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P/E Ratios and Value Investor Attention

Jordan Moore
Rowan University, moorejs@rowan.edu

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Jordan Moore[1]
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Abstract

Price-earnings (P/E) ratios, the most popular value proxy, are widely reported using the last four quarters of earnings. Corresponding earnings yields (4QEP) have significantly greater return predictability than lagged earnings yields or current book-to-market ratios. The weekly pattern in returns is consistent with individual investor trading activity. The return predictability is robust to fundamentals, price momentum, earnings momentum, volume, and liquidity. 4QEP relates positively to volume and liquidity and negatively to idiosyncratic volatility. Financial data providers only report P/E ratios for stocks with positive earnings; 4QEP only predicts returns, volume, and liquidity for these stocks.

[1]Simon Business School, University of Rochester. Email: jordan.moore@simon.rochester.edu. I am grateful to Ron Kaniel, Rob Ready, and Jerry Warner for their extensive guidance and encouragement. I would also like to thank Jozef Drienko, Jacquelyn Gillette, Einar Kjenstad, Robert Novy-Marx, Anisha Nyatee, Robert Parham, Aurelien Philippot, Bryce Schonberger, Bill Schwert, Maxim Sokolov, Michael Ungeheuer, Mihail Velikov, Hao Zou, and seminar participants at Ithaca College, Rowan University, 2015 Australasian Finance and Banking Conference, 2016 Midwest Finance Association Annual Meeting, 2016 Eastern Finance Association Annual Meeting, 2016 Whitebox Advisors Graduate Student Conference at Yale, 2016 Northern Finance Association Annual Meeting, and 2017 SGF Conference for helpful comments and suggestions.

1. Introduction

Active equity investors seeking abnormal returns are likely to search for value stocks.[1] Price-earnings (P/E) ratios are by far the most popular proxy for fundamental value and are widely quoted using a recent price and earnings from the last four quarters.[2] This paper provides evidence that trailing-four-quarter P/E ratios are salient to individual value investors with limited attention. Value investors search for stocks with low, positive P/E ratios, so the most appealing value stocks have high trailing-four-quarter earnings yields (4QEP).[3] Stocks with the highest 4QEP are attractive to all individual value investors, so they earn significant positive abnormal returns on high trading volumes. Barber and Odean (2008) argue that individual investors, who rarely hold short positions, have thousands of stocks to potentially purchase and only a few stocks in their portfolios to potentially sell.[4] Some individual value investors will sell low 4QEP stocks in their portfolios, while the majority of individual value investors will refuse to consider buying these stocks. Stocks with the lowest 4QEP earn low returns on low trading volumes, consistent with a decrease in individual investor buying.

Kahneman (1973) establishes attention as a scarce resource that limits cognitive ability. Individual investors are more likely than institutional investors to face binding attention constraints because they devote fewer resources to making investment decisions. Merton (1987) associates a positive attention shock in the form of an increase in the number

[1] Graham and Dodd (1934) encourage investors to identify assets with low prices relative to underlying fundamentals. Asness et al. (2013) document a value premium in equities, equity indices, bonds, currencies, and commodities.

[2] Figure 1 shows the Google Search Volume Index (SVI) for topics plausibly related to fundamental value proxies and illustrates the P/E ratio's unrivaled popularity. Among the 12 sorting variables for the value anomalies described in Hou et al. (2014), only four variables attract material search volume: P/E ratios, P/B ratios, market leverage, and dividend yield. P/E ratios generate the highest SVI in every month of the sample, which covers 2004-2017. The average SVI for P/E ratios is 6.9 times larger than the average SVI for P/B ratios.

[3] Consistent with Fama and French (1993), value stocks have high fundamental value relative to price.

[4] Barber and Odean (2000) note that the average (median) individual account holds 4.3 (2.6) equity positions.

of investors who know about a stock with a higher equilibrium price. Barber and Odean (2008) find that individual investors are especially likely to purchase attention-grabbing stocks.[5] If indvidual value investors with attention constraints search for stocks with low P/E ratios, then stocks with the highest 4QEP should earn a return premium on abnormally high volume.

Kaniel et al. (2008) show that individual investors provide liquidity by purchasing stocks following recent declines, consistent with predictions in Stoll (1978) and Grossman and Miller (1988). Also, individual investors are especially susceptible to the disposition effect, the tendency to sell stocks to realize gains.[6] The increase in sales by individual investors following positive returns provide another source of liquidity-providing trading activity. This paper provides evidence that stocks with high 4QEP are more liquid than expected. A trading strategy of buying illiquid stocks and selling liquid stocks is especially profitable for stocks with high 4QEP. In Jacobs and Hillert (2015) predictive regressions, stocks with the highest 4QEP are at least 20% more liquid than expected.

The lowest 4QEP stocks include those with negative earnings in the trailing four quarters. An important institutional detail is that market data providers do not publish P/E ratios for stocks with negative earnings. As an arbitrary example, Figure 2 shows Google Finance stock quotations for Ford Motor Company (F) and Tesla Motors (TSLA). Ford has positive earnings and a published P/E ratio while Tesla has negative earnings and does not have a published P/E ratio. Although Tesla may produce more exciting automobiles, Ford is more likely to capture the attention of value investors. For stocks

[5]Previous studies relate attention proxies to subsequent returns. These include trading volume [Gervais et al. (2001) and Kaniel et al. (2012)], search volume [Da et al. (2011)], and proximity to the 52-week high [George and Huang (2004), Li and Yu (2012)]

[6]For instance, Odean (1998) finds robust evidence of the disposition effect in the trading activity of individual investors at a large discount brokerage. Hartzmark (2015) finds that individual investors tend to sell the stocks in their portfolios with extreme returns, and are much more likely to sell the stocks with the largest gains than the largest losses.

with positive earnings, P/E ratios are earnings multiples, while for stocks with negative earnings, P/E ratios have no economic meaning. When Graham and Dodd (1934) promoted the use of P/E ratios, it was rare for public companies to have negative earnings, but since the mid-1980s, at least a quarter of US public firms have negative earnings.

For stocks with positive earnings, the distribution of 4QEP conveys variation in visibility and fundamentals. For stocks with negative earnings, 4QEP only reflects variation in fundamentals. If 4QEP predicts value investor attention, then it should predict greater variation in trading activity for stocks with positive earnings. In fact, 4QEP only predicts returns and changes in trading volume in the positive earnings subsample. Also, strategies based on buying illiquid stocks are only profitable in the positive earnings subsample. If individual value investors ignore all stocks without published P/E ratios, then stocks with negative earnings should exhibit excessive idiosyncratic volatility. In Fama and French (2015) asset-pricing tests and Fama and MacBeth (1973) regressions, negative earnings are associated with a significant increase in idiosyncratic volatility. Finally, I report results from an event study of all stocks crossing the zero P/E threshold. Controlling for size and earnings momentum, a published P/E ratio is associated with a significant increase in volume and liquidity. Evidence from institutional filings suggests that some institutions trade stocks in anticipation that they will cross zero P/E. After earnings are released, these institutions trade with individuals.

Average value strategy returns using 4QEP are nearly twice as those using either lagged earnings yields or current book-to-market ratios. Among these value proxies, 4QEP is also the best predictor of trading volume by a significant margin. In a monthly time-series regression from 1973 to 2015, a long-short value-weighted decile 4QEP strategy earns an average value-weighted monthly return of 106 basis points with an annual Sharpe ratio of 0.84. The strategy earns a significant positive alpha in the Fama and French

(2015) five-factor model, which includes controls for exposure to market beta, size, value, profitability, and investment. Furthermore, 4QEP still predicts returns within portfolios already sorted on market leverage, previous returns, share prices, or earnings momentum. These characteristics are important because they relate mechanically to 4QEP or changes in 4QEP. There is a strong weekly pattern in the daily strategy returns consistent with the patterns that Lakonishok and Maberly (1990) and Abraham and Ikenberry (1994) document in individual investor trading.

P/E ratios are arguably the most popular metric for the most popular investment strategy. This paper contributes to the literature on limited attention and individual investor behavior by analyzing the relation between 4QEP and trading activity. Although attention constraints apply more to small individual investors, previous empirical studies present evidence of limited attenion in equity market prices.[7] The findings in this paper have meaningful policy implications. Would calculating P/E ratios using a more stable earnings measure reduce short-term trading in stocks with the highest earnings yields? Would publishing E/P ratios instead of, or in addition to, P/E ratios, lead to lower volatility in stocks with negative earnings?

2. Data

Graham and Dodd (1934) advocate constructing P/E ratios by averaging several years of earnings. Likewise, Campbell and Shiller (1999) build a cyclically-adjusted P/E ratio (CAPE) using a long time series and business cycle adjustments. However, P/E ratios in popular financial data sources such as the Wall Street Journal, Financial Times, Bloomberg,

[7] Cohen and Frazzini (2008) show that the stock prices of supplier firms adjust slowly to changes in future earnings expectations of customer firms. Hou et al. (2009) find that stocks with lower investor attention do not respond fully to relevant fundamental information, contributing to the earnings momentum anomaly. DellaVigna and Pollet (2009) show that the stock price reaction to earnings is delayed when companies announce on Fridays, while Hirshleifer et al. (2009) show that the reaction is delayed when many other firms release earnings on the same day.

and Google, typically use earnings from the four most recent quarters. Value investors search for stocks with low, positive P/E ratios, so the most attractive stocks have the highest values of 4QEP. In practice, when 4QEP$\leq$0, there is no published P/E ratio. However, since data providers typically report EPS even when it is negative, investors can construct 4QEP for these stocks with minimal cost.[8]

Data on prices, volumes, returns, and shares outstanding for US equities are from CRSP. All returns are adjusted for delistings. Reporting dates and accounting items are from Compustat. Quarterly earnings for public US firms are widely available in Compustat starting in January 1972. Since four quarters of prior earnings data are necessary to calculate 4QEP, the sample for asset pricing tests covers 1973-2015. Only common stocks (CRSP Share Code 10 or 11) are included in the sample. In this paper, I calculate 4QEP as: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{PRC_{i,t}}$.

I calculate 4QEP in this way because of parsimony, consistency with prior literature, resilience to measurement error, and broadness of coverage. EPSX12, the Compustat 12-month moving average EPS, is the sum of the last four quarterly split-adjusted EPS values. I manually adjust EPSX12 for any stock splits since the release of the most recent quarterly earnings. PRC is the CRSP monthly closing share price. The earnings in EPSX12 excludes "extraordinary items," consistent with prior studies on P/E ratios and earnings momentum.[9] The earnings in EPSX12 is "basic," so net income is scaled by the number of shares currently outstanding, rather than the expected number of shares outstanding after any stock option exercises. Estimating expected dilution depends on the choice of an option pricing model and its parameter values, inducing measurement error.

[8]See Figure 2 for an example of published stock quotations for positive and negative earnings stocks.

[9]For instance, see Basu (1977, 1983), Foster (1977), Foster et al. (1984), Bernard and Thomas (1989, 1990), and Livnat and Mendenhall (2006).

There are many other ways to calculate 4QEP. EPSPI12 is basic EPS excluding extraordinary items. EPSF12 is diluted EPS excluding extraordinary items. EPSFI12 is diluted EPS including extraordinary items. The number of firm-months with valid EPSX12 is around twice the number with valid EPSPI12, EPSF12, or EPSFI12.[10] The 4QEP calculation assumes a constant number of shares outstanding over the last four quarters and does not account for corporate actions including share buybacks and employee option exercises. An alternative 4QEP calculation uses the price and earnings for the entire firm instead of a share of the firm. In this case, earnings are the sum of the four most recent values of Compustat quarterly net income (NIQ) or income before extraordinary items (IBQ), and the price is the current market capitalization. The return predictability of 4QEP is robust to all of these alternatives.[11]

Table 1 presents summary statistics on the distribution of 4QEP. The top panel summarizes changes in the cross section of 4QEP over time. The number of CRSP common stocks with valid 4QEP increases from around 2300 in the 1970s to around 6500 during the dot-com boom of the late 1990s, then falls to around 3600 in 2015. As the number of public companies increase, the percentage of firms with positive 4QEP and the median 4QEP both decrease. From 1996 to 2015, more than 30% of all CRSP stocks have negative earnings and the median published P/E ratio is around 30. On average, small firms have lower 4QEP than big firms, so the median 4QEP understates the market 4QEP in every subsample. The bottom panel presents time-series average cross-sectional rank correlations between different versions of 4QEP. For each month, I calculate 4QEP rank correlations for the sample with valid 4QEP using all four measures. The rank correlation between any pair of 4QEP variables is at least 92%, suggesting that the method of calculating 4QEP for a list of stocks is not likely to significantly change their rankings. Since the largest

[10] Differences in coverage cannot be explained by firm size or industry membership.

[11] The top panel of Table 11 presents these results.

discrepancies are concentrated in the smallest stocks, using value-weighted portfolios in asset pricing tests diminish these differences further.

In monthly asset pricing tests, I assume that earnings are available at the close of the last trading day of the reporting month. In daily or weekly asset pricing tests, I assume that earnings are available at the close of the first trading day after the reporting date. In all cases, the Compustat RDQ field determines the reporting date. DellaVigna and Pollet (2009) examine a large sample of earnings announcement dates in Compustat and reporting dates in major media sources and show that RDQ is on or after the earnings announcement date. Therefore, my assumptions about earnings availability are realistic for an individual investor. The quarterly earnings data are updated for adjustments and are not "point in time." Livnat and Mendenhall (2006) evaluate earnings momentum strategy returns using Compustat and a proprietary point-in-time database. The returns are nearly identical, suggesting that results are not sensitive to Compustat earnings restatements.

The distribution of 4QEP is a proxy for individual value investor attention. At the end of each month, week, or day, I rank all stocks on $4QEP_{i,t}$ and convert the ranking to a percentile. This variable has the name $4QEPPct_{i,t}$.[12] Major financial data providers typically publish P/E ratios using the market price and the four most recent quarters of earnings per share (EPS). Nevertheless, for several reasons, 4QEP is an imperfect proxy. These confounding factors include alternative 4QEP calculations, delays in adjusting P/E ratios for new quarterly earnings, and earnings restatements. For these reasons, my primary identification strategy is to evaluate returns, trading volumes, liquidity, and volatility for portfolios of stocks sorted on 4QEP.

[12]Converting to a percentile controls for variation in the number of stocks in the sample over time.

3. Trailing-Four-Quarter P/E Ratios and Return Predictability

Previous studies show that stocks with high E/P ratios subsequently earn higher average returns. Basu (1977, 1983) finds that P/E ratios predict average returns for NYSE stocks, controlling for size. Jaffe et al. (1989) confirm these findings in an extended sample and show that P/E ratios predict returns outside of January. However, Fama and French (1992) show that P/E ratios have insignificant return predictability in a cross-sectional regression which also includes P/B. These findings use annual earnings. Since 1970, public US firms report earnings at least every quarter. Therefore, asset pricing tests using annually-updated financial ratios do not accurately measure the relative attention content of P/E and P/B as value metrics.

3.1. HML with Different Value Proxies

Fama and French (1993) construct a portfolio that mimics a long-short value investing strategy. This portfolio, known as HML, is long stocks with a high book-to-market ratio and short stocks with a low book-to-market ratio. Stocks are independently sorted into two market capitalization portfolios (B, S) and three book-to-market portfolios (H,M,L). The portfolios are assigned at the end of every June, and book-to-market ratio uses annual earnings and market capitalization from the previous December. There are six portfolios defined by the two independent sorts (SH, BH, SM, BM, SL, BL). The monthly HML return is: $r_{HML,t} = 0.5 * (r_{SH,t} - r_{SL,t}) + 0.5 * (r_{BH,t} - r_{BL,t})$ and each portfolio return is the value-weighted average stock return. To highlight the importance of four-quarter-trailing P/E ratios for value investor attention, I construct HML using different value proxies and compare the return predictability. This test is in the spirit of Asness and Frazzini (2013), who show that the construction of HML substantially changes the correlation between value and momentum strategy returns.

Table 2 presents the average monthly returns for different versions of HML. The first specification is the Fama and French (1993) version, which has an average monthly return of 35 basis points overall, 50 basis points for small stocks, and only 20 basis points for large stocks. Trading strategies are generally more profitable among small stocks because small stocks are illiquid, have less analyst coverage, and are more costly to trade. The second specification uses the annual E/P ratio as the value proxy, updating portfolio assignments every June based on data from the previous December. This specification has similar average monthly returns of 40 basis points overall, 52 basis points for small stocks, and 28 basis points for large stocks. The next specification uses the real-time B/P ratio as the value proxy and earns similar average returns: 37 basis points overall, 49 basis points for small stocks, and 25 basis points for large stocks. However, constructing HML from 4QEP doubles average returns: 71 basis points overall, 84 basis points for the small stocks, and 58 basis points for the large stocks. The t-statistics for the difference in 4QEP HML returns and the first three HML returns are 2.81, 3.90, and 2.46 respectively. The 4QEP return spread premium is broad based. Among the four specifications, the SL and BL portfolios both earn the lowest average returns, and the SH and BH portfolios both earn the highest average returns.

Next, I construct HML using 4QEP in subsamples of stocks with positive and negative earnings.[13] Market data providers do not publish P/E ratios for stocks with negative EPS, so the relative return predictability of 4QEP in the two samples provides insight about whether 4QEP proxies for value investor attention. The average HML return for the positive earnings subsample is very similar to the average return in the full sample. On the other hand, the average monthly return in the negative earnings subsample is an insignificant 22 basis points. Among big stocks, the average return of 43 basis points for

[13]Stocks with 0 EPS over the last four quarters do not have published P/E ratios and are included in the negative earnings sample.

negative earnings stocks is similar to the average return of 53 basis points for positive earnings stocks. However, among small stocks, the average return is zero basis points for negative earnings stocks versus 81 basis points for positive earnings stocks. The lack of a published P/E ratio is especially detrimental to the performance of small stocks, which already suffer from lower analyst and media coverage.

I also construct HML using 4QEP in subsamples of stocks depending on whether they are expected to announce earnings. Beaver (1968) finds that stocks earn larger returns in months with expected earnings announcements. Frazzini and Lamont (2007) show that the largest premium is for firms with high trading volume around previous announcements. Following Frazzini and Lamont (2007), I assume stocks are expected to report quarterly earnings in a calendar month if they reported in the same calendar month of the previous year. By construction, the expected earnings sample includes approximately one-third of firms each month. In all six HML portfolios, average returns are higher in the expected earnings sample, consistent with Beaver (1968) and Frazzini and Lamont (2007). Bhushan (1989) identifies a strong relation between analyst coverage and firm size. Since earnings announcements and analyst reports are substitute measures of attention, the earnings announcement month premium is between 14 and 44 basis points for the big stock portfolios and between 51 and 63 basis points for the small stock portfolios. Average HML returns are very similar in the two subsamples, suggesting that the attention effects of P/E ratios and earnings announcements are independent.

3.2. Time-Series Regressions

Table 3 reports summary results from four monthly time-series regressions using the Fama and French (2015) five-factor model. I assign stocks to portfolios according to the most recent value of 4QEP. For each monthly observation in each time-series regression, the dependent variable is the monthly time series of value-weighted long-short portfolio returns. The independent variables include monthly returns of factor-mimicking portfolios which proxy for the market risk premium (MKT), size (SMB), value (HML), profitability (RMW), and investment (CMA). Monthly factor returns for MKT, SMB, HML, RMW, and CMA are from Kenneth French's website.[14] Fama and French (2015) describe how to construct these portfolios.

The first specification assigns stocks to decile portfolios using NYSE breakpoints. Hou et al. (2014) suggest these asset pricing tests to determine whether cross-sectional anomalies are robust. The average monthly long-short return is 1.06% with a t-statistic of 3.96 and annualized Sharpe ratio of 0.60. The alpha is economically and statistically significant. Since variation in 4QEP reflects variation in both value and profitability, it is not surprising that the long-short portfolio has substantial loadings on HML (0.48) and RMW (1.30). The second specification also assigns stocks to decile portfolios, but does not employ NYSE breakpoints. This provides a benchmark to evaluate tests using quintile portfolio assignments for positive and negative earnings subsamples. The quintile strategies cannot use NYSE breakpoints because the limited number of NYSE stocks with negative earnings stocks would result in empty portfolios. Ignoring NYSE breakpoints, extreme decile portfolios have a higher concentration of microcaps. As a result, the typical average long-short return is around 12% larger while the standard error is around 22% larger. The five-factor alpha is also moderately higher because factor loadings are similar, with slightly attenuated HML betas and moderately higher RMW betas.

Finally, I form quintile portfolios for the positive and negative earnings subsamples. In the positive EPS subsample, the average long-short return and five-factor alpha are both significant. In the negative EPS subsample, the average long-short return and five-factor

[14]Kenneth French's data library is located at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

alpha are both insignificant. The average long-short return is 140% larger in the positive EPS subsample, while the standard error is 120% larger in the negative EPS subsample. Stocks with negative EPS have greater common factor volatility and idiosyncratic volatility. By construction, 4QEP sorts for positive EPS stocks take long (short) positions in stocks with low (high) market capitalizations. The opposite relation holds for negative EPS stocks. Because of this, the positive EPS strategy has significant positive loadings on SMB and HML while the negative EPS strategy has significant negative loadings on SMB and HML. In fact, the five-factor alpha is quantitatively higher in the negative EPS sample, but the excess volatility in these stocks renders the alpha insignificant. The histogram in Figure 3 is instructive because it shows returns for all five quintile portfolios in both subsamples. The average return is monotonically increasing across the positive EPS portfolios, but lacks any clear pattern across the negative EPS portfolios. The variation is clearly larger for stocks with positive EPS and concentrated among stocks with the highest earnings yield.

Figure 4 illustrates the persistence of real-time P/E ratio and P/B ratio strategy returns over time.[15] Comparing these two strategies is instructive because P/E ratios and P/B ratios incorporate new information at the same rate. The earnings and book value per share both update when quarterly earnings are announced, and the price updates monthly. Value-weighted decile P/B strategies earn relatively constant average returns the first 24 months following portfolio formation. On the other hand, P/E strategy returns decline from more than 1% in the first month to less than 60 basis points in the third month and less than 40 basis points in the sixth month. These return patterns are consistent with the idea that investors pay much more attention to P/E ratios than to P/B ratios. The return spread between the long sides of the strategies adjusts much more quickly than the return

[15]The sorting variable for the P/B strategy is the B/P ratio using the most recent quarterly Compustat book value of equity and the most recent CRSP market capitalization. See Fama and French (1993) for how to calculate book equity from individual balance sheet items. The sorting variable for the P/E strategy is 4QEP.

spread between the short sides. Every individual value investor can buy stocks with high 4QEP. The price impact of these purchases leads to an increase in price and a decline in 4QEP. On the other hand, individual investors rarely hold short positions, so the negative attention from the absence of a P/E ratio will mostly result in fewer potential buyers. Even if this lower demand causes the stock price to fall, the stock will not appear "cheaper" to value investors if the trailing EPS is negative.

Table 4 presents average value-weighted long-short decile 4QEP strategy returns for a 4QEP strategy for each day of the week. Lakonishok and Maberly (1990) show that individual investors are most active in selling stocks on Mondays. They are most likely to evaluate their portfolios over the weekend and submit sell orders that execute on Monday. The average daily return is 5.27 basis points, but there is a considerable day-of-the-week effect. Average returns decrease monotonically from 20.1 basis points on Mondays to -1.93 basis points on Fridays. This variation is driven by the short side of the strategy. The average return spread between the top decile and the market ranges from 2.02 to 6.00 basis points for the five weekdays. The average return spread between the market and the bottom decile decreases monotonically from 14.40 basis points on Mondays to -7.93 basis points on Fridays. Abraham and Ikenberry (1994) show that Mondays only have low returns when they follow Fridays with negative returns. The high 4QEP strategy returns on Mondays are concentrated on days that follow negative market returns on the previous Friday.[16] The average return is 12.3 basis points on Mondays following positive market returns and 29.4 basis points on Mondays following negative market returns, of which 26.8 basis points comes from the short side. This weekly and conditional pattern in daily returns suggests that individual investor trading drives 4QEP returns.

[16]If the market is closed on Friday, I use the market return on the most recent trading day.

3.3. Double-Sorted Portfolios

These asset-pricing tests evaluate the performance of portfolios of stocks controlling for 4QEP and another variable of interest. These variables include market capitalization of equity (ME), book-to-market ratio (BE/ME), gross profitability (GP/AT), asset growth (dAT), market leverage (AT/ME), return momentum [R(12,1)], monthly reversals [R(1,0)], low share price (1/PRC), earnings momentum (SUE), volume rank (VR), and illiquidity (ILLIQ). The first four control for risk factors in the Fama and French (2015) five-factor model. I constuct ME and BE/ME as in Fama and French (1992), GP/AT as in Novy-Marx (2013), and dAT as in Cooper et al. (2008). Because financial firms have extremely large balance sheets, the Novy-Marx (2013) and Cooper et al. measures are not available for financial firms, those with SIC codes between 6000-6999.

Other controls are mechanically related to levels or changes in prices or earnings. Stocks with high 4QEP may generate large earnings relative to the market value of equity because they employ substantial leverage. The proxy for market leverage is the Bhandari (1988) measure (AT/ME), which also updates every June using annual Compustat data and excludes financial firms. 4QEP also relates negatively to low share prices. Hou et al. (2014) identify low share price as a "market frictions" anomaly, citing Miller and Scholes (1982). Cross-sectional variation in 4QEP only changes because of differences in recent returns or quarterly earnings. Thus, it is important to control for short-term reversals, price momentum, and earnings momentum. Jegadeesh (1990) finds that stocks with poor performance in the previous month earn high returns. Jegadeesh and Titman (1993) show that stocks with high returns in the previous year continue to earn high returns. A large literature starting with Ball and Brown (1968) finds evidence of "earnings momentum" in the sense that stocks with positive quarterly earnings surprises earn high returns for several subsequent months.

Following Carhart (1997), the price momentum proxy is the cumulative return from the end of month $t-12$ to the end of month $t-1$, and following Jegadeesh (1990), the month t return proxies for short-term reversals. The proxy for earnings momentum is standardized unexplained earnings (SUE), calculated as in Chan et al. (1996). Since Foster et al. (1984) show that a seasonal random walk model describes the time series of quarterly earnings, Chan et al. (1996) define "unexplained" earnings (UE) relative to this model: $UE_{i,t} = EPSPXQ_{i,t} - EPSPXQ_{i,t-4}$. Then, SUE is UE scaled by its time-series standard deviation.

Other popular measures of earnings momentum are the cumulative abnormal return (CAR) in a window around the earnings announcement date and UE relative to analyst forecasts. However, the Chan et al. (1996) SUE measure directly maps to changes in 4QEP and provides a challenging test for the P/E attention hypothesis. A long-short 4QEP strategy is consistent with an earnings momentum strategy, but loads negatively on a price momentum strategy. Chan et al. (1996) find that momentum in prices and earnings have independent return predictability, but Chordia and Shivakumar (2006) show that returns to price momentum strategies are insignificant after controlling for earnings momentum. Novy-Marx (2015) shows that earnings momentum trading strategies improve after controlling for price momentum. The salience of P/E ratios could help explain the preeminence of the earnings momentum anomaly.

The final two sorting variables are proxies for investor attention that are not related to P/E ratios. Gervais et al. (2001) show that abnormal trading volume predicts subsequent US equity returns. Kaniel et al. (2012) find this premium in most international equity markets as well. The volume rank (VR) is the quintile of a stock's share volume on the last day of the calendar month relative to its share volume for the last 50 trading days. Liquidity and volume are related. Illiquid stocks receive less attention, have greater asymmetric information, and trade at a steeper discount. The proxy for liquidity is the Amihud (2002) illiquidity ratio (ILLIQ), the average daily absolute return scaled by dollar volume: $ILLIQ_{i,t} = \sum_k \frac{|ret_{i,t-k}|}{prc_{i,t-k} * vol_{i,t-k}}$. In these tests, ILLIQ is calculated from days in the last 12 calendar months.

Table 5 presents average value-weighted monthly returns for double-sorted portfolios. The left panel shows excess returns, portfolio returns net of the risk-free rate, for portfolios of stocks in the highest 4QEP quintile within each quintile of each sorting variable. For reference, the average monthly value-weighted excess return of the market portfolio is 51 basis points. Of the 55 quintile double sorted portfolios, the average returns of 54 are quantitatively larger than the average market return. Furthermore, all 54 portfolios have excess returns that are significant at the 5% level even though the average portfolio holds 4% of all stocks. High 4QEP stocks earn high returns even when they have other features that predict low returns. The center panel presents excess returns for portfolios of stocks with negative 4QEP. Of these 55 portfolios, only 22 earn average returns quantitatively larger than the market return, and only eight have significant excess returns.

Does cross-sectional variation in 4QEP predict the performance of other trading strategies? The right panel of Table 5 presents value-weighted quintile long-short returns for each sorting variable within each quintile of $4QEPPct$. Fundamental strategies have lower returns after controlling for 4QEP. Value, profitability, and investment long-short strategy returns are significant in only six of 15 tests. Strategies employing monthly reversals are most profitable among stocks with high 4QEP. As these stocks decline in price, they become the most attractive value stocks in 4QEP terms and are most likely to gain positive attention from individual value investors. Following the same logic, it is intuitive that momentum strategies are most profitable for stocks with low 4QEP. When stocks have negative earnings, a decline in price encourage buying by value investors looking at P/E ratios. Market capitalization, liquidity, and share price are positively correlated, and the profitability of all three strategies vary positively with 4QEP. This suggests that value investors are more likely to learn about and purchase small, illiquid, or low-priced stocks that are near the top of the 4QEP distribution.

4. Trailing-Four-Quarter P/E Ratios and Individual Investor Behavior

In the Merton (1987) model, the risk and return characteristics of any stock are “known” by some fraction of investors. A positive attention shock in the form of a broader base of potential investors is associated with a higher equilibrium price. If individual investors purchase stocks with the highest 4QEP, this outward demand shift should also translate to an increase in trading activity. In addition, liquidity in stocks with high 4QEP should improve because individual investors trade in a contrarian manner. Conversely, there should be higher idiosyncratic volatility in low 4QEP stocks if individual value investors are unwilling to buy or hold them.

4.1. Volume Return Predictability

Table 6 presents data on volume return predictability for the HML portfolios from Table 2. For every stock-month observation, I calculate the volume return as $VRet_{i,t} = ln(\frac{SHVOL_{i,t}}{SHVOL_{i,t-1}})$. The volume return is the change in the log of share turnover. Lo and Wang (2000) argue that share turnover is the logical measure of trading activity and taking the logarithm is appropriate given the substantial skewness. I calculate the value-weighted VRet for the six size and book-to-market portfolios and calculate the VRet for each HML specification as in Fama and French (1993). The HML portfolio using 4QEP strongly predicts innovations to trading volume. The average volume return for small stocks with high 4QEP is 219 basis points higher than the average volume return for small stocks with low 4QEP, versus a spread of 56 basis points for big stocks. Although the HML portfolio constructed using real-time P/B ratios also predicts volume returns, the average volume return is less than half of the average HML VRet using 4QEP.

The relation between 4QEP and volume returns is only statistically significant in the positive earnings sample. In the negative earnings sample, stocks with higher (less negative) 4QEP have lower average volume returns than stocks with lower 4QEP. Notably, for all three portfolios of small negative earnings stocks, average monthly volume returns are negative. Although there is a significant relation between 4QEP volume returns in both the earnings and non-earnings subsamples, the volume return spread is more than 50% larger in the non-earnings subsample. When there is no earnings news, 4QEP still determines variation in attention, and the volume return predictability is strong and consistent across both small and big stocks. On the other hand, when there is earnings news, the VRet spread is stronger among small stocks, but much weaker among big stocks. Figure 5 presents a histogram of the time-series average of monthly value-weighted volume returns for each of the 100 percentile 4QEP portfolios. It is evident that there is a strong positive relation between 4QEP and innovations to trading volume.

4.2. Cross-Sectional Variation in the Liquidity Premium

Amihud (2002) shows that illiquid stocks earn higher returns than liquid stocks in both the time series and cross section of US stocks. Since the Amihud (2002) ratio is a measure of price impact, illiquidity implies low volume, holding volatility constant. If cross-sectional variation in trading volume arises primarily from "noise trading," lower trading volumes imply a higher probability of informed trading. In the Easley et al. (2002) model, investors should earn higher average returns for holding these stocks. If illiquid stocks earn high average returns because they trade at steeper discounts to their fundamental values, then owning illiquid stocks should be especially profitable when these discounts are likely to narrow. In this case, high 4QEP encourages value investors to learn about, and potentially purchase illiquid stocks. In the Merton (1987) framework, there are more investors who "know" about the stock, leading to a higher equilibrium price.

The results in Table 7 support this reasoning. Each month, I assign stocks to three 4QEP portfolios: negative (Neg), positive but outside the highest quintile (Low), and inside the highest quintile (High). Independently, I assign stocks to quintile portfolios based on the Amihud (2002) illiquidity ratio. In the top panel, the Amihud (2002) ILLIQ measure uses all days from the previous 12 months. Within each liquidity quintile, 4QEP strongly predicts variation in stock returns. The 4QEP High portfolio always has the highest average return of the three 4QEP portfolios and the 4QEP Neg portfolio always has the lowest. All five 4QEP High portfolios earn higher average returns than the market portfolio, while all five 4QEP Neg portfolios earn lower average returns. The difference between the High and Neg portfolio is significant at the 10% level for the most liquid quintile and is significant at the 1% level for all four of the other quintiles. On the other hand, there is no liquidity premium within the 4QEP Neg portfolios; all five portfolios earn average excess monthly returns between 24 and 31 basis points. Within the 4QEP Low portfolios, there is a 28 basis point premium, significant at the 10% level. Within the 4QEP High portfolios, there is a 67 basis point premium, significant at the 1% level. In the bottom panel, Amihud (2002) illiquidity ratio portfolio assignments only use days in the most recent calendar month. Once again, within each liquidity quintile, the 4QEP High portfolio earns the highest average returns and the 4QEP Neg portfolio earns the lowest average returns. There is still no liquidity premium in the 4QEP Neg portfolios and there is not even a liquidity premium in 4QEP Low portfolios. Using this more timely measure, there is only a premium in high 4QEP stocks.

4.3. Predictive Liquidity Regressions

Previous studies analyzing trading data suggest that individual investors tend to provide liquidity when purchasing or selling stocks. Kumar and Lee (2006) analyze the Odean (1998) large discount brokerage data and find that intense individual investor buying is concentrated in stocks with low market capitalization, low share prices, and high book-to-market ratios. Barber and Odean (2008) find that individual investors are net buyers of stocks with recent large negative returns. Kaniel et al. (2008) analyze a non-overlapping data set to show that individual investors provide liquidity by purchasing stocks with poor recent performance. Individual investors who already own stocks with high 4QEP are especially likely to sell these stocks following a price appreciation. Individuals are especially susceptible to the disposition effect, the tendency to take profits. Shefrin and Statman (1985) and Odean (1998) find robust evidence of the disposition effect in the trading activity of individual investors. Because of contrarian trading by individual investors, stocks with high 4QEP are likely to be more liquid than expected.[17]

I test whether 4QEP predicts liquidity by estimating Jacobs and Hillert (2015) panel OLS regressions. The dependent variable is log(ILLIQ), constructed from one month of daily data. The sample includes CRSP common stocks that trade on the NYSE and AMEX exchanges. I exclude NASDAQ stocks because Atkins and Dyl (1997) find that NASDAQ trades are double counted. The controls include variables that Chordia et al. (2007) identify as cross-sectional determinants of trading activity. These include POSRET $[max(ret_{i,t-1}, 0)]$ and NEGRET $[min(ret_{i,t-1}, 0)]$, which proxy for the positive relation between extreme returns and subsequent trading activity. The other controls are book

[17] If individuals purchase stocks after a negative return and sell stocks after a positive return, this trading activity will reduce the magnitude of the daily returns when calculating the Amihud (2002) illiquidity ratio. However, at the microstructure level, it's possible that these investors cross the bid ask spread and take liquidity at intraday horizons.

leverage, book-to-market, beta, share price, firm age, market capitalization, magnitude of the most recent earnings surprise, and volatility of the last eight quarters of earnings. The share price, firm age, and market capitalization are all calculated in log terms and the earnings variables use basic quarterly EPS excluding extraordinary items and scaled by the stock price. Other independent variables include an intercept, calendar year dummies, and Fama and French (1997) industry dummies. Following Jacobs and Hillert (2015), I calculate betas using the Dimson (1979) method to control for asynchronous trading.[18]

Figure 6 presents the average residuals for all observations in each 4QEP percentile. Clearly, stocks with high 4QEP are substantially more liquid than expected. This liquidity premium is in excess of 20% for stocks with the highest 4QEP. This result is consistent with the hypothesis that high 4QEP stocks attract the liquidity providing trades of individual investors. I estimate the regression for the NASDAQ sample and find a similar, though more volatile, pattern in the residuals. NASDAQ stocks have more volatile returns and quarterly earnings. Also, the NASDAQ time series is 10 years shorter.

4.4. Idiosyncratic Volatility

If many investors pay close attention to a stock, the stock price should trade in a narrow range around its "fundamental" value. If the price deviates significantly from this value, many investors are motivated to buy the stock at a discount or sell the stock at a premium. On the other hand, a stock that receives less attention is more likely to deviate significantly from its fundamental value. Ang et al. (2006, 2009) show that stocks with high idiosyncratic volatility earn low expected returns. If a clientele of individual value investors are unwilling to buy or hold stocks with negative earnings, then these stocks may exhibit excessive idiosyncratic volatility.

[18]The regression R^2 is 0.93.

One way to formally investigate whether stocks with negative earnings have greater idiosyncratic volatility is by pricing test assets. I price the 25 Fama and French (1993) portfolios formed on market capitalization and book-to-market ratio. Following Fama and French (1993), I assign stocks to portfolios every June and calculate monthly value-weighted returns for all 25 portfolios. I estimate a monthly time-series regression for the 25 test assets using the Fama and French (2015) five-factor model. The pricing error, $A|a_i|$, is the average absolute value of the coefficient estimates on the intercepts in the 25 time-series regressions. Table 8 presents the results from these asset pricing tests. In the sample of all stocks with valid 4QEP, the pricing error is 7.96 basis points. The pricing error is 7.96 basis points for the subsample of stocks with positive earnings and 50.85 basis points for the negative earnings subsample. However, the negative earnings subsample has only 36% as many stocks, so the portfolios are less diversified. Furthermore, the average negative earnings stock has a market capitalization that is 15% as large and a market-to-book (M/B) ratio that is more than 80% higher than the average positive earnings stock.

To control for these discrepancies, I construct two matched samples of stocks with positive and negative earnings. Both matching algorithms ensure that there are the same number of stocks in all 25 portfolios in every month. For each portfolio in each month, I compare the number of stocks with positive earnings (N_p) and negative earnings (N_n). In the Extreme ME Match algorithm, if $N_n < N_p$, the positive earnings portfolio includes only the N_n stocks with the smallest market capitalization. If $N_p < N_n$, the negative earnings portfolio includes only the N_p stocks with the largest market capitalization. In the Extreme M/B Match algorithm, if $N_n < N_p$, the positive earnings portfolio includes only the N_n stocks with the largest M/B. If $N_p < N_n$, the negative earnings portfolio includes only the N_p stocks with the smallest M/B. In the Extreme ME Match, the average pricing error is 142% larger in the negative earnings sample and in the Extreme M/B Match, the average pricing error is 231% larger in the negative earnings sample. This suggests that not publishing P/E ratios for stocks with negative earnings potentially results in an economically significant inefficiency.

In a complementary test, I estimate monthly Fama and MacBeth (1973) regressions of idiosyncratic volatility. Following Ang et al. (2006, 2009), idiosyncratic volatility is the time-series standard deviation of ϵ_i^2 in the time-series regression estimate for each stock using a month of daily returns: $R_{i,t} = \alpha_i + \beta_i R_{MKT,T} + s_i R_{SMB,T} + h_i R_{HML,T} + r_i R_{RMW,T} + c_i R_{CMA,T} + \epsilon_i$. While Ang et al. (2006, 2009) estimate the Fama and French (1993) model, I estimate the Fama and French (2015) model because stocks with positive and negative earnings have systematically different loadings on the profitability factor. In the second stage, I calculate Newey-West (1987) standard errors with 12 lags to accommodate annual seasonality in factor returns. In the first specification, the only independent variables are an intercept and a negative earnings dummy. The average daily idiosyncratic volatility is 2.22% for stocks with positive earnings and 3.93% for stocks with negative earnings. However, stocks with negative earnings are smaller and have higher valuation ratios. The second test includes controls for market capitalization and book-to-market ratio, as well as share price because idiosyncratic volatility may be negatively related to share price for microstructure reasons. As expected, small market capitalization, high market-to-book, and low share price are all significantly related to higher idiosyncratic volatility. Nevertheless, controlling for these exposures, stocks with negative earnings have an average excess daily standard deviation of 60 basis points.

5. The Zero P/E Threshold

By studying measures of trading activity for stocks crossing the zero P/E threshold, it's possible to estimate the economic significance of a published P/E ratio. Because individual value investors pay attention to 4QEP, a positive P/E ratio includes a fractional portion of an out-of-the-money put option. If a stock with positive earnings has negative abnormal returns, then a lower P/E ratio attracts individual value investor buying. This is evident from the strong positive relation between 4QEP and the profits of short-term reversal strategies. Because stock prices are positive, P/E ratios only cross above or below zero when a new quarterly earnings release flips the sign of the total earnings from the trailing four quarters. Between 1973 and 2015, there are 16764 times when a stock crosses into positive P/E territory and 19420 occasions when a stock crosses into negative P/E territory.

I analyze the distribution of 4QEP to evaluate whether there is evidence of systematic earnings management in order to obtain a published P/E ratio. Degeorge et al. (1999) construct a test statistic that evaluates the distribution of frequencies in a histogram near the area of a critical threshold. The null hypothesis is that the empirical distribution is smooth near the threshold point. I use the Compustat FQTR field to divide the panel of 4QEP values into subsamples corresponding to each fiscal quarter. The Degeorge et al. (1999) test statistic is 0.46, 0.29, and 0.66 for the fiscal quarters 1, 2, and 3, and 3.04 for fiscal quarter 4.[19] In other words, the evidence suggests that firms manage accounting information to provide positive annual earnings, but not to provide positive total earnings in the trailing four quarters.

5.1. Trading Activity

I calculate event-time cumulative abnormal returns (CAR) for every crossing stock using an event window of [-120,+60] days relative to the crossing date. CARs are calculated following the Foster et al. (1984) procedure.[20] Expected returns use estimates from a

[19] There are approximately 175,000 observations in each of the four subsamples. I construct the test statistic using $r = 5$ and a bin width of 0.005. The Appendix of Degeorge et al. (1999) describes how to construct the test statistic.

[20] Results are robust to calculating buy-and-hold abnormal return (BHAR) instead of CAR for the various

market-adjusted model in which every stock has a beta of 1 relative to the equal-weighted index of CRSP common stocks in the same NYSE market capitalization decile. The event-time pattern of CARs for the crossing groups is consistent with the fact that all stocks crossing above zero P/E have positive earnings surprises and all stocks crossing below zero P/E have negative earnings surprises.[21] Stocks crossing above zero P/E have positive CARs of around 5% in the 60 days prior to the event, 2% in the two-day window around the event, and a 1.5% "drift" in the 60 days following the event. Stocks crossing below zero P/E have a similar profile of negative CARs.

To estimate the economic significance of a published P/E ratio, I construct a matched sample with one eligible matching stock for each crossing stock. Eligible stocks release earnings on the same day and have the same directional earnings surprise, but do not cross zero P/E. The matching procedure uses the "nearest neighbor" principle of Abadie and Imbens (2006). Livnat and Mendenhall (2006) show that measuring earnings surprise as $SUE = (EPSX12_{i,t} - EPSX12_{i,t-3})/PRC_{i,t-1}$ preserves the largest proportion of the sample. It is also the SUE measure most closely related to 4QEP. The distance function is defined: $D_{i,j} = |Rank(SUE)_i - Rank(SUE)_j|$ where $Rank$ is the cross-sectional ranking on the crossing day. A distance function defined as: $D_{i,j} = |Rank(SUE)_i - Rank(SUE)_j| + |Rank(ME)_i - Rank(ME)_j|$ produces a worse match on both market capitalization and earnings surprise.

The top panel of Figure 7 shows event-time CARs for both crossing portfolios and both matched portfolios. Event-time CARs for the Cross+ and Match+ samples and event-time CARs for the Cross- and Match- samples exhibit the same pattern because they have the same exposure to earnings momentum. However, the relative performance

event windows.

[21] "Surprises" are relative to a seasonal random walk model.

of the Cross+ and Cross- samples show an asymmetry consistent with the asymmetry in 4QEP long-short strategy returns. The bottom panel of Figure 7 shows average event-time CARs for the difference between the Cross+ and Match+ sample (Diff+) and the difference between the Cross- and Match- sample (Diff-). Stocks crossing above zero P/E outperform the matched sample in the 120 days prior to the cross, but the matched sample starts to outperform after the crossing event. This suggests that sophisticated investors purchase these stocks before the cross and sell the shares to unsophisticated investors after the cross. On the other hand, stocks crossing below zero P/E underperform the matched sample both before and after the event. Because some shares are impossible or expensive to short sell, limits to arbitrage impede sophisticated traders from profiting from expected underperformance of the Cross- stocks following the cross.

Table 9 presents measures of trading activity for the stocks in the crossing and matched portfolios. For each quantity, I calculate the test-statistic for the difference in means between the crossing and matched samples using both OLS standard errors and standard errors clustered by calendar quarter. Clustering errors by quarter controls for the cross-sectional correlation in SUE in a particular fiscal quarter. The average size of stocks in both crossing samples are statistically indistinguishable from their matched samples. The average SUE for stocks in both crossing portfolios are statistically larger than their matched samples. This is because of the restriction that the crossing stock and matching stock release earnings on the same day. The crossing stock often has a larger earnings surprise than any eligible matching stock. However, the average difference between the crossing and matched samples in $\Delta E/P$ ranking translates to less than one ranking spot in a universe of around 4000 stocks.

The average Cross+ stock earns a significant CAR of 1.03% in the [-60,0] window and a significant CAR of 29 basis points in the [-1,0] window relative to the average Match+

stock. Conversely, the average Cross- stock earns a significant CAR of -1.93% and -30 basis points in the two windows relative to the average Match- stock. The excess CAR of the Cross+ sample fully reverses within the first 60 days following the earnings release, while the Cross- sample continues to underperform after the earnings release. The table also presents the average changes in volume and liquidity for each event window relative to the estimation window. Cross+ stocks earn significant average volume returns of 1.66% relative to Match+ stocks, while Cross- stocks earn significant average volume returns of 4.04% less than Match- stocks. Cross+ stocks improve their liquidity by an economically and statistically significant average of 11.4% relative to Match+ stocks, while Cross- stocks have similar liquidity to Match- stocks. These findings are consistent with the volume and liquidity profiles in Figure 5 and Figure 6.

5.2. Institutional Ownership

The bottom panel of Table 9 presents the average variation in institutional ownership for the four samples in event time. I merge the stocks in the cross and matched sample with institutional holdings data from the Thomson-Reuters database of SEC 13F filings. Investment managers with more than $100 million in assets under management must file 13F reports quarterly, detailing all equity holdings of more than 10,000 shares or $200,000. Because the Thomson-Reuters data starts in 1980, the crossing and matched samples are reduced by around 10%. Following Frazzini (2006), I filter out any entries showing that an institution owns more than 100% of all shares outstanding for a single stock.[22] Although the 13F data classifies managers by type, there are substantial and uncorrectable errors with the type classification algorithm, so I only consider total institutional ownership.

Stocks in the Cross and Match samples are held by an average of approximately

[22]Because of these types of erroneous entries, data on the number of institutions is more resilient to measurement error than data on the proportion of individual ownership.

40 institutions prior to the crossing event. The quarter of the crossing event is Q(0) and the table presents relative changes in breadth of institutional ownership [ΔNInst] from Q(-3) to Q(1). The average Cross+ stock has an statistically significant positive ΔNInst in each quarter from Q(-3) to Q(0) relative to the average Match+ stock. The total net change is approximately 2.1 institutions or 5% of the baseline. The relative change in ownership between Cross+ and Match+ stocks in Q(1) is statistically indistinguishable. The pattern is similar for the stocks crossing below zero P/E, though statistically weaker, perhaps reflecting some unwillingness by certain institutions to cut existing positions. The average Cross- stock has an negative ΔNInst in each quarter from Q(-3) to Q(0) relative to the average Match+ stock. The difference is strongly significant in Q(-1) and marginally significant in two of the three other quarters, perhaps reflecting the higher costs of short selling. The total net change is approximately 1.4 institutions or 3% of the baseline. The relative change in ownership between Cross- and Match- stocks in Q(1) is statistically indistinguishable. These results are consistent with the pattern of event-time CARs and the idea that some sophisticated investors profit by anticipating a crossing event and trading ahead of it.

6. Robustness

Cross-sectional variation in 4QEP predicts returns and trading volumes, but only for stocks with positive earnings. This suggests that P/E ratios convey information about investor attention as well as fundamentals. This section shows that the main results of this paper are robust. A long-short P/E attention strategy earns significant returns regardless of how I calculate earnings yield. Average long-short returns are significant in a variety of cross-sectional and time-series subsamples.

6.1. Alternative Specifications

I measure 4QEP as the 12-month trailing basic EPS excluding extraordinary items scaled by the share price. This calculation is parsimonious, has broad coverage in the CRSP and Compustat databases, and minimizes measurement error. However, it is important to test whether results are robust to alternative measures of 4QEP. The top panel of Table 10 presents average monthly long-short returns for P/E attention strategies using 10 methods to calculate 4QEP. The first four specifications calculate 4QEP using different Compustat variables for the trailing earnings. EPSX12 and EPSF12 are basic and diluted EPS excluding extraordinary items. EPSPI12 and EPSFI12 are basic and diluted EPS including extraordinary items. In the next four specifications, the earnings is the sum of the four most recent values of Compustat quarterly EPS. EPSPXQ and EPSFXQ are basic and diluted quarterly EPS, while EPSPIQ and EPSFXQ are basic and diluted quarterly EPS including extraordinary items. In the final two specifications, 4QEP is constructed using the total earnings and price for all of the firm's equity instead of a single share. 4QEP is the sum of Compustat net income excluding (IBQ) or including (NIQ) extraordinary items for the four most recent quarters scaled by the product of the CRSP share price and Compustat quarterly shares outstanding (CSHOQ). All 10 methods of calculating 4QEP alternatives produce economically and statistically significant results, with average monthly returns of at least 88 basis points and test statistics of at least 3.

6.2. Subsamples

The bottom panel of Table 10 reports average monthly returns for the benchmark strategy in several subsamples. I divide the time series into early and late subsamples of 21 years and six months. The average monthly long-short return is 106 basis points in the early subsample and 107 basis points in the late subsample. The standard error is about 50% larger in the late subsample, primarily due to volatile returns during the late 1990s. Next, I evaluate whether attention effects of P/E ratios are clustered at a few obvious round numbers. Several studies demonstrate clustering at round numbers and other visible figures.[23] I construct a sample (No RNX) that removes all stocks that crossed P/E thresholds of zero, 10, or 20. These three "big figures" are the most likely candidates for attention clustering. Average returns for the No RNX subsample are slightly below average, yet remain highly economically and statistically significant.

If 4QEP only captures variation in fundamental risk, then high strategy returns could be compensation for low returns during bad economic periods. Lakonishok et al. (1994) use three variables to proxy for periods of poor economic conditions: poor market performance, recessions, and low real GDP growth in the following quarter. Following Lakonishok et al. (1994), I use data from Kenneth French's website to measure market performance, National Bureau of Economic Research (NBER) data on recessions, and data from the US Department of Commerce Bureau of Economic Analysis (BEA) to determine GDP growth.[24]

The average monthly long-short return of the benchmark strategy for the full sample is 1.06%. For the half of months with the lowest market return, the average long-short strategy return is 2.61%. For the quarter of the sample with the lowest market return, the average return is 3.96%. The average long-short return is higher than average during NBER recession months. However, the statistical significance is marginal because only

[23]For instance, Yule (1927) documents the tendency for individuals to provide round numbers in survey responses. Harris (1991) finds that US equities are far more likely to trade at integer prices. Benartzi and Thaler (2001) find that investors are likely to allocate retirement savings uniformly across funds, regardless of the distribution of underlying asset allocations. Baker et al. (2012) find that in acquisitions, there is clustering in target prices at the 52-week high.

[24]The data on recession dates are available at: http://www.nber.org/cycles.html. The US experiences seven recessions comprising about 16% of the sample. Recessions include 11/73-3/75, 1/80-7/80, 7/81-11/82, 7/90-3/91, 3/01-11/01, and 12/07-6/09. The BEA website is: http://www.bea.gov.

16% of the time series are recession months. The strategy earns 1.56% on average during the half of months with subsequent quarterly real GDP growth below the median. During the quarter of months with the worst future GDP growth, the strategy earns an average monthly return of 2.94%. These results are not consistent with a risk explanation for the P/E attention strategy returns. The above average returns during poor economic conditions could be aided by the disposition effect. When the market declines, long-only individual value investors are more likely to hold paper losses. They are unlikely to sell high 4QEP stocks to realize a loss, so the long-short strategy earns high returns.

7. Conclusion

Individual value investors with limited attention are likely to use trailing-four-quarter P/E ratios to identify potential investments and to evaluate existing positions. If the trading activity of these investors is economically meaningful, then 4QEP can predict subsequent returns. This return predictability is robust to fundamentals, price momentum, earnings momentum, volume, and liquidity. The variation in return predictability in positive and negative earnings subsamples, the influence of 4QEP on strategy returns, the pattern in daily average returns, and the relation to trading volumes, liquidity, and idiosyncratic volatility all provide corroborating evidence.

If trailing-four-quarter P/E ratios attract significant individual investor attention, this raises policy implications. First, if financial data providers were required to actually report E/P ratios or earnings yields, investors could easily observe variation in fundamental earnings yields among stocks with negative P/E ratios. This could reduce the excessive idiosyncratic volatility in these stocks. Second, if financial data providers were required to display P/E ratios calculated using a more sophisticated and stable calculation, such as the Campbell and Shiller (1988) measure, investors would see less turnover among the most appealing value stocks. This could lead to a reduction in excessive trading by individuals in the stocks with the lowest trailing four quarter P/E ratios. Experiments in the laboratory or field would help to identify potential improvements in how to communicate fundamental information to individual investors.

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Table 1: Summary Statistics on 4QEP For all US common stocks with valid total basic earnings per share (EPS) in the past 12 months (Compustat field: EPSX12), and valid monthly closing share price (CRSP field: PRC), the Trailing Four Quarter E/P (4QEP) is: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{PRC_{i,t}}$. The top panel presents summary statistics for the cross section of 4QEP. The full sample covers 1973-2015 and is divided into subsamples ending every five years. The average monthly number of US common stocks in each subsample with valid $4QEP_{i,t}$ is N Valid 4QEP. The average monthly percentage of stocks with positive $4QEP_{i,t}$ in terms of number of firms (market capitalization) is % N (MC) Pos 4QEP. The average monthly quartile breakpoints of $4QEP_{i,t}$, quoted in percent, are 25, 50, and 75 PCTL 4QEP%. The bottom panel presents time-series average cross-sectional rank correlations between different versions of 4QEP where some measure of EPS for the trailing four quarers is scaled by stock price. EPSPI12, EPSF12, and EPSFI12 are Compustat trailing four quarters of basic EPS including extraordinary items, diluted EPS excluding extraordinary items, and diluted EPS including extraordinary items respectively. In each month, rank correlations are calculated among stocks with valid 4QEP using all four measures.

Subsample	N Valid 4QEP	% N Pos 4QEP	% MC Pos 4QEP	25PCTL 4QEP%	50PCTL 4QEP%	75PCTL 4QEP%
1973-1975	2253	91.9	99.4	7.6	12.9	18.0
1976-1980	2372	91.9	99.1	8.3	12.5	16.4
1981-1985	3144	82.8	96.4	3.7	8.3	12.2
1986-1990	4229	71.9	94.1	-1.5	5.1	8.5
1991-1995	5074	70.4	92.1	-2.5	4.2	7.2
1996-2000	6478	67.5	91.2	-4.0	3.7	7.2
2001-2005	5113	64.0	91.3	-8.2	3.2	6.4
2006-2010	4327	66.0	93.0	-8.1	3.3	6.7
2011-2015	3569	69.3	94.5	-2.4	3.9	6.4

Rank Correlations	$EPSX12_{i,t}$	$EPSPI12_{i,t}$	$EPSF12_{i,t}$	$EPSFI12_{i,t}$
$EPSX12_{i,t}$	1	0.93	0.95	0.92
$EPSPI12_{i,t}$		1	0.94	0.99
$EPSF12_{i,t}$			1	0.96
$EPSFI12_{i,t}$				1

Table 2: Return Predictability of HML using Different Value Proxies I construct eight versions of HML, the Fama and French (1993) portfolio that is long value stocks and short growth stocks. The sample covers 1973-2015. Specification 1 replicates HML in Fama and French (1993) using the annual B/P ratio, updated at the end of each June. The value proxy in Specification 2 is the annual E/P ratio, defined as Compustat annual income before extraordinary items (IB) scaled by CRSP market capitalization (PRC*SHROUT), updated at the end of each June. Specifications 3 and 4 use B/P and E/P, updated monthly, to proxy for value. The B/P ratio is calculated using book value from the most recent Compustat quarterly data, scaled by closing share price (CRSP field PRC). Monthly E/P strategies use basic EPS in the past 12 months (Compustat field EPSX12), scaled by closing share price. Specifications 5-8 use the monthly E/P value proxy in various subsamples. Specifications 5 and 6 estimate HML using stocks with positive earnings (Pos) and negative earnings (Neg) only. To form diversified portfolios for these subsamples, I construct unconditional 30th and 70th breakpoints among stocks with positive or negative earnings, ignoring NYSE breakpoints. Specifications 7 and 8 estimate HML using stocks expected to report quarterly earnings (Earn) and stocks not expected to report quarterly earnings (No Earn), based on the algorithm in Frazzini and Lamont (2007). The top panel reports the average monthly percent return (Ret) for the HML portfolios, with t-statistics in brackets. T-statistics for the excess HML returns of specification 4 above the return of specifications 1, 2, and 3 are in parentheses. The bottom panel shows the average monthly value-weighted Ret for the six size and book-to-market portfolios (SL, SM, SH, BL, BM, BH).

Specification	1	2	3	4	5	6	7	8
Value Proxy	B/P	E/P	B/P	E/P	E/P	E/P	E/P	E/P
Rebalance	June	June	Month	Month	Month	Month	Month	Month
Sample	All	All	All	All	Pos	Neg	Earn	No Earn
HML Ret	0.35	0.40	0.37	0.71	0.67	0.22	0.68	0.73
t:HML(S)	[2.68]	[2.76]	[2.32]	[4.51]	[5.30]	[0.79]	[3.83]	[4.70]
t:HML(4)-HML(S)	(2.81)	(3.90)	(2.46)					
SL Ret	0.86	0.87	0.93	0.82	0.91	0.61	0.97	0.73
SM Ret	1.25	1.22	1.16	1.11	1.17	0.61	1.41	0.97
SH Ret	1.36	1.39	1.42	1.66	1.72	0.61	1.74	1.60
BL Ret	0.87	0.82	0.85	0.72	0.77	0.51	1.05	0.54
BM Ret	1.00	0.99	0.99	0.95	0.97	0.44	1.39	0.76
BH Ret	1.07	1.11	1.09	1.29	1.29	0.94	1.64	1.13

Table 3: Return Predictability of 4QEP in Monthly Time-Series Regressions I estimate four monthly time-series regressions using the Fama and French (2015) five-factor model and this table reports summary results. The sample covers 1973-2015. For each specification, the table reports the average value-weighted monthly long-short return, Fama and French (2015) five-factor alpha, and factor loadings. The sorting variable is the Trailing Four Quarter E/P (4QEP), defined as: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{PRC_{i,t}}$, where EPSX12 is Compustat total basic earnings per share in the past 12 months and PRC is CRSP monthly closing share price. In specification 1, all stocks are sorted into decile portfolios using NYSE breakpoints. In specification 2, all stocks are sorted into decile portfolios without using NYSE breakpoints. In specification 3, only stocks with positive EPS are sorted into quintile portfolios without using NYSE breakpoints. In specification 4, only stocks with negative EPS are sorted into quintile portfolios without using NYSE breakpoints. For each monthly observation in each time-series regression, the dependent variable is the percentage return of a value-weighted long-short portfolio. Independent variables include a monthly time series of intercepts and monthly returns of five factor-mimicking portfolios that control for the market risk premium (MKT), size (SMB), value (HML), profitability (RMW), and investment (CMA). The monthly time series for MKT, SMB, HML, RMW, and CMA are from Kenneth French's data library. T-statistics are in brackets.

	1	2	3	4
Portfolios	10	10	5	5
NYSE	Y	N	N	N
Sample	All	All	Pos	Neg
L-S Return	1.06	1.19	0.70	0.29
	[3.96]	[3.64]	[4.29]	[0.81]
Alpha	0.75	0.88	0.37	0.48
	[3.52]	[3.25]	[2.65]	[1.42]
MKT	-0.22	-0.28	0.03	-0.27
	[-4.45]	[-4.44]	[0.77]	[-3.38]
SMB	-0.15	-0.22	0.16	-0.53
	[-1.95]	[-2.38]	[3.32]	[-4.44]
HML	0.48	0.32	0.83	-0.70
	[4.86]	[2.57]	[13.0]	[-4.44]
RMW	1.30	1.59	0.28	0.71
	[12.4]	[12.1]	[4.16]	[4.28]
CMA	-0.20	-0.12	-0.23	0.28
	[-1.31]	[-0.60]	[-2.33]	[1.17]

Table 4: Return Predictability of 4QEP by Day of Week For all US common stocks with a valid total basic earnings per share (EPS) in the past 12 months (Compustat field EPSX12), and valid monthly closing share price (CRSP field PRC), the Trailing Four Quarter E/P (4QEP) is: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{PRC_{i,t}}$. At the end of each day, all stocks are assigned to deciles of 4QEP using NYSE breakpoints. The top row of the top panel shows the average daily return, in basis points, of a value-weighted portfolio that is long all stocks in decile 10 of 4QEP and short all stocks in decile 1 of 4QEP. The second row shows the average daily return, in basis points, of a value-weighted portfolio that is long all stocks in decile 10 of 4QEP and short all NYSE, NASDAQ, and AMEX common stocks in CRSP (MKT). The third row shows the average daily return, in basis points, of a value-weighted portfolio that is long MKT and short all stocks in decile 1 of 4QEP. The sample covers 1973-2015. Each row shows average returns, in basis points, on Mondays (M), Tuesdays (T), Wednesdays (W), Thursdays (R), and Fridays (F). The bottom panel shows the average daily returns for these three long-short portfolios on Mondays that follow positive market returns on the previous Friday [M(F+)] and Mondays that follow negative market returns on the previous Friday [M(F-)]. T-statistics are in brackets.

	M	T	W	R	F
E/P 10 - E/P 1	20.10	8.69	2.58	-3.07	-1.93
	[7.53]	[3.61]	[1.07]	[-1.31]	[-0.83]
E/P 10 - MKT	5.68	5.12	4.11	2.02	6.00
	[4.39]	[4.16]	[3.30]	[1.70]	[5.29]
MKT - E/P 1	14.40	3.57	-1.53	-5.09	-7.93
	[5.51]	[1.64]	[-0.70]	[-2.46]	[-3.85]
	M(F+)	M(F-)			
E/P 10 - E/P 1	12.30	29.40			
	[3.22]	[8.15]			
E/P 10 - MKT	8.07	2.61			
	[4.90]	[1.28]			
MKT - E/P 1	4.24	26.80			
	[1.10]	[8.06]			

Table 5: Return Predictability of 4QEP in Double-Sorted Portfolios At the end of each month, I assign all stocks to quintiles of each sorting variable in the left column. The controls for size (ME), value (BE/ME), profitability (GP/AT), investment (dAT), and market leverage (AT/ME) use annual data updated at the end of every June. Controls for price momentum [R(12,1)] monthly reversals [R(1,0)], earnings momentum (SUE), volume rank (VR), illiquidity (ILLIQ), and low share price (1/PRC), and are updated monthly. All quintile assignments except for VR use NYSE breakpoints. Section 3.3 describes how to calculate every sorting variable. For all US common stocks with a valid total basic earnings per share (EPS) in the past 12 months (Compustat field EPSX12), and valid monthly closing share price (CRSP field PRC), the Trailing Four Quarter E/P (4QEP) is: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{PRC_{i,t}}$. At the end of each month, all stocks are assigned to quintiles of 4QEP using NYSE breakpoints. The left panel (L High) shows average returns in excess of the monthly risk-free rate for value-weighted portfolios that are long every stock in quintile 5 of 4QEP, controlling for quintile of the sorting variable. The center panel (L Neg) shows average returns in excess of the monthly risk-free rate for value-weighted portfolios that are long every stock with negative 4QEP, controlling for quintile of the sorting variable. The right panel shows average long-short returns for value-weighted extreme quintile strategies for each sorting variable, controlling for quintile of 4QEP. The sample covers 1973-2015. T-statistics are in brackets.

	L High					L Neg					L-S Sort				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
ME	1.38	1.38	1.34	1.07	0.88	0.26	0.15	0.21	0.19	0.50	0.03	0.15	0.28	0.31	0.50
	[5.04]	[5.10]	[5.15]	[4.39]	[4.01]	[0.67]	[0.38]	[0.53]	[0.49]	[1.40]	[0.12]	[0.80]	[1.55]	[1.87]	[2.75]
BE/ME	0.45	0.74	0.78	0.91	0.97	0.21	0.69	0.41	0.59	0.65	0.36	0.15	0.14	0.11	0.52
	[1.68]	[2.98]	[3.36]	[3.84]	[4.27]	[0.57]	[1.96]	[1.10]	[1.71]	[1.94]	[1.42]	[0.87]	[0.77]	[0.52]	[2.79]
GP/AT	0.81	0.71	0.80	1.06	1.06	0.47	0.10	0.65	0.62	1.03	0.29	0.38	0.44	0.35	0.25
	[3.72]	[2.84]	[3.44]	[4.04]	[4.20]	[1.31]	[0.30]	[1.83]	[1.66]	[2.70]	[1.36]	[2.33]	[2.46]	[1.98]	[1.26]
dAT	1.14	0.87	0.84	0.64	0.75	0.62	0.81	0.67	0.35	-0.14	0.56	0.16	0.20	0.02	0.38
	[4.35]	[3.85]	[3.79]	[2.70]	[2.70]	[1.89]	[2.54]	[1.75]	[0.87]	[-0.35]	[3.02]	[0.84]	[1.15]	[0.09]	[1.99]
AT/ME	0.63	0.72	0.86	0.92	0.89	-0.08	0.50	0.60	0.59	0.67	0.56	0.06	-0.11	-0.04	0.26
	[2.28]	[2.85]	[3.70]	[4.22]	[3.34]	[-0.19]	[1.40]	[1.69]	[1.86]	[1.95]	[2.02]	[0.29]	[-0.59]	[-0.19]	[1.00]
1/PRC	0.73	1.12	1.23	1.25	1.24	0.37	0.64	0.17	0.29	0.07	-0.30	0.19	0.32	0.51	0.51
	[3.32]	[4.88]	[5.01]	[4.47]	[3.59]	[0.95]	[1.67]	[0.47]	[0.81]	[0.18]	[-0.99]	[0.78]	[1.31]	[2.21]	[1.91]
R(12,1)	0.70	0.98	0.95	1.06	1.28	-0.45	0.51	0.72	0.80	0.80	1.43	0.70	0.65	0.43	0.58
	[2.19]	[3.93]	[4.27]	[4.85]	[4.61]	[-1.10]	[1.44]	[2.21]	[2.47]	[2.28]	[5.08]	[2.64]	[2.16]	[1.58]	[2.14]
R(1,0)	1.49	1.22	1.04	0.88	0.69	0.41	0.66	0.62	0.19	-0.16	0.02	0.35	0.51	0.71	0.80
	[4.81]	[4.99]	[4.62]	[3.91]	[2.78]	[0.97]	[1.80]	[1.66]	[0.57]	[-0.46]	[0.07]	[1.70]	[2.32]	[3.51]	[3.37]
SUE	0.85	0.91	1.00	1.22	1.22	-0.04	0.43	0.69	0.56	0.84	0.63	0.56	0.21	0.35	0.38
	[3.33]	[3.70]	[4.08]	[5.29]	[5.54]	[-0.11]	[1.18]	[1.92]	[1.52]	[2.16]	[3.47]	[4.01]	[1.44]	[2.36]	[2.33]
VR	0.77	0.81	0.97	1.22	1.30	-0.45	-0.06	0.21	0.41	1.14	0.98	0.57	0.31	0.67	0.53
	[3.11]	[3.28]	[4.30]	[5.22]	[5.10]	[-1.25]	[-0.15]	[0.56]	[1.06]	[3.08]	[4.82]	[3.75]	[2.21]	[4.79]	[3.52]
ILLIQ	0.90	1.17	1.23	1.39	1.52	0.31	0.24	0.27	0.24	0.28	0.11	0.17	0.28	0.37	0.62
	[4.10]	[4.72]	[4.65]	[5.24]	[6.04]	[0.86]	[0.62]	[0.71]	[0.61]	[0.75]	[0.46]	[1.01]	[1.73]	[2.32]	[3.65]

Table 6: Volume Return Predictability of HML with Different Value Proxies I construct eight versions of HML, the Fama and French (1993) portfolio that is long value stocks and short growth stocks. The sample covers 1973-2015. Specification 1 replicates HML in Fama and French (1993) using the annual B/P ratio updated every June. The value proxy in Specification 2 is the annual E/P ratio, defined as Compustat annual income before extraordinary items (IB) scaled by CRSP market capitalization (PRC*SHROUT), updated at the end of each June. Specifications 3 and 4 use B/P and E/P, updated monthly, to proxy for value. The B/P ratio is calculated using book value from the most recent Compustat quarterly data, scaled by closing share price (CRSP field PRC). Monthly E/P strategies use basic EPS in the past 12 months (Compustat field EPSX12), scaled by closing share price. Specifications 5-8 use the monthly E/P value proxy in various subsamples. Specifications 5 and 6 estimate HML using stocks with positive earnings (Pos) and negative earnings (Neg) only. To form diversified portfolios for these subsamples, I construct unconditional 30th and 70th breakpoints among stocks with positive or negative earnings, ignoring NYSE breakpoints. Specifications 7 and 8 estimate HML using stocks expected to report quarterly earnings (Earn) and stocks not expected to report quarterly earnings (No Earn), based on the algorithm in Frazzini and Lamont (2007). The top panel reports the average percent volume return ($VRet_{i,t} = ln(\frac{SHVOL_t}{SHVOL_{t-1}})$) for the HML portfolios, with t-statistics in brackets. T-statistics for the excess HML volume returns of specification 4 above the return of specifications 1, 2, and 3 are in parentheses. The bottom panel shows the average monthly value-weighted VRet for each of the six size and book-to-market portfolios (SL, SM, SH, BL, BM, BH).

Specification	1	2	3	4	5	6	7	8
Value Proxy	B/P	E/P	B/P	E/P	E/P	E/P	E/P	E/P
Rebalance	June	June	Month	Month	Month	Month	Month	Month
Sample	All	All	All	All	Pos	Neg	Earn	No Earn
HML VRet	-0.73	-0.10	0.65	1.38	1.38	0.45	1.04	1.67
t:HML(S)	[-2.50]	[-0.37]	[1.82]	[5.02]	[4.79]	[0.53]	[2.27]	[5.44]
t:HML(4)-HML(S)	(6.57)	(7.04)	(2.27)					
SL VRet	0.22	-0.22	-0.15	-0.74	-0.59	-0.16	8.27	-4.10
SM VRet	-0.04	0.05	0.01	0.30	0.42	-0.53	11.44	-4.18
SH VRet	-0.50	-0.05	1.22	1.45	1.42	-0.84	11.89	-2.58
BL VRet	1.31	1.19	1.20	0.81	0.80	-0.87	9.05	-2.22
BM VRet	0.77	0.92	0.71	0.84	0.86	0.11	7.61	-1.75
BH VRet	0.57	0.81	1.13	1.37	1.55	0.71	7.51	-0.41

Table 7: 4QEP and the Profitability of Liquidity Strategies For all US common stocks with a valid total basic EPS in the past 12 months (Compustat field EPSX12), and valid monthly closing share price (CRSP field PRC) , the Trailing Four Quarter E/P (4QEP) is: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{PRC_{i,t}}$. At the end of each month, I assign stocks to three 4QEP portfolios: negative EPS (Neg), positive EPS but not in the highest quintile (Low), and the highest quintile (High). Independently, at the end of each month, I assign stocks to quintiles of the Amihud (2002) illiquidity ratio (ILLIQ), defined as the average daily absolute return scaled by dollar volume: $ILLIQ_{i,t} = \sum_{k=1} \frac{|dret_{i,t-k}|}{dprc_{i,t-k} * dvol_{i,t-k}}$. In the top panel, ILLIQ is calculated from days in the last year (1Y), while in the bottom panel, ILLIQ is calculated from days in the last month (1M). ILLIQ quintile assignments use NYSE breakpoints. The table shows average monthly value-weighted double-sorted portfolio returns in excess of the monthly risk-free rate. In addition, the table shows average monthly returns for long-short 4QEP portfolios (High-Neg) controlling for ILLIQ quintile and long-short ILLIQ portfolios (5-1) controlling for 4QEP portfolio. The sample covers 1973-2015. T-statistics are in brackets.

ILLIQ (1Y)	ILL-Q1	ILL-Q2	ILL-Q3	ILL-Q4	ILL-Q5	5-1
4QEP Neg	0.31	0.24	0.27	0.24	0.28	-0.03
	[0.86]	[0.62]	[0.71]	[0.61]	[0.75]	[-0.13]
4QEP Low	0.44	0.60	0.63	0.62	0.72	0.28
	[2.26]	[2.68]	[2.75]	[2.60]	[3.08]	[1.83]
4QEP High	0.83	1.18	1.20	1.38	1.50	0.67
	[3.79]	[4.83]	[4.62]	[5.33]	[5.99]	[4.01]
High-Neg	0.52	0.94	0.92	1.14	1.23	
	[1.89]	[3.21]	[3.56]	[4.77]	[5.77]	
ILLIQ (1M)	ILL-Q1	ILL-Q2	ILL-Q3	ILL-Q4	ILL-Q5	5-1
4QEP Neg	0.36	0.18	0.34	0.31	0.11	-0.22
	[1.02]	[0.45]	[0.90]	[0.77]	[0.31]	[-0.85]
4QEP Low	0.45	0.52	0.64	0.56	0.54	0.09
	[2.31]	[2.37]	[2.80]	[2.34]	[2.32]	[0.58]
4QEP High	0.82	1.11	1.25	1.30	1.37	0.55
	[3.75]	[4.55]	[4.93]	[4.94]	[5.43]	[3.26]
High-Neg	0.47	0.93	0.91	1.00	1.26	
	[1.69]	[3.17]	[3.62]	[4.11]	[6.75]	

Table 8: 4QEP and Idiosyncratic Volatility The top panel presents results from asset pricing tests using the Fama and French (2015) model. At the end of every June, I independently assign stocks to five portfolios based on ME and five portfolios based on the previous fiscal year's B/M. For each of the 25 double-sorted portfolios, I calculate monthly value-weighted returns [$R_{P(i),t}$], and estimate $R_{P(i),t} = \alpha_i + \beta_{MKT} R_{MKT,t} + \beta_{SMB} R_{SMB,t} + \beta_{HML} R_{HML,t} + \beta_{RMW} R_{RMW,t} + \beta_{CMA} R_{CMA,t} + \epsilon_{P(i)}$. The top panel presents summary statistics and test results for three samples: all stocks with valid EPSX12, stocks with positive EPSX12, and stocks with negative EPSX12. Results include time-series averages of the number of stocks (Avg N), cross-sectional average market capitalization (Avg ME), cross-sectional average market-to-book ratio (Avg M/B), and average absolute alpha coefficient estimate for the 25 regressions (A$|a_i|$). The table presents the same statistics for two matched samples of stocks with positive and negative earnings. For each portfolio-month observation, I calculate the number of stocks with positive earnings (N_p) and negative earnings (N_n). In the Extreme ME Match, if $N_n < N_p$ ($N_p < N_n$), the positive (negative) sample contains the N_n (N_p) stocks with the smallest (largest) market capitalization. In the Extreme M/B Match, if $N_n < N_p$ ($N_p < N_n$), the positive (negative) sample contains the N_n (N_p) stocks with the largest (smallest) M/B. The bottom panel presents results from monthly Fama and MacBeth (1973) idiosyncratic volatility regressions. The dependent variable, idiosyncratic volatility, is the square root of the average squared residual from a monthly time-series regression of daily stock returns on an intercept and the daily Fama and French (2015) factor returns. The independent variables include an intercept, a negative earnings dummy, and the logs of market capitalization [log(ME)], book-to-market ratio [log(BM)], and share price [log(PRC)]. In the second stage, I calculate standard errors using the Newey-West (1987) correction with 12 lags to accommodate annual seasonality in factor returns. Coefficient estimates are quoted in percent. The sample covers 1973-2015. T-statistics are in brackets.

Pricing 25 Portfolios Formed on ME and B/M	Avg N	Avg ME ($M)	Avg M/B	A$\|a_i\|$ b.p.
All Valid EPSX12	3879.1	1836.8	3.06	7.96
Positive EPSX12	2842.5	2436.5	2.48	7.96
Negative EPSX12	1036.6	370.4	4.51	50.8
Extreme ME Match Positive	942.8	229.7	2.55	21.2
Extreme ME Match Negative	942.8	418.2	4.13	51.4
Extreme M/B Match Positive	942.8	600.6	3.50	15.2
Extreme M/B Match Negative	942.8	409.6	3.14	50.3

Fama and MacBeth Regressions	1	2
Intercept	2.22	4.68
	[26.40]	[20.85]
$1_{EPSX12<=0}$	1.71	0.60
	[20.82]	[11.04]
log(ME)		-0.03
		[-1.96]
log(BM)		-0.23
		[-11.53]
log(PRC)		-0.94
		[-13.52]
Average R^2	0.09	0.33

Table 9: Event Study of Stocks Crossing the Zero P/E Threshold This table reports characteristics and measures of trading activity for stocks crossing the zero P/E threshold. For US common stocks with valid total basic EPS in the past 12 months (Compustat field EPSX12), and valid monthly closing share price (CRSP field PRC), 4QEP is: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{PRC_{i,t}}$. Earnings are updated at the end of the first trading day after the report date (Compustat field RDQ). Because stock prices are positive, 4QEP only crosses above (Cross +) or below (Cross -) zero when quarterly earnings are released. For each crossing stock, I select a single matching stock (Match+, Match -) from among stocks that release earnings on the same day, have an earnings surprise in the same direction, and do not cross zero P/E. The sample covers 1973-2015. There are 16764 observations in the Cross+ and Match+ samples and 19420 observations in the Cross - and Match - samples. The matching stock is the nearest neighbor, where the distance function is defined as: $D_{i,j} = |Rank(\Delta E/P)_i - Rank(\Delta E/P)_j|$. The top panel presents average values of ME (market capitalization of equity in million USD), SUE (Δ E / P), cumulative abnormal returns (CAR), changes in trading volume [$\Delta VOL = log\frac{SHVOL_{event}}{SHVOL_{estimation}}$], and changes in the Amihud (2002) illiquidity ratio [$\Delta ILLIQ = log\frac{ILLIQ_{event}}{ILLIQ_{estimation}}$] between the [-120,-61] estimation window and three event windows. Abnormal returns in CAR are relative to a market-adjusted model, in which every stock has a beta of 1 relative to the equal-weighted index of CRSP common stocks in the same NYSE market capitalization decile. The bottom panel presents average changes in the breadth of institutional ownership [Δ NInst=NInst(Q[t])-NInst(Q[t-1])] from three quarters prior to the crossing date to one quarter following the crossing date. T-statistics using OLS standard errors are in brackets and t-statistics using standard errors clustered by calendar quarter are in parentheses.

Sample	ME (M USD)	SUE ($\Delta E/P$)	CAR [-1,0]	CAR [-60,0]	CAR [1,60]	ΔVOL [-1,0]	ΔVOL [-60,0]	ΔVOL [1,60]	ΔILLIQ [-1,0]	ΔILLIQ [-60,0]	ΔILLIQ [1,60]
Cross +	883.0	0.13	2.03	6.97	1.57	36.1	5.15	10.5	-88.1	-11.1	-28.9
Match +	905.1	0.12	1.74	5.94	2.81	28.2	4.49	8.93	-78.1	-4.31	-17.5
Diff +	-22.1	0.01	0.29	1.03	-1.24	8.35	0.71	1.66	-9.58	-6.74	-11.4
t-OLS	[-0.24]	[13.6]	[2.27]	[2.85]	[-3.88]	[6.54]	[1.04]	[1.99]	[-5.83]	[-7.52]	[-9.50]
t-ClustQ	(-0.22)	(9.85)	(1.89)	(2.03)	(-2.95)	(5.41)	(0.92)	(1.89)	(-4.66)	(-6.09)	(-7.81)
Cross -	758.3	-0.15	-1.76	-8.81	-1.38	10.1	-0.91	-3.58	-34.8	15.0	27.5
Match -	725.5	-0.14	-1.46	-6.88	1.01	9.35	1.13	0.36	-35.9	16.5	27.3
Diff -	32.8	-0.01	-0.30	-1.93	-2.39	0.31	-2.04	-4.04	1.22	-1.68	-0.04
t-OLS	[0.75]	[-6.60]	[-2.83]	[-5.69]	[-5.97]	[0.27]	[-3.24]	[-5.40]	[0.83]	[-2.12]	[-0.04]
t-ClustQ	(0.67)	(-4.60)	(-2.43)	(-4.10)	(-3.88)	(0.23)	(-2.43)	(-4.80)	(0.62)	(-1.62)	(-0.03)

Sample	Δ NInst Q[-3]	Δ NInst Q[-2]	Δ NInst Q[-1]	Δ NInst Q[0]	Δ NInst Q[1]
Diff +	0.36	0.60	0.65	0.42	0.10
t-OLS	[2.02]	[3.25]	[3.02]	[1.92]	[0.44]
t-ClustQ	(2.18)	(2.97)	(3.01)	(1.38)	(0.41)
Diff -	-0.28	-0.22	-0.62	-0.26	0.07
t-OLS	[-1.67]	[-1.22]	[-3.66]	[-1.72]	[0.36]
t-ClustQ	(-1.47)	(-1.29)	(-3.29)	(-1.36)	(0.25)

Table 10: Robustness Test Results This table summarizes time-series average monthly returns for decile long-short value-weighted portfolios, using NYSE breakpoints. The top panel presents average monthly long-short returns using 10 calculations for the Trailing Four Quarter E/P (4QEP). Tests 1-4 use 4QEP defined as Compustat trailing four quarters of EPS scaled by CRSP closing share price (PRC). EPSX12 and EPSF12 are basic and diluted EPS excluding extraordinary items. EPSPI12 and EPSFI12 are basic and diluted EPS including extraordinary items. In tests 5-8, the 4QEP calculations use the sum of Compustat quarterly EPS earnings for the last four quarters scaled by PRC. EPSPXQ and EPSFXQ are basic and diluted EPS excluding extraordinary items, and EPSPIQ and EPSFXQ are basic and diluted EPS including extraordinary items. In tests 9 and 10, 4QEP uses total earnings for the firm scaled by the market capitalization of the firm's equity. The earnings are Compustat quarterly net income excluding (IBQ) and including (NIQ) extraordinary items from the last four quarters, and market capitalization is the product of PRC and Compustat quarterly shares outstanding (CSHOQ). The bottom panel presents average monthly long-short returns in nine different cross-sectional or time-series subsamples. Test 11 (All) is the full sample, which covers 1973-2015. Tests 12 (Early) and 13 (Late) cover 1/1973-6/1994 and 7/1994-12/2015 respectively. Test 14 (No RNX) removes all stocks that crossed the zero, 10, or 20 P/E thresholds in the previous month. Tests 15-19 are based on tests from Lakonishok et al. (1994). Test 15 (MKT < 50) includes months when the market return is below the median. Test 16 (MKT < 25) includes months when the market return is below the 25th percentile. Test 17 (REC) comprises NBER recession months. Test 18 (GDP < 50) includes months when the following quarterly real GDP growth is less than the median. Test 19 (GDP < 25) includes months when the following quarterly real GDP growth is below the 25th percentile. T-statistics are in brackets. N is the number of months in the sample.

	1	2	3	4	5	6	7	8	9	10
	$\frac{EPSX12}{PRC}$	$\frac{EPSF12}{PRC}$	$\frac{EPSPI12}{PRC}$	$\frac{EPSFI12}{PRC}$	$\frac{\sum EPSPXQ}{PRC}$	$\frac{\sum EPSFXQ}{PRC}$	$\frac{\sum EPSPIQ}{PRC}$	$\frac{\sum EPSFIQ}{PRC}$	$\frac{\sum IBQ}{PRC*CSHOQ}$	$\frac{\sum NIQ}{PRC*CSHOQ}$
L-S	1.06	0.97	0.91	1.04	0.98	0.99	0.90	0.96	1.03	0.88
	[3.96]	[3.35]	[3.12]	[3.61]	[3.77]	[3.81]	[3.54]	[3.74]	[3.96]	[3.48]
N	516	516	516	516	516	516	516	516	516	516
	11	12	13	14	15	16	17	18	19	
	All	Early	Late	No RNX	MKT < 50	MKT < 25	REC	GDP < 50	GDP < 25	
L-S	1.06	1.06	1.07	0.99	2.61	3.96	1.54	1.56	2.94	
	[3.96]	[3.60]	[2.38]	[3.65]	[7.58]	[6.79]	[1.72]	[3.61]	[4.81]	
N	516	258	258	516	258	129	78	258	129	

Figure 1: Relative Google Search Volume for Value Proxies This figure shows the Google Search Volume Index (SVI) for various value proxies from January 2004 to April 2017. Data are from Google Trends (https://www.google.com/trends). The SVI is the number of web searches that Google assigns to specific search terms or broad topics. The "P/E Ratio" series charts searches for the price-earnings ratio topic. Common search terms that Google assigns to the price-earnings ratio topic include p/e, pe ratio, p/e ratio, price earnings, price earnings ratio, and price to earnings. The "P/B Ratio" series charts searches for the P/B ratio topic. Common search terms that Google attributes to the P/B ratio topic include p/b, pb ratio, p/b ratio, price book, book to price, price book ratio, price book value, market book ratio, and market to book. The "Market Leverage" series charts searches for the debt-to-equity ratio topic. Common search terms that Google attributes to the debt-to-equity ratio topic include debt ratio, equity ratio, debt to equity and equity debt ratio. The "Dividend Yield" series charts searches for the dividend yield search term because there is no related topic. The SVI series is normalized so the topic-month observation with the most searches has a value of 100. This observation corresponds to the price-earnings ratio topic in October 2008. The monthly ratio of the SVI for P/E Ratio to the SVI for P/B Ratio ranges from 4.25 to 14.40 with an average of 6.86. The monthly ratio of the SVI for P/E Ratio to the SVI for Market Leverage ranges from 2.18 to 5.15 with an average of 3.07. The monthly ratio of the SVI for P/E Ratio to the SVI for Dividend Yield ranges from 2.53 to 9.00 with an average of 4.54.

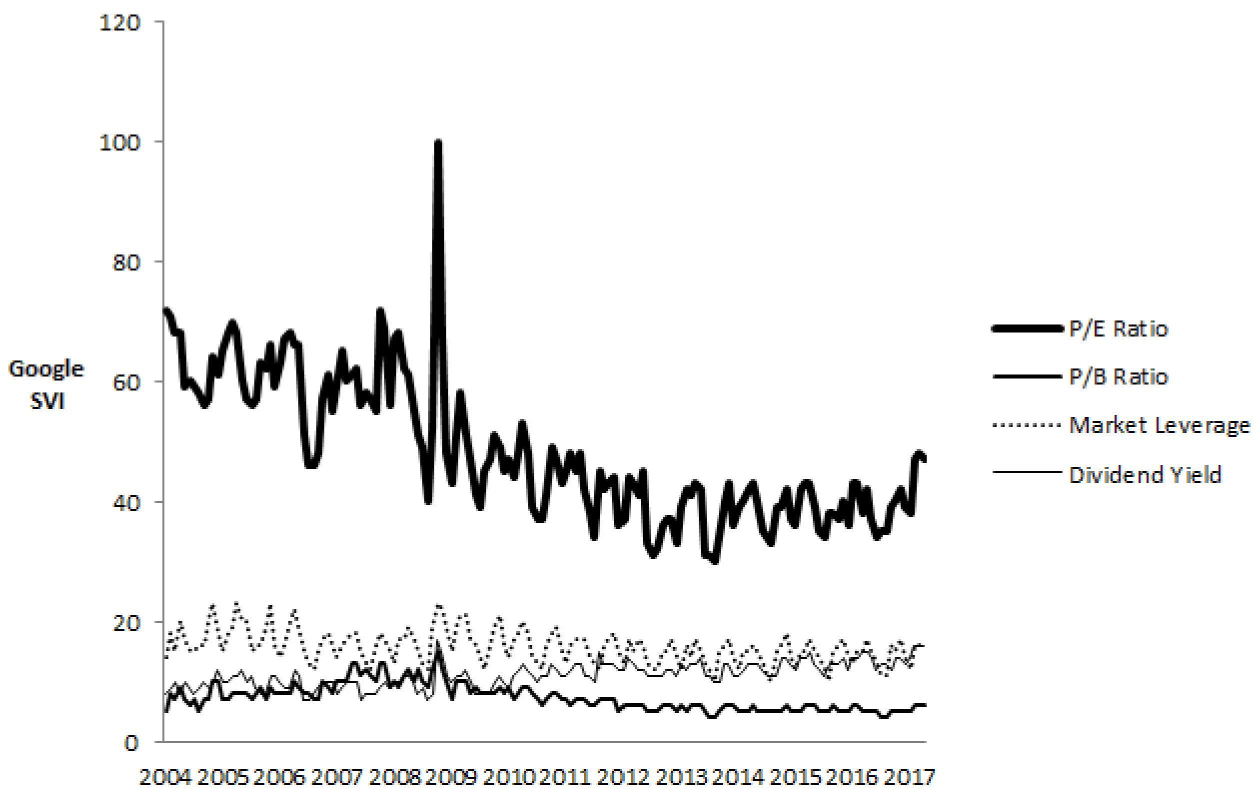

Figure 2: Published P/E Ratios for Stocks with Positive and Negative EPS This figure shows two screenshots of published stock quotations from Google Finance (https://www.google.com/finance). The stock quotations are from February 22, 2017. The top screenshot shows a quotation for Ford Motor Company (F) and the bottom screenshot shows a quotation for Tesla Inc (TSLA). Ford Motor Company has a published P/E ratio of 11.03, the share price of $12.67 scaled by the (four quarter trailing) EPS of $1.15. Tesla Motors Inc. has a share price of $273.51 and EPS of -$6.53, and there is no published P/E ratio.

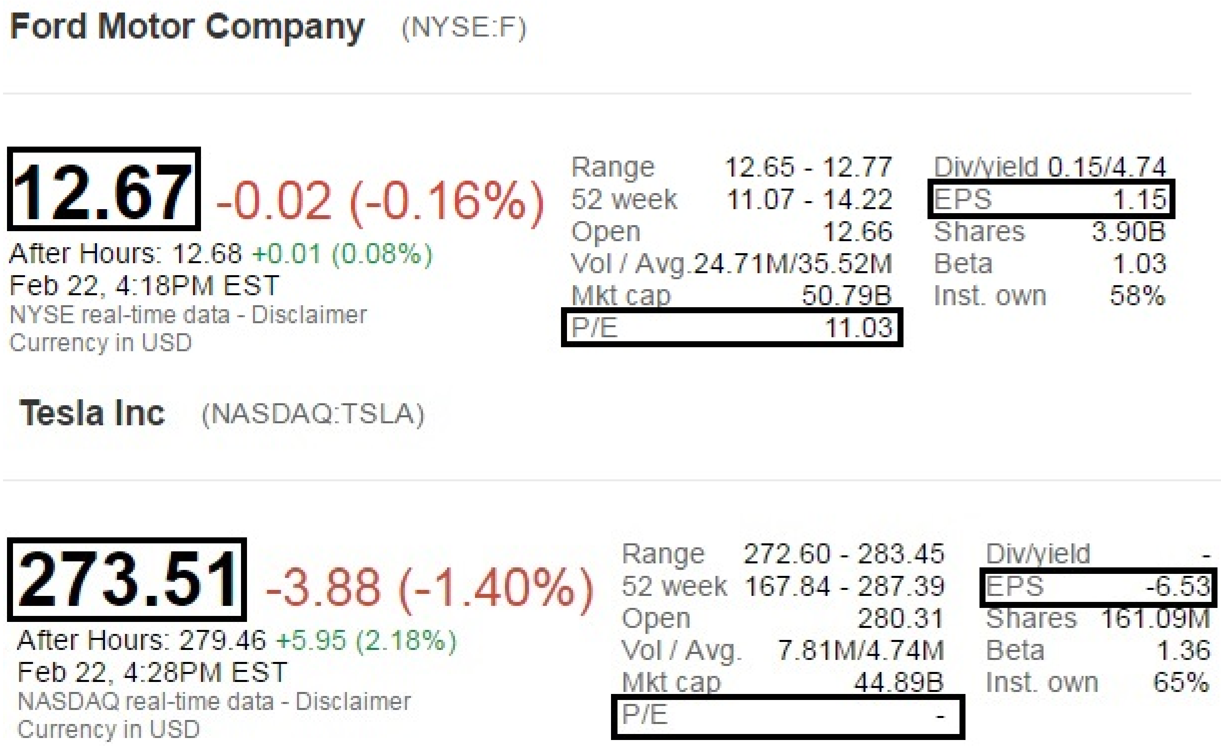

Figure 3: Average Returns for Stocks with Positive and Negative EPS Each bar in this histogram shows a portfolio's average monthly value-weighted return in excess of the one-month T-bill rate, reported in basis points. Monthly T-bill rates are from Kenneth French's data library. In each month, stocks are divided into those with positive and negative earnings, measured as total basic EPS in the past 12 months (Compustat field EPSX12). Then, stocks in both the positive and negative earnings samples are assigned to quintile portfolios of 4QEP, defined as $4QEP_{i,t} = \frac{EPSX12_{i,t}}{PRC_{i,t}}$, where PRC is the CRSP monthly closing share price . N1 (P1) is the portfolio of negative (positive) earnings stocks with the smallest 4QEP and N5 (P5) is the portfolio of negative (positive) stocks with the largest 4QEP. The sample covers 1973-2015. To form diversified portfolios within these subsamples, quintile portfolio assignments do not use NYSE breakpoints.

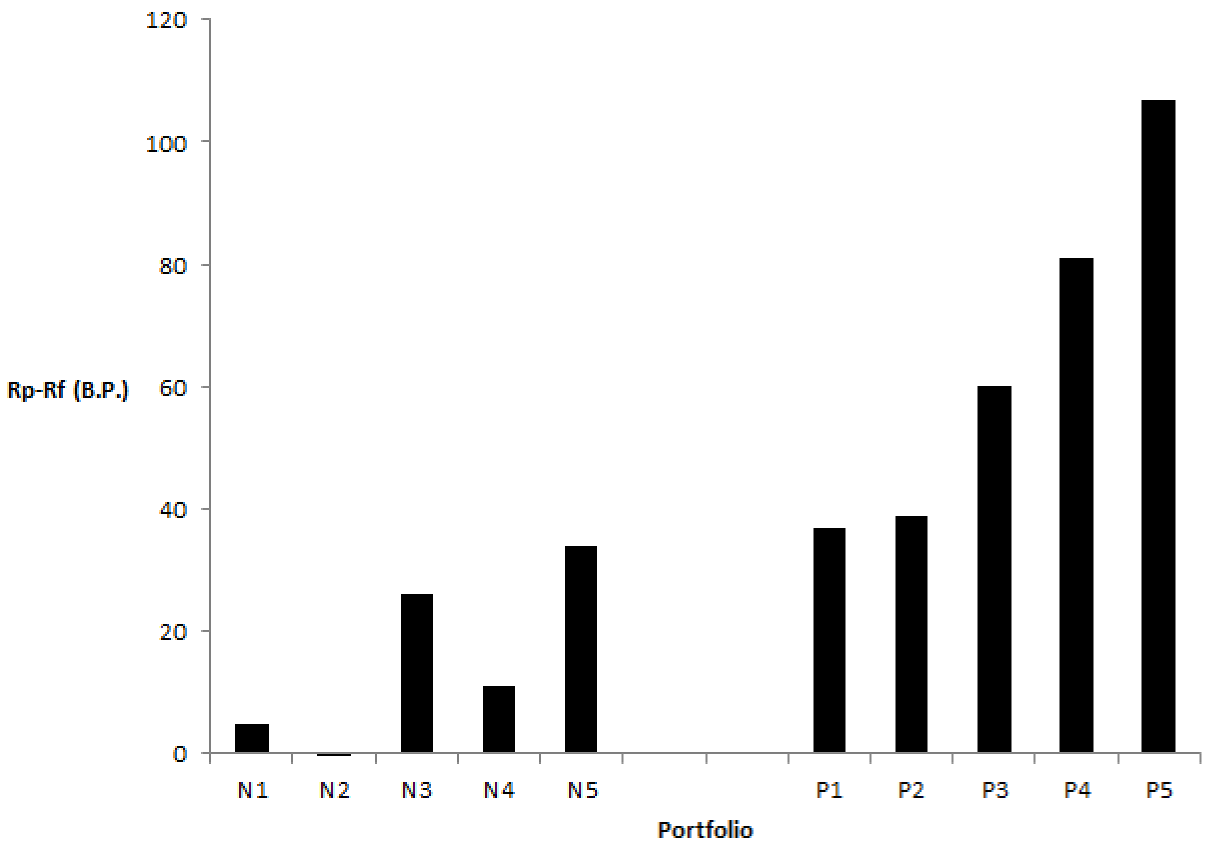

Figure 4: Return Predictability for Real-Time P/E Ratios and P/B Ratios The top panel shows long-short returns for two value-weighted extreme decile portfolios in the first 24 months following portfolio formation. The sample covers 1973-2015. The solid line shows the performance of a real-time P/B strategy. The sorting variable, B/P, is Compustat quarterly book value of equity scaled by CRSP market capitalization. Fama and French (1993, 2015) describe how to calculate the book value of equity. The dotted line shows the performance of a real-time P/E strategy. The sorting variable, E/P, is Compustat quarterly 12-month trailing basic EPS scaled by CRSP share price. In both strategies, decile portfolio assignments use NYSE breakpoints. The bottom panel deconstructs the excess return of the E/P strategy over the B/P strategy into long and short components. The solid line shows value-weighted percentage returns for a portfolio that is long stocks in decile 10 of E/P and short stocks in decile 10 of B/P. The dashed line shows value-weighted percentage returns for a portfolio that is long stocks in decile 1 of B/P and short stocks in decile 1 of E/P.

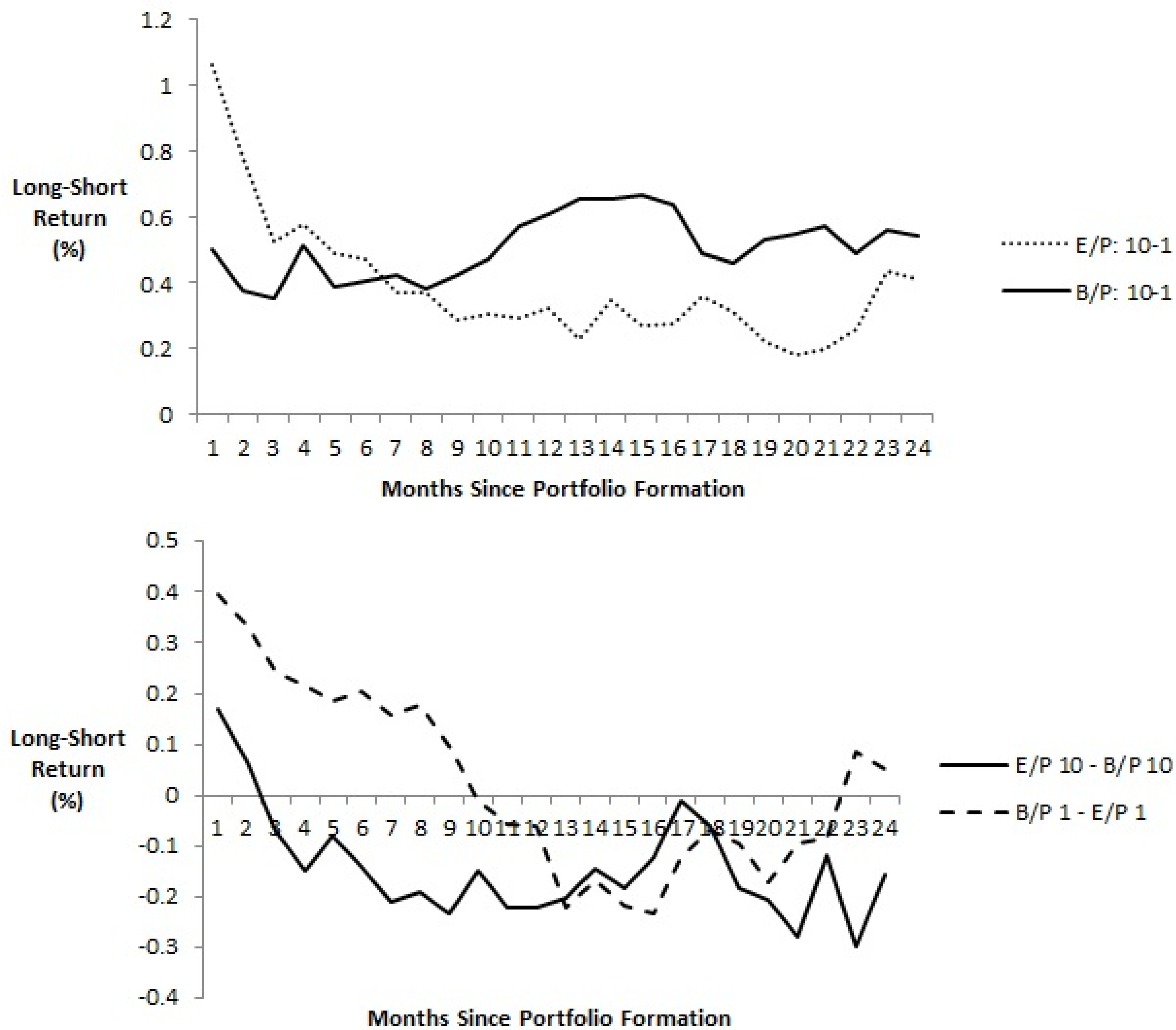

Figure 5: Monthly Volume Return Predictability for 4QEP For US common stocks with valid total basic EPS in the past 12 months (Compustat field EPSX12) and valid monthly closing share price (CRSP field PRC), 4QEP is: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{PRC_{i,t}}$. Every month, I assign stocks to percentiles of 4QEP, ignoring NYSE breakpoints. Each bar in this histogram shows the value-weighted average monthly volume return [$VRet_{i,t} = ln(\frac{SHVOL_t}{SHVOL_{t-1}})$] of each 4QEP percentile portfolio. The sample covers 1973-2015.

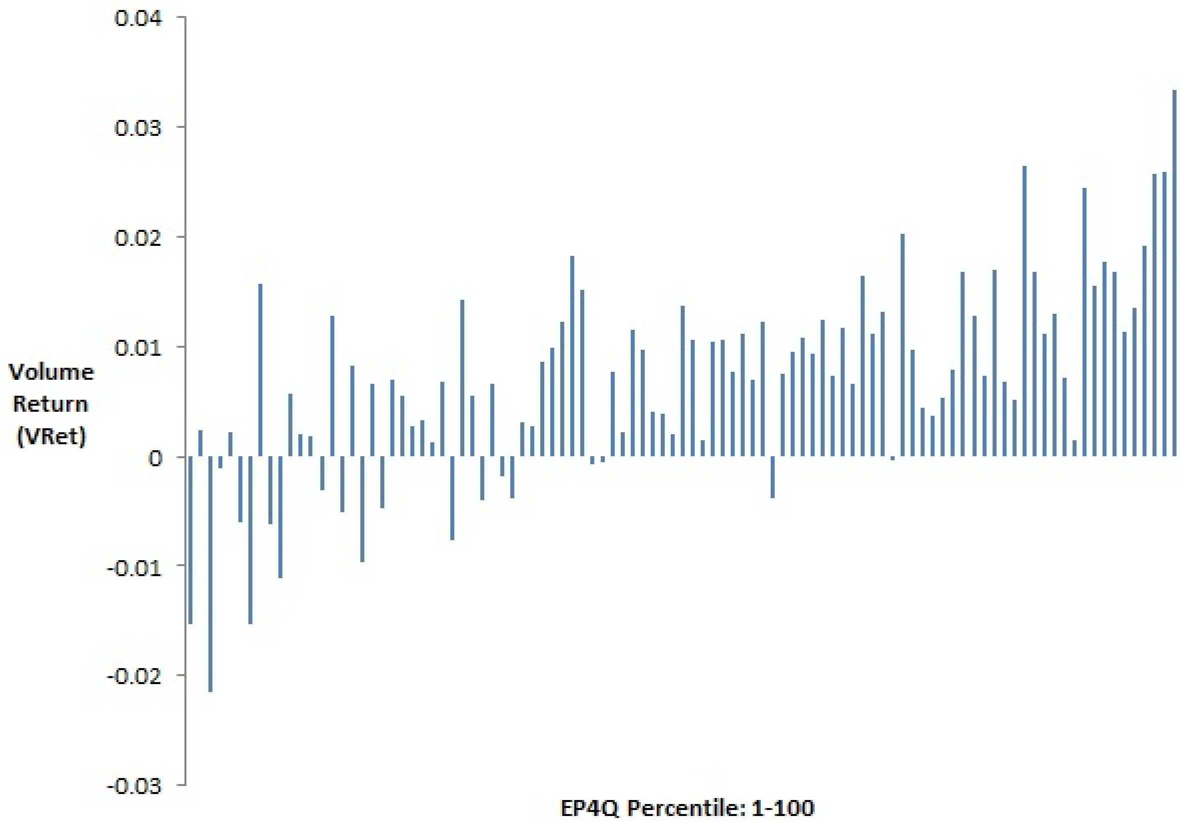

Figure 6: Average Residuals in Predictive Illiquidity Regressions This histogram shows the distribution of average residuals from estimating a predictive panel OLS regression. The dependent variable is illiquidity, measured as the log of the Amihud (2002) illiquidity ratio [log($ILLIQ_{i,t}$)] calculated using days in the current calendar month. Independent variables include an intercept, binary indicators for each calendar year, binary indicators for each of the Fama and French (1997) industries, and control variables from Chordia et al. (2007). These control variables include the "positive return" [max(ret,0)] from the previous month, the "negative return" [min(ret,0)] from the previous month, book leverage, the book-to-market ratio, beta, the log of the share price, the log of firm age, the log of market equity, the magnitude of the most recent earnings surprise and the volatility of the last 8 quarters of earnings. All controls are calculated as in Chordia et al. (2007) except for beta, which uses the Dimson (1979) procedure to control for asynchronous trading. The sample covers 1973-2015, includes common stocks listed on the NYSE or AMEX, and includes 928,045 stock-month observations. The R^2 of the regression is 0.93. For all US common stocks with valid total basic EPS in the past 12 months (Compustat field EPSX12), and valid monthly closing share price (CRSP field PRC), the Trailing Four Quarter E/P (4QEP) is: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{PRC_{i,t}}$. Each bar in the histogram shows the average OLS regression residual for observations in each percentile of $4QEP_{i,t}$.

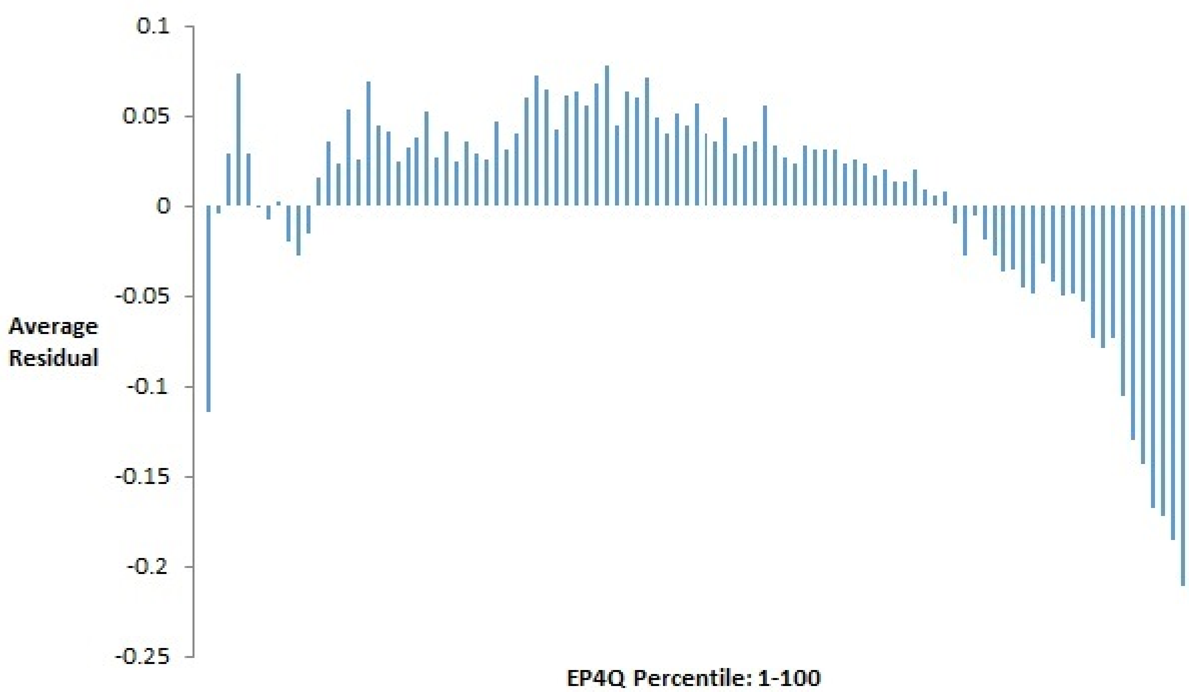

Figure 7: Event-Time Returns of Stocks Crossing the Zero P/E Threshold The top figure shows event-time returns for stocks crossing above zero P/E (Cross +) and stocks crossing below zero P/E (Cross -). For US common stocks with valid total basic EPS in the past 12 months (Compustat field EPSX12), and valid monthly closing share price (CRSP field PRC), 4QEP is: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{PRC_{i,t}}$. Earnings are updated at the close of the first trading day after the report date (Compustat field RDQ). Because stock prices are positive, 4QEP only crosses the zero P/E threshold when new quarterly earnings are released. The x-axis is the event time, in days, relative to the crossing date. The thick solid line and thin solid line show event-time returns for the Cross + and Cross - portfolios. For each crossing observation, I find the nearest neighbor from among other stocks which release earnings on the same day, have an earnings surprise in the same direction, and do not cross zero P/E. The nearest neighbor is the stock meeting these criteria with the smallest distance to the crossing stock, where distance is: $D_{i,j} = |Rank(\Delta E/P)_i - Rank(\Delta E/P)_j|$. The thick dotted line and thin dotted line show event-time returns for the Match + and Match - portfolios. The vertical axis is daily cumulative abnormal return (CAR) from a market-adjusted model, in which every stock has a beta of 1 relative to the equal-weighted index of CRSP common stocks in the same NYSE market capitalization decile. The bottom figure shows the average difference in CARs between the Cross+ and Match+ portfolios (Diff+) and between the Cross- and Match- portfolios (Diff-) The sample covers 1973-2015.