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Rankings of Published Price-Earnings Ratios and Value Investor Attention

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Rankings of published price-earnings ratios and value investor attention

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Abstract

Price-earnings (P/E) ratios are the most popular proxy for fundamental value and are widely published using a common methodology. This paper explores whether stocks with high P/E rankings are especially salient to individual investors with attention constraints. Consistent with the role of attention, P/E rankings predict the returns of strategies based on size, liquidity, and short-term reversals as well as increases in trading volume and liquidity. Financial data providers publish P/E ratios for stocks with positive earnings, but do not publish P/E ratios for stocks with negative earnings. P/E rankings predict returns and changes in trading volumes for stocks with positive earnings, but not for stocks with negative earnings. In an event study of all stocks which cross the 0 P/E threshold, the value of a positive P/E ratio is around 2.25%. Stocks which cross into positive P/E territory trade more actively than stocks which cross into negative P/E territory. Overall, a value-weighted extreme decile P/E attention strategy earns average monthly returns of 119 basis points from 1973 to 2015 with an annual Sharpe ratio of 0.94. These strategy returns are robust to fundamental factors and momentum in prices and earnings individually.

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1. Introduction

The relation between attention and stock returns is well documented. Kahneman (1973) establishes the importance of attention as a scarce cognitive resource which influences the decision-making process of all individual investors. Merton (1987) hypothesizes that for any asset, a broader investor base is associated with more diversified private information, a lower required discount rate, and a higher price. Gervais et al. (2001) and Kaniel et al. (2012) document a positive relation between current relative volume and future returns in equity markets. Barber and Odean (2008) relate high volumes, extreme returns, and news coverage to net purchases by individual investors. I extend this literature by considering published price-earnings (P/E) ratios as another important attention-grabbing characteristic. If enough value investors with attention constraints search for stocks in a list ranked by published P/E ratios, then these rankings can influence stock returns, trading volumes, and liquidity.

Empirical results support the P/E attention hypothesis. In a monthly time-series regression from 1973 to 2015, a long-short decile strategy based on P/E rankings and changes in rankings earns an average value-weighted monthly return of 119 basis points with an annual Sharpe ratio of 0.94. Strategies earn significant alphas in the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and the Fama and French (2015) five-factor model. These factor models include controls for exposure to market beta, size, value, profitability, investment, and price momentum. P/E rankings can only change because of relative changes in price or relatively strong or weak year-over-year quarterly earnings. Nevertheless, P/E rankings still predict strong variation in returns within portfolios which are already sorted on past returns or earnings momentum.

Stoll (1978) proposes a model in which individuals act as dealers willing to provide liquidity when institutional participants require immediate execution. Kaniel et al. (2008) show evidence that individuals do in fact provide liquidity by purchasing stocks following recent declines. If individual investor attention is positively correlated with P/E rankings, then these rankings should predict the returns of trading strategies which attempt to profit from short-term reversals. Likewise, the added visibility of high P/E rankings should predict the profitability of strategies which involve buying small or illiquid stocks. Furthermore, if stocks with high P/E rankings attract additional investor attention, then the added participation of these investors should predict higher trading volumes. The data support all of these predictions.

I use data from Google Trends to establish the unrivaled popularity of P/E ratios as measures of fundamental value. Google Trends has a new feature providing users a search volume index (SVI) for a "topic" rather than a very specific "search term." This SVI is a standardized time series of internet searches for search terms which Google attributes to the broader topic. Da et al. (2011) show a positive relation between the SVI for individual ticker symbols and subsequent cross-sectional variation in abnormal turnover and future returns. Figure 1 shows the SVI time series for topics that could plausibly proxy for fundamental value. Specifically, I consider the sorting variables for the 12 value anomalies in Hou et al. (2014). There are only four variables with non-trivial search volume: P/E ratios, P/B ratios, market leverage, and dividend yield.[2] P/E ratios have the highest SVI in every single week of the sample, which extends from January 2004 to April 2016. The average SVI for P/E ratios is 6.9 times larger than the average SVI for P/B ratios.

It is straightforward to estimate the P/E rankings at the end of any trading day. Major financial data providers publish P/E ratios using the most recent intraday or closing price and the four most recent quarters of earnings per share (EPS). Table 1 shows P/E rank-

[2]The value anomalies are listed in Appendix A, or in Hou et al. (2014) Table 2, Panel B

ings for S&P 400 Midcap stocks on two dates: August 31, 2015 and November 30, 2015. Between August and November, four stocks enter the list of 20 stocks with the highest P/E rankings : CYH, CAA, TEX, and RCII. These four stocks are especially salient to a value investor who regularly evaluates S&P 400 stocks with the highest P/E rankings and who has the resources to pay attention to about 20 stocks. The expected aggregate effect of this individual investor attention is a higher equilibrium price and an increase in trading volume for any of these four stocks.

P/E rankings could proxy for fundamental risk rather than value investor attention. To address this objection, I rely on an important institutional detail. P/E ratios for stocks with negative earnings are not published. Figure 2 shows Google Finance stock quotations for Ford Motor Company (F) and Tesla Motors Inc (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. For stocks with positive earnings, P/E rankings convey information about both visibility and fundamentals. For stocks with negative earnings, P/E rankings only convey information about fundamentals. Strategies based on P/E rankings or changes in rankings only earn significant returns and predict changes in trading volumes in the sample of stocks with positive earnings. I also conduct an event study of all stocks crossing the 0 P/E threshold and estimate the value of a positive P/E ratio at around 2.25%. Stocks which cross into positive P/E territory have greater abnormal trading volume than stocks which cross into negative P/E territory.

The remainder of the paper is organized as follows. Section 2 develops the hypothesis by reviewing prior literature on attention and stock returns. Section 3 describes the data and the construction of important variables. Section 4 summarizes asset pricing test results showing that P/E rankings predict returns and volumes only for stocks with positive earnings. Section 5 provides evidence that stocks with high P/E rankings attract individual investors to provide liquidity. Section 6 studies the performance and trading activity for stocks crossing the 0 P/E threshold and for stocks with extremely high P/E rankings. Section 7 shows that the main empirical results are robust. Section 8 concludes.

2. Hypothesis Development

My hypothesis is that rankings of published P/E ratios predict stock returns because P/E ratios influence value investor attention. I construct variables to model the rational behavior of value investors, including active equity mutual funds, hedge funds, proprietary trading firms, and individuals. If the trading activity of these investors is economically meaningful, then a measure which proxies for expected changes in value investor order flow can predict subsequent returns.

As Grossman and Stiglitz (1980) argue, there must be some equilibrium level of market inefficiency to justify the efforts of active investors. Value investors face attention constraints because investment opportunities depend on stock prices and stock prices are volatile. Peng and Xiong (2006) show that limited attention forces investors to focus on market- and sector-specific news at the expense of firm-specific news. Hou et al (2009) find that investor attention can lead to both insufficient responses to relevant information and excessive responses to irrelevant information. Abel et al (2013) demonstrate that investors apply some state-dependent rule for portfolio rebalancing when there are nontrivial fixed costs of attention.

Many empirical studies suggest that the marginal investor faces binding attention constraints. Cohen and Frazzini (2008) show that investors with limited attention fail to fully adjust the stock prices of supplier firms for changes in their customers' future earnings expectations. DellaVigna and Pollet (2009) show that if companies release earnings news on Fridays, when investor attention is more limited, the stock price reaction is more delayed. Hirshleifer et al. (2009) show that the price response to unexpected earnings is more delayed when investors are distracted with a large number of firms release earnings on the same day.

The relation between proxies for investor attention and stock returns is empirically robust. Gervais et al. (2001) identify a positive relation between relative volume and subsequent returns for US stocks. Kaniel et al. (2012) show that this high-volume return premium is present in most international equity markets. Da et al. (2011) show a positive relation between Google search frequency and future returns. Barber and Odean (2008) directly relate three measures of investor attention to increased net purchases by individual investors: high relative volumes, extreme returns, and frequent news appearances. Attention is also likely to influence an investor's decision to sell stocks. Hartzmark (2015) shows that both retail and institutional investors are substantially more likely to sell the stocks in their portfolio with the highest and lowest returns. This finding suggests that investors rank stocks in their portfolios on returns, and those at both extremes of the ranked list are especially salient.

Newsworthy events and well-publicized price levels are also correlated with future returns. Frazzini and Lamont (2007) find that stocks earn larger returns in months with expected earnings announcements. Hartzmark and Solomon (2013) find evidence of larger returns for firms during months with expected dividend payments. George and Huang (2004) show that a stock's proximity to its 52-week high predicts much of the Jegadeesh and Titman (1993) momentum anomaly. Li and Yu (2012) show that proximity of the Dow Jones Industrial Average to its 52-week high forecasts future market returns.[3] The existence of binding investor attention constraints is consistent with extensive evidence of price clustering at

[3] On the other hand, proximity of an index of all NYSE/AMEX stocks to its 52-week high, which is economically more meaningful but far less visible, does not predict future market returns.

round numbers and other visible figures. Appendix B lists 13 published papers documenting round number clustering in a variety of asset classes and other environments.

Value investors facing attention constraints must use some numerical criteria to screen or sort for undervalued stocks. Published P/E ratios are likely candidates for screening or sorting variables. P/E ratios are popular valuation metrics since Graham and Dodd (1934), widely published in financial quotes, and frequently referenced in news stories. Benjamin Graham advocates using several years of earnings to calculate P/E ratios. Likewise, Campbell and Shiller (1999) construct a P/E measure using a long time series and business cycle adjustments. However, P/E ratios published in popular financial data sources such as the Wall Street Journal, Financial Times, Bloomberg, or Google, are typically calculated using four trailing quarters of net income.

I construct a trading strategy using a proxy for investor attention based on published P/E rankings and show that the strategy earns economically and statistically significant returns. However, the fact that P/E ratios proxy for value could drive the strategy returns. Basu (1977, 1983) finds that P/E ratios predict NYSE stock returns after controlling for size. However, Fama and French (1992) show P/E ratios are insignificant in a cross-sectional regression which also includes P/B. The book value of equity depends on a firm's lifetime retained earnings, while P/E ratios capture only one year of financial performance. Investors see new fundamentals once per quarter, while Fama and French (1992, 1993) update fundamentals annually. Since four trailing quarters of earnings are more volatile than the book value of equity, tests using annual updating may not accurately measure the relative attention content of P/E and P/B.

Because earnings are in the denominator, P/E ratios are also related to profitability. Novy-Marx (2013) and Fama and French (2015) argue that the relation between profitability and expected stock returns is consistent with the valuation equation implied by clean surplus accounting. Fama and French (2008) demonstrate that an earnings-to-equity profitability measure does not reliably predict stock returns. Novy-Marx (2013) identifies gross profitability, measured as the ratio of gross profits to assets, as a robust source of cross-sectional variation in stock returns. Ball et al. (2015) construct a measure of operating profitability which adjusts gross profits for current expenditures on sales, general, and administrative expenses excluding research and development. It's important to show that the profitability of P/E attention strategies is not due to exposure to one of these fundamental profitability measures.

3. Data

Data on prices, volumes, returns, and shares outstanding for US equities are from CRSP. All returns are adjusted for delistings. Reporting dates and quarterly fundamentals data are from Compustat. The sample period for data collection begins in January of 1972, when quarterly earnings for a large number of public US firms become available. Since four quarters of prior earnings data are necessary to calculate a trailing 4Q P/E ratio, the sample for asset pricing tests starts in January of 1973. The sample ends in December of 2015. Only common stocks (CRSP Share Code 10 or 11) are included in the sample. I don't exclude any stocks because of liquidity reasons or industry membership.

The trailing 4Q E/P ratio for each stock-month or stock-day observation is calculated to match the P/E ratio published by popular market data providers, such as the Wall Street Journal, Financial Times, Bloomberg, or Google. E/P ratios are simply the reciprocal of P/E ratios. Unlike P/E ratios, E/P ratios are monotonic measures of value. In practice, when E/P$\leq$0, no value for P/E is published. However, negative EPS values are reported, so there is minimal cost to construct trailing 4Q E/P ratios for these stocks. [4]

In this paper, I calculate the 4Q E/P is calculated as:

$$4QEP_{i,t} = \frac{EPSX12_{i,t}}{|PRC_{i,t}|}$$

The numerator refers to the CRSP EPS for the last 12 months, and it actually sums the last four quarterly EPS values. The denominator is the CRSP monthly closing share price, and the absolute value acknowledges the CRSP convention of reporting the price as the negative of the bid/ask average when there is no trading activity in the month. The earnings in $EPSX12_{i,t}$ is "excluding extraordinary items." Net income excluding extraordinary items is used extensively in prior literature on P/E ratios, post-earnings announcement drift, and earnings momentum[5]. The earnings in $EPSX12_{i,t}$ is "basic," so the net income is scaled by the number of shares actually outstanding, rather than adjusting for the dilutive effect of stock option awards. I choose to use basic EPS because estimating the effect of dilution depends on choosing parameter values in an options pricing model and introduces measurement error. There are three alternative versions of the CRSP EPSX12 field. EPSPI12 is basic EPS excluding extaordinary items. EPSF12 is diluted EPS excluding extraordinary items. EPSFI12 is diluted EPS including extraordinary items. Replacing EPSX12 with any of these alternatives in the numerator has minimal effect on the results of asset pricing tests.

The measurement of the trailing 4Q E/P ratio assumes that the number of shares outstanding is constant over the last four quarters. In fact, the number of shares outstanding changes between quarterly earnings releases for reasons including share buybacks and employee option exercises. Alternative calculations of trailing P/E ratios would employ the

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

[5] For instance Basu (1977, 1983) on P/E ratios and cross-sectional stock returns, and Foster (1977), Foster et al. (1984), Bernard and Thomas (1989, 1990), and Livnat and Mendenhall (2006) on PEAD

price and earnings measures on an aggregate basis, rather than on a per-share basis. The numerator of the trailing 4Q E/P ratio would be the sum of the four most recent values of either Compustat quarterly net income (NIQ) or Compustat income before extraordinary items (IBQ). The trailing four quarters of net income would be scaled by the total market capitalization, the product of the share price and the appropriate shares outstanding. Compustat fields CSHFDQ and CSHPRQ are quarterly numbers of shares outstanding for fully diluted and basic EPS calculations respectively. Once again, using any of these alternative measures for trailing 4Q P/E ratios has minimal effect.

Among the eight possible measures for trailing 4Q P/E ratios, the differences depend on extraordinary items, the effect of dilution, and actual changes in the number of shares outstanding over the last four quarters. In the vast majority of cases, the effects of these modeling choices are minimal. For instance, NIQ and IBQ only differ in approximately 16% of firm-quarter observations in the sample. Many of the differences are minimal, and many of the largest discrepancies are concentrated among the smallest stocks, so the effect is reduced further by employing asset pricing tests using value-weighted portfolios.

In the monthly asset pricing tests in this paper, I assume investors know quarterly earnings on the close of the last trading day of the calendar month in which earnings are reported. The earnings release date is determined by Compustat field RDQ. It is possible that in a very small percentage of firm-month observations, earnings are released after the market closes on the last trading day of the month. On the other hand, the average calendar month includes approximately 21 trading days, so if earnings reports are distributed uniformly throughout the month, the monthly P/E attention strategies exclude excess returns from the first 10 or 11 trading days after new earnings are available.

Evaluating analogous strategies using daily data will provide an estimate of the extent to which monthly strategies understate gross returns available to investors. In the daily asset pricing tests in this paper, I assume investors know quarterly earnings on the close of the first trading day after the reporting date, based on RDQ. If RDQ is accurate, this assumption guards against cases when earnings are not released until after the market closes. Della Vigna and Pollet (2009) evaluate an extensive sample of earnings announcement dates in Compustat as well as media sources and they show that if there is any discrepancy between RDQ and the actual earnings announcement, then RDQ actually occurs a day later.

Unfortunately, Compustat quarterly earnings are not "point in time." The quarterly earnings in the NIQ fields are the final adjusted earnings and may not match the earnings an investor sees when the company releases quarterly financials. Livnat and Mendenhall (2006) use a proprietary point-in-time database as well as Compustat to construct decile PEAD strategies. The average quarterly long-short returns using the two databases on the same strategy are within about 10 basis points. The Livnat and Mendenhall (2006) finding suggests that results in this paper are not sensitive to earnings restatements in Compustat.

Table 2 presents summary statistics on published P/E ratios. The top panel summarizes changes in the cross section of published P/E ratios over time by dividing the sample into subsamples ending every five years. The number of CRSP common stocks with valid published P/E ratios increases from around 2300 in the 1970s to a high of around 6500 in the late 1990s, coinciding with the dot-com boom, before falling to around 3600 in 2015. Public companies are acquired or delisted on an ongoing basis. The marginal stocks choosing to go public or remain public at any given time tend to be small growth firms with volatile earnings. As the number of public companies increase, the percentage of firms with positive published P/E ratios declines and the median E/P ratio decreases. From 1996 to 2015, around one-third of all stocks in the CRSP database have negative values of 4QEP and the median published P/E ratio is around 30. Since smaller companies have lower E/P ratios, the median E/P ratio for individual firms understates the value-weighted E/P ratio for the market in every subsample.

The bottom panel of Table 2 presents the time-series average cross-sectional rank correlations of different versions of 4QEP, using different variables to represent the trailing four quarters of EPS. EPSPI12 is the Compustat trailing four quarters of basic EPS including extraordinary items. EPSF12 is the Compustat trailing four quarters of diluted EPS excluding extraordinary items. EPSFI12 is the Compustat trailing four quarters of diluted EPS including extraordinary items. In each month, rank correlations are calculated for the set of stocks which have valid 4QEP using all four measures. This sample includes approximately 50% of the observations in the top sample. The rank correlation between any pair of variables is at least 92%, suggesting the P/E rankings at any given time are very similar regardless of whether a particular market data provider uses basic or diluted shares or uses earnings excluding or including extraordinary items.

The primary variables of interest in this paper use 4Q E/P rankings and changes in rankings to proxy for investor attention. P/E rankings proxy for the attention of long-term investors, or those who search a list of stocks ranked by published P/E ratios for the first time. Changes in P/E rankings proxy for the attention of short-term investors, or those who search a list of stocks ranked by published P/E ratios frequently, and are especially likely to notice stocks which move up the list substantially. To proxy for rankings, I assign each stock to a percentile of $4QEP_{i,t}$ at the end of each month or day, and this variable is called $4QEPPct_{i,t}$. To proxy for change in rankings, I calculate $4QEPPct_{i,t} - 4QEPPct_{i,t-1}$ for each stock at the end of each month or day, and then convert this value to a percentile. This variable is called $4QEPPctChg_{i,t}$. For strategies with daily rebalancing, I use a lag of 21 days to calculate $4QEPPctChg_{i,t}$, which facilitates comparison with monthly strategies.

Finally, I construct a measure which considers both rankings and changes in rankings. At the end of each month or day, I calculate $4QEPPct_{i,t} + 4QEPPctChg_{i,t}$ for each stock at the end of each month or day, and then convert this value to a percentile. This variable is called $4QEPPctTotal_{i,t}$. The mapping of actual investor attention to these sorting variables depends on the uninformative prior that among value investors, the threshold where attention is exhausted is uniformly distributed across stocks. In fact, actual value investor attention is unobservable. However, if P/E attention return spreads result from value investor attention, there should be corroborating evidence, such as variation in subsequent trading volumes and liquidity.

In Fama and MacBeth (1973) regressions, the dependent variables in the first stage are the monthly returns of individual stocks. These returns are either CRSP monthly holding period returns or delisting returns. Some of the control variables are lagged values of monthly returns are independent variables. The cumulative return from the end of month $t-12$ to the end of month $t-1$ represents the Jegadeesh and Titman (1993) momentum characteristic. The month t return proxies for the Jegadeesh (1990) short-run reversals characteristic.

The log of market capitalization and log of book-to-market ratios for each stock are lagged as in Fama and French (1992). The market capitalization and book value from December of year $t-1$ are available to investors at the end of June of year t. The Novy-Marx (2013) gross profits-to-assets ratio and Cooper et al. (2008) asset growth ratio are calculated using the same timetable. The Novy-Marx (2013) and Cooper et al. (2008) measures are not calculated for financial firms, those with SIC codes between 6000-6999. The profitability and investment characteristics for year t are calculated from Compustat annual data as:

$(GP/AT)_t = \frac{REVT_t - COGS_t}{AT_t}$

$dAT_t = \frac{AT_t}{AT_{t-1}}$

To account for PEAD, I calculate SUE each month as in Chan et al. (1996). First, they measure unexplained earnings as the earnings surprise based on the finding by Foster et al. (1984) that the seasonal random walk model is a good description of the time series of quarterly earnings:

$UE_{i,t} = EPSPXQ_{i,t} - EPSPXQ_{i,t-4}$

Then, the unexplained earnings is scaled by the standard deviation over the trailing eight quarters:

$SUE_{i,t} = \frac{UE_{i,}}{\sigma_{UE_{i,t-1...t-8}}}$

Other popular measures of earnings momentum are abnormal return around the earnings announcement date and earnings relative to analyst forecast. However, the SUE measure in Chan et al. directly maps to changes in the trailing four quarters of earnings used in published P/E calculations and provides the most challenging test of the P/E attention hypothesis.

Another sorting variable is the volume rank in Gervais et al. (2001). At the end of each day, I calculate the volume rank (VR) as the ranking of a stock's share volume on that day of the month compared to the share volume on the last 50 trading days. This VR is converted to quintiles, such that a stock-day is assigned to quintile 5 if the VR is between 41 and 50 and in quintile 1 if the VR is between 1 and 10. If the overall market volume is especially high or low on a particular trading day, the distribution of VRs across stocks is likely to be skewed accordingly.

The final sorting variable I employ in this paper is the Amihud (2002) illiquidity measure, defined as the average daily absolute return scaled by volume over the previous 252 days:

$ILLIQ_{i,t} = \sum_{k=1}^{252} \frac{|ret_{i,t-k}|}{vol_{i,t-k}}$

In time-series regressions, positions in month t portfolios are weighted by market capitalization measured at the close of month $t-1$. Monthly factor returns for portfolios controlling for market excess return (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and momentum (UMD) are from Ken French's website.[6] The method for constructing these portfolios are described in Fama and French (1993) and in Carhart (1997).

Lakonishok et al. (1994) analyze the performance of value strategies in various subsamples to evaluate whether the returns are due to mispricing or risk. Repeating their analysis, I use data provided by the National Bureau of Economic Research (NBER) which characterize months as expansion months or recession months.[7] In the sample, the US goes through seven recessions comprising about 16% of the time series.[8] For the daily strategies, recession days are those which belong to an NBER recession month. Following Lakonishok et al. (1994), I construct subsamples based on quarterly US real GDP growth in the next quarter, since the stock market is considered a leading indicator of the business cycle. Business cycle data used to construct these subsamples are from the US Department of Commerce Bureau of Economic Analysis (BEA).[9]

4. Positive and Negative P/E Stocks

When a stock's P/E ranking increases, this conveys information about improving funda-

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

[7] The data on recession dates are available at: http://www.nber.org/cycles.html

[8] Recessions in the sample: 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

[9] The BEA website is: http://www.bea.gov

mentals in the form of a better earnings yield, but also represents greater visibility. P/E ratios are published for stocks with positive earnings, but are not published for stocks with negative earnings. For stocks with positive earnings, P/E ratios convey information about both visibility and fundamentals. For stocks with negative earnings, P/E ratios only convey information about fundamentals. Examining the relative return and volume predictability of P/E rankings for stocks with positive and negative earnings separately provides insight about the attention value of P/E rankings.

4.1. HML with different value proxies

Fama and French (1993) construct a portfolio which is long value stocks and short growth stocks. This portfolio is known as HML, which stands for high-minus-low. The HML portfolio is long stocks with a high book-to-market ratio (value stocks) and short stocks with a low book-to-market ratio (growth stocks). Figure 3 describes how these portfolios are formed by sorting stocks independently based on size, measured by market capitalization, and the book-to-market ratio. Stocks are assigned to portfolios every June, based on financial data and market capitalization from the previous December. Thus, data used to form the Fama and French (1993) HML portfolio are between six and 18 months old.

In Table 3, I evaluate the average monthly returns of HML portfolios from 1973 to 2015 using different value proxies. The first specification is the actual HML construction in Fama and French (1993). The average monthly return is 35 basis points. Small stocks have less liquidity, less analyst coverage, and higher trading costs, so typically any given strategy earns a larger return spread among smaller stocks. The HML portfolio constructed in Fama and French (1993) earns 50 basis points among small stocks and only 20 basis points among large stocks. In the second specification, I use E/P as the value proxy, but once again update portfolio assignments every June based on data from the previous

December. This specification has return performance very similar to HML using book-to-market updated annually. The strategy earns average monthly returns of 40 basis points, with small stocks earning a spread of 52 basis points versus only 28 basis points for the large stocks. In the next two specifications, I use the same value proxies, but the values are updated monthly to reflect the published values of these proxies observable by institutional investors. The real-time version of book-to-market earns similar returns to the annually updated variables: 37 basis points overall, 49 basis points among small stocks and 25 basis points among large stocks. However, the HML portfolio using the real-time version of the E/P ratio earns substantially higher returns than the other three specifications: 71 basis points overall, 84 basis points in the small stocks and 58 basis points in the large stocks.

The next two specifications evaluate the performance of HML using the real-time P/E ratio for subsamples of stocks with positive and negative earnings.[10] The positive earnings subsample has very similar performance to the full sample. The average HML return, test statistic, and individual portfolio returns in the positive earnings subsample are all very similar to those in the full sample. The performance of HML in the negative earnings subsample is quite different. The average monthly performance is an insignificant 22 basis points a month. The average monthly HML returns attributable to large stocks with negative P/E ratios is 43 basis points, similar to the 53 basis points for positive stocks. However, the monthly HML returns attibutable to small stocks with negative P/E ratios is 0 basis points for small stocks, versus 81 basis points for positive stocks. This result suggests that the absence of P/E rankings is especially detrimental for small stocks, which also tend to have less liquidity, trading volume, and analyst coverage.

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

The final two specifications show the performance of HML using the real-time P/E ratio for stocks in the month following quarterly earnings and for all other months. Because stocks release quarterly earnings every three months, the post earnings sample contains around one third of the observations. Overall, the HML returns are similar in both specifications: 76 basis points for the post-earnings subsample and 66 basis points for the other subsample. However, large stocks earn average returns of 70 basis points in the post-earnings sample and 45 basis points in the other subsample. Small stocks earn average monthly returns of 84 basis points in the post-earnings subsample and 88 basis points in the other subsample. This split is consistent with the idea that after earnings, analysts are more likely to produce new reports for large stocks, increasing the duration of attention from the earnings release.

I also calculate a monthly volume return for each portfolio. For every stock-month observation, I calculate the volume return as $VRet_{i,t} = ln(\frac{SHVOL_t}{SHVOL_{t-1}})$. Then I calculate portfolio returns for each of the six portfolios and calculate the VRet for HML as in Fama and French (1993). The HML portfolio constructed using real-time P/E ratios strongly predicts innovations to trading volume. Small stocks with high P/E rankings have trading volumes which are 219 basis points higher then small stocks with low P/E rankings, versus a spread of 56 basis points for large stocks. Although the HML portfolio constructed using real-time P/B ratios also predicts relative volumes, the relation is more than twice as strong for the version of HML which uses P/E ratios. The relation between P/E ratios and volume returns is also limited to stocks with positive earnings. Among stocks with negative earnings, HML does not significantly predict volume returns. For all three portfolios of small stocks with negative earnings, monthly average portfolio volume returns are negative.

Table 4 describes the performance of the different variations of HML in spanning tests with the other fundamental factors in the Fama and French (2015) five-factor model, which augment the factors in the orignal three-factor model with profitability (RMW) and investment (CMA) factors. In these spanning tests, there are five monthly time-series regression. In each regression, the dependent variable is one of the factors, and the independent variables include an intercept and the four other factors. In any of the time-series regressions, a positive and significant intercept suggests the factor is orthogonal to the other four factors. In other words, an investor would earn higher risk-adjusted returns from increasing portfolio exposure to that factor return. Notably, Fama and French (2015) find that their value factor is redundant in the five-factor model.

I repeat these spanning tests using the HML returns from the first six specifications in Table 3 as well as the MKT, SMB, RMW, and CMA returns from Ken French's website. The first specification in Table 4 confirms the Fama and French (2015) result: the intercept estimate in the HML spanning test is insignficant, but the intercept estimates for the other four factors are positive and significant.[11] Replacing the lagged annual BE/ME ratio with the lagged annual E/P ratio does not alter this result. The E/P ratio considers only the most recent full year of earnings, so it is more strongly related to the operating profitability variable used to construct RMW. As a result, the intercept estimate in the test with RMW as the dependent variable decreases from 40 basis points to 26 basis points, though it remains highly statistically significant. Likewise, replacing the lagged annual BE/ME with the real-time BE/ME does not alter the inference.

On the other hand, constructing HML using the real-time E/P ratio changes the results substantially. The intercept estimate for HML is now a significant 33 basis points per month (t-statistic = 2.93). The intercept estimates for MKT, SMB, and CMA are very

[11]The sample in Fama and French (2015) starts in 1963 while the sample in this paper starts in 1973 because of the requirement for four quarters of EPS in Compustat.

similar to those in specification 1, but the intercept estimate for RMW drops from 40 basis points per month to 15 basis points per month. Nevertheless, the intercept estimate is still significant at the 5% level. The results in specification 5 are the most striking. The value proxy in this test is HML constructed using a real-time E/P ratio among stocks with positive earnings. In this test, all five factor-mimicking portfolios have positive intercept estimates which are economically significant and statistically significant at the 1% level. In other words, when the value factor is constructed using the most popular measure of value and the stocks which are actually ranked according to this measure, all five factors in the Fama and French (2015) model are able to explain average returns even after controlling for exposure to the other four factors. Using the subsample of negative earnings stocks, the intercept estimates are similar, but the estimate on HML is no longer significant. Based on the results in the previous table, this is likely because small negative earnings stocks do not produce an average return spread, but still contribute to the volatility of HML returns.

4.2. Time-Series Regressions

Table 5 reports summary results from 48 monthly time series regressions, estimated using four different factor models for 12 different specifications. For each specification, I report the average monthly long-short return and the monthly alpha for each of the factor models. For each monthly observation in each time-series regression, the dependent variable is the percentage return of a value-weighted long-short portfolio. Specifications differ across four dimensions: the sorting variable, the number of portfolios stocks are assigned to in each month, whether portfolio assignments use NYSE breakpoints, and which stocks are included. The three sorting variables are the three P/E attention measures: P/E rankings ($4QEPPct$), changes in P/E rankings ($4QEPPctChg1M$), and the total of rankings and changes in rankings ($4QEPPct$). There are three samples: all stocks, stocks with positive earnings, and stocks with negative earnings. The independent variables are a monthly time series of intercepts and monthly returns of one or more factor mimicking portfolios. The CAPM model includes only MKT, the market excess return, as an independent variable. The three-factor model of Fama and French (1993) also includes SMB and HML, the factor-mimicking portfolios for size and value. The four-factor model of Carhart (1997) augments the three-factor model with the UMD momentum factor. The Fama and French (2015) five-factor model augments the three-factor model with RMW and CMA, proxies for profitability and investment premiums. The monthly time series for MKT, SMB, HML, UMD, RMW, and CMA are all from Ken French's data library.

The first three specifications show that each individual sorting variable produces positive and significant long-short return spreads. These tests use NYSE breakpoints to form portfolios and market capitalization to weight positions, as suggested by Hou et al. (2014). The strategy using $4QEPPct$ earns an average monthly long-short return of 1.06%, with a t-statistic of 3.96, which corresponds to an annual Sharpe ratio of 0.60. The strategy using $4QEPPctChg1M$ earns an average monthly long-short return of 0.81%, with a t-statistic of 5.30, which corresponds to an annual Sharpe ratio of 0.81. The strategy using $4QEPPctTotal$ earns an average monthly long-short return of 1.19%, with a t-statistic of 6.14, which corresponds to an annual Sharpe ratio of 1.19. The fact that the $4QEPPctTotal$ strategy earns higher and more significant long-short returns than either of the other strategies suggests stocks such as those in Table 1 which move into the top of the P/E rankings are especially likely to attract positive investor attention. All three strategies earn economically and statistically significant positive alphas under any of the four factor models. This is true despite the mechanical correlation between P/E rankings and fundamental value and profitability. In fact, these strategies do have substantial positive loadings on both HML and RMW, for instance the $4QEPPctTotal$ specification has a factor loading of 0.45 on HML and a loading of 0.57 on RMW. Nevertheless, the alpha for these P/E attention strategies are highly economically and statistically significant after controlling for these exposures to fundamental value and profitability.

The next three specifications use the same sorting variables and decile portfolio assignments, but do not employ NYSE breakpoints. This provides a benchmark to compare with quintile strategies using positive and negative earnings subsamples. The quintile strategies cannot use NYSE breakpoints because the relative scarcity of negative earnings stocks among NYSE stocks would lead to empty portfolios. By ignoring NYSE breakpoints, extreme decile portfolios tend to include stocks which are smaller and more volatile. As a result, the typical average long-short return is slightly larger in magnitude and the t-statistic is slightly smaller in magnitude. For all three sorting variables, the average long-short return and alphas using each of the four factor models are all positive and significant at the 1% level.

Finally, the sample is subdivided into stocks with positive and negative earnings. For each group, stocks are then divided into five portfolios based on each of the three sorting variables. The results for the two groups are very distinct. For the positive stocks, the average long-short returns are positive and significant and all four alphas are positive and significant for all three sorting variables. For the negative stocks, all of the average long-short returns are insignificant and only the three factor alpha for $4QEPPct$ is positive and significant. In other words, for stocks with positive earnings and published P/E ratios, both the rankings and changes in rankings produce strong variation in average returns. For stocks with negative earnings and without published P/E ratios, neither the rankings nor changes in rankings produce strong variation in average returns. Figure 4 shows this result more vividly by displaying histograms of the average excess returns for the five negative portfolios and five positive portfolios for each strategy. For all three strategies, the returns increase monotonically across the five positive earnings portfolios, but are not monotonic across the negative earnings portfolios. The variation is clearly quite a bit larger for stocks with positive earnings, and concentrated near the extreme of the P/E rankings.

5. P/E Rankings and Innovations to Trading Volume and Liquidity

In this section, I explore the mechanism that explains the relation between P/E rankings and

5.1. Volume Returns

If P/E rankings predict returns because of attention rather than fundamentals, they should also predict trading volume. It is the variation in order flow from long-term buyers and the associated price pressure that drives the variation in stock returns. Table 6 evaluates the relationship between P/E rankings and trading volume. For each stock with positive share volume in the previous two months, I calculate a monthly volume return in log terms: $VolRet_{i,t} = ln(\frac{SHVOL_t}{SHVOL_{t-1}})$ Trading volumes increased substantially during the sample and as a result, the average monthly volume return is around 1%. Furthermore, given the underlying trend in trading volumes, larger stocks are likely to have larger average increases in trading volume as markets become more liquid.

To control for the increasing volume trend and the role of size, I construct portfolios which are independently sorted at the end of each month based on size (ME) and published P/E ratio (4QEP). Stocks are assigned to quintile portfolios using NYSE breakpoints. Controlling for size, long-short quintile portfolios formed on 4QEP have positive and significant average monthly volume returns in every quintile. The average monthly long-short returns are around 2% for the smaller stocks and around 1.1% for the larger stocks. This finding is consistent with the role of P/E rankings in predicting returns for size and liquidity strategies. Controlling for 4QEP, long-short quintile portfolios formed on size only have positive and significant average monthly volume returns in one of the quintiles.

5.2. The Performance of Liquidity Strategies

Jegadeesh (1990) shows that a strategy that buys stocks with the lowest returns in the most recent month and shorts stocks with the highest returns in the most recent month earns positive returns. Table 7 shows that returns to these strategies based on short-term reversals are increase monotonically across quintiles of P/E rankings. Regardless of P/E rankings, stocks with the worst performance are highly visible to investors. Barber and Odean (2008) show that stocks with extreme recent returns attract purchases by individual investors. Kaniel et al. (2008) also find that individual investors provide liquidity to institutions buy buying the stocks with the worst recent performance. However, as the results show, average monthly quintile short-term reversal strategies earn an insignificant 2 basis points in the lowest quintile of P/E rankings, and increase monotonically from 35 basis points in the second quintile to 51, 71, and 80 basis points in the third, fourth, and fifth quintiles respectively. Many stocks in quintile 1 have negative P/E ratios, so poor return don't even effect P/E rankings. Stocks in quintile 2 and 3 are likely to have P/E ratios in the 20s or higher, so potential buyers of these stocks aren't likely to be very sensitive to changes in the P/E rankings. Stocks in the top quintile of P/E rankings, with a rise in the rankings resulting from recent underperformance, are those which have attracted the most new investor attention.

Size and liquidity are highly related. Trading a constant number of shares in a stock with a smaller number of shares outstanding incurs larger price impact and thus more illiquidity. The Amihud (2002) illiquidity measure and market capitalization have average cross-sectional correlations of around -60%. Unconditionally, small stocks have higher average returns than large stocks and illiquid stocks have higher average returns than liquid stocks. Small and illiquid stocks tend to trade at an equilibrium price that is a greater discount to its fundamental value. One fundamental reason for this discount is that asymmetric information is likely to be a greater concern for smaller firms. For instance, Bhushan (1989) and others show that firm size is strongly positively related to analyst coverage. Easley et al. (2002) show that in a theoretical framework, investors should earn higher average returns for holding stocks with a greater asymmetric information and a higher probability of informed trading.

If small and illiquid stocks trade at a discount, then a trading strategy of purchasing small and illiquid stocks is especially likely to earn profits when these discounts are likely to decline. In other words, if P/E rankings strongly influence attention, then stocks with high P/E rankings should attract investors to acquire private information and reduce asymmetry, narrowing the discount. The results in Table 7 support this rationale. Both size and liquidity strategies only earn significant long-short returns among stocks with the highest P/E rankings, and returns are mostly increasing across quintiles.

5.3. Predictive Panel Regressions of Trading Volume and Liquidity

Table 8 reports results from 12 predictive panel regressions which estimate whether P/E rankings actually predict innovations to trading volume and liquidity. These 12 specifications correspond to three dependent variables and four independent variables of interest. The four dependent variables include the log of share turnover (VOL) (VOL=$log\frac{SHVOL_t}{SHROUT_t}$), the log of the Amihud (2002) illiquidity factor (ILLIQ) calculated from the days in the most recent calendar month, and the monthly differences of these two variables (Δ VOL, Δ ILLIQ). The independent variables of interest are the P/E rankings (R), change in rankings (C), or the total of rankings and change in rankings (T). In all of the regressions, I restrict the sample to stocks trading on the NYSE or AMEX exchanges because of the finding by Atkins and Dyl (1997) that trades on NASDAQ are frequently double counted.

Each panel regression includes a series of control variables used in the Chordia et al. (2007) analysis of the cross-sectional determinants of trading activity. These control variables include POSRET (NEGRET), which is the return from the previous month if it is positive (negative) and zero otherwise. These two variables control for the positive relation between extreme returns and subsequent trading activity. Other controls include book leverage, the book-to-market ratio, beta, the log of the price per share, the log of the 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. The share price, firm age, and market capitalization are all calculated in log terms and the earnings-related measures are calculated using basic quarterly earnings per share excluding extraordinary items, and scaled by the stock price. Other independent variables include an intercept, dummies for each calendar year, and dummies for each of the Fama and French (1997) industries. Following Jacobs and Hillert (2015), I calculate betas using the method of Dimson (1979) to control for the effect of asynchronous trading and I calculated standard errors double clustered by firm and month.

The first three specifications show that none of the three independent variables of interest have signficant coefficient estimates in predicting share turnover. However, P/E rankings are quite persistent since quarterly EPS is positively autocorrelated and each quarterly earnings remains in the P/E calculation for twelve months. However, there is a strong economic and statistical predictive relation between P/E rankings and liquidity. Specifically, the stock with the highest P/E ranking has an Amihud (2002) illiquidity ratio that is 17.7% lower than the stock with the lowest P/E ranking. This is consistent with the idea the added buy orders orders individual investors replaces the buy orders from institutional liquidity providers and leads to higher equilibrium prices.

In the last six specifications, I estimate the model using first differences in the logs of share turnover and illiquidity as dependent variables. These dependent variables represent abnormal volume and abnormal illiquidity. P/E rankings are insignificant in predicting abnormal volume, but this is unsurprising since P/E rankings tend to be very persistent. It is more instructive to consider the predictive power of changes in P/E rankings on changes in volume and liquidity. In these specifications, the stock with the largest change in P/E rankings has abnormal volume which is 5.58% higher and abnormal illiquidity which is 3.13% lower than the stock with the largest decline in P/E rankings. Both of these relations are highly statistically significant even after controlling for the double clustering of standard errors.

6. Special Cases: The 0 P/E Threshold and Stocks with Extremely High P/E Rankings

If value investors with attention constraints search a list of stocks ranked by P/E ratio, those stocks with very high rankings should be especially salient. This section measures whether stocks with very high P/E rankings earn especially large returns.

6.1. Event Study of Stocks Crossing 0 P/E

Since P/E rankings predict stock returns for stocks with positive earnings, but not for stocks with negative earnings, it is interesting to evaluate the event-time performance of stocks which cross above and below the 0 P/E threshold. Figure 5 shows the event-time returns. from an event study. Because stock prices are positive, P/E ratios can only cross above or below 0 when the release of quarterly earnings flips the sign of the total earnings from the trailing four quarters. In the 1973-2015 sample, there are about 16000 events in which stocks cross into positive P/E territory and about 19000 events in which stocks cross into negative P/E territory.

The solid lines in Figure 5 show event-time average returns of the two crossing portfolios. As in Foster et al. (1984), the figure shows returns from 60 days before the quarterly reporting date leading to the threshold crossing to 60 days after the reporting date. Returns are cumulative abnormal returns (CAR), calculated according to the method of Foster et al. (1984). Specifically, the expected return is based on a market-adjusted model, and every stock has a beta of 1 relative to the equal-weighted index of CRSP common stocks in the same decile of market capitalization, using NYSE breakpoints.

The event-time returns of these crossing groups are consistent with the fact that the stocks crossing above 0 P/E have a positive earnings surprise and stocks crossing below 0 P/E have a negative earnings surprise, relative to a seasonal random walk model. Stocks which cross above 0 P/E have positive abnormal returns of around 4% in the 60 days prior to the event, 3% in the two-day window around the event, and a 2% "drift" in the 60 days following the event. Stocks crossing below 0 P/E have a similar profile of negative abnormal returns before, during, and after the event.

To control for the fact that I am selecting on a long-short earnings surprise strategy, I construct a matched sample using the "nearest neighbor" principle of Abadie and Imbens (2006). For each crossing observation, I find the nearest neighbor from other stocks which release earnings on the same day, have an earnings surprise in the same direction, and do not cross 0 P/E. The nearest neighbor is the stock meeting these criteria with the closest distance to the crossing stock. For crossing stock i and matching stock j, I define distance as: $D_{i,j} = |Rank(ME)_i - Rank(ME)_j| + |Rank(SUE)_i - Rank(SUE)_j|$. Figure 5 also shows the event-time CARs of the neighbor portfolio. Since the matched sample also loads on a long-short earnings surpise strategy, the event-time returns have the same pattern have the same shape as the crossing sample. However, the spread in the matched sample is smaller than the spread in the crossing sample, and the difference in the spreads can be construed as the economic value of crossing the 0 P/E threshold. It appears that crossing the 0 P/E threshold is worth around 2% and is largely anticipated by the market.

Table 9 evaluates the statistical significance of crossing the 0 P/E threshold. The top panel of Table 9 shows whether the crossing sample and matched sample are similar. For stocks crossing above the 0 threshold, the difference in mean market capitalization between crossing sample and matched sample is statistically indistinguishable. However, stocks in the crossing sample have higher average book-to-market ratios than stocks in the matched sample. The same relations hold in the stocks crossing into negative P/E territory. The crossing and matched samples have indistinguishable market capitalizations, but the crossing sample has a larger mean book-to-market ratio. On a long-short basis, the crossing sample has a smaller average book-to-market ratio than the matched sample. This suggests that the larger CAR spread earned by the long-short crossing strategy is unlikely to be related to differences in HML exposure.

The bottom panel of Table 9 shows statistically what Figure 5 shows graphically. Relative to the matched sample, stocks crossing above 0 P/E earn a statistically significant excess CAR of 2.16 percent in the [-60,0] window and a statistically significant excess CAR of 58 basis points in the [-1,0] window. Conversely, relative to the matched sample, stocks crossing below 0 P/E earn a statistically significant excess CAR of -2.39 percent in the [-60,0] window and a statistically significant excess CAR of -18 basis points in the [-1,0] window. However, for stocks crossing into both positive and negative P/E territory, CARs for the crossing sample and matched sample are statistically indistinguishable for the [1,60] window. It's not surprising that the spread occurs prior to the event date, because sophisticated investors can anticipate when these crossings will occur, based on analyst forecasts.

Figure 6 shows the relative innovations to trading volume for stocks crossing above and below 0 P/E. Because stocks only cross the 0 P/E threshold when new earnings are released, the stocks crossing into positive territory and the stocks crossing into negative territory are matched on earnings, an important contributor to variation in trading volume identified in Frazzini and Lamont (2007). Furthermore, stocks which are close to the threshold of 0 P/E are also likely to have similar firm characteristics. I calculate subsequent relative volume in event time for the 50 days after the reporting date relative to the average volume for the 50 days prior to the reporting date, based on the duration of the formation and test periods in Gervais et al. (2001). For each stock-day observation, I calculate the relative volume (RV) as: $RV_{i,t} = \frac{SHVOL_{i,t}}{\sigma_{k=-50}^{k=-1} SHVOL_{i,k}}$. The blue bars in Figure 6 show the ratio of the mean RV for stocks crossing above 0 P/E to the mean RV for stocks crossing below 0 P/E. The red bars show the ratio of the median RV for stocks crossing above 0 P/E to the median RV for the stocks crossing below 0 P/E. Both of these ratios are consistently above 1, implying that the stocks crossing into positive territory are more actively traded than the stocks crossing into negative territory. The time-series average of the ratio of mean RVs is 1.12 and is greater than one in 43 of the 50 days. The time-series average of the ratio of median RVs is 1.10 and is greater than one in all 50 days.

6.2. Returns for Stocks with Extreme P/E Rankings

Table 10 shows the excess returns of value-weighted portfolios of stocks with high P/E rankings. Excess returns are portfolio returns minus the monthly or daily risk-free rate. The top panel consists of portfolios which are formed at the end of each month and held for one month. First, I calculate the average monthly excess returns for portfolios of stocks with a specific value of $4QEPPct$ ranging from 86 to 100. Since these values are percentiles, the number of stocks in a portfolio ranges from about 20 to 60 during the sample. Each individual portfolio earns average monthly excess returns substantially higher than the average monthly excess return of the market portfolio during the same time period. Furthermore, the excess returns are highest for the portfolios of stocks with the very highest P/E rankings. For example, the average excess returns of stocks in portfolios between 96 and 100 are 27% higher than the average excess returns of stocks in portfolios between 86 and 90. The three portfolios with the highest returns are the portfolios of the stocks in the 96th, 97th, and 98th percentile of P/E rankings.

The second row shows excess returns for portfolios which restrict membership to stocks that have increased in P/E ranking since the previous month. These stocks are especially salient, because increasing in ranking is equivalent to qualifying for a particular screen for the first time. The third row shows excess returns for portfolios which restrict membership to stocks that have increased in P/E ranking by at least five percentile points since the previous month. These stocks are even more salient, because they qualify for a larger number of investor screens for the first time. For 14 of the 15 individual percentile portfolios, average monthly excess returns are strictly increasing across the three rows. Furthermore, among stocks with increasing rankings, average excess returns are 24% higher for portfolios between 96 and 100 than for portfolios between 86 and 90. Among stocks with substantial increases in rankings, this excess return premium for stocks with extreme P/E rankings increases to 35%.

In the bottom panel of Table 10, I sort stocks into percentiles of $4QEPPct$ at the end of each day instead of at the end of each month. To mitigate any microstructure effects stemming from the increased probability of making an extreme P/E portfolio by closing at the bid price, I require that investors hold the portfolio for 20 days. For the unconditional portfolios of all stocks with a particular percentile, this increases the average monthly returns by about 6%, but the average returns are more than 40% higher for the stocks which have increased more than five percentile points. For all 15 individual percentile portfolios, average monthly excess returns are strictly increasing across the three rows. Average excess returns are between 13% and 40% higher for portfolios between 96 and 100 than for portfolios between 86 and 90.

In Table 11, I show excess returns of portfolios in the top quintile of $4QEPPct$, controlling for the quintile assignment in each of the nine sorting variables. Excess returns are defined as portfolio returns above the monthly risk-free rate. As a basis of comparison, the average monthly excess return of the market portfolio during the same time period is 51 basis points. Of the 45 quintile double sorted portfolios, 44 of these earn average returns are larger than the market return. Furthermore, all of these portfolio returns are significant at the 5% level even though on average they only hold 4% of the stocks in the market. In other words, even stocks with characteristics which predict below average returns, such as weak profitability, aggressive investment, or poor earnings momentum, earn above average returns if they also have high P/E rankings. Only the worst BE/ME quintile portfolio earns below market returns, and these average monthly portfolio returns are only six basis points less than average monthly market returns.

7. Robustness

P/E rankings predict stock returns and trading volumes, but only for stocks with positive earnings. This suggests that P/E ratios are a valuable measure of investor attention, in addition to the information they convey about fundamentals. This section shows that the main results of the paper are robust. A long-short P/E attention strategy earns significant returns with persistent performance, and the returns are significant in a variety of relevant subsamples.

7.1. Performance Persistence

Table 10 tracks the performance of a single value-weighted long-short P/E attention strategy for 24 months after portfolio formation, rather than assuming monthly rebalancing. Specifically, this strategy buys stocks in the highest $4QEPPctTotal$ decile and shorts stocks in the lowest $4QEPPctTotal$ decile, based on NYSE breakpoints. Although the strategy earns the largest returns in the first month after portfolio formation, individual returns in each of the first five months are positive and significant. The strategy continues to earn money consistently in the first two years following portfolio formation, earning a total of more than 3% in the last eleven months of the first year and more than 3% more in the second year. Strategies based on P/E rankings are likely to be highly correlated with strategies based on fundamental value and profitability, both of which predict variation in returns for multiple years after portfolio formation. Bernard and Thomas (1989, 1990) show that when stocks have a positive earnings surprise, the performance tends to reverse when earnings are released four quarters later. This could describe the relatively poor performance from 11 to 13 months following portfolio formation.

7.2. Subsamples

In Table 11, I divide the full 43-year sample into an early and late sample, each of which is 21 years and six months. I evaluate the performance of the same benchmark strategy, the value-weighted decile $4QEPPctTotal$ strategy using NYSE breakpoints, in both subsamples. The average monthly long-short return is 116 basis points in the early sample and 122 basis points in the late sample. Likewise, the strategy alpha is slightly higher in the second sample using all four factor models. The test statistic for the long short returns and alphas are smaller on average in the second half of the sample, primarily due to volatile strategy returns during the late 1990s.

When calculating the P/E attention variables, I assume that marginal attention is uniformly distributed across the P/E rankings. This assumption is consistent with an uninformative prior distribution of marginal attention across the aggregate investor base. In reality, marginal attention may cluster at obvious values, such as round numbers.[12] In Table 12, I deconstruct the same benchmark decile $4QEPPctTotal$ strategy into two subsamples. The first subsample (RNX) contains all extreme-decile observations in which a stock crosses a key round-number P/E ratio threshold. Stocks in the long (short) portfolio include those in decile 10 (1) of $4QEPPctTotal$ which cross above (below) 0, or which cross below (above) 10 or 20 P/E. These three "big figures" are by far the most likely candidates for clustered investor attention. Stocks in the long (short) portfolios of the complementary (No RNX) subsample are in decile 10 (1) of $4QEPPctTotal$, but do not cross any of the key round number thresholds.

The RNX subsample strategy earns an average long-short return that is about 15% larger than the average return for the full sample. The standard deviation of monthly returns is substantially larger, in part because there are not nearly as many positions in the portfolios each month. Also, stocks can only cross the 0 P/E threshold when earnings are released, and stock returns are more volatile during earnings months. When all of the stocks crossing the three key round number thresholds are removed, the complementary subsample strategy earns an averager long-short return that is identical to the average return for the full sample, although the standard deviation is slightly larger. This analysis suggests that clustering of attention at round number P/E thresholds is not a substantial cause of the unconditional strategy returns.

If P/E attention strategies earn positive alphas because of a fundamental risk premium, they should perform very poorly during bad economic states. Table 13 splits the benchmark

[12] See Appendix B for a list of citations of round number clustering.

decile $4QEPPctTotal$ strategy into five additional subsamples which represent periods of poor economic conditions. Lakonishok et al. (1994) use three proxies to evaluate whether value strategy returns are due to risk or mispricing: market performance, recessions, and the next quarter's real GDP growth. I estimate market return as the sum of the monthly market risk premium and monthly risk free rate from Ken French's website. The recession designation depends on whether the NBER characterizes the month as a recession month. Finally, real US GDP growth depends on the finalized quarterly figure published by the BEA. None of these characteristics are known in advance as you form portfolios at the close of month t, not knowing whether month $t + 1$ will be a "good" or "bad" economic state.

The benchmark strategy earns an average monthly long-short return of 1.19%. When the market return is below the median, the average return is 1.72%. When the market return is in the lowest quartile, the average is even better, at 2.08%. The strategy also outperforms its unconditional average during NBER recession months. The strategy earns approximately its unconditional average during the half of months with below median subsequent quarterly GDP growth. During the quarter of the sample with the worst future GDP growth, the strategy earns an average monthly return of 1.55%. In all cases, the subsample strategy returns are statistically significant. These results are consistent with Lakonishok et al. (1994), who fail to find evidence for a risk-based explanation of value strategy performance.

7.3. Double-Sorted Portfolios

Table 16 presents results from monthly time-series tests of portfolios which are independently sorted into quintiles across two dimensions. One dimension is the ranking of published P/E ratio: $4QEPPct$ The second dimension is one of nine other sorting variables known to predict variation in stock returns. These sorting variables include the seven controls in the Fama and MacBeth (1973) regressions: market equity (ME), book-to-market ratio (BE/ME), gross profitability ratio (GP/AT), asset growth ratio (dAT), prior year return excluding the most recent month R(12,1), prior month return R(1,0), and standardized unexplained earnings (SUE). Two additional factors are the volume rank (VR) of the final day of the month, as calculated in Gervais et al. (2001), and the Amihud (2002) illiquidity factor (ILLIQ). Quintile portfolio assignments for all variables except VR are based on NYSE breakpoints. Positions in all portfolios are weighted by market capitalization.

The left panel of Table 16 shows the performance of long-short double-sorted $4QEPPct$ portfolios. Each cell shows the average monthly return of the portfolio which is long every stock in quintile 5 of $4QEPPct$ and short every stock in quintile 1, conditional on belonging to the appropriate quintile of the other sorting variable. The long-short $4QEPPct$ portfolios earn positive average long-short returns in every quintile of every sorting variable, although the results are not always significant. The portfolio performance is worst for stocks already sorted on BE/ME, GP/AT, and dAT. Of the 15 quintile portfolios for these variables, the long-short $4QEPPct$ strategy returns are significant at the 5% level in three portfolios, and significant at the 10% level in five additional portfolios. Among the other 30 quintile portfolios, the long-short $4QEPPct$ strategy returns are significant at the 5% level in 28 portfolios.

The right panel of Table 16 examines the other dimension of the independent double sorts. How does variation in P/E rankings predict the performance of other trading strategies? The $4QEPPct$ strategy has the weakest predictability after controlling for the fundamental characteristics of volume, profitability, and investment. The converse is also true. These fundamental strategies have the weakest performance after controlling for the P/E rankings. Value long-short strategies are only significant in the highest quintile of P/E rankings. Profitability strategies are only significant in three of the $4QEPPct$ quintiles and investment strategies are only significant in two of the $4QEPPct$ quintiles. This implies that attention and fundamentals are likely to both play a part in the trading activity of value investors.

8. Conclusion

Individual value investors with limited attention are likely to use published P/E ratios to identify potential investments. If the trading activity associated with this attention is economically meaningful, then published P/E rankings and changes in rankings can predict subsequent returns. P/E attention strategy alphas are economically and statistically significant after controlling for size, value, profitability, investment, short-term reversals, price momentum, and earnings momentum. These strategies are consistently profitable in a wide variety of subsamples and are not strongly related to fundamental risk. The returns in positive and negative earnings subsamples, the predictable behavior in strategy returns, and the relation to future trading volumes and liquidity provide corroborating evidence.

Gervais et al. (2001) identify relative volume and Barber and Odean (2008) identify extreme recent returns as characteristics which predict cross-sectional variation in stock returns through investor attention. Variation in both relative volume and extreme recent returns changes stock rankings in a number of highly visible variables. Relative volume directly influences average volume, which is a variable considered in liquidity screens. Recent returns influence a number of these characteristics, including last price, market capitalization, P/E ratio, and betas. Further study into the role of investor behavior relating to highly visible characteristics is a promising avenue for understanding the relation between limited investor attention and asset prices.

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Appendix A: Value Strategies and Relevant Google Trends Topics Hou et al. (2014) examine 74 anomalies to develop their factor model. The table summarizes the 12 value-versus-growth anomalies, which is listed in Table 2 Panel B of their paper. For each anomaly, I use Google Trends (https://www.google.com/trends) to identify plausibly related search topics or terms. The topics or search terms with non-negligible search volume are listed in the table. P/B Ratio, Price-earnings ratio, and debt-to-equity ratio are Google Trends topics and Dividend Yield is a Google Trends search term.

Author(s)	Year	Sorting Variable	Google Trends Topic
Rosenberg, Reid, and Lanstein	1985	Book-to-market equity	P/B Ratio
De Bondt and Thaler	1985	Reversal	
Elgers, Lo, and Pfeiffer	2001	Analysts' earnings forecasts-to-price	
Litzenberger and Ramaswamy	1979	Dividend Yield	Dividend Yield
Boudoukh et al.	2007	Net Payout Yield	
La Porta	1996	Long-term growth forecasts of analysts	
Bhandari	1988	Market leverage	Debt-to-equity ratio
Basu	1983	Earnings-to-price	Price-earnings ratio
Lakonishok, Shleifer, and Vishny	1994	Cash flow-to-price	
Boudoukh et al.	2007	Payout yield	
Lakonishok, Shleifer, and Vishny	1994	Sales growth	
Dechow, Sloan, and Soliman	2004	Equity duration	

Appendix B: Evidence of Clustering at Round Number Values

Author(s)	Year	Asset Class or Environment
Yule	1927	Survey data
Niederhoffer	1966	US Equities
Stevenson and Bear	1970	Commodity Futures
Harris	1991	US Equities
Christie and Schultz	1994	US Equities
Ball et al	1995	Gold
Grossman et al.	1995	London Stock Exchange Equities
Benartzi and Thaler	2001	Asset Allocation
Kandel et al.	2001	Israeli IPOs
Osler	2003	Foreign Exchange
Thomas and Morowitz	2005	Retail Prices
Baker et al.	2012	M&A target prices
Olsen	2013	Danish tax rates

Table 1: S&P 400 Stocks with High Published P/E Rankings This table shows the 20 stocks in the S&P 400 index with the highest published P/E rankings after the close of trading on August 31, 2015 and November 30, 2015. Stocks with high P/E rankings actually have low positive P/E ratios. P/E ratios are from Bloomberg and are computed using the most recent closing price and the sum of the four most recently reported quarterly values of earnings per share. Stocks in the S&P 400 consists of US common stocks with market capitalizations ranked between 100-500, commonly known as "mid cap" stocks. The stocks in the November column with underlined tickers were not among the 20 stocks with the highest P/E rankings at the end of August.

31-Aug-2015	30-Nov-2015
ATW	ATW
RDC	DNR
X	NE
NE	DAN
DNR	JOY
CRC	RDC
RE	TRN
TRN	TGI
DAN	CYH
WNR	CAA
TCO	NSR
RNR	RE
TGI	WNR
NSR	TEX
OA	RCII
JOY	TCO
ENH	RNR
AVT	ENH
CSC	ARW
ARW	AVT

Table 2: Summary Statistics on Published P/E Ratios, 1973-2015 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 calculated as: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{|PRC_{i,t}|}$. The top panel shows summary statistics on the cross-section of published P/E ratios during the sample. The full sample is divided into subsamples ending every five years. For each subsample, the values in the second column (N Valid 4QEP) are the average monthly number of US common stocks with valid $4QEP_{i,t}$. The values in the third column (% Positive 4QEP) are the average monthly percentages of valid $4QEP_{i,t}$ which are positive. The values in the fourth column (Median 4QEP%) are the average monthly median $4QEP_{i,t}$ among stocks with valid $4QEP_{i,t}$, quoted in percent. The bottom panel shows the time-series average cross-sectional rank correlations of different versions of 4QEP, using different variables to represent the trailing four quarters of EPS. EPSPI12 is the Compustat trailing four quarters of basic EPS including extraordinary items. EPSF12 is the Compustat trailing four quarters of diluted EPS excluding extraordinary items. EPSFI12 is the Compustat trailing four quarters of diluted EPS including extraordinary items. In each month, rank correlations are calculated for the set of stocks which have valid 4QEP using all four measures. This sample includes approximately 50% of the observations in the top sample.

Subsample	N Valid 4QEP	% Positive 4QEP	Median 4QEP%
1973-1975	2253	91.9	12.9
1976-1980	2372	91.9	12.5
1981-1985	3144	82.8	8.32
1986-1990	4229	71.9	5.14
1991-1995	5073	70.4	4.18
1996-2000	6478	67.5	3.70
2001-2005	5112	64.0	3.21
2006-2010	4327	66.0	3.30
2011-2015	3568	69.3	3.86

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 3: Predicting Returns and Abnormal Volumes with Different Value Proxies: 1973-2015 I construct eight versions of HML, the Fama and French (1993) factor-mimicking value portfolio. The first specification replicates the HML factor in Fama and French (1993). Firms are independently sorted into two size portfolios (S=Small, B=Big) and three book-to-market portfolios (H=High, M=Medium, L=Low) at the end of each June. The portfolio assignments depend on the market equity at the end of the previous December and the book equity from the previous fiscal year. The breakpoint of the size portfolio is the 50th percentile of market equity for NYSE firms and the breakpoints of the book-to-market portfolios are the 30th and 70th percentiles of book-to-market for NYSE firms. The second specification uses the E/P ratio to proxy for value, and updates the CRSP annual income before extraordinary items (IB) each June. The third and fourth specifications use monthly values of ME, book to price, and earnings from the trailing four quarters to form portfolios monthly. Market equity is calculated using the most recent monthly CRSP price (PRC) and number of shares outstanding (SHROUT). Book-to-market is updated monthly using the most recently available Compustat quarterly values to calculate book equity. 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 real-time 4QEP is: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{|PRC_{i,t}|}$. The fifth specification estimates HML using only stocks with positive earnings (Pos), and the sixth specification estimates HML using only stocks with negative earnings (Neg). To construct diversified portfolios in these subsamples, I construct unconditional 30th and 70th breakpoints, ignoring NYSE membership, for the positive and negative earnings samples. In the seventh and eighth specifications, I limit the sample of stocks to those which are expected to report quarterly earnings in the most upcoming month (Earn) and those which are not expected to report quarterly earnings (No Earn), based on the algorithm described in Frazzini and Lamont (2007). This table reports the average monthly percent return (Ret) and percent volume return (VRet) for the HML portfolios, with t-statistics in brackets. I calculate VRet as $VRet_{i,t} = ln(\frac{SHVOL_t}{SHVOL_{t-1}})$. The middle and lower panels show the average monthly Ret and VRet for each of the six portfolios.

Specification	1	2	3	4	5	6	7	8
Value Proxy	$\frac{BE}{ME}$	$\frac{IB}{ME}$	$\frac{BEQ}{ME}$	$\frac{EPSX12}{PRC}$	$\frac{EPSX12}{PRC}$	$\frac{EPSX12}{PRC}$	$\frac{EPSX12}{PRC}$	$\frac{EPSX12}{PRC}$
Rebalance	June	June	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly
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
	[2.68]	[2.76]	[2.32]	[4.51]	[5.30]	[0.79]	[3.83]	[4.70]
HML VRet	-0.73	-0.10	0.65	1.38	1.38	0.45	1.04	1.67
	[-2.50]	[-0.37]	[1.82]	[5.02]	[4.79]	[0.53]	[2.27]	[5.44]
SL Ret	0.86	0.87	0.93	0.82	0.91	0.61	0.97	0.72
SM Ret	1.25	1.22	1.16	1.11	1.17	0.61	1.41	0.96
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	1.06	0.54
BM Ret	1.00	0.99	0.99	0.95	0.97	0.44	1.40	0.76
BH Ret	1.07	1.11	1.09	1.29	1.29	0.94	1.64	1.60
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 4: Monthly Spanning Test Results with Different Value Proxies: 1973-2015 I construct six versions of HML, the Fama and French (1993) factor-mimicking value portfolio. The first specification replicates the HML factor in Fama and French (1993). Firms are independently sorted into two size portfolios (S=Small, B=Big) and three book-to-market portfolios (H=High, M=Medium, L=Low) at the end of each June. The portfolio assignments depend on the market equity at the end of the previous December and the book equity from the previous fiscal year. The breakpoint of the size portfolio is the 50th percentile of market equity for NYSE firms and the breakpoints of the book-to-market portfolios are the 30th and 70th percentiles of book-to-market for NYSE firms. The second specification uses the E/P ratio to proxy for value, and updates the CRSP annual income before extraordinary items (IB) each June. The third and fourth specifications use monthly values of ME, book to price, and earnings from the trailing four quarters to form portfolios monthly. Market equity is calculated using the most recent monthly CRSP price (PRC) and number of shares outstanding (SHROUT). Book-to-market is updated monthly using the most recently available Compustat quarterly values to calculate book equity. 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 real-time 4QEP is: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{|PRC_{i,t}|}$. The fifth specification estimates HML using only stocks with positive earnings (Pos), and the sixth specification estimates HML using only stocks with negative earnings (Neg). To construct diversified portfolios in these subsamples, I construct unconditional 30th and 70th breakpoints, ignoring NYSE membership, for the positive and negative earnings samples. In each specification, I estimate monthly spanning tests of MKT, SMB, HML, RMW, and CMA. I report the coefficient estimate of alpha for each dependent variable, with corresponding t-statistics in brackets. The monthly returns for MKT, SMB, RMW, and CMA are from Ken French's website.

Specification	1	2	3	4	5	6
Value Proxy	$\frac{BE}{ME}$	$\frac{IB}{ME}$	$\frac{BEQ}{ME}$	$\frac{EPSX12}{PRC}$	$\frac{EPSX12}{PRC}$	$\frac{EPSX12}{PRC}$
Rebalance	June	June	Monthly	Monthly	Monthly	Monthly
Sample	All	All	All	All	Pos	Neg
$\alpha : y = MKT$	0.86	0.85	0.85	0.92	0.85	0.88
	[4.63]	[4.67]	[4.61]	[5.01]	[4.56]	[4.83]
$\alpha : y = SMB$	0.32	0.34	0.33	0.37	0.36	0.34
	[2.55]	[2.68]	[2.63]	[2.90]	[2.78]	[2.66]
$\alpha : y = HML$	-0.04	0.07	0.04	0.33	0.38	0.39
	[-0.44]	[0.65]	[0.25]	[2.93]	[3.33]	[1.44]
$\alpha : y = RMW$	0.40	0.26	0.41	0.15	0.30	0.37
	[4.58]	[3.46]	[4.55]	[1.98]	[3.43]	[4.14]
$\alpha : y = CMA$	0.28	0.35	0.37	0.30	0.31	0.48
	[4.54]	[4.77]	[5.01]	[3.97]	[3.96]	[5.96]

Table 5: Monthly Portfolio Time-Series Regressions with P/E Attention Variables, 1973-2015 This table reports summary results from 48 monthly time-series regressions, which I estimate using four different factor models for 12 different specifications. For each specification, I report the average monthly long-short return and the monthly alpha for each of the factor models. T-statistics are in brackets. For each monthly observation in each time-series regression, the dependent variable is the percentage return of a value-weighted long-short portfolio. Specifications differ across four dimensions: the sorting variable (Variable), the number of portfolios stocks are assigned to in each month (N), whether portfolio assignments use NYSE breakpoints (NYSE), and which stocks are included (Sample). The three sorting variables are P/E rankings (R), the change in P/E rankings (C), and the total rank of rankings and changes in rankings (T). There are three samples, all stocks (All), stocks with positive earnings only (Pos), and stocks with negative earnings only (Neg). The independent variables are a monthly time series of intercepts and monthly returns of one or more factor mimicking portfolios. The CAPM model includes only MKT as an independent variable. The three-factor model includes MKT, SMB, and HML. The four-factor model includes MKT, SMB, HML, and UMD. The five-factor model includes MKT, SMB, HML, RMW, and CMA. The monthly time series for MKT, SMB, HML, UMD, RMW, and CMA are from Ken French's data library.

Variable	R	C	T	R	C	T	R	C	T	R	C	T
N	10	10	10	10	10	10	5	5	5	5	5	5
NYSE	Y	Y	Y	N	N	N	N	N	N	N	N	N
Sample	All	All	All	All	All	All	Pos	Pos	Pos	Neg	Neg	Neg
L-S Return	1.06	0.81	1.19	1.19	0.77	1.35	0.70	0.62	0.96	0.29	0.22	-0.06
	[3.96]	[5.30]	[6.14]	[3.64]	[5.00]	[5.79]	[4.29]	[4.55]	[5.99]	[0.81]	[0.82]	[-0.21]
CAPM Alpha	1.30	0.76	1.26	1.47	0.71	1.51	0.76	0.55	0.94	0.47	0.33	0.10
	[5.12]	[4.94]	[6.50]	[4.72]	[4.63]	[6.62]	[4.65]	[4.12]	[5.80]	[1.34]	[1.26]	[0.36]
3F Alpha	1.15	0.76	1.08	1.39	0.73	1.31	0.41	0.55	0.70	0.79	0.38	0.23
	[4.82]	[4.88]	[5.72]	[4.68]	[4.71]	[5.99]	[2.99]	[4.04]	[4.60]	[2.36]	[1.40]	[0.83]
4F Alpha	1.02	0.84	1.16	1.04	0.79	1.29	0.65	0.66	0.93	0.10	0.09	-0.21
	[4.22]	[5.27]	[6.03]	[3.53]	[5.00]	[5.78]	[4.99]	[4.77]	[6.26]	[0.33]	[0.34]	[-0.79]
5F Alpha	0.75	0.70	0.92	0.88	0.68	0.97	0.37	0.53	0.70	0.48	0.36	0.18
	[3.52]	[4.34]	[4.90]	[3.25]	[4.24]	[4.61]	[2.65]	[3.79]	[4.49]	[1.42]	[1.29]	[0.64]

Table 6: Monthly Portfolio Time-Series Volume Regressions: 1973-2015 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 calculated as: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{|PRC_{i,t}|}$. At the end of each month, all stocks are assigned to quintiles of 4QEP ($4QEPPct_{i,t}$). Independently, at the end of each month, all stocks are assigned to quintiles based on the most recent available value of market capitalization (ME). All quintile assignments are based on NYSE breakpoints. For each stock with positive share volume in the previous two months, the volume return is: $VolRet_{i,t} = ln(\frac{SHVOL_t}{SHVOL_{t-1}})$ The table shows average volume returns of equal-weighted portfolios which are long every stock in quintile 5 and short every stock in quintile 1 of the second sorting variable (Var2), controlling for quintile assignment of the first sorting variable (Var1). T-statistics are in brackets.

Var1	Var2	1	2	3	4	5
ME	4QEP	1.96	2.26	1.90	1.17	1.12
		[4.28]	[4.76]	[3.65]	[2.30]	[2.21]
4QEP	ME	0.67	1.89	0.88	-0.07	-0.18
		[0.62]	[2.36]	[1.19]	[-0.10]	[-0.22]

Table 7: P/E Rankings and Liquidity Strategy Returns, 1973-2015 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 calculated as: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{|PRC_{i,t}|}$. At the end of each month, all stocks are assigned to quintiles of 4QEP ($4QEPPct_{i,t}$). Independently, at the end of each month, all stocks are assigned to quintiles based on the most recent available value of each sorting variable in the left column. R(1,0) is the most recent CRSP monthly return: $R(1,0) = ret_{i,t}$. ME is the market equity using the CRSP monthly closing price and shares outstanding: $ME_{i,t} = |PRC_{i,t}| * SHROUT_{i,t}$. ILLIQ is the Amihud (2002) illiquidity factor, which is the sum of the average CRSP daily absolute return scaled by dollar volume over the previous 252 days: $ILLIQ_{i,t} = \sum_{k=1}^{252} \frac{|dret_{i,t-k}|}{|dprc_{i,t-k}| * dvol_{i,t-k}}$ All quintile assignments are based on NYSE breakpoints. The left panel shows average monthly returns of value-weighted long-short quintile strategies, controlling for quintile assignment of 4QEP. T-statistics are in brackets.

Sorting Variable	Strategy	4QEPQ1	4QEPQ2	4QEPQ3	4QEPQ4	4QEPQ5
R(1,0)	Q1-Q5	0.02	0.35	0.51	0.71	0.80
		[0.07]	[1.70]	[2.32]	[3.51]	[3.37]
ME	Q1-Q5	0.03	0.15	0.28	0.31	0.50
		[0.12]	[0.80]	[1.55]	[1.87]	[2.75]
ILLIQ	Q5-Q1	0.17	0.14	0.17	0.36	0.56
		[0.79]	[0.88]	[1.21]	[2.40]	[3.58]

Table 8: Predictive Panel Regressions for Trading Volumes and Liquidity: 1973-2015 This table reports summary results for 12 predictive panel OLS regressions. Each regression is defined by a dependent variable (RHS Var), an independent variable of interest (LHS Var), and a sample of stocks. There are four dependent variables: the log of share turnover (VOL) (VOL=$log\frac{SHVOL_t}{SHROUT_t}$), the log of the Amihud (2002) illiquidity factor (ILLIQ) calculated from the days in the most recent calendar month, and the monthly differences of these two variables (Δ VOL, Δ ILLIQ). The independent variable of interest is either the P/E rankings (R), change in rankings (C), or the total of rankings and change in rankings (T). All three of these variables are calculated in percentile terms at the end of each month. The sample includes all CRSP common stocks which trade on the NYSE or AMEX exchanges (NA). In each regression, other independent variables include an intercept, dummies for each calendar year and each of the Fama and French (1997) industries, and the control variables used in Chordia et al. (2007). These control variables include the positive return from the previous month, the negative return from the previous month, book leverage, the book-to-market ratio, beta, the log of the price per share, the log of the 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 used the method of Dimson (1979) to control for the effect of asynchronous trading. For each regression, I report the coefficient estimate (Coeff), the OLS t-statistic (t-OLS), and the t-statistic using standard errors double clustered by firm and month (t-DC). Coefficient estimates are reported as percentage differences between the stock at the 100 percentile (highest value) and the stock at the 0 percentile (lowest value).

RHS Var	VOL	VOL	VOL	ILLIQ	ILLIQ	ILLIQ	Δ VOL	Δ VOL	Δ VOL	Δ ILLIQ	Δ ILLIQ	Δ ILLIQ
LHS Var	R	C	T	R	C	T	R	C	T	R	C	T
Sample	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Coeff	0.17	-1.09	-0.49	-17.7	-0.80	-7.66	1.10	5.58	3.30	-3.20	-3.13	-2.91
t-OLS	[0.46]	[-3.26]	[-2.04]	[-46.1]	[-2.32]	[-31.10]	[4.48]	[25.4]	[21.00]	[-13.10]	[-14.30]	[-18.60]
t-DC	[0.07]	[-1.29]	[-0.52]	[-8.94]	[-1.09]	[-7.24]	[1.47]	[15.28]	[9.03]	[5.82]	[-11.49]	[-10.18]

Table 9: Event Study of Stocks Crossing the 0 P/E Threshold: 1973-2015 This table reports characteristics and returns of all stocks crossing the 0 P/E threshold. At the end of each day, 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), 4QEP is calculated as: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{|PRC_{i,t}|}$. Earnings are updated at the end of the first trading day after the report date, based on Compustat field RDQ. Because stock prices are positive, 4QEP can only cross above or below 0 when quarterly earnings are released. For each crossing observation, I find the nearest neighbor from other stocks which release earnings on the same day, have an earnings surprise in the same direction, and do not cross 0 P/E. The nearest neighbor is the stock meeting these criteria with the closest distance, defined as $D_{i,j} = |Rank(ME)_i - Rank(ME)_j| + |Rank(SUE)_i - Rank(SUE)_j|$. The cumulative abnormal return (CAR) for each day is based on a market-adjusted model, where every stock has a beta of 1 relative to the equal-weighted index of CRSP common stocks in the same decile of market capitalization, using NYSE breakpoints. The top panel reports the mean market capitalization and book-to-market ratio for each sample. The middle and bottom panels report the CAR for different windows for the stocks crossing into positive and negative P/E territory.

Sample	Variable	Cross	Match	Diff
Neg→Pos	ME	882.2	905.7	-19.10
				[-0.43]
Neg→Pos	BM	0.99	0.77	0.14
				[5.41]
Pos→Neg	ME	757.5	762.4	-2.69
				[-0.07]
Pos→Neg	BM	1.36	0.97	0.33
				[5.37]
Neg→Pos	CAR[-1,0]	2.03	1.43	0.58
				[5.11]
Neg→Pos	CAR[-60,0]	6.97	4.81	2.16
				[6.98]
Neg→Pos	CAR[1,60]	1.56	1.54	0.02
				[0.07]
Pos→Neg	CAR[-1,0]	-1.76	-1.57	-0.18
				[-1.89]
Pos→Neg	CAR[-60,0]	-8.81	-6.42	-2.39
				[-7.85]
Pos→Neg	CAR[1,60]	-1.37	-1.60	0.23
				[0.74]

Table 10: Excess Returns for Stocks with Extreme P/E Rankings: 1973-2015 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 calculated as: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{|PRC_{i,t}|}$. At the end of each month, all stocks are assigned to percentiles of 4QEP ($4QEPPct_{i,t}$). This table reports the average excess returns and relative volumes for stocks in each of the top 15 percentile portfolios of 4QEP. In the top panel, I form portfolios at the end of each month. The panel reports the monthly excess returns in percent for three strategies. The first row (All) consists of every stock in the percentile 4QEP portfolio. The second row (+1) consists of stocks in the percentile 4QEP portfolio which increased in 4QEP percentile since the end of the previous month. The third row (+5) consists of stocks in the percentile 4QEP portfolio which increased in 4QEP percentile by at least five percentile points since the end of the previous month. In the bottom panel, I form portfolios at the end of each day and hold all positions for 20 days. The panel reports the daily excess returns in basis points for three strategies. The first row (All) consists of every stock in the percentile 4QEP portfolio. The second row (+1) consists of stocks in the percentile 4QEP portfolio which increased in 4QEP percentile since the end of the previous day. The third row (+5) consists of stocks in the percentile 4QEP portfolio which increased in 4QEP percentile by at least five percentile points since the end of the previous day. The excess returns ($R_p - R_f$) are monthly or daily value-weighted portfolio returns in excess of the monthly risk-free rate. The time series of monthly and daily risk-free rates are from Ken French's website. T-statistics are in parentheses.

	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100
Monthly															
All	0.89	0.86	1.07	0.89	1.22	1.21	1.17	0.88	1.17	1.22	1.36	1.25	1.53	1.21	0.92
	[3.53]	[3.45]	[4.44]	[3.31]	[4.62]	[4.58]	[4.40]	[3.27]	[4.09]	[4.04]	[4.73]	[4.15]	[4.70]	[3.57]	[3.05]
+1	1.27	1.32	1.36	1.21	1.66	1.61	1.39	1.38	1.35	1.76	1.75	1.80	1.88	1.78	1.24
	[4.20]	[4.67]	[4.60]	[3.86]	[5.30]	[5.37]	[4.48]	[4.34]	[3.93]	[4.86]	[5.11]	[4.89]	[4.68]	[4.12]	[2.78]
+5	1.73	1.55	1.57	2.04	1.75	1.86	1.82	1.85	1.91	1.69	2.43	2.02	2.39	2.46	2.40
	[4.32]	[3.76]	[3.97]	[4.79]	[4.03]	[4.72]	[4.15]	[4.06]	[4.02]	[3.34]	[4.32]	[3.82]	[3.68]	[4.34]	[3.78]
Daily															
All	4.55	4.88	5.28	5.30	5.51	5.93	6.00	5.42	5.73	6.39	6.49	7.18	6.78	6.57	6.38
	[4.05]	[4.33]	[4.58]	[4.53]	[4.74]	[4.99]	[4.92]	[4.37]	[4.51]	[4.95]	[4.89]	[5.06]	[4.57]	[4.35]	[4.35]
+1	5.33	5.83	6.39	6.38	6.55	6.74	7.35	6.90	6.32	7.79	8.21	8.17	8.83	8.12	9.14
	[4.50]	[4.96]	[5.34]	[5.17]	[5.33]	[5.37]	[5.73]	[5.35]	[4.72]	[5.64]	[5.84]	[5.44]	[5.29]	[4.72]	[4.40]
+5	11.86	13.93	13.45	14.06	16.06	13.97	17.95	13.68	16.87	15.20	15.90	15.14	15.21	16.31	17.07
	[5.05]	[5.95]	[5.75]	[5.74]	[6.76]	[5.25]	[5.95]	[4.61]	[5.66]	[5.06]	[4.84]	[4.44]	[4.23]	[3.93]	[3.10]

Table 11: Monthly Portfolio Time-Series Regressions: Double Sorts, 1973-2015 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 calculated as: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{|PRC_{i,t}|}$. At the end of each month, all stocks are assigned to quintiles of 4QEP ($4QEPPct_{i,t}$). Independently, at the end of each month, all stocks are assigned to quintiles based on the most recent available value of each sorting variable in the left column. The controls for size [log(ME)], value [log(BE/ME)], profitability (GP/AT), and investment (dAT) are calculated based on calendar year t financial statements and assumed known at the end of June in year $t + 1$. Controls for price momentum [R(12,1), the return from the end of month $t - 12$ to the end of month $t - 1$] and short-term reversals [R(1,0), the return from the end of month $t - 1$ to the end of month t], are assumed known at the end of month t. The control for earnings momentum is standardized unexplained earnings (SUE), the change in year-over-year basic EPS excluding extraordinary items (Compustat field: EPSPXQ), scaled by the standard deviation of the last eight quarterly year-over-year changes. Quarterly earnings needed to calculate SUE are assumed known as of the reporting date's month end based on Compustat field RDQ. VR is volume rank, which is the quintile of a stock's share volume on the final day of the month compared to the share volume on the last 50 trading days. ILLIQ is illiquidity, measured as the average daily absolute return scaled by volume over the previous 252 days. All quintile assignments except for VR are based on NYSE breakpoints. The table shows average returns in excess of the monthly risk-free rate of value-weighted portfolios which are long every stock in quintile 5 of 4QEP, controlling for quintile assignment of the other sorting variable. T-statistics are in brackets.

	1	2	3	4	5
ME	1.38	1.38	1.34	1.07	0.88
	[5.04]	[5.10]	[5.15]	[4.39]	[4.01]
BE/ME	0.45	0.74	0.78	0.91	0.97
	[1.68]	[2.98]	[3.36]	[3.84]	[4.27]
GP/AT	0.81	0.71	0.80	1.06	1.06
	[3.72]	[2.84]	[3.44]	[4.04]	[4.20]
dAT	1.14	0.87	0.84	0.64	0.75
	[4.35]	[3.85]	[3.79]	[2.70]	[2.70]
R(12,1)	0.70	0.98	0.95	1.06	1.28
	[2.19]	[3.93]	[4.27]	[4.85]	[4.61]
R(1,0)	1.49	1.22	1.04	0.88	0.69
	[4.81]	[4.99]	[4.62]	[3.91]	[2.78]
SUE	0.85	0.91	1.00	1.22	1.22
	[3.33]	[3.70]	[4.08]	[5.29]	[5.54]
VR	0.77	0.81	0.97	1.22	1.30
	[3.11]	[3.28]	[4.30]	[5.22]	[5.10]
ILLIQ	0.92	1.14	1.17	1.25	1.48
	[4.14]	[4.54]	[4.41]	[4.97]	[6.53]

Table 12: Persistence of Monthly P/E Attention Strategy Returns 1973-2015 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 calculated as: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{|PRC_{i,t}|}$. At the end of each month, all stocks are assigned to percentiles of 4QEP ($4QEPPct_{i,t}$). At the end of each month, all stocks are also assigned to percentiles of the change in $4QEPPct_{i,t}$ from month $t-1$ to month t ($4QEPPctChg1M_{i,t}$). At the end of each month, stocks are sorted into ten deciles based on the average of $4QEPPct_{i,t}$ and $4QEPPctChg1M_{i,t}$. Decile assignments are based on NYSE breakpoints. This table presents monthly and cumulative percent returns for value-weighted portfolios which are long every stock in decile 10 and short every stock in decile 1 for the first 24 months following portfolio formation. T-statistics for monthly returns are in brackets.

Month	Monthly Return	Cumulative Return	Month	Monthly Return	Cumulative Return
1	1.19	1.19	13	0.11	4.42
	[6.14]			[0.70]	
2	0.74	1.94	14	0.50	4.94
	[3.77]			[3.02]	
3	0.43	2.37	15	0.34	5.29
	[2.32]			[2.05]	
4	0.67	3.06	16	0.25	5.55
	[3.63]			[1.54]	
5	0.46	3.54	17	0.34	5.91
	[2.44]			[1.95]	
6	0.25	3.79	18	0.44	6.37
	[1.47]			[2.74]	
7	0.32	4.13	19	0.14	6.52
	[1.81]			[0.84]	
8	0.09	4.22	20	0.20	6.73
	[0.50]			[1.23]	
9	-0.30	3.91	21	-0.03	6.70
	[-1.71]			[-0.18]	
10	0.11	4.03	22	0.52	7.25
	[0.66]			[3.14]	
11	0.11	4.14	23	0.33	7.61
	[0.64]			[2.15]	
12	0.15	4.30	24	0.17	7.79
	[0.89]			[1.07]	

Table 13: Subsample Analysis by Date, Monthly Portfolio Time-Series Regressions, 1973-2015 This table reports summary results for 12 monthly time series regressions, specified by three time periods and four factor models. 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 calculated as: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{|PRC_{i,t}|}$. At the end of each month, all stocks are assigned to percentiles of 4QEP ($4QEPPct_{i,t}$). At the end of each month, all stocks are also assigned to percentiles of the change in $4QEPPct_{i,t}$ from month $t-1$ to month t ($4QEPPctChg1M_{i,t}$). At the end of each month, stocks are sorted into ten deciles based on the average of $4QEPPct_{i,t}$ and $4QEPPctChg1M_{i,t}$. Decile assignments are based on NYSE breakpoints. For each monthly observation in these time series regressions, the dependent variable is the percentage return of a value-weighted portfolio which is long every stock in decile 10 and short every stock in decile 1. The three time periods include the full sample (1/1973-12/2015), the first half of the full sample (1/1973-6/1994), and the second half of the sample (7/1994-12/2015). The independent variables are a monthly time series of intercepts and monthly returns of one or more factor mimicking portfolios. The independent variables are a monthly time series of intercepts and monthly returns of one or more factor mimicking portfolios. The CAPM model includes only MKT as an independent variable. The three-factor model includes MKT, SMB, and HML. The four-factor model includes MKT, SMB, HML, and UMD. The five-factor model includes MKT, SMB, HML, RMW, and CMA. The monthly time series for MKT, SMB, HML, UMD, RMW, CMA, and STR are all from Ken French's data library. T-statistics are in brackets.

Time Period	L-S Return	CAPM Alpha	3F Alpha	4F Alpha	5F Alpha
1/1973-12/2015	1.19	1.26	1.08	1.16	0.92
	[6.14]	[6.50]	[5.72]	[6.03]	[4.90]
1/1973-6/1994	1.16	1.16	0.91	1.25	0.86
	[5.48]	[5.44]	[4.29]	[5.99]	[3.86]
7/1994-12/2015	1.22	1.40	1.31	1.30	1.05
	[3.75]	[4.40]	[4.35]	[4.25]	[3.35]

Table 14: Subsample Analysis by Round Number P/E Crossings, Monthly Portfolio Time-Series Regressions, 1973-2015 This table reports summary results for 12 monthly time series regressions, specified by three samples and four factor models. 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 calculated as: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{|PRC_{i,t}|}$. At the end of each month, all stocks are assigned to percentiles of 4QEP ($4QEPPct_{i,t}$). At the end of each month, all stocks are also assigned to percentiles of the change in $4QEPPct_{i,t}$ from month $t-1$ to month t ($4QEPPctChg1M_{i,t}$). At the end of each month, stocks are sorted into ten deciles based on the average of $4QEPPct_{i,t}$ and $4QEPPctChg1M_{i,t}$. Decile assignments are based on NYSE breakpoints. For each monthly observation in these time series regressions, the dependent variable is the percentage return of a value-weighted portfolio which is long every stock in decile 10 and short every stock in decile 1. The first sample (All) keeps every stock in the extreme decile portfolios. The second sample (RNX) only keeps stocks which have crossed a P/E of either 0, 10, or 20 in the extreme decile portfolios. The third sample (No RNX) removes all stocks which have crossed a P/E of either 0, 10, or 20 in the extreme decile portfolios. The independent variables are a monthly time series of intercepts and monthly returns of one or more factor mimicking portfolios. The independent variables are a monthly time series of intercepts and monthly returns of one or more factor mimicking portfolios. The CAPM model includes only MKT as an independent variable. The three-factor model includes MKT, SMB, and HML. The four-factor model includes MKT, SMB, HML, and UMD. The five-factor model includes MKT, SMB, HML, RMW, and CMA. The monthly time series for MKT, SMB, HML, UMD, RMW, CMA, and STR are all from Ken French's data library. T-statistics are in brackets.

Sample	L-S Return	CAPM Alpha	3F Alpha	4F Alpha	5F Alpha
All	1.19	1.26	1.08	1.16	0.92
	[6.14]	[6.50]	[5.72]	[6.03]	[4.90]
RNX	1.37	1.33	1.16	1.23	1.18
	[4.85]	[4.66]	[4.04]	[4.21]	[4.00]
No RNX	1.19	1.30	1.11	1.17	0.82
	[5.46]	[6.04]	[5.28]	[5.45]	[4.02]

Table 15: Subsample Analysis by Economic Conditions, Monthly Portfolio Time-Series Regressions, 1973-2015 This table reports summary results for six monthly time series regressions. 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 calculated as: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{|PRC_{i,t}|}$. At the end of each month, all stocks are assigned to percentiles of 4QEP ($4QEPPct_{i,t}$). At the end of each month, all stocks are also assigned to percentiles of the change in $4QEPPct_{i,t}$ from month $t-1$ to month t ($4QEPPctChg1M_{i,t}$). At the end of each month, stocks are sorted into ten deciles based on the average of $4QEPPct_{i,t}$ and $4QEPPctChg1M_{i,t}$. Decile assignments are based on NYSE breakpoints. For each monthly observation in these time series regressions, the dependent variable is the percentage return of a value-weighted portfolio which is long every stock in decile 10 and short every stock in decile 1. The first sample (All) is the full sample. The second sample consists of all months when the market performance was below the median performance in the full sample. The third sample consists of all months when the market performance was below the 25th percentile of performance in the full sample. The fourth sample consists of NBER recession months. The fifth sample consists of months belonging to any quarter in which the following quarter has real GDP growth below the median GDP growth in the full sample. The sixth sample consists of months belonging to any quarter in which the following quarter has real GDP growth below the 25th percentile of GDP growth in the full sample. For each sample, I report the average percentage return and the number of months. T-statistics are in brackets.

Sample	N	L-S Return
All	516	1.19
		[6.14]
Below 50 MKT	258	1.72
		[6.73]
Below 25 MKT	129	2.08
		[4.83]
Recession	78	1.65
		[2.19]
Below 50 GDP	258	1.17
		[3.67]
Below 25 GDP	129	1.55
		[3.24]

Table 16: P/E Rankings and Liquidity Strategy Returns, 1973-2015 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 calculated as: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{|PRC_{i,t}|}$. At the end of each month, all stocks are assigned to quintiles of 4QEP ($4QEPPct_{i,t}$). Independently, at the end of each month, all stocks are assigned to quintiles based on the most recent available value of each sorting variable in the left column. The controls for size [log(ME)], value [log(BE/ME)], profitability (GP/AT), and investment (dAT) are calculated based on calendar year t financial statements and assumed known at the end of June in year $t+1$. Controls for price momentum [R(12,1), the return from the end of month $t-12$ to the end of month $t-1$] and short-term reversals [R(1,0), the return from the end of month $t-1$ to the end of month t], are assumed known at the end of month t. The control for earnings momentum is standardized unexplained earnings (SUE), the change in year-over-year basic EPS excluding extraordinary items (Compustat field: EPSPXQ), scaled by the standard deviation of the last eight quarterly year-over-year changes. Quarterly earnings needed to calculate SUE are assumed known as of the reporting date's month end based on Compustat field RDQ. VR is volume rank, which is the quintile of a stock's share volume on the final day of the month compared to the share volume on the last 50 trading days. ILLIQ is illiquidity, measured as the average daily absolute return scaled by volume over the previous 252 days. All quintile assignments except for VR are based on NYSE breakpoints. The left panel shows average returns of value-weighted portfolios which are long every stock in quintile 5 of 4QEP and short every stock in quintile 1 of 4QEP, controlling for quintile assignment of the other sorting variable. The left panel shows average returns of value-weighted portfolios which are long every stock in quintile 5 and short every stock in quintile 1 of the other sorting variable, controlling for quintile assignment of 4QEP. T-statistics are in brackets.

	1	2	3	4	5	1	2	3	4	5
ME	1.07	0.93	0.82	0.70	0.60	0.03	0.15	0.28	0.31	0.50
	[5.70]	[4.28]	[3.61]	[3.05]	[2.71]	[0.12]	[0.80]	[1.55]	[1.87]	[2.75]
BE/ME	0.18	0.21	0.12	0.38	0.34	0.36	0.15	0.14	0.11	0.52
	[0.72]	[0.95]	[0.60]	[1.78]	[1.78]	[1.42]	[0.87]	[0.77]	[0.52]	[2.79]
GP/AT	0.42	0.45	0.33	0.49	0.38	0.29	0.38	0.44	0.35	0.25
	[1.84]	[2.14]	[1.37]	[1.93]	[1.42]	[1.36]	[2.33]	[2.46]	[1.98]	[1.26]
dAT	0.45	0.24	0.43	0.18	0.63	0.56	0.16	0.20	0.02	0.38
	[2.07]	[1.17]	[1.77]	[0.74]	[2.69]	[3.02]	[0.84]	[1.15]	[0.09]	[1.99]
R(12,1)	1.30	0.89	0.65	0.55	0.45	1.43	0.70	0.65	0.43	0.58
	[5.46]	[4.40]	[3.35]	[2.67]	[1.99]	[5.08]	[2.64]	[2.16]	[1.58]	[2.14]
R(1,0)	1.23	0.82	0.87	0.49	0.45	0.02	0.35	0.51	0.71	0.80
	[4.88]	[3.90]	[3.85]	[2.19]	[1.98]	[0.07]	[1.70]	[2.32]	[3.51]	[3.37]
SUE	0.83	0.58	0.45	0.87	0.56	0.63	0.56	0.21	0.35	0.38
	[3.70]	[2.38]	[1.85]	[3.40]	[2.20]	[3.47]	[4.01]	[1.44]	[2.36]	[2.33]
VR	0.83	0.86	0.77	0.84	0.37	0.98	0.57	0.31	0.67	0.53
	[3.21]	[3.61]	[3.06]	[3.40]	[1.44]	[4.82]	[3.75]	[2.21]	[4.79]	[3.52]
ILLIQ	0.72	0.63	0.63	0.94	1.11	0.17	0.14	0.17	0.36	0.56
	[3.31]	[2.61]	[2.48]	[4.20]	[5.98]	[0.79]	[0.88]	[1.21]	[2.40]	[3.58]

Figure 1: Relative Google Search Volume, 2004-2016 This figure shows the relative Google Search Volume of various value proxies from January 2004 to April 2006. Data are from Google Trends (https://www.google.com/trends). Search volumes include all Google web searches which Google attributes to various topics or search terms. The "P/E" Ratio series charts searches for the price-earnings ratio topic. Common search terms which 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 which 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 which 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. Volumes are normalized so the topic-week observation with the most searches is assigned a volume of 100. This observation corresponds to the number of searches for the price-earnings ratio topic during the week from October 5, 2008 to October 11, 2008. The weekly ratio of the search volume for P/E Ratio to the search volume for P/B Ratio ranges from 3.53 to 17.67 with an average of 6.90. The weekly ratio of the search volume for P/E Ratio to the search volume for Market Leverage ranges from 2.06 to 7.83 with an average of 3.17. The weekly ratio of the search volume for P/E Ratio to the search volume for Dividend Yield ranges from 2.50 to 12.79 with an average of 4.68.

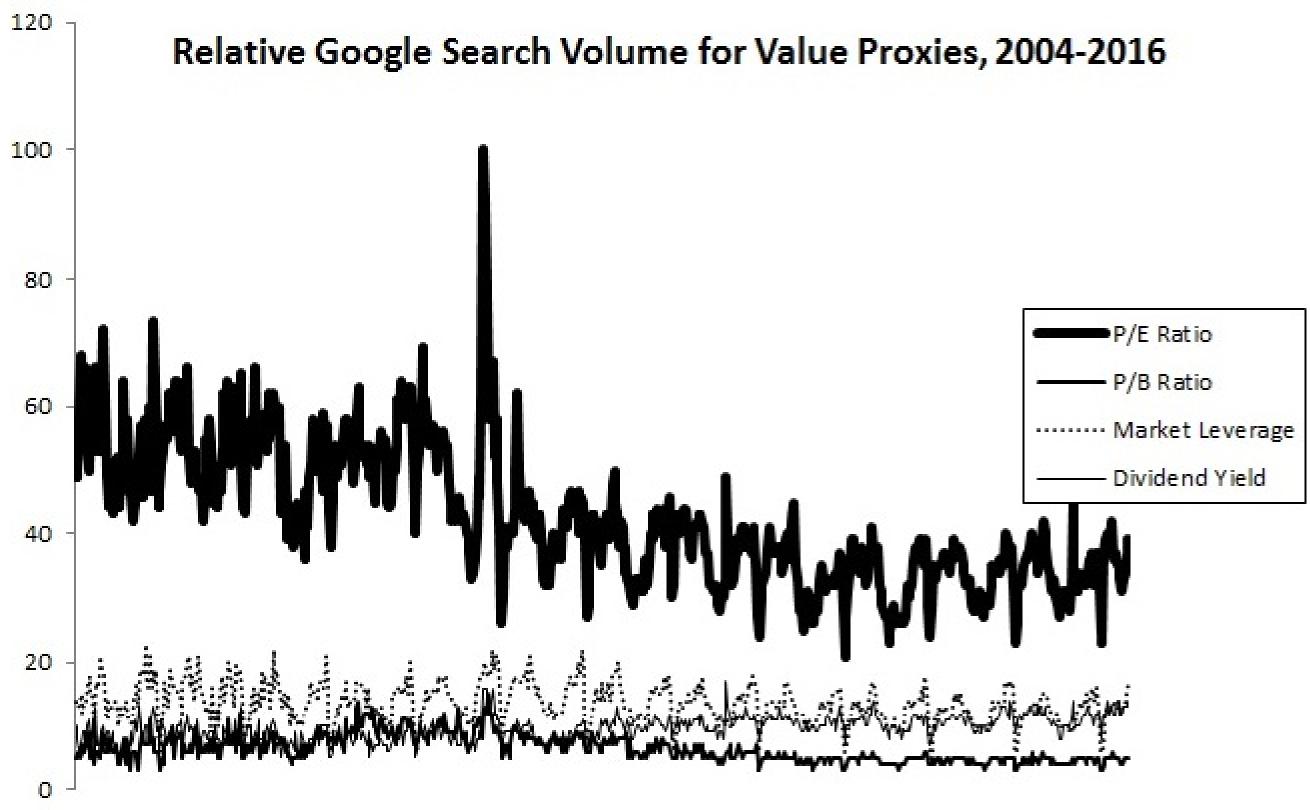


Figure 2: Published P/E Ratios for Positive and Negative P/E Stocks These figures show screen shots of two published stock quotations from Google Finance (https://www.google.com/finance). The screen shots are from April 22, 2016. The top figure shows a quotation for Ford Motor Company (F) and the bottom figure shows a quotation for Tesla Motors Inc. (TSLA). Ford Motor Company has a share price of \$13.59 and earnings per share (EPS) of \$1.84 in the trailing 12 months, and the published P/E is 7.37, the quotient of these two numbers. Tesla Motors Inc. has a share price of \$251.18 and EPS of -\$6.90 and the P/E is not published.

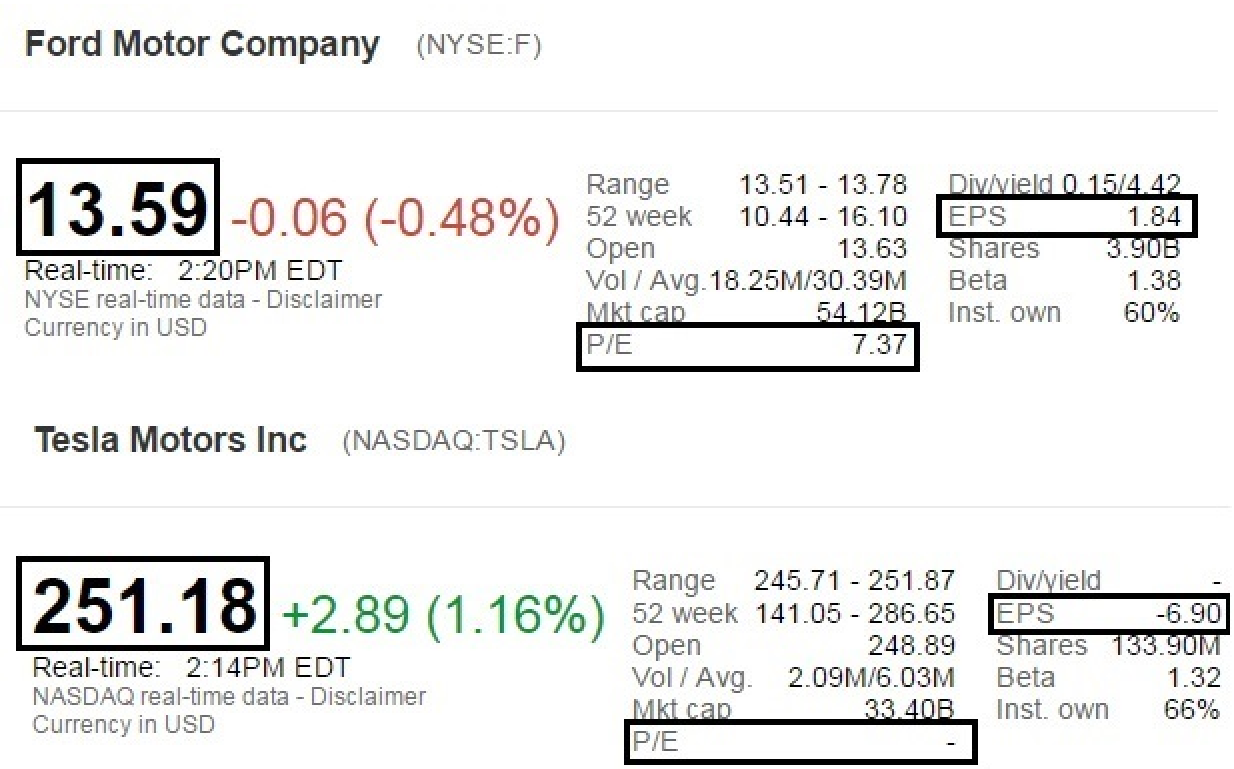
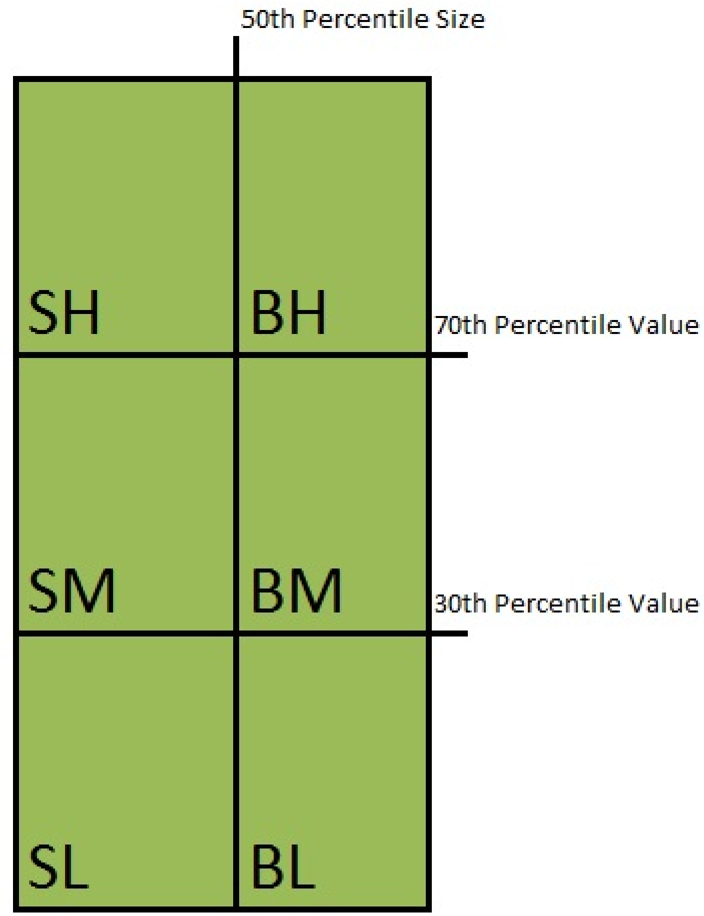


Figure 3: Calculating HML Returns Stocks are independently sorted into two portfolios using a proxy for size and three portfolios using a proxy for value. Stocks above the 50th percentile in size are big (B) and stocks below the 50th percentile in size are small (S). Stocks above the 70th percentile in value are high (H), stocks between the 30th and 70th percentile in value are medium (M), and stocks below the 30th percentile in value are low (L). In total, stocks fall into one of six portfolios depending on their size and value designations (SH, BH, SM, BM, SL, BL). At the end of each month, the return of that portfolio is the value-weighted average of the returns of all stocks assigned to that portfolio at the end of the previous month. The monthly return of HML, the factor-mimicking value portfolio is $r_{HML,t} = 0.5*(r_{SH,t} - r_{SL,t}) + 0.5*(r_{BH,t} - r_{BL,t})$



$$r_{HML,t} = 0.5 * \left(r_{SH,t} - r_{SL,t}\right) + 0.5 * \left(r_{BH,t} - r_{BL,t}\right)$$

Figure 4: Monthly Excess Returns for Published P/E Rankings Portfolios, 1973-2015 Each bar in this histogram represents the average monthly excess return of a value-weighted portfolio. Excess returns are portfolio returns net of the one-month treasury bill rate, reported in basis points. Monthly T-bill rates are from Ken French's data library. The sorting variables for the strategies are either P/E rankings (R), changes in P/E rankings (C), or the total rank of P/E rankings and changes in P/E rankings (T). For each strategy, stocks are divided into those with positive and negative earnings, based on total basic earnings per share (EPS) in the past 12 months (Compustat field EPSX12). Then, stocks in both the positive and negative earnings samples are divided into quintile portfolios. N1 (P1) is the portfolio of negative (positive) earnings stocks with the highest value and N5 (P5) is the portfolio of negative (positive) stocks with the lowest value. To ensure well-diversified portfolios, the portfolio assignments do not use NYSE breakpoints.

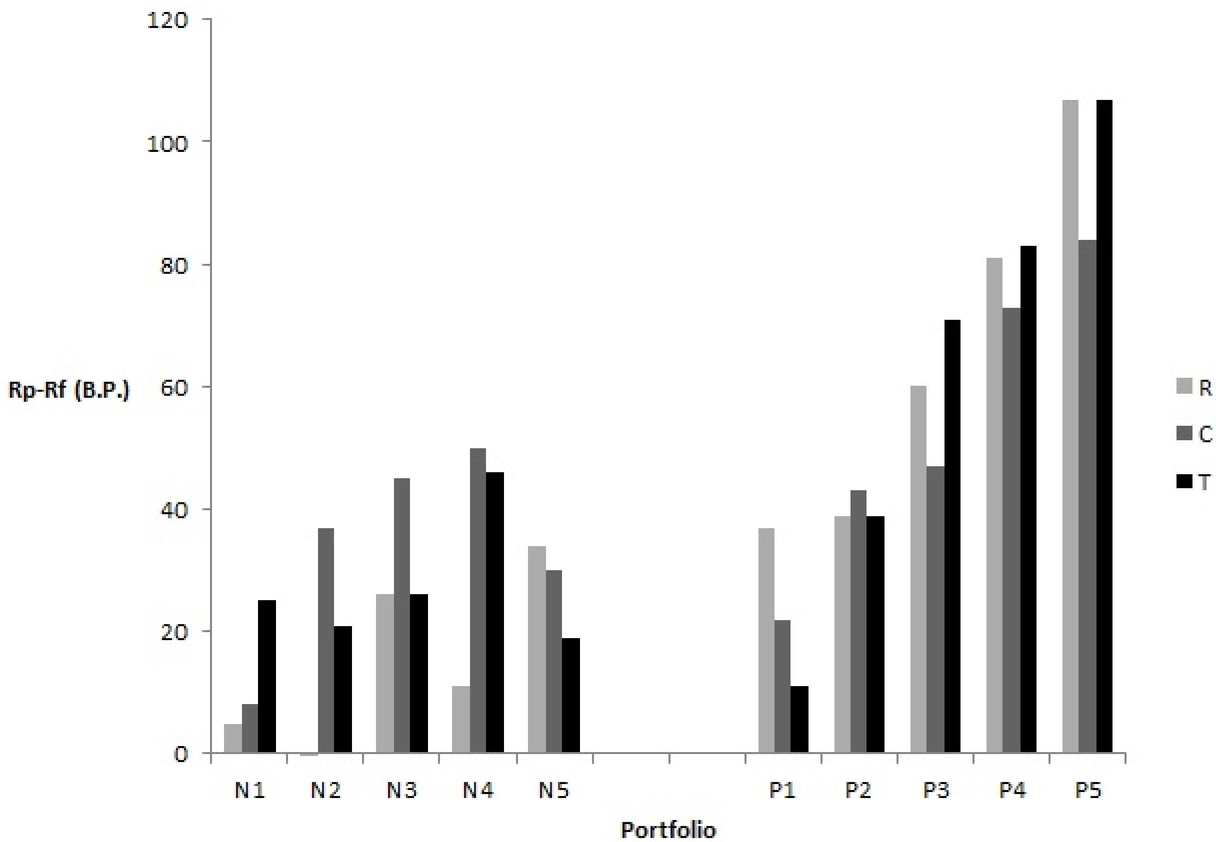


Figure 5: Returns of Stocks Crossing Above 0 P/E vs Below 0 P/E, 1973-2015 This figure shows the event-time returns of stocks crossing above 0 P/E versus stocks crossing below 0 P/E. At the end of each day, US common stocks with a valid total basic earnings per share (EPS) in the past 12 months (Compustat field EPSX12), and valid monthly closing share price (CRSP field PRC), 4QEP is calculated as: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{|PRC_{i,t}|}$. Earnings are updated at the end of the first trading day after the report date, based on Compustat field RDQ. Because stock prices are positive, 4QEP can only cross above or below 0 when quarterly earnings are released. The x-axis is the number of days relative to the P/E = 0 crossing date. The thick solid line shows the returns for stocks crossing into positive P/E territory. The thick dotted line shows the returns for stocks crossing into negative P/E territory. The thin solid line and dotted line are the returns of matched samples. For each crossing observation, I find the nearest neighbor from other stocks which release earnings on the same day, have an earnings surprise in the same direction, and do not cross 0 P/E. The nearest neighbor is the stock meeting these criteria with the closest distance, defined as $D_{i,j} = |Rank(ME)_i - Rank(ME)_j| + |Rank(SUE)_i - Rank(SUE)_j|$. The vertical axis is daily cumulative abnormal return (CAR), based on a market-adjusted model, where every stock has a beta of 1 relative to the equal-weighted index of CRSP common stocks in the same decile of market capitalization, using NYSE breakpoints.

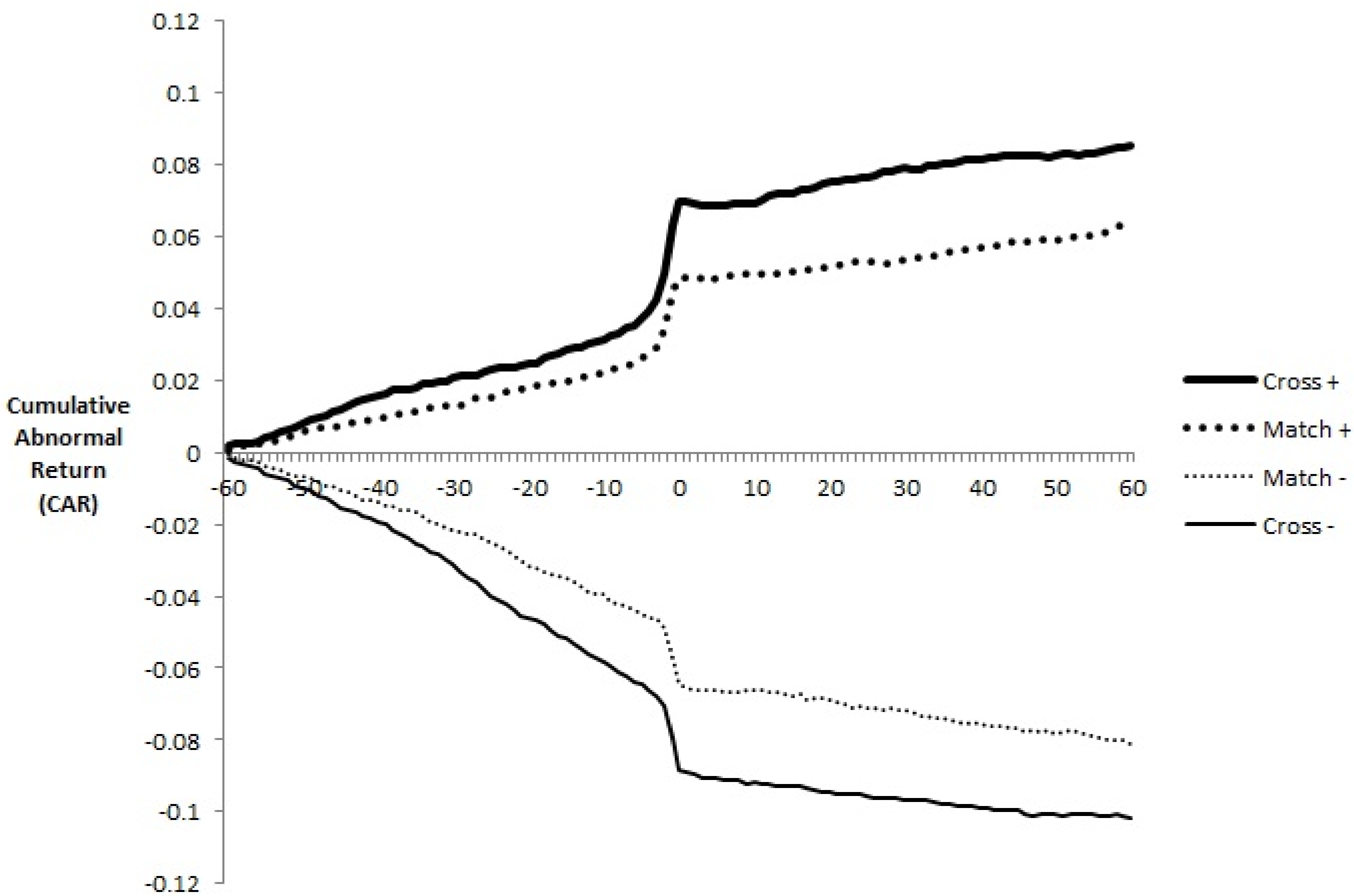


Figure 6: Relative Volume of Stocks Crossing Above 0 P/E vs Below 0 P/E, 1973-2015
This figure shows the relative trading volume of stocks crossing above 0 P/E versus stocks crossing below 0 P/E. At the end of each day, US common stocks with a valid total basic earnings per share (EPS) in the past 12 months (Compustat field EPSX12), and valid monthly closing share price (CRSP field PRC), 4QEP is calculated as: $4QEP_{i,t} = \frac{EPSX12_{i,t}}{|PRC_{i,t}|}$. Earnings are updated at the end of the first trading day after the report date, based on Compustat field RDQ. Because stock prices are positive, 4QEP can only cross above or below 0 when quarterly earnings are released. The x-axis is the number of days since the P/E = 0 crossing date. The blue bars show the ratio of mean relative volume (RV) for the stocks crossing above 0 P/E to the mean relative volume for the stocks crossing below 0 P/E. The red bars show the ratio of median relative volumes for the stocks crossing above 0 P/E to the median relative volumes for the stocks crossing below 0 P/E. RV is calculated as: $RV_{i,t} = \frac{SHVOL_{i,t}}{\sigma_{k=-50}^{k=-1} SHVOL_{i,k}}$