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Can investors profit from security analyst recommendations?: New evidence on the value of consensus recommendations[☆]

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ABSTRACT

This paper revisits the question of whether investors can benefit from consensus recommendations of stock market analysts in US equity markets. To examine the profitability net of transactions cost, we calculate several measures of transactions costs based on effective tick spreads and others. We find that transactions cost becomes noticeably lower from 2001 and the strategy of purchasing 'strong buy' stocks and shorting 'strong sell' stocks yields the abnormal returns of 4.7–5.8% per year during the period of 2001–2016, even after accounting for transactions cost. We also find that 'strong buy (sell)' stocks are growth (value) firms and short-term winners (losers). We discuss our empirical results in the context of market efficiency.

1. Introduction

Can investors profit from security analyst recommendations? Since Womack (1996) has shown that analysts appear to have stock-picking abilities, there have several venues of research related to the value of analyst recommendation: (1) level versus change in recommendations, (2) bias of recommendations such as more optimistic recommendations, (3) after-transaction-cost performance, (4) international evidence, (5) different sample periods, and so on.[1] Among these factors, accounting for transactions cost is important because what investors and researchers care about are returns net of transactions cost. And, as Novy-Marx and Velikov (2016) emphasize, transactions cost always reduces strategy profitability, increasing data-snooping concerns. For US stock market, an influential study of Barber et al. (2001) shows that, after accounting for transactions cost, none of the strategies designed to take advantage of the consensus recommendations earns significant abnormal returns in US stock market during the period of 1985–1996. With all this in mind, by extending the sample period up to 2016 and considering a more realistic transactions cost, we find that the strategy of 'long the most recommended stocks and short the least recommended stocks' earns the annualized abnormal return of 4.7–5.8% during the period of 2001–2016.[2] Our result strongly suggests that, even with transactions cost, the *level* of analyst recommendations can be valuable.

To answer whether investors can benefit from consensus recommendations, we construct five portfolios (strong buy, buy, neutral, sell and strong sell) based on over 700,000 recommendations of 17,290 analysts from I/B/E/S database and form a zero-cost portfolio of 'long the most recommended stocks and short the least recommended stocks.' To measure the profitability net of trading costs, we

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[1] We briefly discuss the related literature and compare with our results in Section 3.2.

[2] We use the terms of transactions cost and trading cost interchangeably. And we use the terms of most (least) recommended stocks, strong buy (sell) stocks, stocks with the most (least) favorable consensus recommendations with the same meaning.

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calculate more realistic and precise trading costs based on Holden (2009) and Goyenko et al. (2009).[3] We obtain several empirical results that are not only different from the finding of Barber et al. (2001) but also interesting enough for future research venues. First, transactions cost has declined significantly from 2001 when decimal stock quotes started.[4] Second, the most recommended stocks earn positive alpha while the least recommended stocks earn negative alpha. Consequently, the strategy of purchasing 'strong buy' stocks and shorting 'strong sell' stocks earns the annualized abnormal return greater than four percent. This result still holds even after accounting for trading costs. We also find that the positive alpha of strong buy stocks is larger in absolute value and more statistically significant than the negative alpha of strong sell stocks. Third, in terms of firm characteristics, the most (least) recommended stocks behave like growth (value) firms and short-term winners (losers). In addition, the most recommended stocks are more sensitive to the market, compared to the least recommended stocks. And, small firms are more concentrated in the portfolio of most recommended stocks.

While our approach builds on Barber et al. (2001), ours are different in several aspects, at least. First, we apply a more realistic transactions cost. While Barber et al. (2001) use 1.31% of share value traded as a proxy of transactions cost for each trading, which do not vary across portfolios and over time, we calculate transactions cost based on Holden (2009) and Goyenko et al. (2009), which is a more precise measure of transactions cost. As existing literature shows that transactions costs are different with firm size and over time, addressing time-varying costs is important.[5] Second, we extend the sample period up to 2016. It is important because we have shown that transactions cost becomes noticeably lower from 2001. Third, even after accounting for transactions cost, our result strongly indicates that the portfolio strategy of using the *level* of consensus recommendations can be profitable.

The rest of the paper is structured as follows. Section 2 explains our data, key variables and portfolio construction. Section 3 applies factor pricing models and explains the empirical results. Section 4 summarizes our finding and discusses future research venues.

2. Data

2.1. Data

Our sample includes all the stocks listed in NYSE, AMEX, and Nasdaq from 1994 through 2016, for which at least one analyst has an outstanding recommendation. The analyst recommendations data is obtained from I/B/E/S database, which converts the original recommendations issued by analysts into 5-point numeric scale, ranging from 1 to 5 (1: strong buy, 2: buy, 3: hold, 4: sell, 5: strong sell).[6] During our sample period of January 1994–December 2016, there are 702,590 recommendations from 17,290 analysts of 1008 brokerage houses. The average number of firms each year is 4678. Our sample is quite comprehensive in that it covers 92.2% of firms in terms of market capitalization and 57.7% in terms of number of firms.[7] Appendix A.1 shows the number of firms and share of market capitalization covered in our sample for each year. We obtain daily stock prices from CRSP (Center for Research in Security Prices).

2.2. Calculating transactions costs and portfolio returns

In constructing portfolios, we assume daily portfolio rebalancing and an immediate end-of-day investor reaction to analyst consensus recommendation changes. As purchasing and selling stocks under these assumptions requires a great deal of trading, it is important to take into account transactions costs, such as the bid-ask spread and the market impact of trading. Barber et al. (2001) estimate the size-weighted average of round-trip transactions cost at 1.31% of share value traded and use it as a proxy of transactions cost for each trading. However, since transactions cost varies for each stock and over time, we calculate transactions cost based on Holden (2009) and Goyenko et al. (2009). Corwin and Schultz (2012) and Chen et al. (2018) show that the performance of this measure based on effective spread is superior to the alternatives particularly from the late 1990s, which coincide with most of the sample period of this paper. In addition, Goyenko et al. (2009) compare several measures of transactions cost and conclude that the performance of the effective tick spread measure is better than other alternatives, especially when one takes computational burden into consideration. To check the robustness of our result, we also calculate transactions cost based on Chung and Zhang (2014) and Fong et al. (2017) and find that the choice of transactions cost does not change our main result.[8] We briefly describe how to calculate

[3] We also calculate transaction costs based on Chung and Zhang (2014) and Fong et al. (2017) and confirm that our result is robust to the choice of transaction cost. We explain this result below.

[4] The US Securities and Exchange Commission ordered all stock markets in the U.S. to convert from fractional quotes of 1/16 to decimal quotes by April 9, 2001.

[5] Existing literature such as Keim and Madhavan (1998), Lesmond et al. (1999), Hasbrouck (2009), Holden (2009), Goyenko et al. (2009) shows that market capitalization is closely related to the cost. Hasbrouck (2009) and Corwin and Schultz (2012) also show that transactions cost varies over time.

[6] Ratings of 4 and 5 are also referred to as 'underperform' and 'sell', respectively

[7] Barber et al. (2001) use over 360,000 recommendations from 269 brokerage houses and 4340 analysts. They cover 90.1% of all listed firms in terms of market capitalization and 46.1% in terms of number of firms.

[8] Abdi and Ranaldo (2017) show that, during the period of 2003–2015, the measure of Chung and Zhang (2014) outperforms those based on Hasbrouck (2009), effective tick, and others. We also consider Fong et al. (2017) because it is based on the methodology of Lesmond et al. (1999) that has been widely used in the literature.

transactions costs of daily stock-level, daily portfolio-level, and monthly portfolio-level in Appendix B.[9]

In regard to constructing portfolios, following Barber et al. (2001), five portfolios are constructed based on the consensus recommendation ratings of the analysts. Consensus recommendation for stock i on date $\tau - 1$, denoted by $C_{i\tau-1}$, is defined as the average of the outstanding recommendations for stock i as of date $\tau - 1$:

$$C_{i\tau-1} = \frac{1}{N_{i\tau-1}} \sum_{j=1}^{N_{i\tau-1}} Rec_{ij\tau-1}, \tag{1}$$

where $Rec_{ij\tau-1}$ is the outstanding recommendation for stock i as of date $\tau - 1$ issued by analyst j, and $N_{i\tau-1}$ is the number of outstanding recommendations for stock i as of date $\tau - 1$. Any recommendations issued within 180 days from date $\tau - 1$ are considered as outstanding. If an analyst has issued more than 1 recommendation within 180 days, then only the most recent recommendation is regarded as outstanding.

Using these average ratings, each covered firm is placed into one of five portfolios as of the close of trading on date $\tau - 1$. The first portfolio consists of the most highly recommended stocks, those for which $1 \le C_{i\tau-1} \le 1.5$. We call this portfolio P1 (strong buy); the second is comprised of firms for which $1.5 < C_{i\tau-1} \le 2$; the third contains firms for which $2 < C_{i\tau-1} \le 2.5$; the fourth is comprised of firms for which $2.5 < C_{i\tau-1} \le 3$; and the fifth portfolio consists of the least favorably recommended stocks, those for which $3 < C_{i\tau-1} \le 5$. We call this P5 (strong sell). Others are called P2, P3, and P4, respectively. And a zero-cost portfolio of purchasing strong buy and shorting strong sell is denoted by (P1–P5). Then the daily value-weighted return for each portfolio is calculated and the monthly return is calculated based on the number of trading day. Net return is defined as gross return net of transactions cost. We explain how to calculate monthly returns from daily returns in Appendix B.

There are two issues that may affect our portfolio returns. One is how to treat recommendations after trading hours. If a recommendation is announced after trading hours, then we treat it as announced during the next trading day, which makes more sense. The other is delisting returns, pointed by Shumway (1997). Our methodology is safe from this issue for the following reasons. First, we obtain security return data from CRSP, which already handles delisting returns properly. Second, while CRSP states that the data does have some missing delisting returns, we confirm that we do not have any after merged with I/B/E/S recommendations dataset.

2.3. Summary statistics

Fig. 1 shows how two kinds of transactions costs have been changing over time for each portfolio, P1 through P5, and (P1–P5). Since Barber et al. (2001) use a fixed 1.31% of share value traded, fluctuations in transactions cost based on Barber et al. (2001) reflect only the changes in turnover. Note that transactions cost based on Holden (2009) has been lower from 2001 when decimal stock price quoting started. This result is also consistent with Hasbrouck (2009). Fig. 2 compares transactions costs of Barber et al. (2001), Chung and Zhang (2014), and Fong et al. (2017). Note that, while the one of Chung and Zhang (2014) is quite large before 2001, transaction costs based on Chung and Zhang (2014), and Fong et al. (2017) become noticeably lower from the early 2000s. During the period of January 2001–December 2016, the correlation coefficients of trading cost based on Holden (2009) with those of Chung and Zhang (2014) and Fong et al. (2017) are 0.78 and 0.90, respectively. Meanwhile the correlation coefficient with one of Barber et al. (2001) is only 0.39. For this reason, we proceed our discussion based on transaction cost of Holden (2009) below and report the results based on those of Chung and Zhang (2014) and Fong et al. (2017) in Appendix.

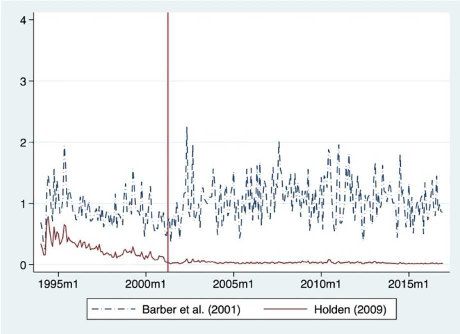
Fig. 3 shows the annualized average returns of five portfolios (P1 through P5) and market excess return. It clearly shows that P1 (strong buy) records the highest average return and P5 gives the lowest return, regardless of return type (gross and net) and sample periods. We perform t-tests to see if they are statistically different.[10] In statistical sense, the average net return of P1 is larger than those of P5 and market excess return during the period of January 1994–December 2016. In addition, the average market excess return is larger than that of P5. During the period of January 2001–December 2016, the average net return of P1 is larger than those of P5 and market excess return, but the average net return of P5 is not statistically different from market excess return. Thus, in terms of average net returns, P1 (strong buy) outperforms both P5 (strong sell) and market excess return in both sample periods. We obtain the same result for the case of gross returns.

If we compare the gross and net returns of two periods (panel (a) versus (b), and (c) versus (d) in Fig. 3), one can easily see that the role of transactions cost becomes less significant after 2001. In panel (a) and (b), the magnitudes of transactions cost ranges from 0.9% point (P2) to 1.5% point (P5). They are not negligible because the annualized return of P5 becomes negative from 0.5% to -1.0% after accounting for transactions cost. When we compare panel (c) and (d), the magnitude of trading cost becomes far smaller, ranging from 0.3% point to 0.4% point. For P1 portfolio, transactions cost takes only 2.8% (= (10.5 − 10.2)/10.5) of gross return. That is, if one earns 10% of gross return, net return is 9.72% .

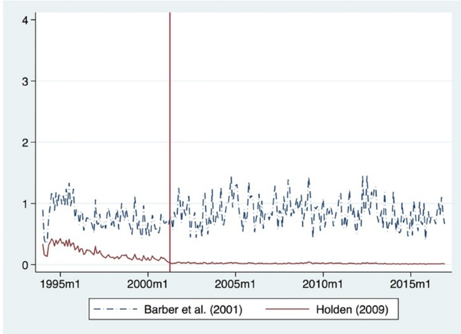
Table 1 reports the average monthly returns, standard deviations, and Sharpe ratios. For returns of P1, P5, and (P1–P5), we report net returns. During the period of January 1994–December 2016, the average monthly return of P1 (strong buy) is highest at 0.84% while P5 (strong sell) is the only portfolio that records the negative return of − 0.09% . The market excess return records 0.63% and

[9] In regard to various measures of transactions cost, see Corwin and Schultz (2012) and Chen et al. (2018). Corwin and Schultz (2012) provide a succinct explanation on various estimators of trading costs such as spread estimators derived from return covariances, transaction price tick size, frequency of zero returns, and others. Chen et al. (2018) calculate various measures of trading costs that reflect illiquidity in US equity markets and show that these measures predict stock market returns and real economic activity. Their measures are based on Roll (1984), Lesmond et al. (1999), Amihud (2002), Holden (2009), Goyenko et al. (2009), Corwin and Schultz (2012), Fong et al. (2017), and others.

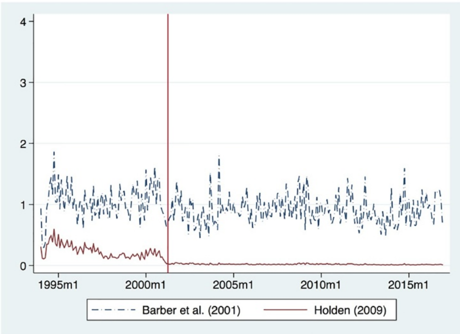
[10] Table C in Appendix C reports the results of t-test.



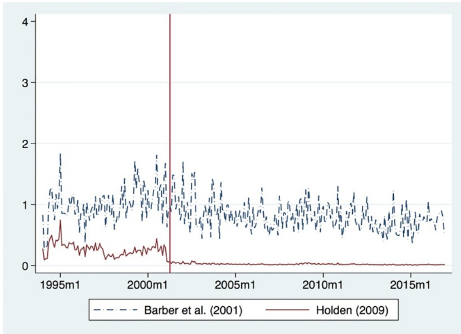
(a) P1 (strong buy)



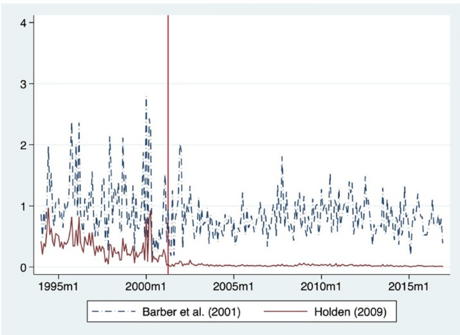
(b) P2



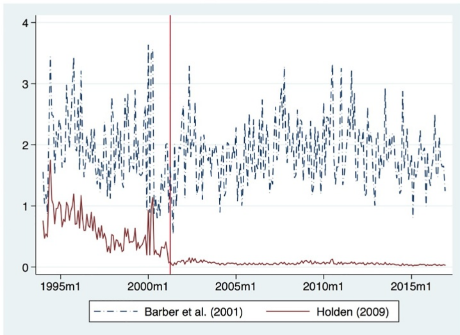
(c) P3



(d) P4



(e) P5 (strong sell)



(f) (P1-P5)

Fig. 1. Comparison of transactions costs: Barber et al. (2001) vs. Holden (2009) Panel (a)–(f) show the time series of two kinds of transactions cost. Barber et al. (2001) uses the fixed round-trip transactions cost of 1.31% of share value traded. Holden (2009), jointly with Goyenko et al. (2009), develops a proxy of transactions cost based on effective tick spreads.

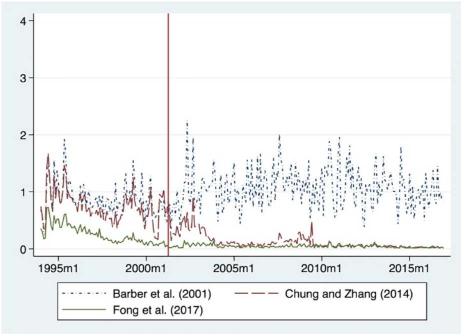
the zero-cost portfolio of (P1–P5) records the third-highest return of 0.47% . In terms of Sharpe ratio, P1 gives the highest Sharpe ratio of 0.17 and those of market excess return and (P1–P5) are 0.14. During the period after 2000, the Sharpe ratio of P1 is highest at 0.18 and that of (P1–P5) is 0.13.[11] Fig. 4 also shows the attractiveness of P1 and (P1–P5) portfolio in terms of cumulative returns. After 2003, P1 starts to outperform market excess return. (P1–P5) also starts to show positive cumulative return from 1999. In the following section, we examine if these portfolios can earn excess returns even after accounting for risk factors (or styles).

3. Empirical results and discussion

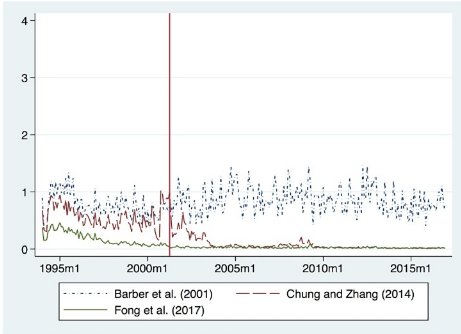
3.1. Main results

Based on Fama and French (1996), Carhart (1997), and Fama and French (2015), we consider four models: (1) CAPM, (2)

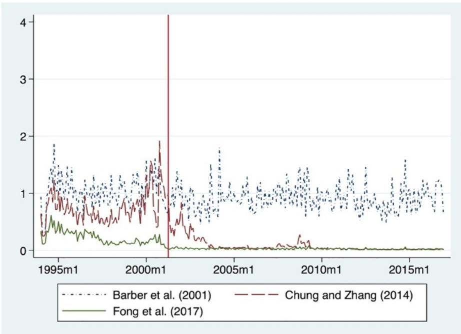
[11] Following Lo (2002) and Ledoit and Wolf (2008), we also test if Sharpe ratios are the same. Table C.2 in Appendix C reports the result. It says that P1 is attractive as much as market excess return portfolio in terms of Sharpe ratio.



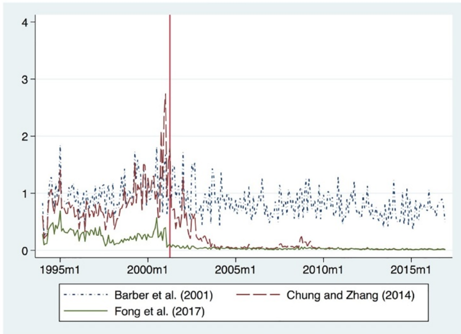
(a) P1 (strong buy)



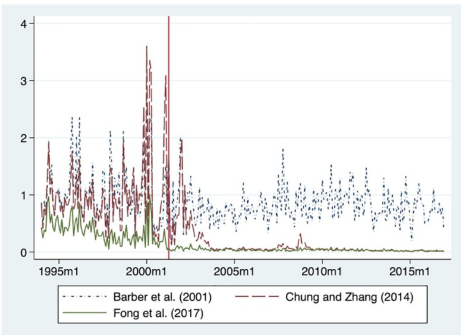
(b) P2



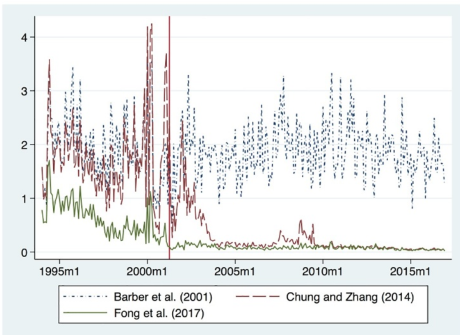
(c) P3



(d) P4



(e) P5 (strong sell)



(f) (P1-P5)

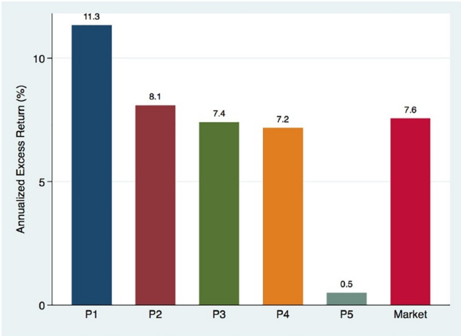
Fig. 2. Comparison of transactions costs: other measures Panel (a)–(f) compare three kinds of transactions costs: Barber et al. (2001), Chung and Zhang (2014), and Fong et al. (2017).

Fama–French three-factor model (FF3 model), (3) Fama–French three-factor model with momentum factor (four-factor model), and (4) Fama–French five-factor model (FF5 model). In the main text, we report the result of Fama–French three-factor model with momentum factor (four-factor model), as shown in Eq. (2):

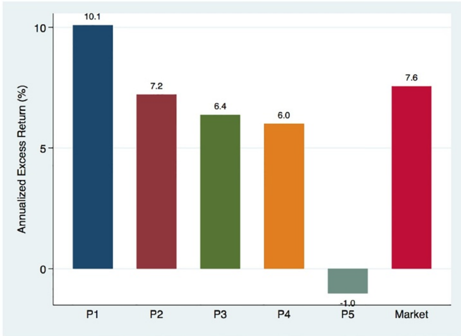
$$r_{it} - r_{ft} = \alpha_i + b_i(r_{Mt} - r_{ft}) + s_i SMB_t + h_i HML_t + m_i WML_t + e_{it}, \tag{2}$$

where r_{it} is the monthly return of portfolio formed on consensus recommendations, r_{ft} is the risk-free rate, and $(r_{Mt} - r_{ft})$ is the monthly value-weighted market return minus the risk-free rate. The terms SMB_t (small minus big), HML_t (high minus low), and WML_t (winner minus loser) are the monthly returns on zero-investment factor-mimicking portfolios designed to capture size, B/M, and momentum, respectively. If one interprets the above factors as "styles" and factor models as a method of performance attribution, a positive alpha (α) implies the abnormal return in excess of what could have been achieved by passive investments in those factors.

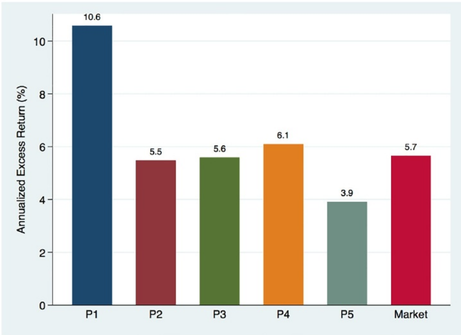
Table 2 shows the main results. While we run four kinds of pricing mode, we report only the result of four-factor model for brevity. It is because four-factor model gives the most conservative estimates of alpha, compared to other models. In addition, in



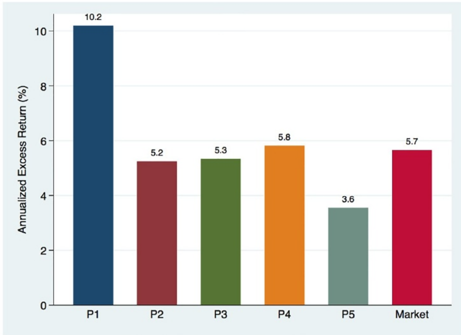
(a) gross returns, 1994m1–2016m12



(b) net returns, 1994m1–2016m12



(c) gross returns, 2001m1–2016m12



(d) net returns, 2001m1–2016m12

Fig. 3. Annualized portfolio returns Panel (a)–(d) show the annualized mean percentage returns earned by portfolios formed on the basis of consensus analyst recommendations for two types of return (gross and net) and two sample periods (January1994–December 2016 and January 2001–December 2016). P1 is a portfolio of 'strong buy' stocks and P5 is a portfolio of 'strong sell' stocks. 'Market' denotes the market excess return.

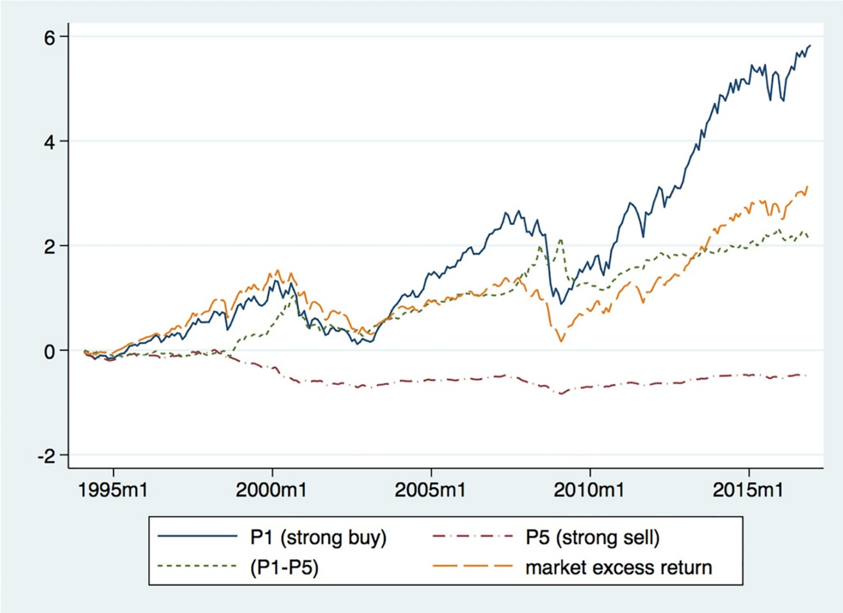
Table 1
Summary statistics This table shows the average monthly returns, standard deviations, and Sharpe ratios for two sample periods. Net returns are used for P1, P5, and (P1–P5),.

	P1	P5	(P1–P5)	mktrf	SMB	HML	RMW	CMA	WML
				January 1994–December 2016					
Average returns	0.84	−0.09	0.47	0.63	0.19	0.24	0.34	0.29	0.41
Standard deviations	5.01	4.90	3.32	4.37	3.18	3.11	2.90	2.13	5.09
Sharpe ratios	0.17	−0.02	0.14	0.14	0.06	0.08	0.12	0.13	0.08
				January 2001–December 2016					
Average returns	0.85	0.30	0.38	0.47	0.40	0.24	0.35	0.25	0.07
Standard deviations	4.79	5.14	2.98	4.38	2.61	2.79	2.36	1.90	5.32
Sharpe ratios	0.18	0.06	0.13	0.11	0.15	0.09	0.15	0.13	0.01

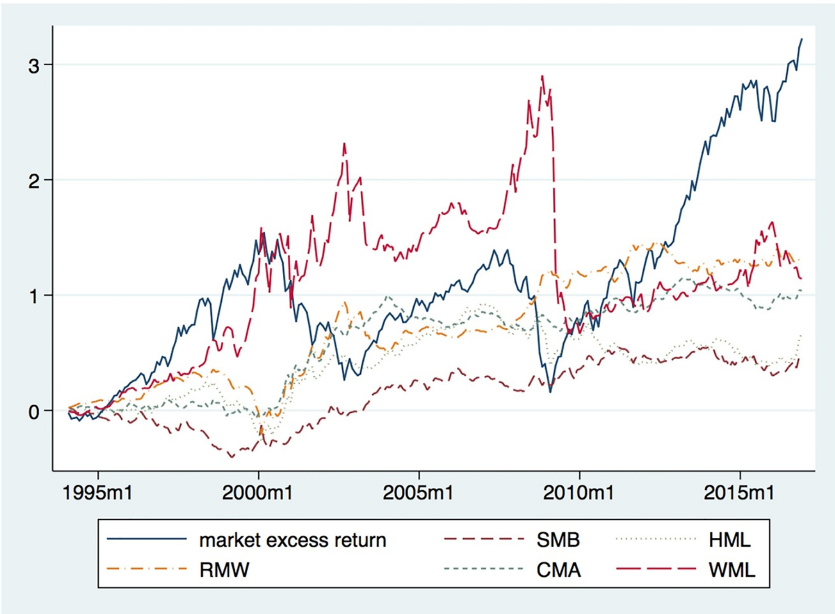
terms of R^2, four-factor model has more explanatory power.[12] Appendix Table D.1–D.4 show all other results. We report four results in panel (a)–(d) depending on return type (gross and net) and sample period (January 1994–December 2016 and January 2001–December 2016). Panel (a) shows that, in terms of gross return, P1 (strong buy) gives a positive alpha while P5 (strong sell) gives a negative alpha during the period of January 1994–December 2016. And, if one exploits a strategy of purchasing strong buy and shorting strong sell, one can earn the abnormal return of 0.626% , which amounts to the annualized return of 7.51% . However, once accounted for transactions cost, the returns become lower. Panel (b) shows that the alpha of P1, net of trading costs, becomes statistically insignificant. And the alpha of (P1–P5) portfolio becomes lower from 0.626% to 0.398% . A different result from panel (a) and (b) highlights the importance of considering transactions cost.

Panel (c) and (d) show the result during the period of January 2001–December 2016 when transactions cost becomes noticeably lower. For both gross and net returns, P1 outperforms and P5 underperforms. And the alphas of (P1–P5) are 0.457% and 0.395% for gross and net return, respectively. Recall that, when we consider the period before 2001, alpha of (P1–P5) becomes remarkably lower from 0.626% to 0.398% when accounting for transactions cost. Meanwhile, when we consider the period of low transactions cost

[12] While we report R^2 in the table, we also confirm this in terms of the adjusted R^2.



(a) P1, P5, (P1-P5), and market excess return



(b) Factor-mimicking portfolios

Fig. 4. Cumulative returns, January 1994–December 2016 Panel (a) shows the cumulative returns of P1, P5, (P1–P5), and market excess return. Panel (b) show the cumulative returns of factor-mimicking portfolios.

from 2001 onward, transactions cost takes only a small part of net returns, which is 0.062% point ($= 0.457 - 0.395$). In terms of the annualized abnormal return, our four-factor model in Table 2 earns 4.74% (= 0.395×12) and FF5 model in Appendix D.4 earns 5.84% (= 0.487×12) even after accounting for transactions cost. Appendix E reports the results of four-factor models when we use transaction costs of Chung and Zhang (2014) and Fong et al. (2017). The monthly abnormal returns (alpha) are estimated at 0.413 and 0.372, which are not much different from 0.395 in Table 2.

Table 2 reports another interesting result. When we examine the patterns of factor loadings, we find that portfolio P1 behaves like growth firms and short-term winners while P5 behaves like value firms and short-term losers. In panel (d), the factor loading for HML increases as we move from P1 to P5. For WML, it declines as we move from P1 to P5. Consequently, (P1–P5) behaves like growth

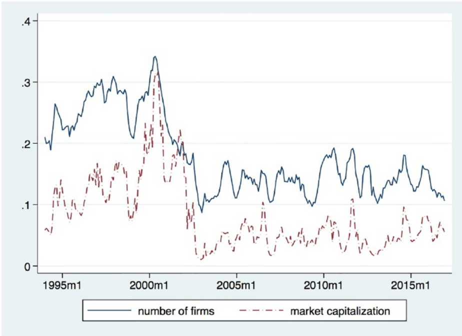
Table 2
Estimated alpha from four-factor model This table shows the results of applying four-factor model (Fama–French three factor with momentum factor) for two kinds of returns (gross and net) and two sample periods (January 1994–December 2016 and January 2001–December 2016). The numbers in parentheses are robust standard errors. *, **, and *** denote p-value < 0.10, p-value < 0.05, and p-value < 0.01, respectively.

	P1 (strong buy)	P2	P3	P4	P5 (strong sell)	(P1–P5)
	(a) gross return, 1994m1–2016m12					
mktrf	1.050***	1.043***	0.955***	0.914***	0.888***	0.161***
	(0.027)	(0.016)	(0.022)	(0.020)	(0.046)	(0.053)
SMB	0.193***	−0.050**	−0.119***	−0.024	0.263***	−0.066
	(0.035)	(0.019)	(0.036)	(0.027)	(0.086)	(0.086)
HML	−0.157***	−0.117***	0.071**	0.222***	0.283***	−0.445***
	(0.042)	(0.024)	(0.033)	(0.030)	(0.072)	(0.075)
WML	0.077***	0.081***	−0.038**	−0.156***	−0.148***	0.221***
	(0.023)	(0.016)	(0.019)	(0.025)	(0.040)	(0.049)
alpha	0.253***	0.021	0.037	0.038	−0.575***	0.626***
	(0.096)	(0.055)	(0.071)	(0.070)	(0.137)	(0.167)
R^2	0.906	0.97	0.935	0.941	0.802	0.365
			(b) net return, 1994m1–2016m12			
mktrf	1.047***	1.040***	0.952***	0.911***	0.885***	0.155***
	(0.027)	(0.016)	(0.022)	(0.020)	(0.047)	(0.052)
SMB	0.198***	-0.046**	-0.113***	-0.019	0.272***	-0.051
	(0.035)	(0.020)	(0.037)	(0.027)	(0.088)	(0.084)
HML	-0.157***	-0.117***	0.070**	0.221***	0.280***	-0.448***
	(0.042)	(0.024)	(0.033)	(0.030)	(0.073)	(0.074)
WML	0.076***	0.080***	-0.040**	-0.158***	-0.149***	0.219***
	(0.023)	(0.016)	(0.019)	(0.025)	(0.041)	(0.048)
alpha	0.150	-0.051	-0.048	-0.058	-0.700***	0.398**
	(0.096)	(0.055)	(0.071)	(0.069)	(0.141)	(0.165)
R^2	0.905	0.969	0.934	0.94	0.794	0.367
			(c) gross return, 2001m1–2016m12			
mktrf	1.048***	1.045***	1.028***	0.959***	0.934***	0.120**
	(0.035)	(0.019)	(0.018)	(0.026)	(0.034)	(0.048)
SMB	0.180***	−0.018	−0.037*	0.053	0.07	0.107
	(0.050)	(0.020)	(0.022)	(0.033)	(0.056)	(0.071)
HML	-0.150***	-0.158***	-0.062**	0.120***	0.395***	-0.548***
	(0.050)	(0.029)	(0.025)	(0.040)	(0.068)	(0.080)
WML	0.089***	0.100***	0.029**	-0.096***	-0.181***	0.271***
	(0.026)	(0.016)	(0.012)	(0.026)	(0.028)	(0.042)
alpha	0.347***	0.004	0.01	0.013	-0.225*	0.457***
	(0.110)	(0.059)	(0.055)	(0.070)	(0.119)	(0.166)
R^2	0.9	0.971	0.976	0.961	0.904	0.441
			(d) net return, 2001m1-2016m12			
mktrf	1.049***	1.045***	1.029***	0.961***	0.936***	0.122**
	(0.034)	(0.019)	(0.018)	(0.025)	(0.034)	(0.048)
SMB	0.180***	-0.019	-0.038*	0.051	0.068	0.105
	(0.050)	(0.020)	(0.022)	(0.033)	(0.056)	(0.071)
HML	-0.150***	-0.159***	-0.062**	0.121***	0.395***	-0.547***
	(0.050)	(0.029)	(0.025)	(0.040)	(0.067)	(0.081)
WML	0.090***	0.101***	0.029**	-0.094***	-0.180***	0.273***
	(0.025)	(0.016)	(0.012)	(0.025)	(0.029)	(0.041)
alpha	0.314***	-0.017	-0.012	-0.011	-0.255**	0.395**
	(0.110)	(0.059)	(0.055)	(0.070)	(0.119)	(0.166)
R^2	0.901	0.971	0.976	0.962	0.905	0.442

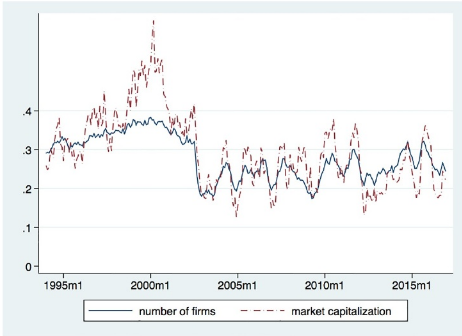
firms and short-term winners. In addition, the factor loading on market excess return (that is, beta) declines as we move from P1 to P5, suggesting that P1 moves more closely with the market itself.[13]

Another thing to note is that small firms are concentrated more in P1 (strong buy). Fig. 5 shows the relative share of firms in each portfolio in terms of number of firms and market capitalization. Panel (a) shows that, except the early 2000s, the relative number of firms in P1 is consistently higher than the relative share of market capitalization in P1. During the sample period, P1 takes 17.9% in terms of number of firms while it takes only 8.1% of market capitalization. Panel (e) shows that the relative share of P5 is relatively low both in terms of number and market capitalization. It reflects the conventional wisdom that analysts are reluctant to make strong sell recommendations. The monthly abnormal returns (alpha) are estimated at 0.413 and 0.372, which are not much different from 0.395 in Table 2.

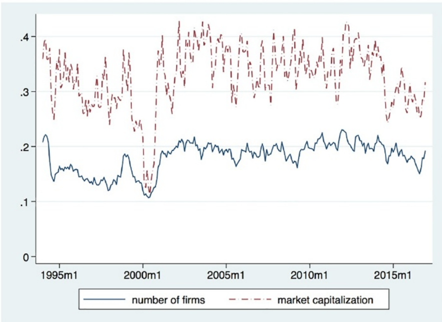
[13] Barber et al. (2001) also report that less favorable analyst ratings are associated with forms of lower market risk and high book-to-market ratios.



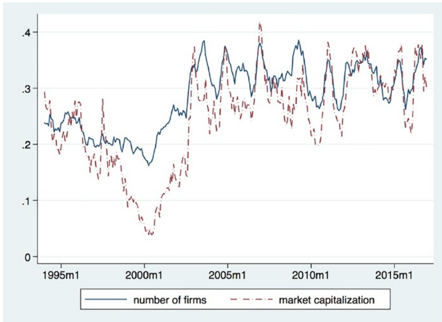
(a) P1 (strong buy)



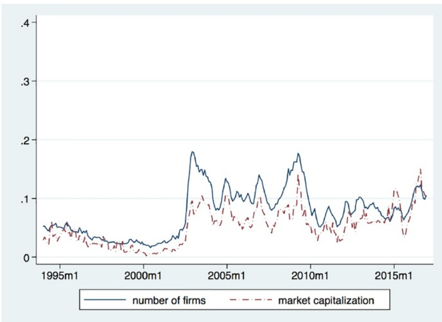
(b) P2



(c) P3



(d) P4



(e) P5 (strong sell)

Fig. 5. Relative shares in terms of number of firms and market capitalization This figure shows the time series of relative shares in terms of number of firms and market capitalization in each portfolio. The shares in each portfolio are calculated at the end of each month.

3.2. Discussion

In this section, we briefly review the related literature and highlight what differentiates our results from previous studies. There have been several venues of research related to the value of analyst recommendation: (1) level vs. change in recommendations, (2) bias of recommendations such as more optimistic recommendations, (3) after-transaction-cost performance, (4) international evidence, (5) different sample periods, and so on.

First, many studies find that consensus recommendations can add value. Jegadeesh and Kim (2006) find that, among G7 countries, US analysts are more skilled. Jegadeesh et al. (2004) find tha both the level and change in consensus recommendations add value, but the latter is a more robust return predictor. Balboa et al. (2009) also find that consensus changes are a valuable tool for making investment decisions between 1994 and 2006. However, many of this line of research do not consider trading cost.

Second, it is well known that analysts make more buy recommendations than sell recommendations. More specifically, Balboa et al. (2008) find that analysts issue a much higher number of buy opinions than sell opinions and sell recommendations seem to be a stronger signal than buy recommendations. Balboa et al. (2009) also show that profitable investment strategies exist when considering a global portfolio based on bias-adjusted recommendations.

Third, as Novy-Marx and Velikov (2016) emphasize, transactions cost is important for profitability. Examining the after-trading-cost performance of anomalies, they find that transaction costs always reduce strategy profitability, increasing data-snooping concerns. They also consider strategies of reducing costs and find that introducing buy/hold spread to make rebalancing more difficult than maintaining a portfolio is most effective. While Barber et al. (2001) show that it is not easy to make profits using consensus recommendations, they apply a fixed transactions cost.

Fourth, international evidence is somewhat mixed. While Jegadeesh and Kim (2006) show that stock prices react significantly to recommendation revisions in all G7 countries except Italy between 1993 and 2002, Azzi et al. (2006) report that, between 1994 and 2003, no evidence suggests that either their recommendations or changes in these recommendations provided any useful information to investors in European countries. However, these studies do not consider transactions cost.

Regarding sample periods, as discussed above, many studies find that transactions cost has signficiantly declined from the early 2000s. Barber et al. (2003) find excluding the year of 2000 and 2001 could have a significant impact on any conclusions they draw about analyst stock recommendations.[14] Strangely, there are not many studies that examine the value of analyst recommendations with a sample that extends to 2010s, starting from 2001 when decimal quotes began in US.

Given the importance of transactions cost and mixed empirical results, our study provides a novel empirical result on the value of consensus recommendations. There are several things that differentiates our study from previous studies: (1) we consider various measures of transactions cost, (2) our sample extends to 2016, covering 2001 when decimal stock quotes started, and (3) portfolio strategies using *levels* of recommendations can be profitable. There can be several research directions related to our result. First, it would be interesting if we would obtain the simliar result when forming portfolios based on *changes* in recommedations, not levels. Second, one can examine how much of additional return the cost-reducing strategy considered by Novy-Marx and Velikov (2016) would earn. Third, one can investigate if levels or changes in recommendations can be explained by firm-characteristic variables.

4. Conclusion

While Barber et al. (2001) show that their investment strategies based on consensus recommendations do not earn positive alpha to investors after a reasonable accounting for transactions costs, they also mention that “the strategies studied here, but applied to different time periods or different stock recommendation data, will be able to generate positive abnormal net returns.” By extending the sample period up to 2016 and considering a more precise transactions cost, we show that the strategy of ‘purchasing strong buy and shorting strong sell’ can earn the annualized abnormal return greater than four percent.

There are several potential explanations for our finding: (1) random chance (data snooping), (2) market inefficiency, and (3) incorrect multi-factor pricing models. In relation to (1), if our estimated abnormal returns are the result of mispricing, they should disappear out-of-sample as the sophisticated investors and traders learn about this mispricing and invest accordingly. Mclean and Pontiff (2016) study the out-of-sample and post-publication return predictability of 97 variables and find that portfolio returns are 26% lower out-of-sample and 58% lower post-publication. Their finding strongly suggests that investors are informed by academic publications. Since our result suggests that prices do not immediately incorporate the information related to analysts’ consensus stock recommendations, our finding is related to (2) as well. To examine the persistence of alpha that we find, it would be best to wait for more data to be accumulated over time. In relation to (3), it would be an interesting topic to examine how analysts pick stocks and why strong-buy (sell) firms are growth (value) firms and short-term winners (losers). Research on the relationship between analysts’ stock-picking and sentiments (or business cycles) such as Kaplanski and Levy (2017) would help answer these questions.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2018.11.008

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[14] We confirm the robustness of our finding by including and excluding these two years.

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