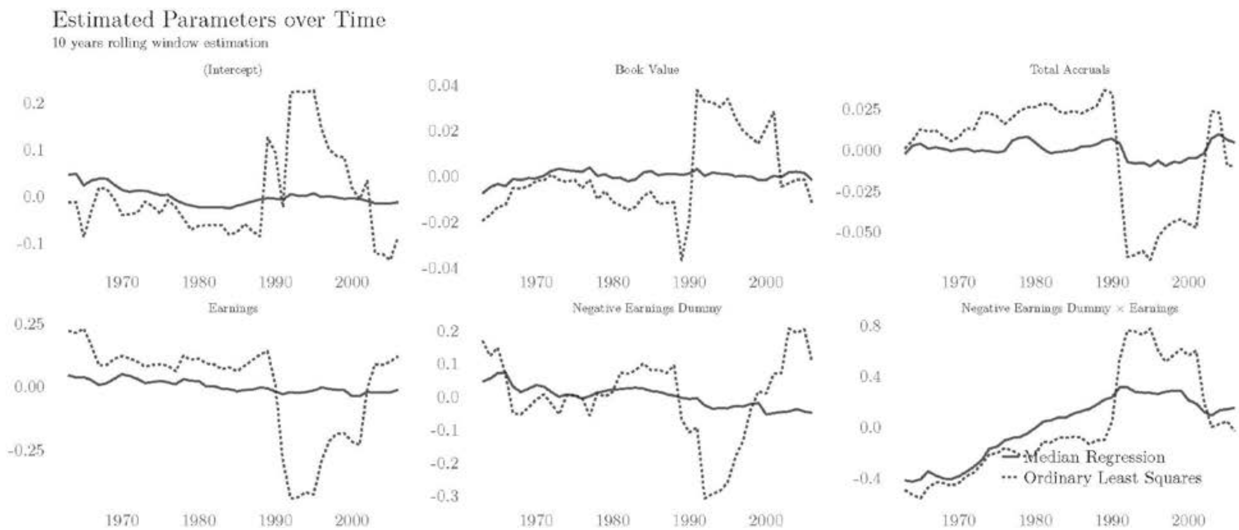
Hou, van Dijk and Zhang (2012) Model



Earnings Persistence Model



Residual Income Model



Supplementary Material

Forecast Accuracy - MSE

This table highlights how median regressions substantially improve the accuracy of earnings forecasts. Accuracy is measured by mean squared error of the forecast from the actual divided by market equity as of the end of the third month after the previous fiscal year-end. HVZ = the Hou, van Dijk and Zhang methodology, EP= Earnings Persistence model, RI=residual income model, and RW = Random walk. Earnings is defined as income before extraordinary items minus special items from Compustat. LS indicates the model is estimated using least squares. We winsorize all levels variables at the one-percent level for LS prediction models. MR indicates that the model is estimated using a median regression. We cluster standard errors in two-dimensions - by firm and by year. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Earnings in year (t+1)	Earnings in year (t+2)	Earnings in year (t+3)
Accuracy of HVZ (LS) – Accuracy of RW	-0.0050	0.0482**	0.1702***
Accuracy of HVZ (MR) – Accuracy of RW	0.0024	-0.0024	0.0435
Accuracy of HVZ (MR) – Accuracy of HVZ (LS)	0.0075	-0.0506***	-0.1267***
Number of observations	115,966	106,573	98,310
Accuracy of EP (LS) – Accuracy of RW	-0.1729	0.0676*	0.2465***
Accuracy of EP (MR) – Accuracy of RW	-0.2032*	-0.0901***	-0.0563**
Accuracy of EP (MR) – Accuracy of EP (LS)	-0.0303***	-0.1578***	-0.3028***
Number of observations	162,705	147,879	135,000
Accuracy of RI (LS) – Accuracy of RW	-0.0400*	-0.0560*	0.0709
Accuracy of RI (MR) – Accuracy of RW	-0.0715***	-0.1113***	-0.0480
Accuracy of RI (MR) – Accuracy of RI (LS)	-0.0315***	-0.0553***	-0.1189***
Number of observations	141,975	129,490	118,593