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When Buffett Meets Bollinger:
An Integrated Approach to Fundamental and Technical Analysis

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Abstract

Motivated by the implication of return extrapolation models that a joint consideration of past price changes and firm fundamentals could efficiently identify stock mispricing, we propose an integrated approach that combines fundamental and technical information. This integrated approach generates substantial economic gains, which are comparable to those of strategies double-sorted on characteristics related to high turnover and trading costs and state-of-the-art machine learning strategies in existing studies. The performance net of transaction costs is still attractive. Simple transaction cost mitigation approaches could further enhance the performance of the integrated approach by reducing portfolio turnover. Consistent with behavioral models, limits to arbitrage and information asymmetry play a significant role in explaining the super performance of this integrated approach.

JEL Classification: G11, G12, G14

Keywords: Fundamental Analysis; Technical Analysis; Arbitrage Risk; Informed Trading

1. Introduction

As the technology evolves and big data explodes, machine learning methods have been becoming popular in finance among both academics and investment professionals because these methods are powerful in handling big data to forecast asset prices. For example, Gu, Kelly, and Xiu (2020) show that some state-of-the-art machine learning strategies generate large economic gains to investors. However, the lack of economic mechanisms is the main criticism of current research and applications of machine learning methods (e.g., Gu et al., 2020).

Moreover, Muller and Schmickler (2020) show that the performance of some simple trading strategies based on *double-sorted* portfolios is *comparable* to that of those machine learning strategies in Gu et al. (2020). In particular, the best-performing double-sorted strategies combines two types of anomalies with high turnover (i.e., short-term reversal) and trading costs (i.e., illiquidity). They argue that the double-sorted strategies are much simpler and have better economic motivations than current machine learning methods.

In this paper, we *complement* Muller and Schmickler (2020) by focusing on the interaction of fundamental analysis and technical analysis. Muller and Schmickler (2020) does not consider technical variables that are popular among investors in industry, although they conduct a comprehensive analysis of the interaction of 102 anomalies from academic research. In fact, technical analysis is widely used in realistic capital markets. In this paper, we are not interested in the effectiveness of technical or fundamental analysis *per se*. Instead, we are interested in whether the *interaction* of fundamental and

technical analysis could also generate *substantial* economic gains, which are comparable to the performance of double-sorted strategies in Muller and Schmickler (2020) and machine learning strategies in Gu et al. (2020).

Our approach does not *randomly* combine two anomalies or variables. The technical-fundamental integrated approach is also well motivated by theoretical models. Merton (1987) observes that investors tend to operate only on a limited information set. If some investors only rely on technical or fundamental information, then it suggests that the market-clearing prices are unlikely to be efficient with respect to the full information set. Hong and Stein (1999) present a model where there exist two types of boundedly rational investors: newswatchers and momentum traders. A key assumption of their model is that newswatchers only trade on fundamental information whereas momentum traders focus exclusively on recent price trend. In the return extrapolation models, Barberis et al. (2015, 2018) also assume that irrational return extrapolators mainly focus on the information on recent past prices and rational fundamental traders focus on firms' fundamentals. Their models explain some facts such as stock market bubbles well.

Specifically, Barberis (2018) argues that a joint consideration of past prices and firm fundamentals could effectively identify overpriced stocks. Barberis (2018, page 98) argues that “in an economy with extrapolators, the difference between price and fundamental value predicts the subsequent return with a negative sign; When the price is high relative to fundamentals, this is a sign that extrapolators have been buying the asset aggressively, causing it to be overpriced; this overvaluation is then followed by a low return.”

Extending the work by Barberis et al. (2015, 2018), Da, Huang, and Jin (2021, hereafter DHJ) build a multi-asset heterogeneous agent model that jointly explain why fundamental and technical analysis can impact the cross-section of stock returns. In this model, they show that the interactions between fundamental investors and traders with extrapolative beliefs can result in a rich pattern of return dynamics, including reversal and momentum that are commonly observed in empirical data. Thus, in our view, the DHJ model provides a strong theoretical foundation that motivates us to further investigate the joint dynamics between technical and fundamental analysis. We provide more in-depth discussion of the DHJ model and its implications on technical and fundamental analysis in the Appendix.

There appears to be a rigid dichotomy between investors who believe in fundamental analysis and those who focus on technical analysis, although we cannot simply classify investors into fundamental traders and technical traders. While legendary fundamental investors such as Benjamin Graham or Warren Buffet frown at the notion of making investment decisions by perusing stock charts, there is ample evidence that technical analysis remains popular among some individual investors. For example, Hoffmann and Shefrin (2014) study a sample of Dutch discount brokerage clients for the period from 2000 to 2006. Among them, 22.83% (11.18%) rely exclusively on technical (fundamental) analysis. Consistent with the profile of an overconfident investor (Barber and Odean, 2000, 2001), Hoffmann and Shefrin report that the technical investors in their sample suffer from high portfolio turnover and negative average month return.¹

¹ The abysmal performance by the technical investors in the Hoffman and Shefrin study is by no means an aberration. For instance, evidence from both the U.S. (Barber and Odean, 2000) and Taiwan (Barber et al., 2014) find that active investors and day traders on average lose money from their trading activities, largely

Does the evidence from individual investors suggest that technical analysis is useless? At least some academic studies on the efficacy of technical analysis offer a glimpse of hope.² For example, Brock, Lakonishock, and LeBaron (1992) show that buy signals from simple technical trading rules such as moving averages deliver high returns. Using nonparametric kernel regression, Lo, Mamaysky, and Wang (2000) find that some technical indicators do provide useful information. More recently, Han, Yang, and Zhou (2013) and Avramov, Kaplanski, and Levy (2018) provide evidence on the cross-sectional and time-series profitability of technical analysis. Hence the consensus has yet to be reached regarding the usefulness of technical analysis.

In contrast, there is an abundance of evidence that the use of fundamental information could lead to superior portfolio performance (e.g., Bernard and Thomas, 1989; Sloan, 1996; Piotroski, 2000; Cooper, Gulen, and Schill, 2008; Novy-Marx, 2013). Importantly, Yan and Zheng (2017) show that the predictive values of many fundamental signals are robust even after accounting for the data-snooping bias.

Our empirical analysis features four well-known fundamental variables and three popular technical indicators. We are not trying to mine the data and pick the best variables. Our goal is to stick to a small set of well-known technical and fundamental variables and check the performance of our proposed integrated approach. These fundamental variables include Piotroski's FSCORE, the standardized unexpected earnings (SUE), the return on equity (ROE), and the book-to-market ratio (BM). It

due to transaction costs and poor trading skills. Alarmingly, Barber et al. (2008) document that, in aggregate, losses suffered by individual investors from Taiwan are equivalent to 2.2% of Taiwan's gross domestic product.

² In a comprehensive survey of technical analysis, Park and Irwin (2007) document that 56 out of a total of 95 modern studies report positive results.

appears that there are many technical indicators used by practitioners.³ To simplify our analysis and to guard against data-snooping bias, we choose three of the most popular indicators: moving average (MA), Bollinger bands (BOLL) first proposed by John Bollinger in the 1980s, and the momentum factor (MOM) first studied by Jegadeesh and Titman (1993).⁴

Our empirical results show that the integrated approach that combines fundamental and technical information earns much higher average returns than the one-dimensional technical or fundamental analysis. For example, we find that the average monthly equal-weighted returns for the univariate technical or fundamental strategies range from 0.48% to 1.30%. In contrast, the average returns of the joint strategies range from 1.12% to 2.40%. In particular, the best joint strategies combine fundamental variables and Bollinger bands.⁵ Our results survive a battery of robustness checks, including risk-adjustments using the Fama-French 5-factor model transaction costs.

If the joint strategies work so well, then why don't rational arbitrageurs (especially institutions) don't act aggressively to arbitrage the profits and eliminate the apparent inefficiency. We hypothesize that there exist two potential explanations: limits to arbitrage and information asymmetry. In the return extrapolation models, Barberis et al. (2015, 2018) show that rational fundamental traders initially will not aggressively enter into severely overpriced stocks whose prices are pushed by irrational return extrapolators

³ For example, stockcharts.com, a popular technical analysis website, lists 55 commonly used technical indicators.

⁴ We choose MOM because, as shown by Hoffmann and Shefrin (2014), the technical investors in their study appear to be followers of the momentum trading strategy as their returns have a significantly positive loading on the momentum factor.

⁵ The strategy based on Bollinger bands is similar to the short-term reversal. These findings are consistent with the main argument in Muller and Schmickler (2020) that short-term reversal is the key component of the best-performing double-sorted trading strategies.

(i.e., mostly individual investors). Limits to arbitrage will prevent rational fundamental traders from arbitraging the overpricing immediately. Rational traders will start to aggressively arbitrage these overpriced stocks when irrational traders start to realize the overpricing of these stocks. Therefore, profits from the short leg of these overpriced stocks contribute significantly to the joint strategy.

In addition to the arbitrage costs and risks mentioned earlier, it is important to realize that investment decisions are usually made under incomplete information. For example, arbitrageurs might wonder who are the traders they are betting against? For our purpose, we focus on the hypothesis that arbitrageurs could be deterred by other informed traders.⁶

Our empirical results show that the joint strategies are more profitable among smaller firms, firms with high idiosyncratic volatility and high probability of informed trading, as well as during periods when investor sentiment is elevated. Taken together, our results support the hypothesis that informed trading and arbitrage risks imposed by noise traders play a significant role in determining the profitability of the joint fundamental-technical trading strategies.

This paper significantly contributes to the literature. First, we provide novel evidence that a simple integrated approach based on fundamental and technical variables could generate substantial economic gains, which are comparable to those of top best-performing strategies in Muller and Schmickler (2020) and machine learning strategies in Gu et al. (2020).⁷ Our integrated approach is *economically* motivated by theoretical

⁶ Heterogenous agent models (e.g., Dieci and He, 2018) might be best at analyzing such a complex scenario but is beyond the scope of this paper.

⁷ Table 5A in Muller and Schmickler (2020) shows that the best joint strategies based on momentum and short-term reversal has a return ranging from 2.3% to 2.6%, and in our paper the strategy based on FSCORE, SUE, or ROE and BOLL has a return ranging from 2.23% to 2.40%. We use the same criteria

models (i.e., return extrapolation models). Second, our results provide strong evidence on the implications of these models. In particular, limits to arbitrage play a significant role in explaining the super performance of the integrated approach.

2. Data and Methodology

The data on stock returns, share prices, trading volumes, and shares outstanding are obtained from CRSP. Our sample focuses exclusively on common stocks (share code 10 or 11) listed on the NYSE, AMEX, and NASDAQ. Financial statement data are collected from Compustat. The sample period is from January 1985 to December 2016. To alleviate concerns about market microstructure biases, we follow standard practice and exclude stocks with prices less than \$5 at the beginning of portfolio holding period. Fama-French factors data are from Kenneth French's website. We also obtain investor sentiment data from Jeffrey Wurgler's website. Following Shumway (1997) and Shumway and Warther (1999), we assign delisting returns of -30% and -50%, respectively, to stocks delisted from NYSE/AMEX and NASDAQ if their delisting returns are missing, equal to zero, or if the delisting is attributable to performance reasons. Our results are also robust to using -100% as the delisting return (Beaver et al., 2007).

for sample stock selection, but their sample period (1970 to 2017) is expected to have higher returns than out sample period (1985 to 2016). In addition, machine learning strategies in Gu et al. (2020) have lower return if stocks with prices less than \$5 are excluded and more recent sample are used.

2.1 Fundamental Indicators

For fundamental analysis, we consider the following four well-known fundamental variables.

2.1.1 FSCORE

The FSCORE metric was first proposed by Piotroski (2000) and has been widely utilized to measure a firm's composite fundamental or financial strength in the extant literature (e.g., Piotroski, 2000; Fama and French, 2006; Piotroski and So, 2012; Zhu, Sun, and Chen, 2019, 2023; Zhu, Sun, Kenneth, and Chen, 2020). It captures a firm's financial strength along three dimensions: profitability as measured by four variables (return on assets, change in return-on-assets, accrual, and operation cash flow), financial leverage or liquidity as measured by three variables (long-term-debt to total-assets ratio, change in current ratio, equity issues), and operation efficiency as measured by two variables (change in gross margin ratio, and asset turnover ratio). Firms with higher FSCORE is considered to have better financial performance. The range of FSCORE is from 0 to 9. For FSCORE-based fundamental strategies, we classify stocks into three groups based on their FSCORE ranking. Specifically, low-, mid-, or high-FSCORE portfolio includes stocks with FSCORE less than four (0-3), between four and six (4-6), or greater than six (7-9), respectively. On average, our sample contains 2211 stocks each month in the sample period.

In Table 1, we report the average monthly equal-weighted returns for portfolios sorted on FSCORE. We find that the high-FSCORE portfolio earns a highly significant return of 1.52% per month (t -statistic = 5.45). In comparison, the low-FSCORE portfolio

earns an insignificant average return of 0.38%. As a result, the long-short FSCORE portfolio gains an impressive 1.14% per month (t -statistic = 7.24). The risk-adjusted average return based on the Fama and French 5-factor model shows that the trading strategy based on FSCORE survives the risk adjustments and has a highly significant model-adjusted return of 0.90% (t -statistic = 8.77).

2.1.2 Standardized Unexpected Earnings

The second fundamental indicator focuses on earnings information, which may be the most important fundamental information. We use standardized unexpected earnings (SUE) to measure earnings surprise. Following standard practice in the earnings momentum and post-earnings announcement drift literature (e.g., Chordia and Shivakumar, 2006; Zhu, Sun, and Tu, 2021), the SUE for firm i in month t is computed as $(E_{iq} - E_{iq-4})/\sigma_{iq}$, where E_{iq} is the most recently announced earnings and σ_{iq} is the standard deviation of $E_{iq} - E_{iq-4}$ over past eight quarters.

For SUE-based fundamental strategy, stocks are assigned into quintile portfolios based on their most recently available SUE at the end of each month and are hold for one month. To avoid stale information on earnings, the gap between the end of formation month and earnings announcement date should be less than 4 months. We take a long (short) position in the quintile portfolio that consists of stocks with the most positive (negative) SUE.

In Table 1, we report the average monthly raw and risk-adjusted returns of equal-weighted portfolios sorted on SUE. We find that the top quintile portfolio with most positive SUE earns a highly significant return of 1.62% per month (t -statistic = 6.08). In

comparison, the bottom quintile SUE portfolio earns an average return of merely 0.54%. The long-short SUE portfolio gains a highly significant 1.08% (t -statistic = 11.27). The results remain unchanged even after risk adjustments from the Fama and French (2015) 5-factor model. In this case, we obtain a model-adjusted return of 0.96% (t -statistic = 10.81).

2.1.3 Return on Equity

The third fundamental indicator is the return on equity (ROE), which is defined as Net Income / Shareholders' Equity. We note that ROE is often used as a key input in various equity valuation models (e.g., Ohlson, 1995) and has been found to have explanatory power for many asset pricing anomalies (e.g., Hou, Xue, and Zhang, 2015). Similar to the case of SUE, we also use the most recently available quarterly data to compute ROE.

For ROE-based fundamental strategy, we sort stocks into quintile portfolios based on their most recently available ROE at the end of each month and hold them for 1 month. To avoid stale financial information, we require that the gap between the end of formation month and earnings announcement date should be smaller than 4 months. We buy (sell) stocks in the quintile portfolio consisting of stocks with the highest (lowest) ROE.

In Table 1, we report the average monthly equal-weighted returns for portfolios sorted on ROE. Similar to the results based on FSCORE and SUE, we document that the long-short ROE portfolio gains a highly significant 1.30% (t -statistic = 5.57) per month. After

adjusting for risk factors, the ROE strategy earns an average monthly return of 0.82% (t -statistic = 6.56).

2.1.4 Book-to-Market Ratio

The fourth fundamental indicator is the book-to-market ratio (BM), which is defined as the ratio of the book value of equity over market value of equity. To ensure data availability to investors, we use a 6-month lag for the book value when constructing BM. We note that BM is often used in the academic literature to capture the value effect (e.g., Fama and French, 1993; Asness, Moskowitz, and Pedersen, 2013), where firms with high (low) BM are considered to be value (growth) stocks.

We sort stocks into quintile portfolios based on their most recently available BM at the end of each month and hold them for 1 month. Our value-investing strategy is to take a long position in high BM stocks and short low BM stocks. In Table 1, we find that the long-short BM portfolio earns an average monthly return of 0.48% (t -statistic = 2.12) in our sample. On a risk-adjusted basis, the average return is much weaker at 0.17% but retains its statistical significance (t -statistic = 2.05).

2.2 Technical Indicators

As we have explained in the introduction, there are numerous technical indicators that are available to investors. However, many of them often use the same price information. For example, MACD, a popular technical indicator, is nothing more than computing the moving average of the differences between two moving averages of prices. Thus, for simplicity and to guard against potential data-snooping bias, we focus on the following three technical indicators.

2.2.1 Moving Average

The price moving average (MA) compares the short-term price trend with the long-term price trend. Notably, not only is the MA popular among practitioners, it is probably also the most thoroughly examined in academic literature (e.g., Brock, Lakonishock, and LeBaron, 1992; Han et al., 2013). In this paper, we use the 20-day MA and 125-day MA to measure the short-term and long-term price trends. These parameters are chosen because they are approximately equal to 1 month and 6 months, respectively. We find that results based on the 200-day long-term MA is quite similar. Specifically, MA is computed as follows: $MA_j^m(L) = \frac{\sum_{l=0}^{L-1} P_{j,d-l}^m}{L}$, where $P_{j,d-l}^m$ is the closing price for stock j on the trading day $d - l$ in month m ; L is the window size used to calculate MA. We use the following trading rule: if $MA(20) > MA(125)$ at the end of portfolio formation month, then it is considered a buy signal; otherwise, it is a sell signal. We note that this MA indicator captures recent price momentum relative to a firm's long-term average price.

In Table 1, we report the average monthly raw and risk-adjusted returns of equal-weighted portfolios sorted on MA. We find that the results from the MA strategy are significant but somewhat weaker than those based on FSCORE, SUE, or ROE. For example, the raw monthly average return of the long-short MA portfolio is only 0.79% with a marginal t -statistic of 1.70. The Fama and French 5-factor model adjusted return is 0.91% with a t -statistic of 2.10, slightly better than the unadjusted average return.

2.2.2 Bollinger Bands

The second technical indicator that we use is the Bollinger Bands (BOLL) proposed by John Bollinger in the 1980s. The BOLL rule sets a (moving) price range for a stock

over a given horizon. The BOLL strategy assumes that prices outside the range are statistical aberrations and therefore will eventually reverse back into the range. The Bollinger Bands consist of: (a) a middle band, which is defined as an N -period simple moving average (MA); (b) an upper band, which is defined as K times an N -period standard deviation of prices above the middle band ($MA + K\sigma$); (c) a lower band, which is defined as K times the N -period standard deviation of prices below the middle band ($MA - K\sigma$).

In this study, we choose $N = 20$ days and $K = 1$. Our results are also robust when setting $k = 2$. We note that the BOLL is a reversal-type technical indicator since it sells stocks that go beyond the upper band and buys stocks fall below the lower band. Thus, the BOLL and the MA are diametrically different in terms of their design philosophy.

In comparison with the results from the MA trading strategy, we report in Table 1 that the portfolio performance based on BOLL is quite impressive. For example, the average monthly raw return of the long-short BOLL portfolio is 0.98% with a highly significant t -statistic of 7.45. The risk-adjusted average return is very similar to the raw return.

2.2.3 Momentum

The third technical indicator that we adopt is the momentum factor (MOM) first proposed by Jegadeesh and Titman (1993). MOM is measured by a firm's past 12-month cumulative returns, skipping the return of the most recent month. We classify MOM as a technical indicator because it only contains historical price information and does not use any fundamental information. We form quintile portfolios by sorting firms based on their MOM rankings. A long-short MOM portfolio is formed by taking a long (short) position

in the top (bottom) quintile firms. Table 1 shows that both the raw and adjusted returns of the MOM portfolio are highly profitable, scoring highly significant monthly averages of 1.23% and 1.25%, respectively.

2.3 Portfolio Strategies

The four fundamental and three technical variables give us a total of seven univariate trading strategies. Our focus is on the joint fundamental and technical strategies, which are obtained by independently sorting on one fundamental variable and one technical indicator.

The trading strategy that we propose takes a long (short) position if both the fundamental and technical indicators give us buy (sell) signals simultaneously. If the signals are contradictory, then we will have zero position in these stocks. Consequently, we obtain a total of 12 joint fundamental-technical strategies. The naming convention for these joint strategies are listed as follows:

Indicator	FSCORE	SUE	ROE	BM
MA	FMA	SMA	RMA	BMA
BOLL	FBOLL	SBOLL	RBOLL	BBOLL
MOM	FMOM	SMOM	RMOM	BMOM

3. Main Results

3.1 Portfolios Double-Sorted on Fundamental and Technical Variables

The results from Table 1 show that independently all 7 fundamental and technical variables provide investors with valuable information, and portfolio strategies build upon any one of these variables can be profitable albeit with varying degrees of success. For

example, judging from their statistical significance, the SUE portfolio appears to be the best performer whereas the BM and MA portfolios lag behind other indicators. Overall, the univariate portfolios typically generate an average monthly return of approximately 1% in our sample with the exception of univariate BM strategy.

In this article, we are interested in knowing whether fundamental and technical variables contain complementary information. If so, can an integrated approach to fundamental and technical investing outperform one-dimensional strategies based on univariate fundamental or technical indicators? Results from Table 2 confirms that the integrated approach indeed outperforms the one-dimensional approach.

Panel A of Table 2 reports the average monthly portfolio raw returns based on the FSCORE and the three technical variables. We find that the integrated approach significantly enhances portfolio performance when compared with the univariate approach shown in Table 1. For instance, in the case of the FMA strategy, the long side of the integrated portfolio earns 1.61% and the short side basically has a zero return. Taken together, the FMA portfolio that takes a long (short) position in firms with high (low) FSCORE and buy (sell) signals from the MA indicator earns an average monthly return of 1.70% with a t -statistic of 7.95, which dwarfs the univariate results from Table 1. Even more impressive is the FBOLL portfolio that combines information from FSCORE and BOLL, which generates an average return of 2.23% with a t -statistic of 9.12. Similarly, the FMOM strategy generates an average return of 2.26% with a t -statistic of 6.92. We notice that in all three cases, the profits come almost exclusively from the long side, which suggests that our results are unlikely to be affected by short-sale constraints.

Panel B of Table 2 documents the results from the integrated portfolio approach using information from SUE and the three technical indicators. The results are very similar to those shown in Panel A of the same table. The highest average return is achieved by the SBOLL portfolio (2.40%), followed by SMOM (1.83%) and SMA (1.48%). These average returns are highly significant in all three cases.

Panel C of Table 2 shows that ROE is perhaps a better match for MA. Combining the information from ROE and MA generates an average monthly return of 1.89% with a highly significant t -statistic of 7.22. The RBOLL strategy (2.33%) and RMOM strategy (2.19%) appear to have similar performance as measured by their average returns.

In Panel D of Table 2, we find that portfolios double-sorted on BM and technical variables do not seem to perform as well as strategies that rely on other fundamental variables. For example, combining the information from BM and MA generates an average monthly return of merely 1.12%. The BBOLL (1.64%) and BMOM (1.61%) portfolios also appear to be inferior to their peers (see Panels A to C). We attribute this finding to the fact that BM does not appear to be a powerful strategy as evidenced by its low average return shown in Table 1. Having said that, we find that the integrated strategy still outperforms the univariate strategy even in the BM case.

To sum up, we document that portfolio performance are significantly enhanced after we apply an integrated approach to jointly incorporate both fundamental and technical information. If we compare side by side the results from Table 1 and Table 2, we find that the average raw monthly returns double from approximately 1% to about 2%.

Table 3 reports the risk-adjusted returns of the joint fundamental and technical portfolio strategies. The risk adjustments are based on the Fama-French 5-factor model

(Fama and French, 2015). We find that our results are robust to the risk adjustments. For example, we show that the integrated fundamental-technical strategy that are long (short) in portfolios with buy (sell) signals from the MA indicator and strongest (weakest) fundamentals earn significant average monthly returns of about 1.5%, which is about 50% higher than the average risk-adjusted returns from the univariate portfolios shown in Table 1. Similar to our findings from Table 2, the combination of BOLL and fundamental variables seems more potent with average risk-adjusted returns ranging from 1.35% to 2.24%, whereas the combination of BM and technical variables generates the weakest results. Overall, we conclude that the integrated fundamental-technical approach helps improve portfolio performance and the results are robust to risk-adjustments from the Fama-French model.

3.2 The Role of Earnings Announcements

The predictive power from the fundamental variables used in this paper could arise from the well-known anomaly of post-earnings announcement drift (Bernard and Thomas, 1989). To study the influence from earnings announcements on our results, we divide our sample into two subsets: the subsample where earnings announcements coincide with the portfolio formation month (EA); and the other subsample where earnings announcements do not coincide with the portfolio formation month (NO-EA).

Panel A of Table 4 reports the results for the joint FSCORE-technical strategies. It appears that for the FMA strategy, the presence of earnings announcements does not make a large difference in terms of the strategy's average returns. In this case, the difference between the EA and NO-EA subsamples is only 0.23% per month (1.85% vs.

1.62%). On the other hand, for the FBOLL strategy, earnings announcements appear to have a dampening effect on its average returns. For example, the strategy scores a highly significant 2.40% in the NO-EA subsample, but only 1.75% in the EA subsample. For the FMOM strategy, the average returns do not seem to differ much across the two subsamples (2.13% vs. 2.37%).

Panels B and C of Table 4 report the results for the integrated strategies that combine technical variables with SUE and ROE, respectively. We find that the general pattern in these two panels are quite similar to Panel A. For example, we find that the joint fundamental-BOLL strategies tend to deliver higher returns in the NO-EA subsample. However, for the joint fundamental-MA strategies, earnings announcements do not appear to have a big impact with the exception of the SMA strategy where the average return is higher in the EA subsample.

However, earnings announcement does seem to have a large impact on BM-related strategies. Specifically, in the case of BBOLL strategy, the average returns are 2.15% (non-EA) vs 0.54% (EA). Likewise, in the case of BMOM strategy, the average returns are 2.08% (non-EA) vs 0.79% (EA).

Overall, these results found in Table 4 are consistent with the fact that BOLL is a reversal-type of strategy whereas MA is a momentum-type strategy. Da et al. (2014) show that short-term reversal strategy is more profitable in the absence of fundamental factors. Hence it is quite conceivable that the lack of earnings news is a more conducive environment to implementing the BOLL strategy. In addition, our findings are largely unaffected by earnings announcement except for the two BM-related strategies.

3.3 Performance Evaluation

The results from Tables 2 and 3 confirm that portfolios with joint fundamental and technical information exhibit superior returns. However, from investors (arbitrageurs)' perspective, we also need to investigate the potential tail risks associated with these portfolio strategies. As an example, Daniel and Moskowitz (2016) find that in spite of its high average return, the well-known momentum trading strategy (Jegadeesh and Titman, 1993) is subject to rare but large crashes. Statistically, its return distribution exhibits left skewness and excessively large kurtosis. Consequently, in this subsection, we study (monthly) Sharpe ratios as well as return distribution moments of the various joint fundamental-technical portfolio strategies. In addition, it is also interesting to investigate if our trading strategies are robust after adjustments for transaction costs.

Table 5 reports the mean return, standard deviation, skewness, kurtosis, Sharp ratio, various transaction cost metrics, and transaction-cost-adjusted metrics of 7 univariate and 12 joint strategies. We focus on three metrics of transaction costs: (a) portfolio turnover, which measures the percentage of stocks that are not in the same portfolio in two consecutive months; (b) the half effective spread, which is defined as the absolute value of the difference between the transaction price and the bid-ask midpoint, scaled by mid-quote; and (c) total transaction cost, which is defined as the sum of products of half effective spread and portfolio turnover ratio from both the long and short legs of a portfolio (Da et al., 2014).

Overall, the results support our main arguments. First, the joint strategies outperform the univariate strategies in term of transaction-cost adjusted returns. For example, all three TA-enhanced FSCORE strategies have the monthly net returns of 1.03%, 0.90%,

and 1.62%, respectively. In contrast, the simple FSCORE strategy has a net return of 0.73% per month. Similar findings hold for SUE, ROE, BM, and other TA strategies. In addition, momentum-enhanced fundamental strategies have the highest net returns due to lower portfolio turnover.

Second, some joint strategies outperform the univariate strategies in term of Sharpe ratio, though other joint strategies have lower Sharpe ratios than the univariate strategies. For example, the simple SUE strategy has the highest Sharpe ratio of 0.60, compared to other univariate strategies. The SBOLL strategy has a higher Sharpe ratio of 0.71, while SMOM has a low Sharpe ratio of 0.31. The SBOLL strategy outperforms the simple SUE strategy in term of Sharpe ratio because the SBOLL strategy has a much higher returns and a relatively higher volatility than the simple SUE strategy. Similarly, the simple FSCORE strategy has a Sharpe ratio of 0.44, while FBOLL has a Sharpe ratio of 0.50 and FMOM has a Sharpe ratio of 0.39. Overall, BOLL-enhanced fundamental strategies have higher Sharpe ratios than the corresponding univariate fundamental strategies in term of Sharpe ratio. MA- and MOM-enhanced fundamental strategies do not consistently outperform the univariate strategies due to high return volatility of joint strategies.

In particular, a closer look at portfolio turnover indicates that all four BOLL-related joint strategies suffer from high portfolio turnover, which exacerbates the transaction cost problem. On the other hand, MOM and MA-related joint strategies seem to enjoy relatively low portfolio turnover ratios, which cuts down their transaction costs. Overall, joint strategies suffer from higher portfolio turnover than the univariate strategies. However, the benefits of jointly considering fundamental and technical information are greater than the trading costs due to higher turnovers.

Taken together, we conclude that the fundamental-technical joint strategies outperform the univariate strategies in term of returns even controlling for transaction costs. However, the joint strategies do not consistently outperform the univariate strategies in term of Sharpe ratio. Specifically, BOLL-enhanced fundamental strategies have higher Sharpe ratios than the corresponding univariate fundamental strategies, while MA- and MOM-enhanced fundamental strategies do not perform better in in term of Sharpe ratio due to high return volatility. However, arbitrage activities are likely dampened by transaction costs due to high portfolio turnover especially for BOLL-related joint strategies.

4. Limits to Arbitrage and Information Asymmetry

Our empirical findings suggest that some firms in the U.S. equity market (as identified by our proposed trading strategies) are apparently mispriced. Hence an interesting question arises: why arbitrageurs don't take advantage of the mispricing and eliminate the inefficiency? We offer two explanations based on limits to arbitrage and information asymmetry. Prior studies (e.g. Pontiff, 2006; Shleifer and Vishny, 1997) find that arbitrageurs are constrained by potentially high transaction costs as well as arbitrage risk in the form of idiosyncratic volatility. In our setting, Barberis et al. (2015, 2018) argue that rational fundamental traders are initially reluctant to aggressively arbitrage the overpricing caused by irrational return extrapolators due to high arbitrage costs confronted by these arbitrageurs.

Alternatively, following Easley et al. (2002) and in our context, if arbitrageurs do not possess private information, then they will be reluctant to trade stocks that have a higher probability of informed trading even if the signals from the joint fundamental-technical strategies suggest otherwise. We present strong evidence that both limits to arbitrage and informed trading are likely explanations of the profitability of the fundamental-technical joint strategies.

4.1 Idiosyncratic Volatility and Arbitrage Risk

Stambaugh, Yu, and Yuan (2015), among others, point out that arbitrage risk is best measured by idiosyncratic volatility (IVOL). Arbitrageurs who use margins and/or take short positions are subject to margin calls when there are chances for a large adverse move in stock price. Therefore, stocks with heightened idiosyncratic volatility can severely deter arbitrageurs even when mispricing is flagrant. If arbitrage risk is a potential explanation of our empirical findings, then we expect our proposed trading strategies to be more profitable among stocks with large IVOL due to the absence of arbitrage activities, and *vice versa*.

In Table 6, we divide our sample into two subsets: high IVOL and low IVOL. Regardless of strategy combinations, portfolio performance is uniformly more impressive when IVOL is high. For example, in the case of MA related strategies, the differences in average returns across the high vs. low IVOL subsamples are 2.30%, 1.90%, 2.16%, and 1.31% for the FMA, SMA, RMA and BMA portfolios, respectively. For the FBOLL, SBOLL, RBOLL, and BBOLL portfolios, in the high (low) IVOL subsamples, the average monthly returns are 3.31% (1.01%), 3.32% (1.44%), 2.96% (1.27%), and 2.22%

(0.86%), respectively. Similar results also hold for MOM-related strategies. Given the significant outperformance by all of our joint strategies in the high IVOL subsamples, we conclude that arbitrage risk is an important determining factor for the success of these strategies.

4.2 Incomplete Information and Informed Trading

In addition to the arbitrage costs and risks mentioned earlier, it is important to realize that investment decisions are usually made under incomplete information. For example, arbitrageurs might wonder who are the traders they are betting against? Are they value-oriented institutional investors or noise traders who only focus on technical signals? More importantly, do they possess superior information that arbitrageurs do not have? Heterogenous agent models (e.g., Dieci and He, 2018) might be best at analyzing such a complex scenario but is beyond the scope of this paper. For our purpose, we focus on the hypothesis that arbitrageurs could be deterred by other informed traders. To test this hypothesis, we rely on the probability of informed trading (PIN) variable to identify firms where informed trading is rampant.

We compute PIN with the Brown and Hillegeist (2007) method, which is an extended version of the popular model proposed by Easley, Kiefer, and O'Hara (1997).⁸ The PIN data set is from Stephen Brown and it covers the sample period from 1993 to 2010.⁹ The PIN is an estimated probability that a trade is from a privately informed

⁸ To save space, we do not discuss the detailed information about the EKO microstructure model and the calculation of PIN data. Brown and Hillegeist (2007) provide detailed information about the model and its assumptions and how the PIN is estimated.

⁹ The PIN data is from <http://scholar.rhsmith.umd.edu/sbrown/pin-data>. We thank Stephen Brown for providing the PIN data.

investor in firm level, directly capturing the extent of information asymmetry among investors in the secondary market (Brown and Hillegeist, 2007). The PIN measure is better than traditional spreads as proxies of information asymmetry. The PIN is based on the imbalance between buy and sell orders among investors.

Evidence from Table 7 indicates our trading strategies are more profitable among firms with higher probability of informed trading. For example, we report that the average returns for the joint fundamental-technical strategies among high PIN firm outperform those among low PIN firms by approximately 1% per month. For example, the RBOLL strategy earns 3.25% (t-statistic = 8.25) in the high PIN sample. By comparison, the same strategy records 1.56% (t-statistic = 2.63) among low PIN firms. The results from other joint strategies are quite similar. Moreover, the joint strategies also outperform the corresponding univariate strategies both in the high PIN and low PIN samples. Taken together, we conclude that the evidence from Table 8 are consistent with the view that information asymmetry (informed trading) is an important deterring factor that contributes to the profitability of our proposed joint strategies.

5. Robustness Tests

5.1 Large Stocks

In this subsection, we conduct the empirical analysis in subsection 3.3 for a subsample of large stocks whose market capitalization is above the median value of all sample stocks. These large stocks are expected to have smaller bid-ask spread and turnover, and lower return volatility, thus suffer from smaller transaction costs.

Table 8 reports the results. Overall, the results based on transaction cost adjusted returns and Sharpe ratios support our main argument that the fundamental-technical joint strategies outperform the univariate fundamental or technical strategies. First, the joint strategies outperform the univariate strategies in term of transaction-cost adjusted returns. For example, all three TA-enhanced FSCORE strategies have the monthly net returns of 0.47%, 0.70%, and 1.05%, respectively. In contrast, the simple FSCORE strategy has a net return of 0.38% per month. In addition, the simple ROE and MOM strategies have best performance among all univariate strategies. However, all three TA-enhanced ROE strategies still outperform the simple ROE strategies. All four FA-enhanced MOM strategies still outperform the simple MOM strategies. Similar findings hold other fundamental and technical strategies.

Second, though the joint strategies do not consistently outperform the univariate strategies in term of Sharpe ratio, BOLL-enhanced fundamental strategies consistently have relatively higher Sharpe ratios. For example, the simple FSCORE, SUE, ROE, and BM have a Sharpe ratio of 0.22, 0.22, 0.18, and 0.07, respectively. The corresponding FBOLL, SBOLL, RBOLL, and BBOLL have a Sharpe ratio of 0.26, 0.35, 0.26, and 0.24, respectively. However, MA and MOM do not enhance the fundamental strategies in term of Sharpe ratio.

Third, we find consistent results based on the transaction cost adjusted Sharpe ratio. BOLL-enhanced fundamental strategies have similar or relatively higher Sharpe ratios than the univariate strategies. For example, the simple FSCORE, SUE, ROE, and BM have a Sharpe ratio of 0.13, 0.15, 0.14, and 0.06, respectively. The corresponding FBOLL, SBOLL, RBOLL, and BBOLL have a Sharpe ratio of 0.13, 0.21, 0.15, and 0.13,

respectively. In contrast, MA do not help enhance the Sharpe ratios of MA-enhanced fundamental strategies. MOM performs better than MA in enhancing the Sharpe ratios of TA-enhanced joint strategies.

In addition, ask-bid spreads are smaller for large stocks than for the whole sample stocks shown in Table 5. However, there is no difference about portfolio turnovers between large stocks and the whole sample stocks. Overall, our results for large stocks indicate that a joint consideration of fundamental and technical information could enhance the performance of the univariate fundamental or technical strategies even after controlling for transaction costs.

5.2 Transaction Cost and Asymmetric Information

In this subsection, we examine whether transaction costs could fully explain the high returns of high PIN stocks, compared to low PIN stocks. To save space, we focus on BOLL-related strategies because BOLL-related strategies suffer from higher transaction costs than MA- and MOM-related strategies.

Table 9 reports the results. First, as expected, high PIN stocks have larger bid-ask spreads than low PIN stocks. For example, the average bid-ask spread of the long leg of SBOLL in the subsample of low PIN stocks is 0.33%, while the average spread is 0.77% in the subsample of high PIN stocks. Second, both high and low PIN stocks have high portfolio turnover. Taken together, high PIN stocks have higher total estimated transaction costs than low PIN stocks. Although high PIN stocks have higher transaction costs than low PIN stocks, high PIN stocks still have higher transaction-cost adjusted returns than low PIN stocks because high PIN stocks have much higher raw returns than

low PIN stocks. For example, the SBOLL has an average monthly raw return of 1.76% and net return of 1.18% in the subsample of low PIN stocks. In contrast, the SBOLL has an average monthly raw return of 3.40% and net return of 2.05% in the subsample of low PIN stocks.

To summarize, information asymmetry (informed trading) is an important deterring factor that contributes to the profitability of our proposed joint strategies.

5.3 Transaction Cost Mitigation

Novy-Marx and Velikov (2016) argue that the effective bid-ask spread measure is conservative in measuring transaction costs, although this measure is not perfect. Although there are many types of transaction costs such as commission fees and market impact, the cost measured by the combination of effective bid-ask spreads and portfolio turnovers could be the main transaction cost.

To mitigate the concern about the practical implication of these joint strategies due to transaction costs, we examine some strategies to mitigate transaction costs. Novy-Marx and Velikov (2016) propose three strategies to mitigate transaction costs. They argue that the buy/hold spread strategies work best. The spirit of these strategies is to reduce the portfolio turnover. Therefore, we propose two strategies that could reduce the portfolio turnover. Our empirical results suggest that these two transaction-cost mitigation strategies work well.

The first strategy is to trade on overlap stocks that are covered in two consecutive formation portfolios. To illustrate, we construct a portfolio at the end of month $t-2$ based on the simple joint strategy rule. At the end of month $t-1$, we construct a new portfolio

based on the simple joint strategy rule. In the beginning of month t , we trade on only stocks that are covered by both the portfolio at the end of month $t-2$ and the other portfolio at the end of month $t-1$. That is, we trade on those overlap stocks that are covered in portfolios in two consecutive months. In such case, we could reduce the formation portfolio turnover rate in month t . Table 10 shows that compared to stocks of simple joint strategies in Table 5, these overlap stocks of most joint strategies have higher or similar returns. For example, the return of the long leg of overlap stocks of FMA is 1.72%, which is larger than 1.61% for the long leg of raw FMA and the return of the short leg is similar for two strategies. These results suggest that this first transaction-cost mitigation strategy works well.

The second strategy is to trade on stocks without rebalancing each month. To illustrate, we construct a portfolio at the end of month $t-2$ based on the simple joint strategy rule. In month $t-1$ and t , investors could hold the formation portfolio at the end of month $t-2$ for two months without rebalancing in month t . In such case, investors could reduce the portfolio turnover and do not incur direct trading costs in month t . Table 10 shows that the portfolio returns for most joint strategies in the 2nd holding month are greater than the net returns that adjust for transaction costs (benchmark returns shown in Table 5). For example, the long leg of FMA has a return of 1.56% and the short leg has a return of 0.12% in the second holding month. The long-short FMA portfolio without rebalancing in the second holding month has a return 1.44%, which is larger than the net return of 1.03% in the first holding month shown in Table 5. These results suggest that this transaction-cost mitigation strategy works well.

6. Discussion and Conclusion

In this paper, we provide interesting new evidence that an integrated approach to fundamental and technical investing can significantly improve portfolio performance. We show that by conditioning on trading signals from both fundamental and technical indicators, the new joint strategies can significantly outperform their one-dimensional counterparts. Our findings are consistent with Muller and Schmickler (2020), who report that the performance of some simple trading strategies based on double-sorted portfolios is comparable to that of those machine learning strategies in Gu et al. (2020). Our results are robust to a number of robustness checks.

Extending the work by Barberis et al. (2015, 2018), Da, Huang, and Jin (2021) build a multi-asset heterogeneous agent model that jointly explain why fundamental and technical analysis can impact the cross-section of stock returns. In their model, they show that the interactions between fundamental investors and traders with extrapolative beliefs can result in a rich pattern of return dynamics, including reversal and momentum that are commonly observed in empirical data. Thus, in our view, the DHJ model provides a strong theoretical foundation that motivates us to investigate the joint dynamics between technical and fundamental analysis.

We also probe two potential explanations of our findings based on limits to arbitrage and information asymmetry. Since our results are much stronger among small firms, we conjecture that arbitrage risks could be an important factor in determining the new strategies' success. We report that all of the joint strategies attain much higher returns among firms with high idiosyncratic volatility, which confirms the important role of

arbitrage risk. In addition, the joint strategies' returns are higher when investor sentiment is elevated, which is consistent with the view that noise traders' trading activities could have a deterring effect on arbitrageurs. Moreover, we find interesting evidence that the joint strategies are more profitable among firms with higher probability of informed trading. We conclude that both limits to arbitrage and informed trading contribute to our empirical findings.

From a theoretical perspective, our findings support De Long et al.'s (1990) view that it is important to account for the actions of both rational arbitrageurs and irrational noise traders in financial markets. This suggests that standard asset pricing models based on the traditional representative agent framework might be too simplistic. Models where investors exhibit heterogeneous beliefs appear to be better at describing certain important characteristics of the market, such as speculative bubbles and market crashes (e.g., Scheinkman and Xiong, 2003; Barberis et al., 2015, 2018). In addition, our results suggest that theoretical models of market inefficiency should consider jointly the roles played by both arbitrage risk and informed trading. In addition, the profitability of our proposed trading strategies appears to support Merton (1987), who claims that investors tend to operate only on a limited information set.

From a practical perspective, our results suggest that investors (arbitrageurs) who are capable of synthesizing both fundamental and technical information can profit from the inefficiency in prices but not without some caveats. First, it is important that such investors understand the direct and indirect costs and risks associated with arbitraging/investing and avoid the over usage of financial leverage. For example, arbitrageurs also suffer from huge losses in the case of recent Gamestop incident. Second,

investors should consider using investor sentiment metrics to gauge noise traders' belief and allocate their capital wisely. Arbitrageurs sometimes confront losses when noise trading is prevalent in the market. More sophisticated arbitrageurs are good at timing trading when sentiment and noise trading are high. Third, they should be wary of firms where the probability of informed trading is high. From this perspective, perhaps investors should heed the words of wisdom from value investors such as Benjamin Graham and Warren Buffett, who urge investors to always use "margin of safety" when evaluating their investment opportunities.

Transaction costs are an important concern for investors. Following the spirit of Novy-Marx and Velikov (2016), we propose two strategies to mitigate the direct trading costs for the joint strategies by reducing the portfolio turnover. We provide evidence that these transaction cost mitigation strategies work well for our proposed integrated approach.

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Table 1: Average Returns to Long-Short Portfolios Sorted on Fundamental or Technical Variables

This table reports average monthly equal-weighted raw and risk-adjusted returns of equal-weighted portfolios separately sorted on four fundamental variables (FSCORE, SUE, ROE, and BM) as well as three technical variables (MA, BOLL, and MOM). At the end of each month, stocks are assigned into three portfolios based on their average FSCORE values from the prior quarter: Low (less than 4), Mid (between 4 and 6), or High (greater than 6). Separately, we also sort firms into portfolios based on their most recent SUE, ROE, and BM quintiles. We take a long (short) position in firms with strong (weak) fundamentals as measured by these fundamental variables. The trading rules based on technical variables are as follows. For MA, we long (short) firms whose short-term MA are above (below) their long-term MA. For BOLL, we take a long (short) position in firms whose prices are below (above) the lower (upper) Bollinger band. For MOM, we long (short) firms that have the largest (smallest) cumulative returns from past 12 months. The portfolio holding period is for one month. The risk-adjusted returns are computed from the Fama-French (2015) five-factor model (FF5). Our sample includes all common stocks from NYSE, AMEX and NASDAQ. Stocks with prices less than \$5 at the end of portfolio formation periods are excluded. The sample period is from January 1985 to December 2016. Newey and West (1987) adjusted t -statistics are reported in parentheses.

	FSCORE		SUE		ROE		BM		MA		BOLL		MOM	
	Raw	FF5	Raw	FF5	Raw	FF5	Raw	FF5	Raw	FF5	Raw	FF5	Raw	FF5
Short	0.38	-0.49	0.54	-0.47	0.27	-0.44	0.70	-0.09	0.23	-0.74	0.57	-0.37	0.28	-0.67
	(1.07)	(-5.51)	(1.89)	(-7.33)	(0.65)	(-4.48)	(2.06)	(-1.34)	(0.48)	(-1.95)	(2.12)	(-4.09)	(0.78)	(-3.66)
Long	1.52	0.41	1.62	0.49	1.57	0.39	1.18	0.08	1.02	0.18	1.55	0.59	1.50	0.57
	(5.45)	(6.12)	(6.08)	(7.45)	(5.29)	(5.01)	(4.1)	(1.3)	(2.57)	(0.65)	(5.43)	(4.99)	(4.51)	(4.13)
Long-Short	1.14	0.90	1.08	0.96	1.30	0.82	0.48	0.17	0.79	0.91	0.98	0.96	1.23	1.25
	(7.24)	(8.77)	(11.27)	(10.81)	(5.57)	(6.56)	(2.12)	(2.05)	(1.70)	(2.10)	(7.45)	(5.94)	(4.63)	(4.03)
Standard deviation	2.62		1.79		3.95		3.63		9.62		2.85		4.90	
Skewness	0.62		-0.97		-1.11		0.77		-1.46		1.28		-0.24	
Kurtosis	5.61		5.54		12.65		5.18		25.92		6.22		8.73	
Sharpe ratio	0.44		0.60		0.33		0.13		0.08		0.34		0.25	

Table 2: Portfolios Double Sorted on Both Fundamental and Technical Variables:

Raw Returns

This table presents the average monthly equal-weighted raw returns of portfolios double sorted on fundamental and technical variables. The technical variables include moving average (MA), Bollinger Bands (BOLL), and Momentum. The fundamental variables are FSCORE, the standardized unexpected earnings (SUE), return on equity (ROE), and book-to-market (BM). MA1 refers to the portfolio consisting of stocks with $MA(20) < MA(125)$ at the end of formation month; MA2 refers to the portfolio consisting of stocks with $MA(20) > MA(125)$; B1 refers to the portfolio consisting of stocks with prices above the upper Bollinger band; B2 refers to the portfolio consisting stocks with prices within the upper and lower bands; and B3 refers to the portfolio consisting of stocks with prices below the lower band. M1 (M5) refers to the bottom (top) quintile momentum portfolios. FA + TA refers to the joint portfolio when we long (short) stocks that have buy (sell) signals from both technical and fundamental indicators. The holding period is 1 month. Our sample includes all common stocks from NYSE, AMEX and NASDAQ. Stocks with prices less than \$5 at the end of portfolio formation periods are excluded. The sample period is from January 1985 to December 2016. Newey and West (1987) adjusted *t*-statistics are reported in parentheses.

Panel A: Portfolios Double-Sorted on FSCORE and Technical Variables

	Moving Average			Bollinger Bands			Momentum		
	MA1	MA2	MA2-MA1	B1	B3	B3-B1	M1	M5	M5-M1
F1	-0.08 (-0.22)	0.71 (2.07)	0.79 (3.97)	-0.03 (-0.08)	0.88 (2.41)	0.91 (3.90)	-0.10 (-0.22)	0.92 (2.28)	1.01 (3.12)
F3	1.19 (4.14)	1.61 (5.66)	0.42 (3.02)	1.09 (3.95)	2.20 (7.05)	1.10 (7.12)	0.98 (2.89)	2.16 (5.99)	1.18 (4.20)
F3-F1	1.27 (7.15)	0.91 (6.24)		1.12 (5.73)	1.31 (7.10)		1.08 (4.94)	1.25 (6.42)	
FA+TA	1.70 (7.95)			2.23 (9.12)			2.26 (6.92)		

Panel B: Portfolios Double-Sorted on SUE and Technical Variables

	Moving Average			Bollinger Bands			Momentum		
	MA1	MA2	MA2-MA1	B1	B3	B3-B1	M1	M5	M5-M1
SUE1	0.27 (0.88)	0.58 (2.12)	0.32 (1.95)	-0.15 (-0.52)	1.15 (3.72)	1.30 (7.91)	0.17 (0.49)	0.88 (2.51)	0.70 (2.41)
SUE5	1.12 (3.93)	1.74 (6.64)	0.62 (4.76)	1.13 (4.16)	2.25 (7.73)	1.12 (6.88)	0.91 (2.53)	2.00 (5.85)	1.09 (3.63)
SUE5-SUE1	0.85 (9.40)	1.16 (10.58)		1.28 (10.53)	1.09 (8.97)		0.74 (5.76)	1.13 (9.02)	
FA+TA	1.48 (9.10)			2.40 (14.39)			1.83 (6.74)		

Panel C: Portfolios Double-Sorted on ROE and Technical Variables

	Moving Average			Bollinger Bands			Momentum		
	MA1	MA2	MA2-MA1	B1	B3	B3-B1	M1	M5	M5-M1
ROE1	-0.20	0.55	0.76	-0.22	0.71	0.93	-0.22	0.80	1.02
	(-0.48)	(1.38)	(3.29)	(-0.52)	(1.79)	(4.00)	(-0.47)	(1.72)	(2.84)
ROE5	1.01	1.69	0.68	1.25	2.11	0.87	0.95	1.97	1.01
	(3.34)	(5.69)	(5.12)	(4.35)	(6.80)	(4.60)	(2.69)	(5.40)	(3.88)
ROE5-ROE1	1.21	1.13		1.52	1.40		1.17	1.16	
	(5.98)	(5.60)		(7.37)	(5.96)		(4.29)	(4.94)	
FA+TA	1.89			2.33			2.19		
	(7.22)			(7.45)			(6.82)		

Panel D: Portfolios Double-Sorted on BM and Technical Variables

	Moving Average			Bollinger Bands			Momentum		
	MA1	MA2	MA2-MA1	B1	B3	B3-B1	M1	M5	M5-M1
BM1	0.25	0.88	0.63	0.11	1.40	1.28	0.01	1.23	1.22
	(0.69)	(2.69)	(3.81)	(0.32)	(4.01)	(6.39)	(0.04)	(3.06)	(4.64)
BM5	0.82	1.37	0.55	0.79	1.75	0.96	0.58	1.63	1.04
	(2.66)	(5.01)	(4.23)	(2.67)	(5.81)	(7.04)	(1.45)	(4.75)	(3.73)
BM5-BM1	0.57	0.49		0.68	0.35		0.57	0.39	
	(2.40)	(2.24)		(2.66)	(1.44)		(2.00)	(1.53)	
FA+TA	1.12			1.64			1.61		
	(4.60)			(5.61)			(5.68)		

Table 3: Portfolios Double Sorted on Both Fundamental and Technical Variables:

Risk-Adjusted Returns

This table presents the average monthly equal-weighted risk-adjusted returns of portfolios double sorted on fundamental and technical variables. The risk adjustments are based on the Fama-French (2015) 5-factor model. The technical variables include moving average (MA), Bollinger Bands (BOLL), and Momentum. The fundamental variables are FSCORE, the standardized unexpected earnings (SUE), return on equity (ROE), and book-to-market (BM). MA1 refers to the portfolio consisting of stocks with $MA(20) < MA(125)$ at the end of formation month; MA2 refers to the portfolio consisting of stocks with $MA(20) > MA(125)$; B1 refers to the portfolio consisting of stocks with prices above the upper Bollinger band; B2 refers to the portfolio consisting stocks with prices within the upper and lower bands; and B3 refers to the portfolio consisting of stocks with prices below the lower band. M1 (M5) refers to the bottom (top) quintile momentum portfolios. FA + TA refers to the joint portfolio when we long (short) stocks that have buy (sell) signals from both technical and fundamental indicators. The holding period is 1 month. Our sample includes all common stocks from NYSE, AMEX and NASDAQ. Stocks with prices less than \$5 at the end of portfolio formation periods are excluded. The sample period is from January 1985 to December 2016. Newey and West (1987) adjusted t -statistics are reported in parentheses.

Panel A: Portfolios Double-Sorted on FSCORE and Technical Variables

	Moving Average			Bollinger Bands			Momentum		
	MA1	MA2	MA2-MA1	B1	B3	B3-B1	M1	M5	M5-M1
F1	-0.96	-0.13	0.82	-0.77	-0.03	0.74	-0.99	0.13	1.12
	(-5.90)	(-0.91)	(3.26)	(-3.83)	(-0.16)	(2.66)	(-4.19)	(0.73)	(3.10)
F3	0.08	0.55	0.47	0.02	1.07	1.05	-0.05	1.05	1.10
	(0.63)	(5.75)	(2.62)	(0.18)	(8.16)	(5.77)	(-0.22)	(6.32)	(3.37)
F3-F1	1.04	0.68		0.79	1.10		0.94	0.92	
	(8.49)	(5.67)		(3.46)	(6.34)		(6.01)	(5.20)	
FA+TA	1.51			1.84			2.04		
	(6.63)			(7.65)			(5.65)		

Panel B: Portfolios Double-Sorted on SUE and Technical Variables

	Moving Average			Bollinger Bands			Momentum		
	MA1	MA2	MA2-MA1	B1	B3	B3-B1	M1	M5	M5-M1
SUE1	-0.72	-0.32	0.39	-1.14	0.18	1.32	-0.85	-0.03	0.81
	(-5.78)	(-2.90)	(1.92)	(-10.05)	(1.28)	(6.89)	(-4.65)	(-0.20)	(2.52)
SUE5	0.07	0.66	0.59	0.07	1.10	1.04	-0.11	0.90	1.01
	(0.56)	(7.27)	(3.31)	(0.47)	(8.92)	(5.25)	(-0.51)	(5.7)	(2.92)
SUE5-SUE1	0.77	0.99		1.21	0.92		0.74	0.93	
	(8.20)	(10.27)		(8.95)	(8.07)		(5.27)	(7.71)	
FA+TA	1.38			2.24			1.75		
	(7.26)			(12.60)			(5.62)		

Panel C: Portfolios Double-Sorted on ROE and Technical Variables

	Moving Average			Bollinger Bands			Momentum		
	MA1	MA2	MA2-MA1	B1	B3	B3-B1	M1	M5	M5-M1
ROE1	-0.93	-0.13	0.80	-0.91	0.02	0.93	-0.99	0.10	1.09
	(-5.60)	(-0.82)	(2.88)	(-4.24)	(0.13)	(3.22)	(-4.41)	(0.50)	(2.76)
ROE5	-0.12	0.56	0.68	0.13	0.99	0.84	-0.17	0.85	1.02
	(-0.89)	(5.95)	(3.99)	(1.07)	(5.96)	(3.90)	(-0.83)	(5.85)	(3.49)
ROE5-ROE1	0.81	0.70		1.16	0.97		0.82	0.75	
	(5.35)	(4.30)		(6.13)	(6.74)		(4.79)	(3.95)	
FA+TA	1.50			1.90			1.84		
	(6.61)			(6.74)			(5.59)		

Panel D: Portfolios Double-Sorted on BM and Technical Variables

	Moving Average			Bollinger Bands			Momentum		
	MA1	MA2	MA2-MA1	B1	B3	B3-B1	M1	M5	M5-M1
BM1	-0.54	0.05	0.59	-0.70	0.61	1.31	-0.72	0.48	1.20
	(-4.05)	(0.44)	(2.85)	(-4.94)	(4.13)	(5.83)	(-3.78)	(3.05)	(3.84)
BM5	-0.28	0.34	0.61	-0.27	0.65	0.92	-0.55	0.56	1.11
	(-2.39)	(3.97)	(4.03)	(-2.20)	(5.73)	(5.95)	(-2.42)	(4.32)	(3.68)
BM5-BM1	0.26	0.29		0.43	0.04		0.17	0.08	
	(2.17)	(2.63)		(2.76)	(0.32)		(0.93)	(0.54)	
FA+TA	0.88			1.35			1.28		
	(4.93)			(6.64)			(4.61)		

Table 4: The Effect of Earnings Announcements

This table presents the average monthly equal-weighted returns of portfolios double sorted on fundamental and technical variables across two subsamples. EA (NO-EA) refers to the subsample where earnings announcements (do not) coincide with the portfolio formation month. The technical variables include moving average (MA), Bollinger Bands (BOLL), and momentum. The fundamental variables are FSCORE, the standardized unexpected earnings (SUE), return on equity (ROE), and book-to-market (BM). MA1 refers to the portfolio consisting of stocks with $MA(20) < MA(125)$ at the end of formation month; MA2 refers to the portfolio consisting of stocks with $MA(20) > MA(125)$; B1 refers to the portfolio consisting of stocks with prices above the upper Bollinger band. B3 refers to the portfolio consisting of stocks with prices below the lower band. M1 (M5) refers to the bottom (top) quintile momentum portfolio. FA + TA refers to the joint portfolio when we long (short) stocks that have buy (sell) signals from both technical and fundamental indicators. The holding period is 1 month. Our sample includes all common stocks from NYSE, AMEX and NASDAQ. Stocks with prices less than \$5 at the end of portfolio formation periods are excluded. The sample period is from January 1985 to December 2016. Newey and West (1987) adjusted t -statistics are reported in parentheses.

Panel A: Earnings Announcement and FSCORE and TA Portfolios

Panel B: Earnings Announcement and SUE and TA Portfolios

	Moving Average							Moving Average					
	EA			NON-EA				EA			NON-EA		
	MA1	MA2	MA2-MA1	MA1	MA2	MA2-MA1		MA1	MA2	MA2-MA1	MA1	MA2	MA2-MA1
F1	-0.17 (-0.48)	0.56 (1.53)	0.76 (2.90)	-0.07 (-0.19)	0.76 (2.23)	0.83 (3.82)	SUE1	0.05 (0.16)	0.26 (0.91)	0.22 (1.17)	0.25 (0.82)	0.64 (2.29)	0.39 (2.20)
F3	1.39 (4.84)	1.68 (5.95)	0.28 (1.65)	1.06 (3.47)	1.54 (5.21)	0.49 (3.02)	SUE5	1.19 (4.06)	1.90 (7.14)	0.70 (4.68)	1.02 (3.38)	1.63 (5.86)	0.61 (4.11)
F3-F1	1.56 (7.85)	1.13 (5.21)		1.13 (5.35)	0.79 (4.43)		SUE5-SUE1	1.17 (8.29)	1.66 (10.90)		0.76 (6.81)	0.99 (7.44)	
FA+TA	1.85 (7.87)			1.62 (6.55)			FA+TA	1.86 (11.61)			1.37 (7.32)		
	Bollinger Bands							Bollinger Bands					
	EA			NON-EA				EA			NON-EA		
	B1	B3	B3-B1	B1	B3	B3-B1		B1	B3	B3-B1	B1	B3	B3-B1
F1	0.19 (0.46)	0.56 (1.59)	0.35 (1.03)	-0.07 (-0.18)	1.13 (2.85)	1.20 (4.81)	SUE1	-0.11 (-0.37)	0.87 (3.08)	0.99 (4.39)	-0.18 (-0.63)	1.26 (3.86)	1.44 (7.77)
F3	1.48 (5.50)	1.93 (5.89)	0.45 (1.99)	0.81 (2.77)	2.33 (7.32)	1.51 (9.58)	SUE5	1.67 (6.62)	2.16 (6.85)	0.45 (1.82)	0.83 (2.85)	2.25 (7.27)	1.42 (7.99)
F3-F1	1.29 (4.79)	1.38 (4.68)		0.88 (4.07)	1.20 (4.97)		SUE5-SUE1	1.78 (8.53)	1.29 (5.86)		1.02 (6.96)	0.99 (6.19)	
FA+TA	1.75 (5.09)			2.40 (8.67)			FA+TA	2.27 (8.22)			2.44 (14.24)		
	Momentum							Momentum					
	EA			NON-EA				EA			NON-EA		
	M1	M5	M5-M1	M1	M5	M5-M1		M1	M5	M5-M1	M1	M5	M5-M1
F1	-0.01 (-0.02)	0.65 (1.35)	0.63 (1.49)	-0.23 (-0.48)	0.99 (2.49)	1.21 (3.52)	SUE1	-0.02 (-0.05)	0.31 (0.83)	0.31 (1.00)	0.14 (0.37)	1.15 (3.16)	1.02 (3.16)
F3	1.23 (3.55)	2.12 (5.77)	0.89 (2.76)	0.72 (1.96)	2.14 (5.76)	1.42 (4.58)	SUE5	1.06 (2.52)	1.94 (5.58)	0.92 (2.6)	0.59 (1.54)	1.93 (5.60)	1.34 (4.38)
F3-F1	1.24 (4.95)	1.51 (5.02)		0.95 (4.13)	1.15 (4.85)		SUE5-SUE1	1.04 (4.08)	1.66 (7.76)		0.45 (2.85)	0.77 (4.88)	
FA+TA	2.13 (6.04)			2.37 (6.73)			FA+TA	1.96 (6.73)			1.79 (6.28)		

Panel C: Earnings Announcement and ROE and TA Portfolios

Panel D: Earnings Announcement and BM and TA Portfolios

	Moving Average							Moving Average					
	EA			NON-EA				EA			NON-EA		
	MA1	MA2	MA2-MA1	MA1	MA2	MA2-MA1		MA1	MA2	MA2-MA1	MA1	MA2	MA2-MA1
ROE1	0.02 (0.05)	0.35 (0.79)	0.32 (1.03)	-0.25 (-0.57)	0.60 (1.50)	0.85 (3.58)	BM1	0.28 (0.76)	1.09 (3.42)	0.81 (3.77)	0.05 (0.14)	0.77 (2.33)	0.71 (3.88)
ROE5	0.90 (2.71)	1.89 (6.22)	0.98 (4.58)	0.95 (3.06)	1.59 (5.26)	0.64 (4.07)	BM5	0.76 (2.22)	1.32 (4.81)	0.57 (2.97)	0.83 (2.68)	1.32 (4.67)	0.49 (3.30)
ROE5-ROE1	0.92 (3.03)	1.54 (5.80)		1.19 (4.76)	0.99 (4.17)		BM5-BM1	0.48 (1.72)	0.24 (0.91)		0.78 (3.10)	0.56 (2.48)	
FA+TA	1.86 (5.73)			1.84 (6.44)			FA+TA	1.04 (3.96)			1.27 (4.79)		
	Bollinger Bands							Bollinger Bands					
	EA			NON-EA				EA			NON-EA		
	B1	B3	B3-B1	B1	B3	B3-B1		B1	B3	B3-B1	B1	B3	B3-B1
ROE1	-0.10 (-0.21)	0.20 (0.46)	0.28 (0.88)	-0.24 (-0.55)	0.90 (2.13)	1.13 (4.44)	BM1	0.45 (1.09)	1.27 (3.58)	0.83 (2.73)	-0.12 (-0.34)	1.44 (4.02)	1.56 (7.07)
ROE5	1.57 (4.48)	1.83 (5.18)	0.26 (0.78)	0.98 (3.18)	2.34 (7.06)	1.37 (6.09)	BM5	1.07 (3.34)	0.98 (3.15)	-0.09 (-0.34)	0.60 (1.95)	2.03 (6.36)	1.43 (8.33)
ROE5-ROE1	1.67 (5.26)	1.64 (4.33)		1.27 (4.40)	1.45 (5.16)		BM5-BM1	0.58 (1.94)	-0.29 (-0.90)		0.72 (2.53)	0.60 (2.24)	
FA+TA	1.92 (4.66)			2.58 (7.97)			FA+TA	0.54 (1.44)			2.15 (6.72)		
	Momentum							Momentum					
	EA			NON-EA				EA			NON-EA		
	M1	M5	M5-M1	M1	M5	M5-M1		M1	M5	M5-M1	M1	M5	M5-M1
ROE1	-0.32 (-0.70)	0.66 (1.20)	0.96 (2.36)	-0.38 (-0.77)	0.92 (1.88)	1.30 (3.48)	BM1	0.43 (1.02)	1.04 (2.39)	0.61 (1.74)	-0.32 (-0.75)	1.23 (3.03)	1.55 (5.50)
ROE5	1.38 (3.48)	1.85 (4.75)	0.49 (1.65)	0.67 (1.67)	2.00 (5.31)	1.33 (4.35)	BM5	0.44 (1.07)	1.22 (3.58)	0.78 (2.32)	0.51 (1.24)	1.77 (4.86)	1.26 (4.13)
ROE5-ROE1	1.70 (5.35)	1.19 (3.28)		1.04 (3.65)	1.08 (4.11)		BM5-BM1	-0.02 (-0.04)	0.18 (0.61)		0.82 (2.87)	0.54 (1.82)	
FA+TA	2.17 (7.20)			2.37 (7.02)			FA+TA	0.79 (2.28)			2.08 (6.53)		

Table 5: Adjustments for Transaction Costs and Performance Evaluation Metrics

This table reports the transaction cost and portfolio performance metrics on simple and joint strategies. Portfolio performance metrics include mean return, standard deviation, skewness, kurtosis, and Sharpe ratio. The transaction cost metrics include: portfolio turnover, half effective spread (defined as the absolute value of the difference between the transaction price and the bid-ask midpoint scaled by mid-quote), and total transaction cost (defined as the sum of products of half effective spread and portfolio turnover ratio from both the long and short legs of a portfolio). Net return is the average monthly return after adjustment for total transaction cost. The technical variables include moving average (MA), Bollinger Bands (BOLL), and momentum (MOM). The fundamental variables are FSCORE, the standardized unexpected earnings (SUE), return on equity (ROE), and book-to-market (BM). Results for both single- and double-sorted portfolios are included. We report spread and turnover statistics for both the long and short legs of a given portfolio. Our sample includes all common stocks from NYSE, AMEX and NASDAQ. Stocks with prices less than \$5 at the end of portfolio formation periods are excluded. The sample period is from January 1985 to December 2016.

Strategies	Spread (Long)	Spread (Short)	Turnover (Long)	Turnover (Short)	Transaction Cost	Raw Return	Standard deviation	Skewness	Kurtosis	Sharpe ratio	Net Return
FSCORE	0.68	0.75	27.26	29.49	0.41	1.14	2.62	0.62	5.61	0.44	0.73
SUE	0.60	0.72	20.48	22.59	0.29	1.08	1.79	-0.97	5.54	0.60	0.79
ROE	0.61	0.86	16.67	20.64	0.28	1.30	3.95	-1.11	12.65	0.33	1.02
BM	0.80	0.61	6.00	5.59	0.08	0.48	3.63	0.77	5.18	0.13	0.40
MA	0.63	0.77	19.99	26.72	0.33	0.79	9.62	-1.46	25.92	0.08	0.46
BOLL	0.91	0.76	77.14	72.62	1.25	0.98	2.85	1.28	6.22	0.34	-0.27
MOM	0.64	0.88	24.65	27.21	0.40	1.23	4.90	-0.24	8.73	0.25	0.83
FSCORE + MA	0.76	0.65	49.28	45.41	0.67	1.70	3.76	0.18	3.90	0.45	1.03
FSCORE + BOLL	0.83	0.77	84.40	81.72	1.33	2.23	4.43	0.42	4.90	0.50	0.90
FSCORE + MOM	0.61	0.87	41.71	44.05	0.64	2.26	5.84	-1.00	6.93	0.39	1.62
SUE + MA	0.65	0.62	46.81	41.66	0.56	1.48	3.20	-0.16	5.67	0.46	0.92
SUE + BOLL	0.71	0.76	84.85	80.74	1.22	2.40	3.37	0.97	3.41	0.71	1.18
SUE + MOM	0.59	0.87	34.93	36.33	0.52	1.83	4.99	-0.52	5.97	0.37	1.31
ROE + MA	0.64	0.74	40.74	38.41	0.54	1.89	4.49	-0.05	4.18	0.42	1.35
ROE + BOLL	0.71	0.90	82.49	80.53	1.31	2.33	5.19	0.34	5.92	0.45	1.02
ROE + MOM	0.59	0.97	29.78	36.24	0.53	2.19	5.62	-0.94	5.65	0.39	1.66
BM + MA	0.74	0.72	22.55	28.35	0.37	1.12	4.48	0.67	5.33	0.25	0.75
BM + BOLL	1.00	0.62	71.51	71.14	1.16	1.64	4.09	0.59	2.95	0.40	0.48
BM + MOM	0.78	0.78	27.74	27.78	0.43	1.61	5.35	-0.37	4.53	0.30	1.18

Table 6: The Effect of Idiosyncratic Volatility

This table presents the average monthly equal-weighted returns of portfolios double sorted on fundamental and technical variables across two subsamples. High IVOL (low IVOL) refers to the subsample where the idiosyncratic risk of a firm is in the top (bottom) tercile of the sample. The technical variables include moving average (MA) and Bollinger Bands (BOLL), and momentum. The fundamental variables are FSCORE, the standardized unexpected earnings (SUE), return on equity (ROE), and book-to-market (BM). MA1 refers to the portfolio consisting of stocks with $MA(20) < MA(125)$ at the end of formation month; MA2 refers to the portfolio consisting of stocks with $MA(20) > MA(125)$; B1 refers to the portfolio consisting of stocks with prices above the upper Bollinger band; and B3 refers to the portfolio consisting of stocks with prices below the lower band. M1 (M5) refers to the bottom (top) quintile momentum portfolio. FA + TA refers to the joint portfolio when we long (short) stocks that have buy (sell) signals from both technical and fundamental indicators. The holding period is 1 month. Our sample includes all common stocks from NYSE, AMEX and NASDAQ. Stocks with prices less than \$5 at the end of portfolio formation periods are excluded. The sample period is from January 1985 to December 2016. Newey and West (1987) adjusted t -statistics are reported in parentheses.

Panel A: Idiosyncratic Volatility and FSCORE and TA Portfolios

Panel B: Idiosyncratic Volatility and SUE and TA Portfolios

	Moving Average							Moving Average					
	High IVOL			Low IVOL				High IVOL			Low IVOL		
	MA1	MA2	MA2-MA1	MA1	MA2	MA2-MA1		MA1	MA2	MA2-MA1	MA1	MA2	MA2-MA1
F1	-0.77 (-1.78)	0.52 (1.10)	1.29 (4.82)	0.77 (2.59)	0.92 (3.94)	0.15 (0.89)	SUE1	-0.35 (-0.98)	0.17 (0.48)	0.52 (2.35)	0.87 (3.55)	0.77 (3.53)	-0.10 (-0.90)
F3	0.82 (2.35)	2.02 (95.72)	1.21 (5.99)	1.43 (5.97)	1.27 (5.62)	-0.16 (-1.48)	SUE5	0.66 (1.82)	2.11 (5.96)	1.44 (6.56)	1.45 (5.58)	1.42 (6.53)	-0.02 (-0.20)
F3-F1	1.50 (6.24)	1.59 (7.02)		0.66 (4.53)	0.35 (3.64)		SUE5-SUE1	1.01 (7.31)	1.93 (11.54)		0.57 (4.73)	0.65 (8.16)	
FA+TA	2.80 (10.21)			0.50 (2.95)			FA+TA	2.45 (11.61)			0.55 (4.44)		
	Bollinger Bands							Bollinger Bands					
	High IVOL			Low IVOL				High IVOL			Low IVOL		
	B1	B3	B3-B1	B1	B3	B3-B1		B1	B3	B3-B1	B1	B3	B3-B1
F1	-0.73 (-1.43)	0.50 (1.06)	1.30 (3.58)	0.79 (3.38)	1.19 (3.73)	0.35 (1.34)	SUE1	-0.90 (-2.32)	1.00 (2.54)	1.89 (7.28)	0.55 (2.50)	0.77 (4.17)	-0.10 (3.41)
F3	1.06 (2.85)	2.58 (5.74)	1.52 (4.77)	1.05 (4.81)	1.81 (7.58)	0.76 (5.35)	SUE5	0.99 (2.62)	2.42 (6.14)	1.43 (5.17)	1.17 (5.71)	1.99 (8.13)	0.83 (5.79)
F3-F1	1.79 (5.92)	2.04 (5.98)		0.26 (1.21)	0.65 (3.16)		SUE5-SUE1	1.89 (9.37)	1.43 (6.61)		0.61 (4.70)	0.87 (6.29)	
FA+TA	3.31 (8.02)			1.01 (4.96)			FA+TA	3.32 (11.47)			1.44 (9.81)		
	Momentum							Momentum					
	High IVOL			Low IVOL				High IVOL			Low IVOL		
	M1	M5	M5-M1	M1	M5	M5-M1		M1	M5	M5-M1	M1	M5	M5-M1
F1	-0.63 (-1.3)	0.67 (1.39)	1.30 (3.59)	0.61 (1.35)	1.22 (3.91)	0.61 (1.59)	SUE1	-0.36 (-0.92)	0.62 (1.39)	0.97 (2.87)	0.59 (1.81)	1.21 (4.79)	0.62 (2.27)
F3	0.79 (2.11)	2.46 (5.70)	1.66 (4.71)	0.91 (2.78)	1.66 (5.95)	0.75 (2.61)	SUE5	0.43 (1.01)	2.15 (4.96)	1.72 (4.63)	1.06 (2.86)	1.77 (7.14)	0.69 (2.58)
F3-F1	1.43 (4.85)	1.78 (6.55)		0.30 (0.87)	0.44 (2.13)		SUE5-SUE1	0.79 (4.03)	1.54 (7.30)		0.49 (2.04)	0.56 (3.63)	
FA+TA	3.09 (7.70)			1.05 (2.89)			FA+TA	2.51 (7.63)			1.18 (4.83)		

Panel C: Idiosyncratic Volatility and ROE and TA Portfolios

Panel D: Idiosyncratic Volatility and BM and TA Portfolios

	Moving Average							Moving Average					
	High IVOL			Low IVOL				High IVOL			Low IVOL		
	MA1	MA2	MA2-MA1	MA1	MA2	MA2-MA1		MA1	MA2	MA2-MA1	MA1	MA2	MA2-MA1
ROE1	-0.74	0.35	1.10	0.58	0.76	0.18	BM1	-0.23	0.80	1.03	0.69	1.02	0.33
	(-1.59)	(0.74)	(4.51)	(1.68)	(2.94)	(0.90)		(-0.52)	(1.94)	(4.95)	(2.73)	(4.62)	(2.15)
ROE5	0.66	2.19	1.54	1.22	1.35	0.13	BM5	0.16	1.53	1.36	1.24	1.14	-0.10
	(1.68)	(5.88)	(7.31)	(4.85)	(5.80)	(1.18)		(0.43)	(4.50)	(6.15)	(4.88)	(5.33)	(-0.88)
ROE5-ROE1	1.39	1.81		0.64	0.59		BM5-BM1	0.39	0.73		0.54	0.12	
	(5.33)	(6.82)		(3.01)	(3.99)			(1.29)	(2.54)		(3.41)	(0.80)	
FA+TA	2.93			0.77			FA+TA	1.75			0.44		
	(9.90)			(3.48)				(6.15)			(2.73)		
	Bollinger Bands							Bollinger Bands					
	High IVOL			Low IVOL				High IVOL			Low IVOL		
	B1	B3	B3-B1	B1	B3	B3-B1		B1	B3	B3-B1	B1	B3	B3-B1
ROE1	-0.81	0.60	1.41	0.70	0.75	0.05	BM1	-0.41	1.17	1.57	0.55	1.21	0.66
	(-1.57)	(1.26)	(4.02)	(2.88)	(2.21)	(0.20)		(-0.86)	(2.63)	(5.11)	(2.26)	(4.71)	(3.17)
ROE5	1.34	2.14	0.81	1.14	1.96	0.83	BM5	0.47	1.82	1.35	1.09	1.41	0.32
	(3.29)	(5.05)	(2.27)	(5.40)	(6.96)	(4.32)		(1.20)	(4.44)	(4.70)	(5.05)	(6.39)	(2.21)
ROE5-ROE1	2.20	1.55		0.44	1.22		BM5-BM1	0.87	0.65		0.54	0.20	
	(7.57)	(4.12)		(2.06)	(5.26)			(2.27)	(1.70)		(2.92)	(1.34)	
FA+TA	2.96			1.27			FA+TA	2.22			0.86		
	(7.15)			(5.12)				(4.84)			(4.07)		
	Momentum							Momentum					
	High IVOL			Low IVOL				High IVOL			Low IVOL		
	M1	M5	M5-M1	M1	M5	M5-M1		M1	M5	M5-M1	M1	M5	M5-M1
ROE1	-0.68	0.53	1.21	0.28	1.13	0.85	BM1	-0.46	1.01	1.47	0.44	1.47	1.03
	(-1.35)	(0.99)	(3.09)	(0.66)	(2.76)	(2.09)		(-1.04)	(2.14)	(4.94)	(1.14)	(4.23)	(2.52)
ROE5	0.74	2.08	1.34	0.84	1.83	1.01	BM5	0.05	1.75	1.70	0.85	1.48	0.63
	(1.75)	(4.69)	(4.11)	(2.39)	(6.39)	(3.66)		(0.10)	(4.36)	(4.49)	(2.13)	(5.59)	(2.04)
ROE5-ROE1	1.42	1.55		0.57	0.70		BM5-BM1	0.51	0.74		0.42	0.01	
	(4.26)	(4.91)		(1.67)	(2.08)			(1.35)	(2.63)		(1.37)	(0.03)	
FA+TA	2.76			1.55			FA+TA	2.21			1.04		
	(7.44)			(4.28)				(6.77)			(3.36)		

Table 7: The Effect of Informed Trading

This table presents the monthly performance statistics of portfolios doubly sorted on fundamental and technical variables across two subsamples categorized by probability of informed trading (PIN). The portfolio returns are equal-weighted. The PIN data are computed using the methodology of Brown and Hillegeist (2007). The fundamental variables are FSCORE, the standardized unexpected earnings (SUE), return on equity (ROE), and book-to-market (BM). The technical variables include moving average (MA), Bollinger band (BOLL), and momentum (MOM). The holding period is 1 month. Our sample includes all common stocks from NYSE, AMEX and NASDAQ. Stocks with prices less than \$5 at the end of portfolio formation periods are excluded. The sample period is from 1993 to 2010. Newey and West (1987) adjusted t -statistics are reported in parentheses.

Panel A: Informed Trading and FSCORE and TA Portfolios							Panel B: Informed Trading and SUE and TA Portfolios						
Moving Average							Moving Average						
	Low PIN			High PIN				Low PIN			High PIN		
	MA1	MA2	MA2-MA1	MA1	MA2	MA2-MA1		MA1	MA2	MA2-MA1	MA1	MA2	MA2-MA1
F1	0.20 (0.32)	0.88 (1.54)	0.69 (1.75)	-0.54 (-1.06)	0.34 (0.71)	0.88 (3.08)	SUE1	0.65 (1.30)	0.93 (2.09)	0.28 (0.83)	-0.07 (-0.18)	0.40 (1.14)	0.47 (2.53)
F3	1.09 (2.43)	1.61 (4.09)	0.52 (1.89)	1.13 (2.80)	1.67 (4.06)	0.54 (2.88)	SUE5	0.86 (1.90)	1.59 (3.95)	0.73 (2.47)	1.24 (3.23)	1.85 (5.28)	0.61 (3.76)
F3-F1	0.89 (2.82)	0.73 (2.30)		1.67 (7.04)	1.33 (6.71)		SUE5-SUE1	0.21 (1.12)	0.66 (4.18)		1.31 (8.91)	1.45 (11.21)	
FA+TA	1.41 (3.61)			2.21 (8.25)			FA+TA	0.94 (2.76)			1.92 (9.73)		
Bollinger Bands							Bollinger Bands						
	Low PIN			High PIN				Low PIN			High PIN		
	B1	B3	B3-B1	B1	B3	B3-B1		B1	B3	B3-B1	B1	B3	B3-B1
F1	0.28 (0.49)	1.39 (2.34)	1.12 (2.67)	-0.69 (-1.26)	0.63 (1.15)	1.32 (3.58)	SUE1	0.16 (0.36)	1.40 (2.72)	1.25 (3.84)	-0.75 (-1.82)	1.08 (2.74)	1.83 (9.00)
F3	0.98 (2.4)	2.04 (4.44)	1.05 (4.14)	1.13 (2.92)	2.14 (4.67)	1.02 (4.11)	SUE5	1.11 (2.71)	1.92 (4.17)	0.81 (2.66)	1.26 (3.7)	2.66 (7.37)	1.39 (6.57)
F3-F1	0.71 (1.94)	0.64 (1.83)		1.82 (5.82)	1.51 (4.93)		SUE5-SUE1	0.95 (4.4)	0.52 (2.03)		2.01 (12.37)	1.58 (7.17)	
FA+TA	1.76 (4.21)			2.83 (7.74)			FA+TA	1.76 (6.29)			3.40 (12.67)		
Momentum							Momentum						
	Low PIN			High PIN				Low PIN			High PIN		
	M1	M5	M5-M1	M1	M5	M5-M1		M1	M5	M5-M1	M1	M5	M5-M1
F1	0.41 (0.55)	1.09 (1.64)	0.69 (1.23)	-0.37 (-0.60)	0.18 (0.30)	0.54 (1.04)	SUE1	0.61 (1.02)	0.98 (1.68)	0.37 (0.68)	-0.12 (-0.25)	0.56 (1.19)	0.68 (1.65)
F3	1.14 (2.18)	2.14 (3.80)	1.00 (2.01)	1.02 (1.97)	2.04 (4.47)	1.02 (2.47)	SUE5	0.82 (1.36)	1.78 (3.25)	0.96 (1.83)	0.99 (1.87)	2.04 (4.72)	1.05 (2.57)
F3-F1	0.73 (1.61)	1.05 (2.92)		1.38 (5.02)	1.86 (6.16)		SUE5-SUE1	0.21 (0.72)	0.79 (3.94)		1.10 (4.56)	1.47 (5.72)	
FA+TA	1.74 (3.18)			2.41 (5.22)			FA+TA	1.16 (2.27)			2.16 (6.51)		

Panel C: Informed Trading and ROE and TA Portfolios							Panel D: Informed Trading and BM and TA Portfolios						
Moving Average							Moving Average						
	Low PIN			High PIN				Low PIN			High PIN		
	MA1	MA2	MA2-MA1	MA1	MA2	MA2-MA1		MA1	MA2	MA2-MA1	MA1	MA2	MA2-MA1
ROE1	0.11 (0.15)	0.98 (1.34)	0.87 (1.75)	-0.44 (-0.77)	0.36 (0.73)	0.80 (3.29)	BM1	0.45 (0.79)	0.88 (1.85)	0.44 (1.41)	-0.32 (-0.62)	0.62 (1.43)	0.94 (3.78)
ROE5	0.84 (1.86)	1.30 (3.25)	0.46 (1.75)	1.01 (2.38)	1.86 (4.39)	0.85 (4.29)	BM5	1.13 (2.29)	1.65 (3.88)	0.53 (1.61)	0.75 (1.76)	1.44 (4.09)	0.69 (3.96)
ROE5-ROE1	0.72 (1.54)	0.32 (0.70)		1.45 (4.50)	1.50 (5.55)		BM5-BM1	0.68 (1.76)	0.77 (2.37)		1.07 (3.18)	0.82 (3.17)	
FA+TA	1.19 (2.29)			2.30 (7.20)			FA+TA	1.20 (2.88)			1.76 (5.21)		
Bollinger Bands							Bollinger Bands						
	Low PIN			High PIN				Low PIN			High PIN		
	B1	B3	B3-B1	B1	B3	B3-B1		B1	B3	B3-B1	B1	B3	B3-B1
ROE1	0.09 (0.11)	0.67 (0.91)	0.58 (1.17)	-0.59 (-1.02)	0.61 (1.14)	1.19 (3.79)	BM1	0.07 (0.14)	1.62 (2.95)	1.55 (4.83)	-0.47 (-0.97)	1.16 (2.44)	1.63 (5.76)
ROE5	0.71 (1.67)	1.64 (3.49)	0.93 (2.88)	1.25 (3.12)	2.66 (6.07)	1.41 (5.32)	BM5	1.26 (2.87)	1.57 (3.43)	0.31 (1.15)	0.64 (1.51)	1.93 (5.03)	1.29 (5.61)
ROE5-ROE1	0.62 (1.34)	0.97 (1.90)		1.84 (5.75)	2.06 (6.26)		BM5-BM1	1.18 (3.31)	-0.05 (-0.13)		1.11 (3.04)	0.77 (2.35)	
FA+TA	1.56 (2.63)			3.25 (8.25)			FA+TA	1.49 (3.40)			2.40 (6.54)		
Momentum							Momentum						
	Low PIN			High PIN				Low PIN			High PIN		
	M1	M5	M5-M1	M1	M5	M5-M1		M1	M5	M5-M1	M1	M5	M5-M1
ROE1	-0.01 (-0.01)	1.05 (1.23)	1.06 (1.64)	-0.32 (-0.50)	0.27 (0.46)	0.59 (1.29)	BM1	0.38 (0.58)	1.11 (1.76)	0.73 (1.63)	-0.43 (-0.80)	0.94 (1.69)	1.37 (3.14)
ROE5	0.75 (1.36)	1.55 (2.8)	0.80 (1.58)	1.00 (2.02)	1.87 (3.93)	0.87 (2.45)	BM5	0.77 (1.23)	1.67 (2.89)	0.90 (1.53)	0.52 (1.06)	1.47 (3.12)	0.95 (2.43)
ROE5-ROE1	0.76 (1.43)	0.50 (1.08)		1.32 (3.50)	1.60 (4.92)		BM5-BM1	0.38 (1.07)	0.56 (1.97)		0.95 (3.57)	0.53 (1.55)	
FA+TA	1.55 (2.77)			2.19 (5.06)			FA+TA	1.29 (2.64)			1.90 (4.80)		

Table 8: Robustness Tests: A Subsample of Large Stocks

This table reports the transaction-cost-adjusted returns and portfolio performance metrics for simple and joint strategies among large stocks whose firm size is above the median value of all sample stocks. The portfolio returns are equal-weighted. Portfolio performance metrics include mean return, standard deviation, skewness, kurtosis, and Sharpe ratio. The transaction cost metrics include: portfolio turnover, half effective spread (defined as the absolute value of the difference between the transaction price and the bid-ask midpoint scaled by transaction price), and total transaction cost (defined as the sum of products of half effective spread and portfolio turnover ratio from both the long and short legs of a portfolio). Net return is the average monthly return after adjustment for total transaction cost. Results for both single- and double-sorted portfolios are included. We report spread and turnover statistics for both the long and short legs of a given portfolio. Our sample includes all common stocks from NYSE, AMEX and NASDAQ. Stocks with prices less than \$5 at the end of portfolio formation periods are excluded. The sample period is from 1985 to 2016.

Strategies	Spread (Long)	Spread (Short)	Turnover (Long)	Turnover (Short)	Transaction Cost	Monthly Return	Standard deviation	Skewness	Kurtosis	Sharpe ratio	Net Return	Adjusted Sharpe Ratio
FSCORE	0.38	0.41	27.42	30.47	0.23	0.61	2.83	0.58	4.49	0.22	0.38	0.13
SUE	0.32	0.37	19.99	22.31	0.15	0.44	1.99	-1.01	10.65	0.22	0.29	0.15
ROE	0.37	0.44	16.52	20.26	0.15	0.74	4.13	-0.38	9.52	0.18	0.59	0.14
BM	0.37	0.36	5.53	5.77	0.04	0.30	4.16	0.61	7.04	0.07	0.26	0.06
MA	0.63	0.77	20.07	25.44	0.32	0.41	3.25	-0.01	9.69	0.13	0.09	0.03
BOLL	0.46	0.42	77.84	72.15	0.66	0.88	3.47	1.58	10.29	0.25	0.22	0.06
MOM	0.37	0.46	25.50	26.73	0.22	0.82	5.83	0.14	9.58	0.14	0.60	0.10
FSCORE + MA	0.36	0.44	38.28	46.72	0.34	0.81	4.57	0.06	3.25	0.18	0.47	0.10
FSCORE + BOLL	0.40	0.39	84.95	80.05	0.66	1.36	5.23	1.00	6.37	0.26	0.70	0.13
FSCORE + MOM	0.35	0.46	42.25	44.04	0.35	1.40	6.58	-0.62	4.62	0.21	1.05	0.16
SUE + MA	0.34	0.39	31.97	41.27	0.27	0.62	3.82	-0.29	6.43	0.16	0.35	0.09
SUE + BOLL	0.34	0.37	84.50	79.24	0.58	1.44	4.08	0.90	5.59	0.35	0.86	0.21
SUE + MOM	0.32	0.43	36.37	36.38	0.27	0.97	6.19	0.08	11.33	0.16	0.70	0.11
ROE + MA	0.39	0.47	29.64	39.57	0.30	0.96	5.37	0.07	4.28	0.18	0.66	0.12
ROE + BOLL	0.40	0.44	82.75	78.34	0.67	1.56	6.10	0.55	4.91	0.26	0.89	0.15
ROE + MOM	0.35	0.49	30.63	35.29	0.28	1.41	6.43	-0.60	3.26	0.22	1.13	0.18
BM + MA	0.39	0.34	33.20	23.13	0.21	0.72	5.07	0.64	5.44	0.14	0.51	0.10
BM + BOLL	0.40	0.36	68.54	71.42	0.53	1.18	4.85	0.72	6.93	0.24	0.65	0.13
BM + MOM	0.38	0.43	29.46	27.98	0.23	1.08	6.38	-0.31	3.77	0.17	0.85	0.13

Table 9: Robustness Tests: Informed Trading and Transaction Costs

This table reports the transaction cost adjusted returns for the joint strategies based on fundamental and technical information across two subsamples categorized by probability of informed trading (PIN). The PIN data are computed using the methodology of Brown and Hillegeist (2007). The fundamental variables are FSCORE, the standardized unexpected earnings (SUE), return on equity (ROE), and book-to-market (BM). The technical variables include Bollinger band (BOLL). We report bid-ask spread and turnover statistics for both the long and short legs of a given portfolio. The transaction cost metrics include: portfolio turnover, half effective spread (defined as the absolute value of the difference between the transaction price and the bid-ask midpoint scaled by mid-quote), and total transaction cost (defined as the sum of products of half effective spread and portfolio turnover ratio from both the long and short legs of a portfolio). Net return is the average monthly return after adjustment for total transaction cost. The holding period is 1 month. The portfolio returns are equal-weighted. Our sample includes all common stocks from NYSE, AMEX and NASDAQ. Stocks with prices less than \$5 at the end of portfolio formation periods are excluded. The sample period is from 1993 to 2010. Newey and West (1987) adjusted t-statistics are reported in parentheses.

Strategies	PIN	Spread (Long)	Spread (Short)	Turnover (Long)	Turnover (Short)	Transaction Cost	Raw Return	Net Return
FSCORE + BOLL	Low	0.37	0.42	85.00	83.65	0.67	1.76	1.09
	High	0.80	0.81	85.23	84.01	1.36	2.83	1.47
SUE + BOLL	Low	0.33	0.37	84.44	81.67	0.58	1.76	1.18
	High	0.77	0.83	86.16	82.39	1.35	3.40	2.05
ROE + BOLL	Low	0.34	0.48	82.46	82.21	0.67	1.56	0.89
	High	0.73	0.88	85.47	81.82	1.34	3.25	1.91
BM + BOLL	Low	0.44	0.35	74.53	73.84	0.58	1.49	0.91
	High	0.89	0.70	70.51	73.48	1.14	2.40	1.26

Table 10: Transaction Cost Mitigation

This table reports the raw returns for various joint strategies based on fundamental and technical information. Panel A and B reports the raw returns for the simple joint strategies with one- and two-month holding period, respectively. Panel C reports the raw returns for overlap stocks. Overlap stocks are defined as stocks that are covered simultaneously in prior two consecutive formation portfolios. The portfolio returns are equal-weighted. Our sample includes all common stocks from NYSE, AMEX and NASDAQ. Stocks with prices less than \$5 at the end of portfolio formation periods are excluded.

Strategies	Panel A		Panel B		Panel C	
	Rebalancing each month (1st month)		Rebalancing each month (2nd month)		Rebalancing each two-month (Overlap stocks)	
	Long leg	Short leg	Long leg	Short leg	Long leg	Short leg
FSCORE + MA	1.61	-0.08	1.56	0.12	1.72	-0.08
FSCORE + BOLL	2.20	-0.03	1.43	0.24	2.85	0.06
FSCORE + MOM	2.16	-0.10	1.90	0.11	2.18	-0.07
SUE + MA	1.74	0.27	1.57	0.40	1.77	0.21
SUE + BOLL	2.25	-0.15	1.29	0.48	2.24	-0.02
SUE + MOM	2.00	0.17	1.69	0.38	1.92	0.11
ROE + MA	1.69	-0.20	1.58	-0.02	1.74	-0.21
ROE + BOLL	2.11	-0.22	1.42	0.21	2.36	0.13
ROE + MOM	1.97	-0.22	1.70	0.04	1.86	-0.21
BM + MA	1.37	0.25	1.28	0.31	1.37	0.26
BM + BOLL	1.75	0.11	1.22	0.55	1.87	0.20
BM + MOM	1.63	0.01	1.59	0.16	1.57	0.12