Multiples for Valuation: Go High, Go Low, Ignore the Middle

Javier Estrada*
IESE Business School | Department of Finance | Av. Pearson 21 | 08034 Barcelona | Spain
Tel: +34 93 253 4200 | Email: jestrada@iese.edu | Web: https://blog.iese.edu/jestrada

Abstract
Multiples such as D/P, P/E and CAPE have long been viewed as being useful to forecast returns over periods of ten or so years. The evidence discussed in this article supports this belief and takes it one step further by showing that multiples are far more useful when they are relatively high or low than when they are somewhere in the middle of their historical range. In fact, relatively high or low multiples are more highly correlated to forward returns in sample, and produce better return forecasts out of sample, than multiples that lie somewhere in the middle.

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1. Introduction

Multiples have been used for stock valuation, and by extension for forecasting stock returns, at least since the early 1920s; however, after more than a century of debate, there does not seem to be a consensus on how successful they are for this purpose. For this reason, this article does not aim to settle a debate that perhaps just cannot be settled; rather, it seeks to highlight a condition that makes multiples relatively more useful for forecasting stock returns.

In a nutshell, the evidence discussed here shows that multiples are more useful for stock return forecasting when they take relatively high or low values rather than values in the middle of their historical range. In fact, relatively high or low multiples are more highly correlated to forward returns in sample, and produce better stock return forecasts out of sample, than multiples that lie somewhere in between.

'High' and 'low' multiples are defined here as those in the top and bottom quartiles when the sample is sorted by a given multiple, with 'middle' multiples being those in the two middle quartiles. To be sure, the results discussed are robust to at least two other definitions of high and low multiples, such as those in the top and bottom deciles, or those being more than one standard deviation above and below the average multiple.

The rest of the article is organized as follows. Section 2 introduces the issue and provides a very brief overview of the literature; section 3 discusses the evidence; and section 4 provides an assessment. An appendix with exhibits concludes the article.

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2. Background

Multiples have been used for stock valuation, and indirectly to forecast stock returns, at least since the early 1920s. In fact, Charles Dow, co-founder of the Wall Street Journal, related dividend yields to stock valuation in his classic *Scientific Stock Speculation* (Dow, 1920), and Benjamin Graham and David Dodd related price-earnings ratios to stock valuation in their classic *Security Analysis* (Graham and Dodd, 1934).

However, more than one century of debate has not settled the issue of how useful multiples are for forecasting stock returns. The fact that different articles use different variables, time periods, and techniques, and even different countries, obviously does not help. Welch and Goyal (2008) summarize the evidence on this issue as of early 2006 and reach a rather pessimistic conclusion, namely, that most variables (models) used to forecast stock returns are unstable or spurious and eventually cease to work. In fact, they conclude that investors would have done just as well by assuming that the expected equity risk premium would be as it has always been. Goyal et al (2024) reach a similar conclusion with evidence extended as of early 2022.

Three multiples are the focus of this inquiry, the dividend yield (D/P), the price-earnings ratio (P/E), and the cyclically-adjusted price-earnings ratio (CAPE).[1] In order to make the results easier to compare to D/P, both P/E and CAPE are inverted so that the analysis ultimately focuses on D/P, E/P, and 1/CAPE, which from this point on will be referred to as the *dividend yield* (DY = D/P), the *earnings yield* (EY = E/P), and the *CAPE yield* (CY = 1/CAPE). Therefore, although the discussion throughout refers to multiples, the variables ultimately used here actually are yields.

Beyond Dow (1920), Rozeff (1984), Campbell and Shiller (1988), and Fama-French (1988) are some of the early advocates of using dividend yields to forecast stock returns. On the contrary, Goetzmann and Jorion (1993) argue that there is no strong statistical evidence indicating that dividend yields can be used to forecast stock returns, with Welch and Goyal (2008) and Goyal et al (2024) largely agreeing with their conclusion.

Furthermore, beyond Graham and Dodd (1934), Basu (1977) was an early advocate of using P/E ratios for stock valuation, and therefore for stock return forecasting. Campbell and Shiller's (1998) influential and prescient article stressed the forecasting ability of both P/E and CAPE and predicted, toward the end of the dot-com bubble, a decline of 40% in real terms in the stock market over the following ten years. Weigand and Irons (2007) also report evidence supporting the use of P/E and CAPE to forecast stock returns, in their case with a less pessimistic outlook for the market than other perspectives at the time.

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[1] As is well known, unlike the P/E, which is based on earnings for a single year, CAPE is based on an average of inflation-adjusted earnings over the previous ten years.

Estrada (2015) finds that P/D, P/E, and CAPE are related to 10-year forward returns, but also finds that these multiples are not helpful for determining a dynamic asset allocation strategy that outperforms a static strategy. Boucher et al (2023) find, unlike most of the previous literature, that the dividend yield, CAPE, and excess CAPE yield help to forecast *short*-term (6/12-month) stock returns. Ma et al (2024) run a horse race of models used to forecast returns 10 and 20 years ahead and find that a decomposition of returns that captures the valuation change through the variation in total return CAPE wins the race. Murphy et al (2025) find that the simple difference between the earnings yield of the stock market and the 10-year TIPS real yield is able to explain one third (one half) of stock returns five (ten) years ahead.

Finally, and importantly for the whole literature about the ability of different multiples and (more generally) variables used to forecast stock returns, Boudoukh et al (2019) argue that the standard use of overlapping observations leads to the overestimation of statistical significance; they also argue that some of the usual adjustments, such as Newey-West standard errors, help very little in alleviating this problem. Given this widely-accepted argument, the discussions below about the significance of the variables considered here should perhaps be thought of as being preceded by the sentence "For whatever is worth, …"

3. Evidence

3.1. Data and Methodology

The data consists of prices, earnings, and dividends for the U.S. stock market, downloaded from Robert Shiller's web page.[2] Returns are quarterly and account for capital gains/losses and dividends. Both nominal and real returns are calculated, the latter taking into account the rate of inflation based on the Consumer Price Index (CPI). The sample period goes from the end of the first quarter of 1871 (Q1/1871) through the end second quarter of 2025 (Q2/2025). Exhibit A1 in the appendix provides some summary statistics on all the relevant variables in the sample.

As already discussed, the three multiples on which the analysis focuses are D/P, P/E, and CAPE, with the last two inverted; hence the focus is on the dividend yield (DY = D/P), the earnings yield (EY = E/P), and the CAPE yield (CY = 1/CAPE). Both dividends and earnings are lagged by one quarter to avoid any look-ahead bias. Over the whole sample period, the average D/P, P/E, and CAPE are 4.2%, 16.4, and 17.6, with an average EY and CY of 6.1% and 5.7%, respectively.[3]

The first step of the analysis consists of calculating nominal and real 10-year *forward* annualized returns over the whole sample period. The first such return is calculated at the end of

[2] See http://www.econ.yale.edu/~shiller/data.htm; the proxy for the U.S. stock market is the S&P 500.
[3] Only the P/E series has two clear outliers, 135.0 and 139.1, which occurred in the second and third quarter of 2009; a third potential outlier, 88.5, occurred in the last quarter of 2009. These three observations are more than three standard deviations away from the mean.

Q2/1871, over the Q3/1871–Q2/1881 period; and the last one at the end of Q2/2015, over the Q3/2015–Q2/2025 period. This yields 577 quarterly (nominal and real) 10-year forward annualized returns, which for ease of exposition will be referred to simply as 'forward returns' from this point on. Unless otherwise stated, all (forward, expected, and observed) returns in this article are calculated over a 10-year period and expressed in annualized terms.

Given a multiple (DY, EY, or CY) and a type of return (nominal or real), the multiple at the beginning of the sample period is paired with the forward return over the subsequent ten years. Similar pairings are then made quarter after quarter until the sample runs out, yielding two quarterly series, one for the multiple and the other for its associated forward returns. To illustrate, the DY, EY, and CY at the end of Q2/1871 are associated to the (nominal and real) returns over the Q3/1871–Q2/1881 period; and the DY, EY, and CY at the end of Q2/2015 are associated to the (nominal and real) returns over the Q3/2015–Q2/2025 period.

This methodology produces quarterly time series of six relationships, namely, DY and forward nominal returns, DY and forward real returns, EY and forward nominal returns, EY and forward real returns, CY and forward nominal returns, and CY and forward real returns. The first step of the analysis is to evaluate the strength of each of these six relationships.

3.2. Multiples and Forward Returns – In-Sample Correlations

Exhibit 1 shows in its second column (All) the correlations between each multiple (DY, EY, and CY) and each type of return (nominal and real) for the full sample. The six correlations have the expected sign and are significantly different from 0 given a two-tailed test and a 5% level of significance. Forward nominal returns are most highly correlated to EY (0.49) and forward real returns are most highly correlated to CY (0.51).

Exhibit 1: Multiples and Forward Returns – In-Sample Correlations

This exhibit shows correlations between three multiples (DY, EY, and CY) and two types of 10-year forward annualized returns (nominal and real). The correlations in the second column (All) are for the full sample; those in the third column (H+L) are only for the top and bottom quartiles when all observations are sorted by a given multiple; and those in the fourth column (Middle) are for the two quartiles in the middle. The figures in parenthesis indicate the cutoff points for the top and bottom quartiles. The figures in square brackets are correlations for a sample of non-overlapping observations. * indicates statistical significance at the 5% level in a two-tailed test. The data is described in Exhibit A1 in the appendix.

	All	H+L	Middle
Panel A: DY		(> 5.38 , < 3.20)	
Nominal returns	0.21* [0.26]	0.30*	0.03
Real returns	0.36* [0.35]	0.45*	0.09
Panel B: EY		(> 8.79 , < 5.49)	
Nominal returns	0.49* [0.61]	0.63*	0.11
Real returns	0.48* [0.57]	0.61*	0.18*
Panel C: CY		(> 8.47 , < 5.01)	
Nominal returns	0.48* [0.45]	0.57*	0.21*
Real returns	0.51* [0.51]	0.66*	0.09

The use of overlapping observations begs at least two comments. First, as already discussed, the significance of correlations is likely to be overstated; however, that is less relevant for the analysis here, which focuses on *relative* (rather than on absolute) correlations. Second, using non-overlapping observations produces correlations (shown in square brackets in the exhibit), which are rather similar to those reported for overlapping observations.

The finding that multiples and forward returns are strongly correlated is not new. The more novel part of the analysis starts by sorting each multiple and its associated forward (nominal and real) returns from the highest to the lowest multiple, and then splitting the ranking into quartiles. The top and the bottom quartiles are then isolated from the two middle quartiles, and correlations are calculated separately for these two groups. For ease of exposition, from this point on those in the top (bottom) quartile will be referred as 'high' ('low') multiples, and those in the two middle quartiles will be referred to as 'middle' multiples.

Correlations between multiples and forward returns for the subsample that groups the top and bottom quartiles (that is, high and low multiples) are shown in the third column (H+L) of Exhibit 1, and those for the subsample that groups the two middle quartiles are shown in the fourth column (Middle). The figures in parenthesis in the H+L column indicate the cutoff points for the quartiles; for example, the top (bottom) quartile for EY consists of all the observations with EY higher than 8.79% (lower than 5.49%).

As these figures clearly show, the correlations in the H+L column are markedly higher than the respective correlations in the Middle column. In fact, although all six correlations in the H+L column are significantly different from 0, four of the six correlations in the Middle column are not; only those correlations between EY and real returns (0.18) and CY and nominal returns (0.21) are. Put differently, multiples are far more closely related to forward returns in sample, and therefore should be more useful for forecasting returns out of sample, when they take relatively high or low values than values somewhere in between.

To elaborate, and to add some precision, DY (EY) [CY] provides a much stronger signal about expected returns when it is roughly lower than 3% (5%) [5%] or higher than 6% (9%) [9%] than when it is somewhere between those figures. Or, put differently, changes in DY within the 3–6% range, or changes in EY or CY within the 5–9% range, do not convey much information about changes in expected returns.

3.3. Multiples and Forward Returns – Out-of-Sample Forecasting

The results discussed so far suggest that multiples and forward returns are strongly correlated, and that such correlation is stronger when multiples are relatively high or low than when they are somewhere in the middle. These in-sample correlations are obviously useful, but the ultimate test of a model is its ability to make accurate forecasts out of sample; that is the issue addressed in this section.

The analysis is implemented in two steps: First, quarterly series of *expected* real returns are produced from models based on the three multiples considered here; and second, those expected real returns are compared to observed real returns in order to evaluate the forecasting ability of the models. All forecasts are made from the expression

$$R_{t+40} = \alpha + \beta \cdot M_t + u_t \quad (1)$$

where R_{t+40} denote expected real returns; M_t is the value of a multiple (DY, EY, or CY); α and β are coefficients to be estimated; u is an error term; and t indexes quarters.[4]

The first alpha and beta from expression (1) are estimated using the first five years (20 quarters) of data, with the first forecast being made at the end of Q1/1876 (for the Q2/1876–Q1/1886 period).[5] After each quarter alpha and beta are re-estimated, progressively adding one new observation, with the last forecast being made at the end of Q2/2015 (for the Q3/2015–Q2/2025 period) based on alpha and beta estimated by using all previous observations. This methodology implies running 558 regressions (518 for CY), producing 558 of estimates of alpha and beta, and generating 558 quarterly real return forecasts, which are then compared to their respective observed real returns. Exhibit 2 summarizes the results.

Panels A1-A3 of the second column (All) show the correlations between forecasted and observed returns (0.39 for DY, 0.48 for EY, and 0.56 for CY) using all the observations in the sample; for all three models the correlations have the expected positive sign and are significantly different from 0. Moreover, for all three models the mean deviation (MD) is less than one quarter of 1% and the mean absolute deviation (MAD) is less than 1%, in both cases in annual terms. These results suggest that DY, EY, and CY provide fairly accurate forecasts of stock returns ten years ahead.

Panels B1-B3 of the second column (All) show the *last* estimates of the intercept (Alpha) and the slope (Beta) from expression (1), which are used to generate the last forecast made by each model, using all previous available observations.[6] All three betas (0.25 for DY, 0.21 for EY, and 0.21 for CY) are, as expected, positive and statistically different from 0.[7] In words, changes in

[4] Forecasts are made and evaluated only for real (but not for nominal) returns. Also, as already stated, all returns are calculated over a 10-year period and expressed in annualized terms.
[5] The sample for CY starts later so the first forecast is made at the end of Q4/1885.
[6] Recall that alpha and beta are estimated progressively adding one observation to each estimation; these results in 558 regressions, and 558 estimates of alpha and beta. Only the last estimates, using all available previous observations, are reported in the exhibit.
[7] As done throughout this article, statistical significance is evaluated with a two-tailed test and a 5% level of significance. In addition, in this case, significance is evaluated using Newey-West's heteroskedasticity- and autocorrelation-consistent covariance matrix.

the three multiples considered do have a meaningful impact on expected returns. Moreover, the alpha for the model based on DY (0.01) is significantly different from 0, but the alphas for the models based on EY (0.00) and CY (0.00) are not.

Exhibit 2: Multiples and Forward Real Returns – Out-of-Sample Forecasting

This exhibit shows in panels A1-A3 summary statistics for the relationship between forecasted and observed 10-year annualized real returns. The forecasts are produced from expression (1) with DY, EY, and CY as explanatory variables. The figures in the second column (All) are for the full sample; those in the third column (H+L) are only for the top and bottom quartiles when all observations are sorted by a given multiple; and those in the fourth column (Middle) are for the two quartiles in the middle. The summary statistics include the correlation between forecasted and observed returns (Rho), the mean deviation (MD), and the mean absolute deviation (MAD). The exhibit also shows, in panels B1-B3, the last estimates of α (Alpha) and β (Beta) from expression (1), which use all the relevant observations. MD and MAD in percent and in annual terms. * indicates statistical significance at the 5% level in a two-tailed test. The data is described in Exhibit A1 in the appendix.

	All	H+L	Middle
Panel A1: DY			
Rho	0.39 *	0.49 *	0.21 *
MD	–0.18	–0.23	–0.19
MAD	0.94	1.05	0.86
Panel A2: EY			
Rho	0.48 *	0.61 *	0.10
MD	–0.05	–0.03	0.00
MAD	0.86	0.81	0.92
Panel A3: CY			
Rho	0.56 *	0.70 *	0.22 *
MD	–0.22	–0.33	–0.18
MAD	0.86	0.84	0.93
Panel B1: DY			
Alpha	0.01 *	0.01 *	0.01
Beta	0.25 *	0.25 *	0.15
Panel B2: EY			
Alpha	0.00	0.00	0.00
Beta	0.21 *	0.21 *	0.21 *
Panel B3: CY			
Alpha	0.00	0.00	0.01
Beta	0.21 *	0.21 *	0.11

Having established in the previous section that multiples and forward returns are more highly correlated when the former are high and low rather than in the middle, panels A1-A3 of the third column (H+L) of Exhibit 2 show results for forecasts from models based only on high (top quartile) and low (bottom quartile) multiples. As before, the first model is estimated using the first 20 quarters of data, with the difference that in this case the 20 quarters take a longer chronological time to happen; this is because only the quarters with high and low multiples are used. Also as before, the estimation of alpha and beta progressively adds quarters over time.

This methodology generates 269 estimates of alpha and beta, and therefore 269 real return forecasts (251 for CY), which as before are then compared to observed real returns. A similar methodology is implemented for the subsample with multiples in the middle, and the results from comparing expected and observed returns for 270 forecasts (249 for CY) are shown in panels A1-A3 of the fourth column (Middle) of Exhibit 2.

A comparison between the H+L and the Middle columns reveals some interesting results. First, the three correlations in panels A1-A3 of the H+L column (0.49, 0.61, and 0.70) are markedly higher than the respective correlations in the Middle column (0.21, 0.10, 0.22), with the MD and MADs being rather similar between columns. These results suggest that the stronger correlation between multiples and forward returns when the former are high or low than when they are somewhere in the middle, reported in Exhibit 1, does lead to the generation of better forecasts.

Second, panels B1-B3 show that the three betas in the H+L column are positive and significant; of the betas in the Middle column, however, only that for EY is significant and those for DY and CY are not. In words, variations in high and low multiples do have an impact on expected returns, whereas variations of multiples in the middle do not have much of an impact, except in the case of EY.

In short, the overall message from Exhibits 1 and 2, which confirm and reinforce each other, is twofold. First, multiples and forward returns are closely related in sample, which leads the former to be useful for forecasting the latter out of sample. And second, relatively high and low multiples are more highly correlated in sample to forward returns than multiples in the middle, and are therefore more useful for forecasting returns out of sample.

3.4. Further Thoughts

This section contains some comments on the analysis of the previous two sections, as well as some extensions and caveats. First, the whole analysis is based on sorting multiples and their associated forward returns from the highest to the lowest multiple and subsequently slicing the data into four quartiles, with the top and bottom quartiles containing high and low multiples (and their associated forward returns), and the two middle quartiles containing the rest of the multiples (and again, their associated forward returns). That is, of course, an arbitrary way of slicing the data; Exhibit A2 in the appendix reports results for two alternatives.

Panels A1-A3 show in the third column (H+L) results for an alternative in which high and low multiples are those in the top and bottom *deciles* (rather than quartiles), with results for the remaining 80% of observations shown in the fourth column (Middle).[8] A comparison between these two columns confirms and reinforces the results already discussed for quartiles. More precisely, all six correlations between multiples and forward returns are markedly higher when multiples are high and low (H+L column) than the respective correlations when multiples are somewhere in between (Middle column).

Panels B1-B3 show results for yet another way of slicing the data. The third column (H+L) shows results for an alternative in which high and low multiples are those more than one

[8] The results for the All column in panels A1-A3 and B1-B3 of Exhibit A2 are the same as those for the All column in Exhibit 1.

standard deviation away from the mean, with results for the observations in between shown in the fourth column (Middle). Once again the results point in the same direction, namely, all six correlations between multiples and forward returns are markedly higher when multiples are high and low (H+L column) than when multiples are somewhere in between (Middle column).

Finally, a caveat. The whole analysis is based on multiples that use dividends and earnings lagged one quarter in order to avoid any look-ahead bias. However, the generation of return forecasts for the subsample of high and low multiples on the one hand, and middle multiples on the other, requires first sorting all the observations and then slicing the data into quartiles, which can only be done after having observed the whole sample. To illustrate, a P/E of (say) 25 can be determined as being 'high' only after having observed the whole sample and determined that it is solidly in the top quartile. In other words, forecasts from a subsample of high and low multiples can only be made after observing the whole sample and determining the range of multiples that are high, low, and in the middle.

That said, the whole analysis here can be thought of as a way of building a model (based on a hypothesis subsequently supported by evidence) that can be used to forecast stock returns from this point on. Moreover, as new data becomes available, the whole analysis could be progressively updated; that is, multiples and their associated returns could be re-sorted, parameters for the models based on high and low multiples could be re-estimated, and subsequent forecasts could be made out of the updated model.

4. Assessment

Multiples have long been used both to assess the valuation of stock markets as well as to forecast their return. How successful different multiples have been for this purpose has long been a source of controversy. The evidence points in both directions, with many papers arguing in favor of the forecasting ability of multiples, and perhaps just as many papers arguing against it. In this regard, the jury is out, to say the least.

The goal of this paper is by no means to try to settle this debate. Instead, the focus is on determining the conditions that would make multiples relatively more successful for forecasting stock returns. Most academics and practitioners are very likely to view stock returns in the long term (ten or so years) as being more predictable than they are in the short term (one month or one year). That issue is not directly addressed here, but the consensus view is embraced and incorporated into the analysis, which focuses on forecasting returns ten years ahead.

The argument advanced here is that multiples and forward stock returns are more closely related when the former are particularly high or low than when they are somewhere in the middle; and the evidence discussed here is in fact consistent with this hypothesis. In fact, the evidence shows that multiples are more highly correlated with forward stock returns in sample, and provide better forecasts of stock returns out of sample, when they are in the top or the bottom quartile of a sorting by multiples than when they are in the two middle quartiles.

The stronger correlation between multiples and forward stock returns when the former are relatively high or low is robust to different definitions of 'high' and 'low' multiples, such as when they are in the top and bottom decile, or when they are more than one standard deviation above or below their historical average. In other words, it is more important to focus on forecasting stock returns mostly when multiples are particularly high or low than to have a precise definition of high and low multiples.

In short, then, although the jury may be out on the ability of multiples to forecast stock returns, the predominant view, taken as given here, is that stock returns are more predictable in the long term than in the short term. Moreover, the evidence discussed here suggests that multiples are more useful to forecast stock returns when they are relatively high or low than when they lie somewhere in the middle. Thus, although this article neither settled nor did it aim to settle a longstanding debate on stock return predictability, it has hopefully established a condition that helps to improve our forecasts of stock returns.

Appendix

Exhibit A1: Data – Summary Statistics

This exhibit shows, for the quarterly series of nominal stock returns (NSR), real stock returns (RSR), and the rate of inflation (Inflation), the number of observations in the sample (T), the arithmetic (AM) and geometric (GM) mean return, volatility (SD), lowest (Min) and highest (Max) return, and annualized GM (AGM) and SD (ASD). It also shows T, AM, SD, Min, and Max for the series of the dividend yield (DY), the price-earnings ratio (P/E), and the cyclically-adjusted price-earnings ratio (CAPE). The sample period is from the end of the first quarter of 1871 (Q1/1871) through the end second quarter of 2025 (Q2/2025). All figures but P/E and CAPE in percent.

	NSR	RSR	Inflation	DY	P/E	CAPE
T	616	616	616	617	617	578
AM	2.6	2.1	0.6	4.2	16.4	17.6
GM	2.2	1.7	0.5			
SD	8.8	8.8	2.2	1.8	9.7	7.4
Min	–40.3	–38.5	–8.5	1.1	5.1	4.8
Max	76.2	78.8	14.6	15.5	139.1	44.4
AGM	9.2	6.9	2.2			
ASD	17.5	17.7	4.4			

Exhibit A2: Multiples and Forward Returns – In-Sample Correlations

This exhibit shows correlations between three multiples (DY, P/E, and CAPE) and two types of 10-year forward annualized returns (nominal and real). The correlations in the second column (All) are for the full sample; those in the third column (H+L) are for 'high' and 'low' multiples as defined in each panel; and those in the fourth column (Middle) are for the observations in between. The figures in parenthesis indicate the cutoff points for 'high' and 'low' multiples. * indicates statistical significance at the 5% level in a two-tailed test.. The data is described in Exhibit A1.

	All	H+L	Middle
Panel A: Deciles			
Panel A1: DY		(> 6.61 , < 1.97)	
Nominal returns	0.21 *	0.45 *	0.09
Real returns	0.36 *	0.60 *	0.24 *
Panel A2: EY		(> 10.97 , < 4.59)	
Nominal returns	0.49 *	0.74 *	0.29 *
Real returns	0.48 *	0.67 *	0.38 *
Panel A3: CY		(> 10.95 , < 3.99)	
Nominal returns	0.48 *	0.67 *	0.42 *
Real returns	0.51 *	0.82 *	0.33 *
Panel B: Beyond 1 Standard Deviation			
Panel B1: DY		(> 6.61 , < 1.97)	
Nominal returns	0.21 *	0.36 *	0.10 *
Real returns	0.36 *	0.51 *	0.27 *
Panel B2: EY		(> 10.97 , < 4.59)	
Nominal returns	0.49 *	0.69	0.19 *
Real returns	0.48 *	0.65	0.29 *
Panel B3: CY		(> 10.95 , < 3.99)	
Nominal returns	0.48 *	0.64 *	0.43 *
Real returns	0.51 *	0.81 *	0.32 *

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