The Review of Asset Pricing Studies

A New Value Strategy

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Traditional value measures performed poorly over the past three decades. We reevaluate the value strategy using a new measure—the ratio of cash-based operating profitability to price (*COP/P*)—and find a zero-investment portfolio that buys the highest-*COP/P* stocks and shorts the lowest-*COP/P* stocks earns monthly returns of 0.78% on a value-weighted basis and 1.04% on an equal-weighted basis. The *COP/P* effect holds even for large-capitalization stocks and exists even in the post-1990 period, when book-to-market does not predict returns. The *COP/P* measure subsumes many widely used value measures and the conservative-minus-aggressive investment factor. (*JEL* G02, G12)

Received: June 18, 2021; Editorial decision: June 5, 2023
Editor: Jeffrey Pontiff
Authors have furnished an Internet Appendix, which is available on the Oxford University Press Web site next to the link to the final published paper online.

Value investing is an investment strategy that involves picking stocks that appear to be trading at less than their intrinsic value. The value strategy has been widely discussed and studied by both academicians and industry practitioners (Graham and Dodd 1934; Fama and French 1992, 1993, 1996; Lakonishok, Shleifer, and Vishny 1994; Asness, Moskowitz, and Pedersen 2013). The value premium is the return achieved by buying securities that appear cheap and selling securities that appear expensive. The value strategy yielded excess returns for decades (Fama and French 1992, 1993; Davis, Fama, and French 2000), leading to the proliferation of value funds. However, recent studies document that the value premium disappears in the past three decades and is negative in the most recent decade (Asness et al. 2015; Arnott et al. 2021; Lev and Srivastava 2019; Fama and French 2020), leading many practitioners to claim the "death of value investing" (*Economist* 2018).[1]

There are three possible interpretations for the disappearing value premium. First, value investing in recent decades is structurally different from the previous

I thank Justin Birru, David Brown, David Ikenberry, Mahendrarajah Nimalendran, Jeffrey Pontiff (editor), Jay Ritter, and Michael Ryngaert and an anonymous referee for valuable comments. All errors are my own. Send correspondence to Baolian Wang, baolian.wang@warrington.ufl.edu.

[1] Most of these studies use book-to-market as their measure of value. We confirm the same results using several other widely used value measures.

The Review of Asset Pricing Studies 14 (2024) 40–83

https://doi.org/10.1093/rapstu/raad014 Advance Access publication 16 November 2023

decades and is no longer viable. In other words, value is dead. Second, returns are noisy and we cannot reject the hypothesis that expected value premiums in the recent decades are the same as in the previous decades, and the lower value premium in the recent decades is a result of statistical randomness (Arnott et al. 2021; Fama and French 2020). Third, the value measures we use may not be the best. Following Fama and French (1992, 1993), the academic consensus settled on the book-to-market ratio as the leading definition of value. However, we know of no theoretical justification for it as the best measure of value. In fact, Fama and French stated, "Different price ratios are just different ways to scale a stock's price with a fundamental, to extract the information in the cross-section of stock prices about expected returns."[2]

We reevaluate the value strategy using a new measure: *COP*/*P*, the ratio of the cash-based operating profitability (*COP*) measure of Ball et al. (2016) to market capitalization. *COP* may provide a more accurate measure of firm fundamentals than the book value of equity. Early advocates of value investing conjectured that book value might not be the best measure of fundamentals (Graham and Dodd 1934). Ball et al. (2020) find that book-to-market predicts returns because the retained earnings component of the book value of equity includes accumulations of past earnings, and the contributed capital component does not convey information about future returns. Earnings may better reflect fundamentals than the book value of equity, especially in recent decades when corporate assets have become increasingly intangible and intangibles are not reflected as clearly on accounting statements as tangibles are (Corrado and Hulten 2010; Enache and Srivastava 2018).

The choice of *COP* over other income statement-based measures is motivated by recent studies examining the relationship between various profitability measures and future stock returns. Novy-Marx (2013) argues that gross profit (revenue minus cost of goods sold) is the cleanest measure of economic profitability because items lower down the income statement are polluted. Ball et al. (2015) argue that selling, general, and administrative expenses (SG&A), the next item after cost of goods sold on the income statement, largely represents expenses incurred to generate the current period's revenue, and is economically similar to cost of goods sold and therefore also should be subtracted in calculating profit. Sloan (1996) finds that the accrual component of earnings has lower persistence than the cash flow component of earnings. Partially based on Sloan (1996), Ball et al. (2016) propose converting operating profitability to a cash basis by subtracting accruals. If *COP* is a better measure of economic fundamentals than others, we expect *COP*/*P* to work better than existing value measures.

Using the panel of U.S. stock returns over the 1963 to 2021 period, we find a strong positive correlation between a firm's *COP/P* and its subsequent returns. Sorting stocks into *COP/P* deciles, we find that the excess returns of both equal-weighted (EW) and value-weighted (VW) portfolios increase almost

[2] https://famafrench.dimensional.com/questions-answers/qa-why-use-book-value-to-sort-stocks.aspx

monotonically as *COP/P* increases. A zero-investment portfolio that buys stocks in the highest *COP/P* decile and shorts stocks in the lowest *COP/P* decile earns monthly excess returns of 1.043% (t = 6.84) for an EW portfolio and 0.779% (t = 4.38) for a VW portfolio.

Standard factor models cannot explain the long-short COP/P portfolio return spread. The capital asset pricing model (CAPM), the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, the Fama and French (2015) five-factor model, the Hou, Xue, and Zhang (2015) q-factor model, the Stambaugh and Yuan (2017) mispricing-factor model, and the Daniel, Hirshleifer, and Sun (2020) behavioral-factor model all leave a significant part of the return spread unexplained. For example, the Fama and French (1993) three-factor alphas are 0.793% (t = 6.65) and 0.784% (t = 5.17) for the EW and VW portfolios, respectively; the Fama and French (2015) five-factor alphas are 0.693% (t = 6.18) and 0.553% (t = 3.62) for the EW and VW portfolios, respectively. Both the three- and five-factor models have the book-to-market value factor (i.e., HML). These results suggest that *COP/P* contains information on the cross-section of stock returns beyond book-to-market.

In contrast to existing value measures, *COP/P* predicts returns even in the most recent decades. The book-to-market measure fails to predict returns in the past three decades, as well as most other existing value measures. The predictive power of *COP/P* for returns holds in different subperiods: one that starts in July 1963 and ends in December 1990 and one that starts in January 1991 and ends in December 2021, while book-to-market does not predict returns in the second subperiod (Asness et al. 2015; Lev and Srivastava 2019). The results also hold when we control for many known return predictors and hold for all size terciles whose size breakpoints are based on stocks listed on the New York Stock Exchange (NYSE). Finally, the *COP/P* effect persists for at least 5 years after portfolio formation.

The *COP/P* effect explains several widely used value measures. We examine this using both the Fama-MacBeth regression methodology and the spanning regression methodology. In spanning regressions, we construct a *COP/P* factor following the standard six-portfolio method of Fama and French (1993, 2015). We find that, in both Fama-MacBeth and spanning regressions, *COP/P* explains several widely used value measures, including book-to-market, dividend-to-price, earnings-to-price, cash flow-to-price, enterprise multiple, and sales-to-price. The measure *COP/P* also subsumes the retained earnings-to-price variable of Ball et al. (2020), who find that the retained earnings-to-price ratio subsumes the book-to-market ratio in predicting the cross-section of returns. The measure *COP/P* also subsumes the asset growth effect. Fama and French (2015) find that their value factor (HML) becomes redundant for describing average returns in their five-factor model, mainly because of the addition of their investment factor (CMA). Our findings show that the *COP/P* factor explains both HML and CMA.

We find evidence consistent with the conjecture that *COP* provides a more accurate measure of fundamentals than the book value of equity. Measuring firm fundamentals directly is difficult. Instead of doing so, we examine two important determinants of firm fundamentals: total cash-flow distributions to stock investors (i.e., payouts) and the payout growth rate. In the Gordon growth model, fundamentals reflect an increasing function of both the level of payouts and the growth rate of payouts. Following Boudoukh et al. (2007), we measure payouts as dividends plus repurchases minus issuances. Compared with book-to-market, *COP/P* is more positively correlated with the current payout-to-market ratio and the payout growth rate. Correlations between book-to-market and the current payout-to-market ratio as well as the payout growth rate are weaker in the second half of the sample period than in the first half, potentially explaining the weakening book-to-market effect. In comparison, correlations between *COP/P* and the current payout-to-market ratio as well as the payout growth rate do not weaken during that period.

The *COP/P* measure differs from the *COP/AT* measure of Ball et al. (2016) both conceptually and empirically. First, different deflators change the economic content of the measures. For example, the book value of equity scaled by the book value of total assets is a leverage measure; the book value of equity scaled by the market capitalization is book-to-market, which is a value measure. After all, *COP/P* measures value and *COP/AT* measures profitability. Second, we construct factor portfolios following the six-portfolio methodology of Fama and French (1993, 2015) for both *COP/P* and *COP/AT* and find that the *COP/P* factor and the *COP/AT* factor are negatively correlated with a correlation coefficient of −0.123. The *COP/P* factor is strongly positively correlated with other value factors, but the *COP/AT* factor is negatively correlated with most value factors. These results suggest that *COP/P* and *COP/AT* capture very different economic fundamentals. Third, the two measures are only modestly correlated with a correlation coefficient of 0.340.[3] The measure *COP/P* is the product of *COP/AT* and *AT/ME* (i.e., total value of book assets divided by market value of equity). The relatively low correlation is partially because *COP/AT* and *AT/ME* are strongly negatively correlated, as more profitable firms (i.e., with a higher *COP/AT* value) tend to have lower *AT/ME* values. Fourth, in Fama-MacBeth regressions, we show that the return predictive power of *COP/P* does not emanate from its two individual components, that is, *COP/AT* and *AT/ME*. If anything, *AT/ME* predicts returns with a negative sign. Ball et al. (2015) find that the return predictive power of gross profit (revenue minus cost of goods sold) and of net income is sensitive to the deflator used. Our analyses show that *COP/P*, the product of *COP/AT* and *AT/ME*, has return predictive power independent of *COP/AT*. The finding that *COP/P* predicts returns after controlling for *COP/AT* and *AT/ME* can be interpreted as *COP/AT* and *AT/ME* having an interesting interactive effect on returns: the marginal effect of *COP/AT* on returns is an increasing function of *AT/ME*.

After establishing the robustness of the predictive power of *COP/P* for returns and its superiority relative to existing value measures, we test whether the *COP/P*

[3] The Spearman correlation between *COP/P* and *COP/AT* is 0.511. Although the Spearman correlation is higher than the Pearson correlation, it still leaves most of the *COP/P* variation unexplained by *COP/AT*.

effect is most consistent with a risk or a mispricing explanation. We show that standard risk-return models (including the conditional CAPM) do not explain the effect. We find evidence consistent with the mispricing explanation. As with many other anomalies (Engelberg, Mclean, and Pontiff 2018), earnings announcements for high-*COP/P* firms are associated with significantly higher abnormal returns than low-*COP/P* firms. We find that 30%–40% of the abnormal returns of the long-short trading strategy are realized around earnings announcements.[4] In addition, consistent with limits to arbitrage (Pontiff 1996; Shleifer and Vishny 1997), the *COP/P* effect is stronger among smaller, less liquid, and more volatile stocks. However, we caution that these results are not conclusive because differentiating between rational and irrational pricing explanations is notoriously difficult (Fama 1998b).

Our study is related to a substantial stream of asset pricing literature that studies the value effect. Several value measures have been analyzed (Basu 1977; Jaffe, Keim, and Westerfield 1989; Chan, Hamao, and Lakonishok 1991; Fama and French 1992; Barbee et al. 1996; Naranjo, Nimalendran, and Ryngaert 1998; Loughran and Wellman 2011). Fama and French (1996) find that the book-to-market effect largely explains most other value measures in early studies. Most of the subsequent studies focus on measuring value using book-to-market. Daniel and Titman (2006), Fama and French (2008), Gerakos and Linnainmaa (2018), Ball et al. (2020), and Golubov and Konstantinidi (2019) examine the information content of different parts of book-to-market to shed light on the driving forces of the value effect. Arnott et al. (2021) and Lev and Srivastava (2019) find that incorporating intangibles into book value calculation improves the value performance, albeit this cannot resurrect the value premium in the recent period. Both rational (e.g., Ball 1978; Fama and French 1993; Berk 1995; Zhang 2005; Lettau and Wachter 2007; Da 2009) and behavioral explanations (Lakonishok, Shleifer, and Vishny 1994; Griffin and Lemmon 2002) have been proposed and tested.

Our main contribution is to reevaluate the value strategy by proposing a new value measure based on *COP/P*. We contribute to the debate of whether value is "redundant" or dead. The main conclusion is that *COP/P* works better than many existing value signals and subsumes them in explaining the cross-section of stock returns. *COP/P* also subsumes the investment factor of Fama and French (2015), but not the other way around. Hence, value is not "redundant." Book-to-market fails to predict returns in the post-1990 period (Asness et al. 2015; Lev and Srivastava 2019) and predicts returns negatively after July 2007 (Arnott et al. 2021). Our evidence shows that the value strategy based on *COP/P* is alive and well even in the recent period. We also present evidence that *COP* is a better measure of firm fundamentals than the book value of equity, especially in the post-1990 period.

[4] One caveat of this test is that, as pointed out by Engelberg, McLean, and Pontiff (2018), although different anomaly returns around earnings announcement days are most consistent with mispricing, they also could be consistent with dynamic risk models, which allow for time-varying risk premiums and time-varying betas (Patton and Verardo 2012; Savor and Wilson 2016).

stock exchange (1, 2, 3)
common equity without finacials (6, 10, 11)
delisting adj. -> missing: set to -30% or -55%

1. Data

~~We obtain monthly stock returns from the Center for Research in Security Prices (CRSP) and annual accounting data from Compustat. Our sample starts with all firms traded on the NYSE, AMEX, and NASDAQ. We exclude securities other than ordinary common shares. We also exclude financial firms, which are defined as firms with the one digit standard industrial classification code of six. We adjust stock returns for delisting. If a delisting return is missing and the delisting is performance related, we set the delisting return to −30% for NYSE and AMEX firms and to −55% for NASDAQ firms (Shumway 1997; Shumway and Warther 1999; Beaver, McNichols, and Price 2007).~~[5]

~~We follow Fama and French (1992) and match the annual accounting data to monthly stock returns. The annual accounting variables in year *t* are matched to monthly returns from July of year *t* + 1 to June of year *t* + 2. The sample consists of firms that have nonmissing current month returns, the market value of equity at the end of the last month, book to market, and *COP/P*. Our analysis of stock returns begins in July 1963 and ends in December 2021. Our sample covers 702 months.~~

~~Following Ball et al. (2020), in Fama and MacBeth (1973) regressions, we exclude microcaps to avoid having them exert undue influence, and, in portfolio sorts and when constructing return factors, we include all stocks and rebalance the portfolios annually at the end of June. Following Fama and French (2008), we define microcaps as stocks with a market value of equity below the 20th percentile of the NYSE market capitalization distribution. These stocks account for only 3% of the total market capitalization but comprise around 60% of all stocks.~~

~~Our new measure of value/growth is *COP/P*, which is defined as the cash-based operating profitability (*COP*) measure proposed by Ball et al. (2016) divided by market capitalization. Specifically, we compute *COP* as operating profitability minus accruals. Operating profitability is defined as revenue minus cost of goods sold and reported SG&A (Ball et al. 2015). As discussed by Ball et al. (2015), Compustat defines its SG&A variables (XSGA) as the sum of firms' actual reported SG&A and expenditures on research and development. Reported SG&A subtracts expenditures on research and development to undo Compustat's adjustment to firms' accounting statements. Accruals are defined as the change in accounts receivable plus the change in inventory and the change in prepaid expenses minus the changes in accounts payable, deferred revenue, and accrued expenses.~~

Table 1 reports the summary statistics for the main variables.[6] ~~We winsorize *COP/P* and other accounting variables (all the variables in Table 1, except *Beta*, *log(ME)*, $R_{1,1}$, $R_{12,2}$, $R_{60,13}$, *ILLIQ*, and *IVOL*) month by month at the 1% level for~~

[5] In Tables IA1-9 and Figures IA1-7 of the Internet Appendix, we produce the results after excluding stocks with a price lower than \$5. Overall, we find very similar results.

[6] See Table A1 of the Appendix for detailed definitions of the major variables.

Table 1
Summary statistics

	Mean	SD	Corr	Low 1	2	3	4	5	6	7	8	9	High 10
COP/P	0.185	0.460	1	−0.300	0.003	0.057	0.096	0.131	0.168	0.210	0.268	0.365	0.854
Beta	1.234	0.767	−0.040	1.360	1.359	1.339	1.242	1.186	1.157	1.147	1.151	1.171	1.227
log(ME)	11.779	1.967	0.012	10.239	11.335	12.008	12.319	12.445	12.375	12.254	12.050	11.737	11.026
log(BM)	−0.527	0.847	0.195	−0.457	−1.022	−1.004	−0.857	−0.713	−0.567	−0.426	−0.269	−0.102	0.152
$R_{1,1}$	0.013	0.152	0.017	0.011	0.007	0.009	0.011	0.013	0.013	0.014	0.015	0.016	0.019
$R_{12,2}$	0.148	0.597	0.052	0.110	0.095	0.117	0.136	0.145	0.149	0.158	0.168	0.180	0.223
$R_{60,13}$	0.644	1.753	−0.053	0.163	0.794	1.149	1.072	0.891	0.735	0.627	0.513	0.383	0.112
ILLIQ	11.715	127.431	0.016	30.591	14.219	8.582	6.221	5.471	5.661	6.063	7.365	10.104	23.660
IVOL	0.027	0.022	−0.049	0.042	0.033	0.028	0.024	0.022	0.022	0.022	0.023	0.025	0.031
COP/AT	0.123	0.209	0.340	−0.231	−0.044	0.138	0.190	0.196	0.194	0.193	0.192	0.193	0.201
D/P	0.016	0.032	0.081	0.011	0.010	0.011	0.015	0.016	0.020	0.019	0.021	0.020	0.016
E/P	−0.005	0.238	0.104	−0.238	−0.035	0.014	0.036	0.048	0.053	0.057	0.053	0.040	−0.077
CF/P	0.120	0.263	0.312	−0.121	0.020	0.070	0.100	0.127	0.148	0.171	0.197	0.229	0.261
IEM	0.110	0.186	0.284	−0.082	0.019	0.071	0.102	0.124	0.144	0.163	0.177	0.193	0.186
S/P	2.498	3.096	0.279	2.801	1.270	1.234	1.409	1.623	1.896	2.211	2.741	3.612	6.192
RE/P	0.096	1.174	0.140	−0.898	−0.147	0.067	0.183	0.247	0.305	0.349	0.354	0.375	0.110
AG	0.239	0.637	−0.194	0.412	0.634	0.474	0.268	0.189	0.142	0.113	0.092	0.065	0.013

This table reports summary statistics for the sample: the mean and standard deviation (SD) of each variable and their pairwise correlations (Corr) with *COP/P*. *COP/P* is cash-based operating profitability divided by market capitalization. We winsorize *COP/P* and other accounting variables (all variables in Table 1, except *Beta*, *log*(*ME*), $R_{1,1}$, $R_{12,2}$, $R_{60,13}$, *ILLIQ*, and *IVOL*) month by month at the 1% level in both tails to mitigate the effects of outliers. The next 10 columns report the mean of each variable by *COP/P* decile. We sort stocks into deciles at the end of June and rebalance annually. We compute the means, standard deviations, and correlations from the cross-section month by month and report the time-series averages of the monthly cross-sectional statistics. Table A1 of the appendix defines the variables. Our sample period starts in July 1963 and ends in December 2021.

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~~both tails to mitigate the effect of outliers. The mean and standard deviation of each variable are reported. Also reported are the pairwise correlations between each variable and *COP*/*P*. The table reports the average of each variable within each *COP*/*P* decile. We sort stocks into deciles at the end of June and rebalance annually. We first calculate the statistics from the cross section of each month and then calculate the time series means of these cross-sectional statistics.~~

~~*Beta* is a stock's beta computed using monthly returns over the previous 5 years, following Fama and French (1992). *log*(*ME*) is the logarithm of the market value of the firm's outstanding equity at the end of month $t-1$. *log*(*BM*) is the logarithm of the firm's book value of equity divided by its market value of equity, where the book-to-market ratio is computed following Fama and French (2008). We fill in the missing book equity values with data from Davis, Fama, and French (2000).[7] Firms with negative book equity values are excluded from our main analysis. $R_{1,1}$ is the stock's return in month $t-1$, which is a control for the short-term reversal effect. $R_{12,2}$ is the stock's buy-and-hold return from the start of month $t-12$ to the end of month $t-2$, which is a control for the momentum effect (Jegadeesh and Titman 1993).~~ $R_{60,13}$ is the stock's buy-and-hold return from the start of month $t-60$ to the end of month $t-13$, which is a control for the long-term reversal effect (DeBondt and Thaler 1985). *ILLIQ* is Amihud's (2002) illiquidity measure, computed using daily data in month $t-1$. *IVOL* is the standard deviation of the stock's daily idiosyncratic returns—relative to the Fama and French (1993) three-factor model—over month $t-1$, following Ang et al. (2006). *AG* is the total asset growth between two consecutive fiscal years, following Cooper, Gulen, and Schill (2008).

Besides book-to-market, we also consider six other value measures: *D*/*P* is the dividend yield, calculated as total dividends paid from July of year $t-1$ to June of year t per dollar of equity in June of year t; *E*/*P* is the earnings-to-price ratio, where earnings are calculated as total earnings before extraordinary items; *CF*/*P* is the cash flow-to-price ratio, where cash flow is calculated as total earnings before extraordinary items, plus depreciation and deferred taxes. *CF* and *COP* differ mainly because *CF* considers income statement items after SG&A, whereas *COP* does not.[8] *IEM* is inverse enterprise multiple, operating income before depreciation divided by enterprise value, where enterprise value is calculated as the market value of equity plus total debt plus preferred stock value minus cash and short-term investments (Loughran and Wellman 2011).[9] *S*/*P* is the sales-to-price ratio, calculated as total revenue divided by total market capitalization (Barbee, Mukherji, and Raines 1996). *RE*/*P* is the ratio of retained earnings to price. We follow Ball et al. (2020) and calculate retained earnings as the retained earnings variable from Compustat minus accumulated other comprehensive income.

[7] The data are available from Kenneth French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

[8] Kenneth French's data library uses the same definitions for *E*/*P*, *CF*/*P*, and *D*/*P* when calculating portfolio returns.

[9] We take the inverse of enterprise multiple to be consistent with other value measures. Our conclusions are unaffected if we use enterprise multiple instead.

Accumulated other comprehensive income is a technical account that accumulates the amount of various paper gains and losses that originate primarily in shocks to the prices of financial assets in which companies have either a long or short position. The U.S. Generally Accepted Accounting Principles do not include accumulated other comprehensive income in retained earnings; however, Compustat adds it to their retained earnings variable. We, therefore, undo the adjustment in calculating *RE/P*. Ball et al. (2020) find that *RE/P* subsumes book-to-market in predicting the cross-section of returns.

There is significant cross-sectional variation in *COP/P*. The average values for *COP/P* are −0.300 and 0.854 for deciles 1 and 10, respectively. As expected, *COP/P* is positively correlated with other value measures. Among all the value measures, the highest correlation is with *CF/P*, with a correlation coefficient of 0.312. *COP/P* is negatively correlated with asset growth. This result is consistent with the existing finding that firms with higher valuation ratios invest more. The correlation between *COP/P* and *COP/AT* is 0.340.[10] *COP/AT* increases from −0.231 in decile 1 to 0.190 in decile 4. From decile 4 to decile 10, although *COP/P* increases from 0.096 to 0.854, there is little change in *COP/AT*. This result suggests that the relation between *COP/P* and *COP/AT* is nonmonotonic. Overall, these low correlations mitigate the concern that *COP/P* is just a repackaging of existing return predictors.

2. Main Results

In this section, we conduct the asset pricing tests of *COP/P* using decile portfolio sorts and the Fama and MacBeth (1973) regression methodology.

2.1 Time-series tests

~~We conduct the decile sort tests as follows.~~ At the end of each June, beginning in 1963 and ending in 2021, we sort stocks into deciles based on *COP/P*. We then compute the average return of each *COP/P* decile portfolio each month over the next year, both equal-weighted and value-weighted. This gives us a time series of monthly returns for each *COP/P* decile, which we use to compute the average return of each decile over the entire sample period. In Table 2, we report the average return of each decile in excess of the risk-free rate, the CAPM alpha, the Fama-French three-factor alpha (Fama and French 1993), the Fama-French-Carhart four-factor alpha (following Carhart (1997), the return adjusted by the three factors of Fama and French (1993) and by a momentum factor), the

[10] Similarly, Ball et al. (2015) find that the correlation between gross profit (or income before extraordinary items) deflated by the market value of equity and gross profit (or income before extraordinary items) deflated by the book value of assets is 0.10 (0.19). Both are lower than the correlation between *COP/P* and *COP/AT*. The absolute magnitude of the correlation *COP/P* and *COP/AT* is similar to that of the correlation between *log*(*ME*) and *log*(*BM*) (−0.299) and the correlation between *log*(*ME*) and *COP/AT*, and significantly lower than the correlation between *log*(*ME*) and *IVOL* (−0.433). *COP/P* is the product of *COP/AT* and *AT/ME*. The relatively low correlation between *COP/P* and *COP/AT* is partially because more profitable firms (i.e., with a higher *COP/AT* value) tend to have lower *AT/ME* value. In other words, *COP/AT* and *AT/ME* are negatively correlated.

Table 2

Time-series tests

Model		Low 1	2	3	4	5	6	7	8	9	High 10	High-minus-Low
Excess returns	EW	0.369	0.187	0.452	0.742	0.868	0.933	1.030	1.073	1.232	1.411	1.043
		(1.17)	(0.65)	(1.74)	(3.22)	(4.03)	(4.42)	(4.79)	(4.99)	(5.32)	(5.28)	(6.84)
	VW	0.175	0.091	0.257	0.641	0.600	0.687	0.753	0.792	0.924	0.954	0.779
		(0.60)	(0.34)	(1.11)	(3.36)	(3.40)	(4.03)	(4.41)	(4.36)	(4.90)	(4.22)	(4.38)
CAPM	EW	−0.702	−0.810	−0.451	−0.082	0.102	0.178	0.262	0.309	0.409	0.490	1.192
		(−5.52)	(−8.06)	(−5.10)	(−1.37)	(1.73)	(3.27)	(4.70)	(5.15)	(6.27)	(5.03)	(8.02)
	VW	−0.668	−0.721	−0.451	0.024	0.023	0.125	0.202	0.218	0.344	0.295	0.963
		(−4.03)	(−5.00)	(−4.00)	(0.33)	(0.36)	(2.10)	(2.98)	(2.72)	(3.74)	(2.33)	(5.62)
Fama-French three-factor	EW	−0.618	−0.503	−0.113	0.082	0.158	0.166	0.174	0.181	0.243	0.175	0.793
		(−5.81)	(−6.39)	(−1.76)	(1.66)	(2.97)	(3.31)	(3.39)	(3.39)	(4.14)	(2.23)	(6.65)
	VW	−0.743	−0.580	−0.255	0.141	0.073	0.130	0.171	0.148	0.192	0.041	0.784
		(−5.35)	(−4.83)	(−2.74)	(2.07)	(1.14)	(2.18)	(2.52)	(1.89)	(2.38)	(0.40)	(5.17)
Fama-French-Carhart four-factor	EW	−0.477	−0.347	−0.029	0.102	0.152	0.151	0.183	0.163	0.228	0.207	0.685
		(−4.48)	(−4.55)	(−0.45)	(2.02)	(2.78)	(2.94)	(3.46)	(2.99)	(3.79)	(2.58)	(5.66)
	VW	−0.604	−0.482	−0.150	0.157	0.063	0.111	0.125	0.080	0.173	0.104	0.708
		(−4.33)	(−3.97)	(−1.60)	(2.27)	(0.96)	(1.82)	(1.82)	(1.01)	(2.10)	(1.02)	(4.59)
Fama-French five-factor	EW	−0.642	−0.426	−0.020	0.098	0.124	0.114	0.117	0.094	0.158	0.051	0.693
		(−6.37)	(−5.75)	(−0.34)	(1.93)	(2.32)	(2.31)	(2.31)	(1.82)	(2.78)	(0.65)	(6.18)
	VW	−0.573	−0.219	−0.001	0.115	−0.004	0.044	0.062	0.084	0.081	−0.020	0.553
		(−4.06)	(−1.97)	(−0.01)	(1.66)	(−0.07)	(0.74)	(0.91)	(1.05)	(1.01)	(−0.20)	(3.62)
Hou-Xue-Zhang q-factor	EW	−0.060	−0.076	0.141	0.190	0.198	0.260	0.301	0.350	0.433	0.581	0.641
		(−0.33)	(−0.57)	(1.42)	(2.73)	(3.04)	(4.30)	(4.20)	(5.13)	(5.35)	(4.94)	(4.02)
	VW	−0.475	−0.183	0.022	0.145	−0.001	0.059	0.027	0.111	0.152	0.170	0.645
		(−3.16)	(−1.37)	(0.20)	(1.88)	(−0.02)	(0.93)	(0.38)	(1.29)	(1.65)	(1.49)	(3.67)
Stambaugh-Yuan mispricing-factor	EW	−0.060	−0.062	0.136	0.176	0.162	0.155	0.250	0.223	0.365	0.536	0.596
		(−0.33)	(−0.44)	(1.28)	(2.31)	(2.24)	(2.32)	(3.32)	(2.95)	(4.19)	(4.42)	(4.19)
	VW	−0.351	−0.080	0.044	0.054	−0.069	0.017	0.007	−0.023	0.137	0.089	0.440
		(−2.63)	(−0.60)	(0.43)	(0.71)	(−0.96)	(0.25)	(0.09)	(−0.26)	(1.41)	(0.72)	(2.75)
Daniel-Hirshleifer-Sun behavioral-factor	EW	0.334	0.195	0.370	0.495	0.539	0.580	0.645	0.696	0.831	1.023	0.690
		(1.29)	(0.99)	(2.44)	(3.83)	(4.33)	(4.71)	(4.74)	(5.05)	(5.19)	(5.08)	(4.36)
	VW	−0.239	−0.234	−0.106	0.032	0.029	0.123	0.059	0.221	0.326	0.324	0.563
		(−1.30)	(−1.62)	(−0.91)	(0.35)	(0.37)	(1.81)	(0.73)	(2.25)	(2.88)	(2.14)	(3.04)

This table reports average monthly excess returns and alphas (in percentages) on both an equal-weighted (EW) and a value-weighted (VW) basis for stock portfolios sorted by *COP*/*P*, which is cash-based operating profitability divided by market capitalization. t-statistics are reported in parentheses. For each month in the sample period, all stocks are sorted into deciles based on *COP*/*P*. For each of the decile portfolios, Low 1 through High 10, we report the average excess return, CAPM factor, Fama-French three-factor alpha, Fama-French-Carhart four-factor alpha, Fama-French five-factor alpha, Hou-Xue-Zhang q-factor alpha, Stambaugh-Yuan mispricing-factor alpha, and Daniel-Hirshleifer-Sun behavioral-factor alpha. In the right-most column we report the excess returns on and alphas of the High-minus-Low portfolios. The sample period runs from July 1963 to December 2021, with three exceptions: in the sample for the Hou-Xue-Zhang q-factor, the analysis starts in July 1967, the Daniel-Hirshleifer-Sun behavioral-factor analysis starts in July 1972, and the Stambaugh-Yuan mispricing-factor analysis ends in December 2016 based on the availability of the factors.

Fama-French five-factor alpha (Fama and French 2015, 2016), the q-theory factor alpha (Hou, Xue, and Zhang 2015), the mispricing-factor alpha (Stambaugh and Yuan 2017), and the behavioral-factor alpha (Daniel, Hirshleifer, and Sun 2020).[11] We adjust VW portfolio return by VW factors and EW portfolio return by EW factors, except for the q-theory factor, the mispricing factor, and the behavioral factor models because EW factors are not available.[12] In the right-most column ("high-minus-low"), we report the difference between the returns of the two extreme decile portfolios. The high-minus-low portfolio is a zero-investment portfolio that buys the stocks in the highest *COP*/*P* decile and shorts the stocks in the lowest *COP*/*P* decile.

The results in the high-minus-low column show that stocks with high *COP*/*P* outperform stocks with low *COP*/*P*. The return spreads for the equal-weighted and value-weighted portfolios are 1.043% ($t = 6.84$) and 0.779% ($t = 4.38$) per month, respectively. The economic magnitudes of the excess returns of the high-minus-low portfolios are sizable. For example, the excess return result implies that, on average, the stocks in the highest *COP*/*P* decile outperform those in the lowest *COP*/*P* decile by 12.5% on an equal-weighted basis and by 9.4% on a value-weighted basis.

Figure 1 presents graphical views of the results in Table 2. Figure 1 plots the equal-weighted excess returns (panel A) and value-weighted excess returns (panel B) on the 10 *COP*/*P* decile portfolios. The figure makes clear two aspects of the results in Table 2, namely, that the returns on the 10 portfolios increase in a nearly monotonic fashion, moving from the lowest *COP*/*P* decile portfolio to the highest *COP*/*P* decile portfolio, and that the results are not driven by the extreme decile portfolios.

Figure 2 plots the average monthly excess returns on the high-minus-low portfolio year by year. Overall, the high-minus-low portfolio performed well in most years, although with some notable exceptions, such as in 2020. The EW high-minus-low portfolio return does not show a significant time trend, and the VW high-minus-low portfolio return is notably lower after 2010. In Table IA10 of the Internet Appendix, we report the results by decades. The high-minus-low portfolio generates positive excess returns in all decades with the exception of the 2020–2021 period, when the VW portfolio generates negative returns. The return spread is statistically significant in most cases.

Figure 3 reports the results for two subperiods. From July 1963 to December 1990, the average monthly high-minus-low portfolio returns are 0.903% ($t = 6.49$) on the equal-weighted basis and 0.776% ($t = 3.63$) on the value-weighted basis,

[11] Data for the Fama and French three factors, the momentum factor, and the Fama and French five factors are from Kenneth French's website. Stambaugh and Yuan's factors are from Robert Stambaugh's website (http://finance.wharton.upenn.edu/~stambaug/). Hou, Xue, and Zhang's factors are from Wharton Research Data Services. The behavioral factors are from Lin Sun's website (https://sites.google.com/view/linsunhome). All these factors cover our full sample period from July 1963 to December 2021, except the q-factors start in July 1967, and the behavioral factors start in July 1972, and the mispricing factors end in December 2016.

[12] We thank an anonymous referee for this suggestion. The results are qualitatively similar if we adjust EW portfolio returns by VW factors.

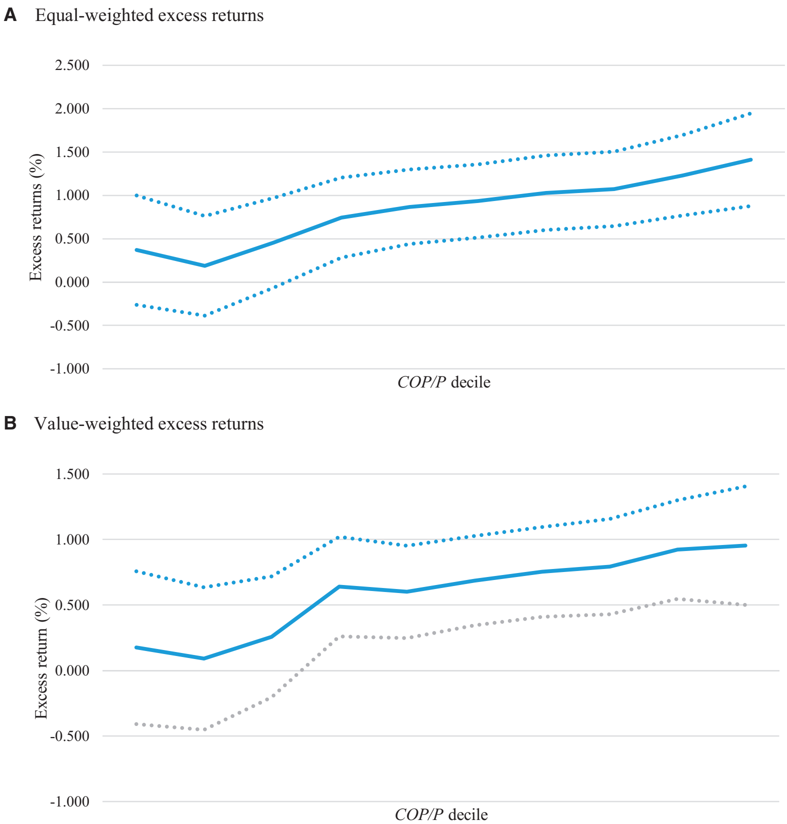


Figure 1
Performance of *COP/P* deciles
For each month in the sample period, we sort all stocks into deciles by *COP/P*—cash-based operating profitability divided by market capitalization—and record the average returns on each decile on both an equal-weighted and value-weighted basis. Using the time series of average returns, we compute the returns in excess of the risk-free rate for the deciles and plot them. Panel A shows equal-weighted returns, and panel B value-weighted returns. The vertical axis represents monthly returns in percentage. The horizontal axis represents the decile portfolios, from decile 1 (low *COP/P*) to decile 10 (high *COP/P*).

respectively. The average returns are even higher in the second subperiod, from January 1991 to December 2021: 1.167% ($t = 4.49$) on the equal-weighted basis and 0.782% ($t = 2.83$) on the value-weighted basis, respectively. In contrast, book-to-market fails to predict returns post-1990 (Asness et al. 2015).

The return spread between the two extreme *COP/P* decile portfolios is robust to the factor model adjustments. The CAPM alphas are 1.192% ($t = 8.02$) and 0.963% ($t = 5.62$) per month for the equal-weighted and value-weighted portfolios, respectively. The CAPM adjustment increases the alphas by about 0.15%–0.20% per month for both the equal-weighted and value-weighted

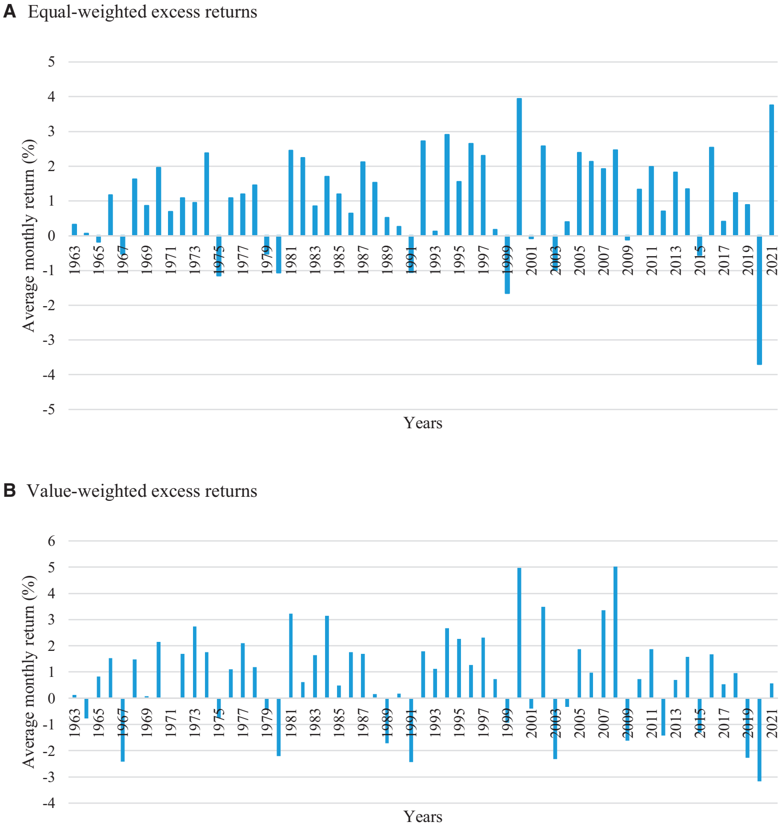
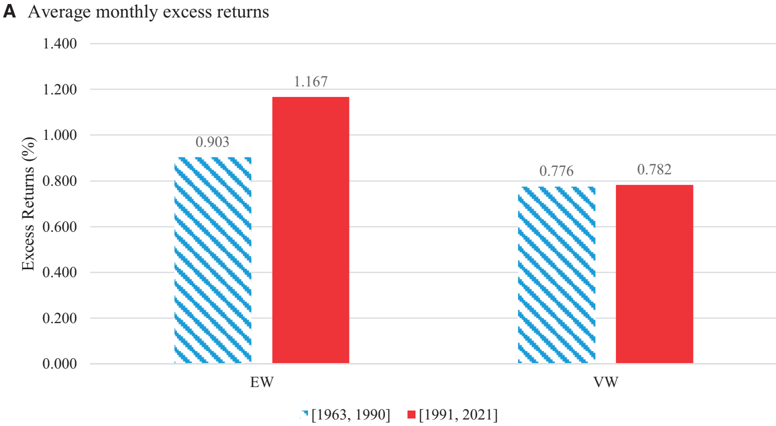


Figure 2
Returns on the *COP/P* strategy by year
This figure plots the average monthly excess returns on the high-minus-low portfolio year by year. *COP/P* is cash-based operating profitability divided by market capitalization. For each month in the sample period, we sort all stocks into deciles by *COP/P* and report the average returns on each decile on both an equal-weighted basis (panel A) and a value-weighted basis (panel B). Using the time series of average returns, we compute the return spread between the highest *COP/P* decile and the lowest *COP/P* decile.

portfolios. The Fama-French three factors and the momentum factor do not explain much of the return spread. The Fama-French five-factor alphas of the high-minus-low portfolio are 0.693% ($t = 6.18$) and 0.553% ($t = 3.62$) per month for the equal-weighted and value-weighted portfolios, respectively.[13] This model explains about

[13] The t-values of the Fama-French five-factor alphas of the long-short portfolio are 6.18 for the equal-weighted portfolio and 3.62 for the value-weighted portfolio, both highly statistically significant, even by the standards suggested by Harvey, Liu, and Zhu (2016) and Harvey (2017). Harvey (2017) proposes an alternative statistical significance analysis approach, known as the minimum Bayes factor, which delivers a Bayesian p-value. A t-value of 3.62 is considered significant at the 1% level, even when the prior belief on the probability that the null (*COP/P* is unrelated to future stock returns) is true is only 10%. See the t-statistic thresholds for minimum Bayes factors in Table III of Harvey (2017).



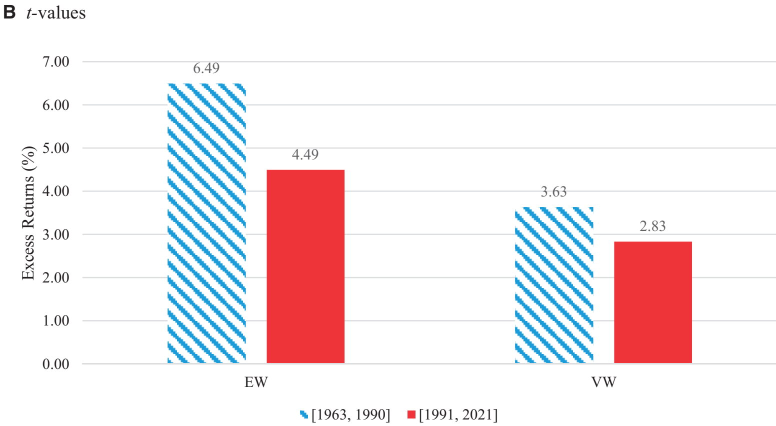


Figure 3
Subperiod analysis
This figure plots average monthly excess returns (panel A) and their *t*-values (panel B) of the high-*COP*/*P* minus low-*COP*/*P* portfolio strategy for two subperiods: one starts in July 1963 and ends in December 1990 and the other starts in January 1991 and ends in December 2021. *COP*/*P* is cash-based operating profitability divided by market capitalization. For each month in the sample period, we sort all stocks into deciles by *COP*/*P* and record the average returns on each decile on both an equal-weighted basis (dashed line) and a value-weighted basis (solid line). Using the time series of average returns, we compute the return spread between the highest *COP*/*P* decile and the lowest *COP*/*P* decile.

one-third of the raw return spread. The q-factor, mispricing factor, and behavioral factor models perform similarly, and all leave a significant part of the return spread unexplained.[14]

14 Asness, Frazzini, and Pedersen (2019) propose a quality-minus-junk factor. In untabulated results, we find that, if we augment the Fama and French five-factor model with the quality-minus-junk factor, the alpha of the high-minus-low *COP*/*P* portfolio 0.764% ($t = 6.31$) on an equal-weighted basis and 0.387% ($t = 2.46$) on a value-weighted basis. The data of the quality-minus-junk factor are downloaded from https://www.aqr.com/Insights/Datasets/Quality-Minus-Junk-Factors-Monthly.

Table 3 reports the factor loadings for the high-minus-low portfolios in the seven asset pricing models and for both the equal- and value-weighted returns. Consistent with the correlations of the characteristics in Table 1, we find that the high-minus-low portfolios have positive loadings on the value factor (HML), the profitability factors (RMW and ROE), and the investment factors (CMA and I/A). The portfolios are also positively correlated with the MGMT factor and the PERF factor of Stambaugh and Yuan (2017), as well as the external finance factor (FIN) of Daniel, Hirshleifer, and Sun (2020). The MGMT factor arises from six anomaly variables representing quantities that firm managements can affect directly. The PERF factor arises from five anomaly variables that are more related to performance and less directly controlled by management. Empirically, MGMT and FIN are positively correlated with the investment factors, and PERF is positively correlated with the profitability factors. The positive loadings of the high-minus-low portfolios on these three factors are perhaps due to their positive correlations with the profitability and investment factors.

2.2 Comparing with other value factors and the investment factor

Next, we construct a factor that captures the effect of *COP/P* and compare it with other value factors and the investment factor of Fama and French (2015). To construct the factor, we follow the six-portfolio methodology of Fama and French (1993, 2015). At the end of each June, stocks are allocated to one of two size groups (small and big), using NYSE market capitalization breakpoints. We then perform an independent sort of stocks into high (i.e., above the 70$^{\text{th}}$ NYSE percentile breakpoint), low (i.e., below the 30$^{\text{th}}$ NYSE percentile breakpoint), and intermediate portfolios based on *COP/P*. The *COP/P* factor is the average value-weighted returns on the two high-*COP/P* portfolios minus the average value-weighted returns on the two low-*COP/P* portfolios.

Figure 4 plots average monthly excess returns (panel A) and their *t*-values (panel B) of the *COP/P* factor portfolio, other value factor portfolios (the *E/P*, *CF/P*, *IEM*, *S/P*, and *RE/P* factors), and CMA for both the pre-1990 and post-1990 periods. All these factors are constructed in the same way as the *COP/P* factor. We drop the *D/P* factor from the analysis because it does not generate a significant mean return. In constructing these factors, nonpositive values are included.[15] Consistent with Asness et al. (2015), Arnott et al. (2021), and Lev and Srivastava (2019), HML is much weaker in the post-1990 period, with a mean of 0.138% and a *t*-value of 0.84. Other value factors and CMA show similar patterns. They are all strongly positive in the pre-1990 period, but none are significant at the 5% level in the

[15] Kenneth French conducted the six-portfolio bivariate sorts on size, *D/P* (or *E/P* or *CF/P*) and made the data available on his website. However, firms with zero dividends (or negative or zero earnings, or negative or zero cash flows) are excluded. If we construct the *E/P* and *CF/P* factors using Kenneth French's data, the mean monthly returns of the *E/P* and *CF/P* factors are 0.044% ($t = 0.83$) and 0.106% ($t = 2.05$), respectively. The factor returns are higher when the factor construction includes nonpositive values. The *D/P* factor, based on French's data, has a mean monthly return of −0.093% ($t = -1.76$). The *RE/P* factor data are from Juhani Linnainmaa. We appreciate that the authors made their data available to us.

Table 3
Factor loadings

Model		MktRf	SMB	HML	UMD	RMW	CMA	I/A	ROE	MGMT	PERF	PEAD	FIN	R^2
CAPM	EW	−0.191												0.068
		(−7.24)												
	VW	−0.312												0.086
		(−8.18)												
Fama-French three-factor	EW	0.075	−0.538	0.632										0.427
		(2.98)	(−12.63)	(15.29)										
	VW	−0.147	−0.410	0.596										0.300
		(−4.14)	(−7.97)	(11.29)										
Fama-French-Carhart four-factor	EW	0.105	−0.538	0.655	0.120									0.440
		(4.03)	(−12.75)	(15.87)	(4.02)									
	VW	−0.130	−0.409	0.630	0.189									0.306
		(−3.57)	(−7.97)	(11.56)	(2.39)									
Fama-French five-factor	EW	0.073	−0.327	0.475		0.650	0.128							0.523
		(3.08)	(−7.40)	(8.42)		(11.80)	(1.48)							
	VW	−0.076	−0.321	0.432		0.330	0.503							0.333
		(−2.04)	(−6.05)	(6.27)		(4.55)	(4.71)							
Hou-Xue-Zhang *q*-factor	EW	0.085	−0.111					0.734	0.321					0.208
		(2.33)	(−2.10)					(8.89)	(5.26)					
	VW	−0.117	−0.356					0.802	0.085					0.238
		(−2.91)	(−6.16)					(8.83)	(1.26)					
Stambaugh-Yuan mispricing-factor	EW	0.129	−0.075							0.656	0.119			0.219
		(3.57)	(−1.57)							(11.89)	(3.34)			
	VW	0.037	−0.199							0.820	0.100			0.318
		(0.91)	(−3.72)							(13.23)	(2.50)			
Daniel-Hirshleifer-Sun behavioral-factor	EW	0.111										0.018	0.537	0.236
		(3.04)										(0.23)	(12.49)	
	VW	−0.046										0.078	0.584	0.265
		(−1.06)										(0.87)	(11.62)	

This table reports factor loadings of a long-short portfolio that, in each month, buys stocks whose *COP*/*P* is in the top decile and sells short stocks whose *COP*/*P* is in the bottom decile. *COP*/*P* is cash-based operating profitability divided by market capitalization. We report the results for seven models (CAPM, Fama-French three-factor model, Fama-French-Carhart four-factor model, Fama-French five-factor model, Hou-Xue-Zhang *q*-factor model, Stambaugh-Yuan mispricing-factor model, and Daniel-Hirshleifer-Sun behavioral-factor model), on both an equal-weighted (EW) and value-weighted (VW) basis. MktRf is the market factor, SMB is the small-minus-big size factor, HML is the high-minus-low value factor, UMD is the up-minus-down momentum factor, RMW is the robust-minus-weak profitability factor, CMA is the conservative-minus-aggressive investment factor, I/A is the investment factor, ROE is the return-on-equity factor, MGMT is a factor that arises from six anomaly variables representing quantities that a firm's management can affect directly, PERF is a factor that arises from five anomaly variables that are more directly related to performance and less directly controlled by management, PEAD is the post-earnings-announcement-drift factor, and FIN is the external finance factor. The sample period runs from July 1963 to December 2021 with two exceptions: in the sample for the Hou-Xue-Zhang *q*-factor, the analysis starts in July 1967, and the Stambaugh-Yuan mispricing-factor analysis ends in December 2016 based on the availability of the factors.

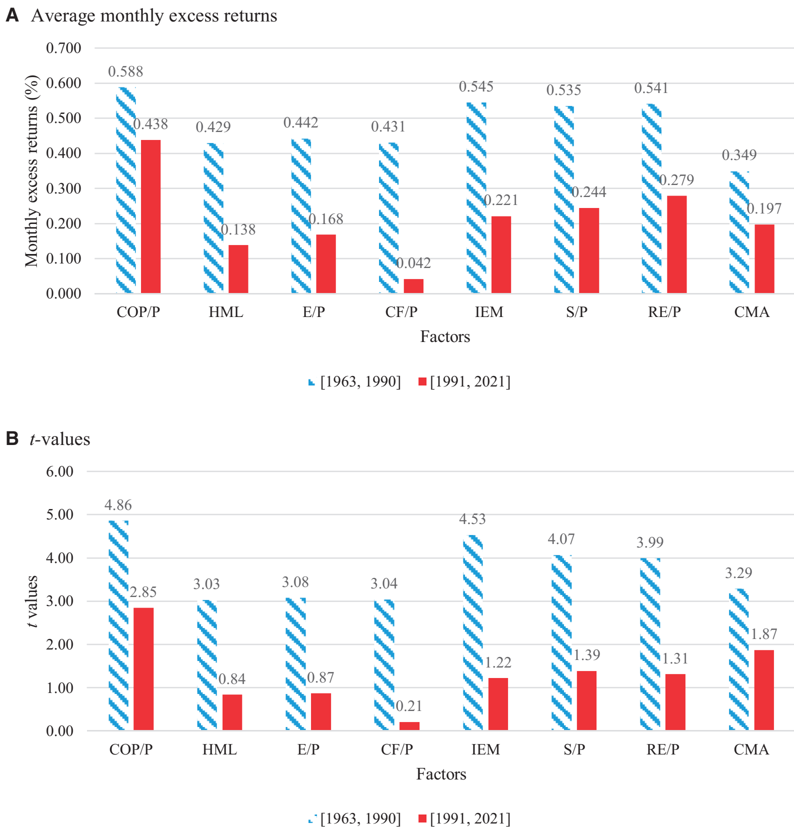


Figure 4
Comparing the *COP/P* factor with other value factors and CMA
This figure plots average monthly excess returns on (panel A) and their *t*-values for (panel B) the *COP/P* factor portfolio and several other value factor portfolios for two subperiods: one that starts in July 1963 and ends in December 1990 and the other that starts in January 1991 and ends in December 2021. All the factor portfolios are constructed based on the six-portfolio methodology of Fama and French (1993, 2015). *COP/P* is cash-based operating profitability divided by market capitalization. HML and CMA are the value and investment factors of Fama and French (2015). E/P is a factor constructed based on the earnings-to-price ratio. CF/P is a factor constructed based on the cash-flow-to-price ratio. IEM is a factor constructed based on the inverse enterprise multiple. S/P is a factor constructed based on the sales-to-price ratio. RE/P is a factor constructed based on the retained-earnings-to-price ratio. Table A1 of the appendix defines the variables.

post-1990 period. The CMA factor is only significant at the 10% level. In contrast, the *COP/P* factor delivers significantly positive returns in both subperiods.

2.3 Fama-MacBeth tests

One advantage of the Fama-MacBeth regression test is that it allows us to examine the predictive power of *COP/P* while controlling for known return predictors. Following Ball et al. (2020), we exclude microcaps to avoid having them exert undue influence.[16] We implement the Fama-MacBeth regressions in the usual way. Each month, starting in July 1963 and ending in December 2021, we run a cross-sectional regression of stock returns (in percentage) in that month on independent variables. In these regressions, we take the natural logarithm of *COP*/*P*. We include the natural logarithm of *COP*/*P* and an indicator variable for nonpositive *COP* values. When *COP* is negative or zero, we replace the logarithm of *COP*/*P* with zero. See Fama and French (1992) and Ball et al. (2020) for similar treatments.

Table 4 reports the time-series averages of the coefficients for the independent variables. The results in the table confirm the findings based on the time-series portfolio analysis. Column 1 reports the regression that does not include any control variables. The coefficient for *COP*/*P* is 0.226 ($t = 4.16$), and the coefficient for the indicator is -1.151 ($t = -5.33$), both statistically significant. We conduct a Hotelling (1931) test for the joint significance of these two variables and find that they are jointly highly statistically significant ($p < .0001$).

In columns 3, 5, and 7 of Table 4, we include the major known predictors of returns as control variables. Columns 2, 4, and 6 include the control variables, but not *COP*/*P*, or the nonpositive *COP*/*P* indicator. Comparing columns 1, 3, 5, and 7 can reveal how the control variables affect the return predictive power of *COP*/*P*. Comparing columns 2 and 3 (or 4 and 5, or 6 and 7) can reveal how *COP*/*P* affects the return predictive power of the control variables.

In columns 2 and 3 of Table 4, we include beta, market capitalization (*log*(*ME*)), book-to-market (*log*(*BM*)), the past month's return ($R_{1,1}$), and the buy-and-hold returns from month $t-12$ to month $t-2$ ($R_{12,2}$). In columns 4 and 5, we add the buy-and-hold return from months $t-60$ to $t-13$ ($R_{60,13}$), the illiquidity measure (*ILLIQ*), and an idiosyncratic volatility measure (*IVOL*). In columns 6 and 7, we further add *COP*/*AT*.

The *COP*/*P* variable and the nonpositive *COP/P* indicator retain significant predictive power, even after we include the major known predictors of returns. Relative to column 1 of Table 4, the magnitudes of the coefficients of *COP*/*P* and the nonpositive *COP*/*P* indicator are smaller after we add control variables in columns 3, 5, and 7. Their magnitudes and *t*-values are the lowest in column 7 but are still statistically significant at the 1% level. *COP*/*P* has a significant impact on the coefficients of the control variables. In column 2, the coefficient of *log*(*BM*) is 0.138 ($t = 2.55$), and in column 3, it becomes 0.033 ($t = 0.71$), no longer statistically significant. In column 6, the coefficient of *COP*/*AT* is 1.215 ($t = 6.90$), and in column 7, after *COP*/*P* is controlled for, it becomes 0.652 ($t = 3.03$), which is less than half the value in column 6.

[16] Table IA11 reports the Fama-MacBeth regression results using weighted least sequares where the estimates are weighted by lagged market capitalization. The results are qualitatively similar in this "value-weighted" Fama-MacBeth analysis. In Table IA12, we report the Fama-MacBeth regression results using all stocks. In the full sample, *COP*/*P* continues to strongly predict stock returns. As we show in Section 3.3, in the all-but-microcap sample, *COP*/*P* subsumes other widely used value measures as well as the asset growth effect. In the full-sample Fama-MacBeth regressions, *COP*/*P* explains significant fractions of the return predictive power of other value measures as well as the asset growth effect, but it does not fully subsume them. In Table IA14, we report the results of time-series tests obtained after excluding the microcaps.

Table 4
Fama-MacBeth regressions

A. Main regressions

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(*COP/P*)	0.226		0.158		0.148		0.118
	(4.16)		(4.76)		(4.61)		(3.20)
COP/P≤0	−1.151		−1.042		−0.931		−0.560
	(−5.33)		(−7.48)		(−6.80)		(−3.47)
Beta		−0.073	−0.026	−0.003	0.029	0.021	0.028
		(−0.73)	(−0.26)	(−0.04)	(0.32)	(0.23)	(0.31)
log(*ME*)		−0.058	−0.081	−0.108	−0.124	−0.123	−0.125
		(−1.87)	(−2.68)	(−3.67)	(−4.26)	(−4.22)	(−4.31)
log(*BM*)		0.138	0.033	0.078	−0.015	0.144	0.033
		(2.55)	(0.71)	(1.53)	(−0.34)	(2.68)	(0.65)
$R_{1,1}$		−3.136	−3.217	−3.013	−3.118	−3.051	−3.140
		(−8.69)	(−8.97)	(−8.10)	(−8.45)	(−8.21)	(−8.51)
$R_{12,2}$		0.709	0.695	0.734	0.717	0.721	0.703
		(5.50)	(5.44)	(5.76)	(5.67)	(5.67)	(5.58)
$R_{60,13}$				−0.036	−0.036	−0.043	−0.039
				(−1.85)	(−1.91)	(−2.22)	(−2.09)
ILLIQ				0.078	0.133	0.061	0.105
				(0.16)	(0.28)	(0.13)	(0.22)
IVOL				−0.204	−0.181	−0.192	−0.184
				(−5.46)	(−4.88)	(−5.16)	(−4.98)
COP/AT						1.215	0.652
						(6.90)	(3.03)
Hotelling test (*COP/P*)	<.0001		<.0001		<.0001		.0019
Average R^2	.017	.070	.077	.083	.089	.086	.092

(continued)

Table 4
Continued

B. Explaining other value measures and the asset-growth effect

	Value = *BM*		Value = *D/P*		Value = *E/P*		Value = *CF/P*		Value = *IEM*		Value = *S/P*		Value = *RE/P*		*AG*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
log(*COP/P*)		0.121		0.132		0.125		0.105		0.132		0.107		0.096		0.101
		(3.34)		(3.38)		(3.29)		(2.93)		(3.57)		(2.54)		(2.51)		(2.38)
COP/P≤0		−0.570		−0.606		−0.572		−0.515		−0.610		−0.468		−0.497		−0.438
		(−3.62)		(−3.69)		(−3.48)		(−3.37)		(−4.10)		(−2.71)		(−3.08)		(−2.47)
log(*Value*)	0.142	0.028	0.021	−0.022	0.071	0.000	0.123	0.041	0.083	−0.030	0.095	0.025	0.111	0.048		
	(2.64)	(0.55)	(0.53)	(−0.62)	(1.52)	(−0.01)	(2.64)	(0.94)	(1.37)	(−0.52)	(2.37)	(0.59)	(3.01)	(1.49)		
Value≤0	−0.097	−0.085	−0.088	0.120	−0.288	−0.115	−0.404	−0.231	−0.587	−0.236	0.162	0.190	−0.245	−0.165		
	(−0.52)	(−0.46)	(−0.45)	(0.67)	(−1.61)	(−0.69)	(−1.67)	(−0.98)	(−2.24)	(−0.89)	(0.51)	(0.59)	(−1.58)	(−1.09)		
AG															−0.311	−0.130
															(−3.41)	(−1.58)
Beta	0.016	0.024	−0.015	0.000	−0.008	0.010	−0.003	0.006	0.018	0.020	0.006	0.015	0.030	0.036	0.018	0.038
	(0.18)	(0.27)	(−0.17)	(0.00)	(−0.09)	(0.12)	(−0.03)	(0.07)	(0.21)	(0.23)	(0.07)	(0.17)	(0.33)	(0.40)	(0.20)	(0.42)
log(*ME*)	−0.125	−0.126	−0.139	−0.127	−0.133	−0.130	−0.133	−0.129	−0.137	−0.135	−0.130	−0.130	−0.137	−0.135	−0.140	−0.130
	(−4.23)	(−4.32)	(−4.77)	(−4.44)	(−4.54)	(−4.48)	(−4.56)	(−4.46)	(−4.62)	(−4.59)	(−4.42)	(−4.49)	(−4.61)	(−4.56)	(−4.77)	(−4.49)
$R_{1,1}$	−2.994	−3.086	−2.751	−2.937	−2.764	−2.919	−2.868	−2.955	−2.884	−2.987	−2.887	−3.026	−2.936	−3.082	−2.904	−3.107
	(−8.08)	(−8.39)	(−7.52)	(−8.09)	(−7.55)	(−8.02)	(−7.88)	(−8.13)	(−7.95)	(−8.24)	(−7.87)	(−8.33)	(−7.81)	(−8.26)	(−7.77)	(−8.40)
$R_{12,2}$	0.723	0.704	0.714	0.675	0.716	0.688	0.704	0.682	0.706	0.690	0.694	0.680	0.714	0.685	0.735	0.707
	(5.77)	(5.66)	(5.89)	(5.62)	(5.76)	(5.58)	(5.72)	(5.56)	(5.73)	(5.61)	(5.54)	(5.48)	(5.70)	(5.51)	(5.79)	(5.61)

(continued)

Table 4
Continued

B. Explaining other value measures and the asset-growth effect

	Value = *BM*		Value = *D/P*		Value = *E/P*		Value = *CF/P*		Value = *IEM*		Value = *S/P*		Value = *RE/P*		*AG*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$R_{60,13}$	−0.042	−0.039	−0.057	−0.043	−0.060	−0.044	−0.050	−0.042	−0.063	−0.043	−0.052	−0.042	−0.051	−0.050	−0.050	−0.042
	(−2.16)	(−2.06)	(−2.78)	(−2.25)	(−2.93)	(−2.34)	(−2.53)	(−2.22)	(−3.08)	(−2.20)	(−2.67)	(−2.20)	(−2.45)	(−2.56)	(−2.30)	(−2.16)
ILLIQ	0.007	0.034	0.104	0.087	0.164	0.112	0.038	0.056	0.107	0.062	0.154	0.092	0.192	0.128	0.154	0.133
	(0.02)	(0.07)	(0.24)	(0.20)	(0.36)	(0.25)	(0.08)	(0.12)	(0.23)	(0.14)	(0.33)	(0.20)	(0.38)	(0.26)	(0.33)	(0.29)
IVOL	−0.198	−0.190	−0.205	−0.192	−0.206	−0.193	−0.200	−0.192	−0.204	−0.199	−0.196	−0.190	−0.182	−0.173	−0.195	−0.181
	(−5.48)	(−5.32)	(−5.95)	(−5.68)	(−5.92)	(−5.62)	(−5.76)	(−5.54)	(−5.83)	(−5.74)	(−5.45)	(−5.35)	(−5.07)	(−4.90)	(−5.19)	(−4.90)
COP/AT	1.184	0.602	0.957	0.554	0.898	0.501	1.023	0.635	0.822	0.497	1.062	0.584	1.101	0.716	1.021	0.719
	(6.87)	(2.85)	(6.03)	(2.90)	(5.69)	(2.56)	(6.67)	(3.39)	(4.78)	(2.49)	(6.55)	(2.62)	(6.82)	(3.69)	(6.11)	(3.46)
Hotelling test (*Value*)	.0308	.7897	.8588	.8011	.2412	.6243	.0287	.5291	.0781	.1667	.0393	.6615	.0098	.2714	.0018	.0646
Hotelling test (*COP/P*)		.0010		.0009		.0017		.0031		.0002		.0022		.0090		.0039
Average R^2	.087	.092	.086	.093	.089	.093	.086	.093	.087	.094	.088	.092	.088	.094	.084	.091

In this table we report average Fama-MacBeth regression slopes and their *t*-values from cross-sectional regressions that predict monthly returns (in percentages). *t*-statistics are reported in parentheses. In panel A we report the main regression results, and in panel B we report the regression results that explain other value measures. The regressions are estimated using data running from July 1963 to December 2021, except for columns 9 and 10 of panel B, for which the data start in July 1964 based on the availability of data on retained earnings. The sample consists of all but microcap firms with positive book values of equity and nonmissing *COP/P* values, except for columns 1 and 2 of panel B, where negative book-to-market observations are included. *COP/P* is cash-based operating profitability divided by market capitalization. The variable $COP/P \leq 0$ is an indicator that equals one for nonpositive *COP/P* values. All but microcap firms are stocks with market value of equity at or above the 20th percentile of the NYSE market capitalization distribution. For the *COP/P* Hotelling test we report the *p*-values for the test of the null that the coefficients of both *log*(*COP/P*) and $COP/P \leq 0$ are jointly zero. For the *Value* Hotelling test we report the *p*-values of the test of the null that the coefficients of *log*(*Value*) and of $Value \leq 0$ are jointly zero. The variables *BM*, *D/P*, *E/P*, *CF/P*, *IEM*, *S/P*, and *RE/P* are book-to-market, dividend yield, earnings-to-price, cash flow-to-price, inverse enterprise multiple, sales-to-price, and retained earnings-to-price, respectively. All the accounting variables, including *COP/P*, are winsorized month by month at the 1% level in both tails. Table A1 of the appendix defines the variables.

Ball et al. (2015) find that the return predictive power of gross profit (revenue minus cost of goods sold) and of net income is sensitive to the deflator used. Specifically, in asset pricing tests, the authors find that gross profit (or net income) deflated by the book value of total assets dominates gross profit (or net income) deflated by market capitalization. The results in column 7 of Table 4 show that, although controlling for *COP*/*AT* reduces the coefficients of *COP*/*P* and the nonpositive *COP*/*P* indicator, both *COP*/*P* and *COP*/*AT* have independent return predictive power. We investigate more on the relationship between *COP*/*P* and *COP*/*AT* in Sections 3.7 and 3.9.

2.4 Explaining other value measures and the asset growth effect

In panel A of Table 4, we find that *COP*/*P* subsumes *log*(*BM*) in explaining the cross-section of stock returns. In panel B, we investigate how *COP*/*P* affects the return predictive power of other value measures. We also examine whether the previous results on *log*(*BM*) are sensitive to how we handle negative observations of the book value of equity.

Besides *log*(*BM*), we consider the same set of value measures as in Section 3.2. For each value measure, we report the results of a regression without *COP*/*P* or the nonpositive *COP*/*P* indicator (but with other control variables) and the results of a regression with *COP*/*P* and the nonpositive *COP*/*P* indicator. We handle these variables in the same way as we handle *COP*/*P*. Specifically, we take the natural logarithm of each variable, and if the numerator is nonpositive, we replace the logarithmic value with zero and include an indicator variable for nonpositive values. We denote these values as *log*(*Value*) and *Value*≤0. In each regression, we report the results of a Hotelling test of whether the coefficients for *log*(*Value*) and *Value*≤0 are jointly zero.

We first report additional results on *log*(*BM*). In panel A of Table 4, we exclude observations with a negative book value of equity. In columns 1 and 2 of panel B, we examine whether the results in panel A are sensitive to how we handle negative observations of the book value of equity. Specifically, we expand the sample for panel A to include firms with nonpositive book values of equity. When the book value of equity is negative or zero, we replace the logarithm of book-to-market with zero and include an indicator variable for nonpositive values. Like Ball et al. (2020), we find that the nonpositive book-to-market indicator is statistically insignificant and that its addition has little impact on the coefficient of *COP*/*P*. In this specification, *COP*/*P* continues to subsume the return explanatory power of *log*(*BM*).[17]

The results in columns 3, 5, 7, 9, 11, and 13 in panel B of Table 4 show that all six value measures have positive coefficients and the nonpositive indicators have negative coefficients, although not all are statistically significant. Their statistical

[17] Including firms with nonpositive book values of equity increases the number of observations by about 3%. Our other results are also robust to the inclusion of these firms.

significance disappears after *COP/P* is added, while *COP/P* itself remains highly statistically significant in all the specifications.

In columns 15 and 16 in panel B of Table 4, we examine whether *COP/P* explains the asset growth effect. Fama and French (2015) construct their investment factor based on asset growth. We do so because firm investments are highly positively correlated with valuation ratios, as indicated by the high correlations between *AG* and the value measures in Table 1. Fama and French's (2015) investment factor (CMA) and value factor (HML) are highly positively correlated, with a correlation coefficient of 0.669. Column 15 shows that the coefficient of *AG* is -0.311 ($t = -3.41$). After controlling for *COP/P* in column 16, we find that the coefficient becomes -0.130 ($t = -1.58$), which is not significant anymore.

Overall, these results show that *COP/P* is a better value measure than the other measures in explaining the cross-section of stock returns. *COP/P* subsumes the return predictive power of all the widely used value measures and explains the asset growth effect. In Section 3.7, we also conduct tests using spanning regressions and confirm these results.

2.5 Firm size and the effect of *COP/P*

Table 5 reports the results by size terciles. Each month, we group all stocks into size terciles based on the NYSE breakpoints. Within each size tercile, we further sort stocks into *COP/P* deciles. The table reports the Fama-French three-factor alphas for the 30 portfolios on an equal-weighted and value-weighted basis. We also report the alphas for each size tercile of the high-*COP/P* minus low-*COP/P* portfolios. The results show that the *COP/P* effect exists for all three size terciles. The effect is weaker among large firms than among small firms. The differences between the smallest and largest terciles in the equal-weighted and value-weighted high-minus-low portfolios are 0.610% ($t = 3.16$) and 0.639% ($t = 3.00$), respectively. However, even among the largest firms, high-*COP/P* stocks outperform low-*COP/P* stocks: the high-minus-low alpha is 0.311% ($t = 2.36$) for equal-weighted portfolios and 0.365% ($t = 2.33$) for value-weighted portfolios. These results show that the *COP/P* effect is not restricted to small firms.

2.6 Predicting returns over increasing horizons

Next, we examine how far ahead *COP/P* predicts returns. In Tables 2 and 4, we consider whether *COP/P* in year t predicts a stock's return from July of year $t+1$ to June of year $t+2$. We now consider whether *COP/P* in year t predicts a stock's return from July of year $t+j$ to June of year $t+j+1$. We examine j up to $j=7$ when we stop finding a significant return spread. Figure 5 illustrates the results. The results in panel A correspond to the equal-weighted alphas and those in panel B correspond to the value-weighted alphas. The alphas that correspond to the $t+j$ label on the horizontal axis are calculated with the Fama-French three-factor model of a long-short portfolio that, each month, buys stocks that were in the highest *COP/P* decile j years previously and shorts stocks that were in the lowest *COP/P*

Table 5

Firm size and the effect of *COP/P*

	Low 1	2	3	4	5	6	7	8	9	High 10	High-minus-Low
A. Equal-weighted alphas											
Small	−0.447	−0.627	−0.383	−0.100	0.165	0.235	0.217	0.356	0.367	0.474	0.921
	(−2.18)	(−3.87)	(−2.66)	(−0.91)	(1.75)	(2.94)	(2.46)	(4.30)	(3.91)	(3.30)	(5.36)
Medium	−0.652	−0.357	−0.062	0.093	0.082	0.031	0.154	0.108	0.244	0.022	0.675
	(−5.80)	(−3.60)	(−0.76)	(1.32)	(1.10)	(0.45)	(2.26)	(1.43)	(2.95)	(−0.24)	(4.68)
Big	−0.285	−0.022	−0.015	0.145	0.051	0.055	0.053	0.122	0.061	0.026	0.311
	(−2.62)	(−0.27)	(−0.24)	(2.31)	(0.87)	(0.84)	(0.87)	(1.83)	(0.88)	(0.30)	(2.36)
Small-Big											0.610
											(3.16)
B. Value-weighted alphas											
Small	−0.715	−0.961	−0.612	−0.163	0.080	0.186	0.051	0.160	0.136	0.289	1.004
	(−4.55)	(−8.05)	(−5.07)	(−1.81)	(1.03)	(2.86)	(0.72)	(2.39)	(1.81)	(1.99)	(6.01)
Medium	−0.677	−0.383	−0.084	0.067	0.053	0.033	0.172	0.093	0.216	0.055	0.732
	(−5.88)	(−3.63)	(−1.00)	(0.95)	(0.68)	(0.46)	(2.43)	(1.19)	(2.51)	(0.58)	(4.98)
Big	−0.255	0.066	0.099	0.199	0.019	0.008	0.136	0.121	0.130	0.110	0.365
	(−2.21)	(0.75)	(1.32)	(2.53)	(0.24)	(0.11)	(1.67)	(1.48)	(1.41)	(1.14)	(2.33)
Small-Big											0.639
											(3.00)

In this table we report the results of time-series regressions indicating how the *COP/P* effect varies with firm size. For each month, we sort all the stocks into terciles based on market capitalization at the end of the previous month. We use NYSE size breakpoints. Within each size tercile, we further sort stocks into deciles based on *COP/P*. We report the Fama-French three-factor alphas for the 30 portfolios on both an equal-weighted basis (panel A) and a value-weighted basis (panel B). For each size tercile, we also report the high-*COP/P* minus low-*COP/P* portfolio alpha and the difference in the high-minus-low portfolio between the small and big terciles (Small–Big). The sample period runs from July 1963 to December 2021. *t*-statistics are reported in parentheses.

decile j years previously. The results for $j = 1$ are the main results reported in Table 2.

Figure 5 shows that *COP/P* has return predictive power for at least 5 years after the portfolio construction. Its predictive power becomes weaker when j becomes larger, but after 5 years, the return predictive power of *COP/P*'s remains: the equal-weighted alpha is 0.338% ($t = 3.49$) and the value-weighted alpha is 0.454% ($t = 2.95$). In fact, *COP/P* continues to predict returns on an equal-weighted basis when $j = 6$, with an alpha of 0.258% ($t = 2.83$).

2.7 Spanning regressions

Table 6 reports the results of spanning regressions. Panel A of Table 6 presents the average monthly returns, standard deviations, and *t*-values for the *COP/P* factor, the five factors of Fama and French (2015), the momentum factor, other value factors (the *E/P*, *CF/P*, *IEM*, *S/P*, and *RE/P* factors), and the *COP/AT* factor. In the Fama-MacBeth regressions (see Table 4), we find that *COP/P* and *COP/AT* have independent return predictive power. We examine their relation further, using spanning regressions. All these factors are constructed in the same way as the *COP/P* factor. The *COP/P* factor's mean return is 0.509%, which is only lower than that of the market factor and the momentum factor. Its *t*-value is 5.09, which is only lower than that of the *COP/AT* factor.

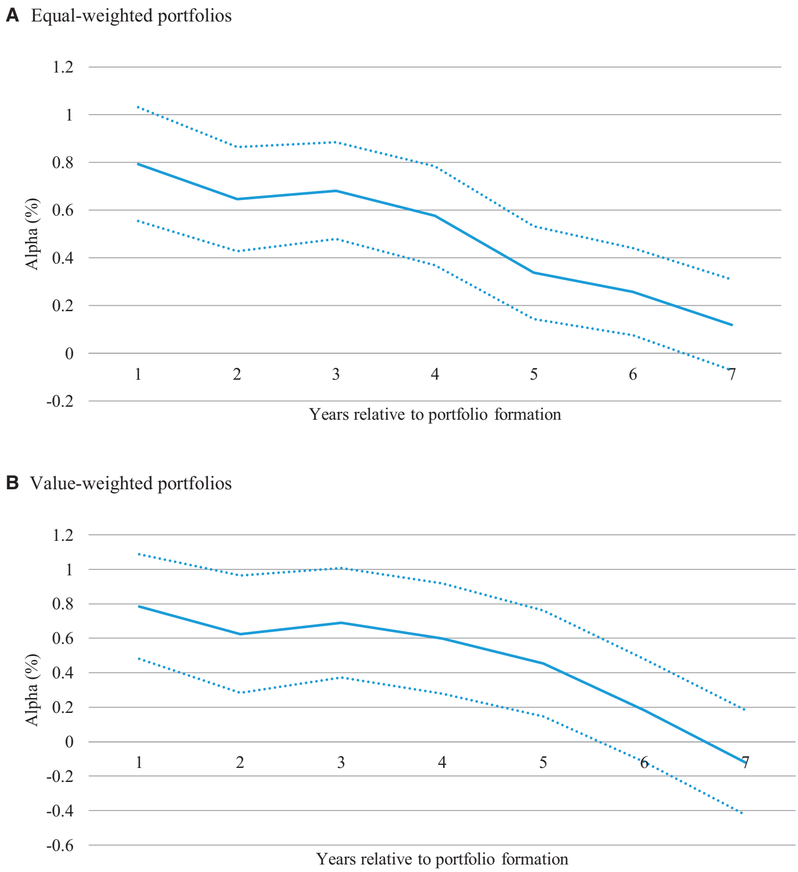


Figure 5
Predicting returns over increasing horizons
This figure plots the Fama-French three-factor alphas on both an equal-weighted basis (panel A) and a value-weighted basis (panel B) for a long–short portfolio that buys (shorts) stocks in the highest (lowest) *COP*/*P* decile at some point in the past. *COP*/*P* is cash-based operating profitability divided by market capitalization. The *x*-axis represents years relative to the year the *COP*/*P* is measured. The results for year $t+j$ are based on the *COP*/*P* measured in year t and the returns are from July of year $t+j$ to June of year $t+j+1$. The solid lines represent the average alphas, and the dotted lines show the 95% confidence intervals (two standard deviations from the solid lines). The results obtained when $j=1$, following the timing convention of Fama and French (1992), are the main results reported in the paper.

Panel B of Table 6 presents the correlations between the factor returns. The correlations provide several important takeaways. First, the *COP*/*P* factor is highly positively correlated with the other value factors: the HML, *E*/*P*, *CF*/*P*, *IEM*, *S*/*P*, and *RE*/*P* factors, with all correlations higher than 0.69. The HML, *E*/*P*, *CF*/*P*, *IEM*, *S*/*P*, and *RE*/*P* factors are also highly positively correlated with each other. These high correlations suggest that these factors capture similar economic fundamentals. In contrast, the *COP*/*AT* factor is negatively correlated with all the value

Table 6
Spanning regressions

A. Average monthly returns and standard deviations

	COP/P	MktRf	SMB	HML	UMD	RMW	CMA	E/P	CF/P	IEM	S/P	RE/P	COP/AT
Mean	0.509	0.589	0.228	0.275	0.625	0.275	0.268	0.297	0.225	0.373	0.381	0.409	0.443
STD	2.630	4.448	3.033	2.904	4.204	2.212	1.983	3.251	3.344	2.948	2.962	3.203	1.940
t-value	5.09	3.51	1.99	2.51	3.94	3.30	3.58	2.42	1.78	3.35	3.40	3.23	6.05

B. Correlations

	COP/P	MktRf	SMB	HML	UMD	RMW	CMA	E/P	CF/P	IEM	S/P	RE/P	COP/AT
COP/P	1												
MktRf	−0.186	1											
SMB	0.057	0.282	1										
HML	0.771	−0.210	−0.019	1									
UMD	−0.083	−0.160	−0.063	−0.217	1								
RMW	0.189	−0.192	−0.350	0.083	0.084	1							
CMA	0.640	−0.375	−0.090	0.669	−0.035	−0.032	1						
E/P	0.698	−0.396	−0.248	0.738	−0.081	0.508	0.492	1					
CF/P	0.777	−0.358	−0.216	0.807	−0.104	0.383	0.610	0.891	1				
IEM	0.844	−0.304	−0.155	0.757	−0.094	0.493	0.572	0.880	0.890	1			
S/P	0.686	−0.034	0.158	0.717	−0.178	0.333	0.466	0.661	0.680	0.738	1		
RE/P	0.756	−0.365	−0.184	0.792	−0.058	0.429	0.648	0.880	0.864	0.874	0.800	1	
COP/AT	−0.123	−0.319	−0.415	−0.274	0.340	0.443	−0.124	0.094	−0.101	0.008	−0.342	−0.054	1

C. Spanning regressions (dependent variable is the monthly COP/P factor return)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Alpha	0.320	0.273	0.146	0.141	0.187	0.165	0.163	0.221	0.142
	(5.00)	(4.22)	(2.42)	(2.45)	(3.38)	(3.64)	(2.73)	(3.69)	(2.25)
MktRf	−0.030	−0.019	0.025	0.061	0.052	0.042	0.011	0.028	0.047
	(−1.96)	(−1.21)	(1.67)	(4.14)	(3.79)	(3.75)	(0.75)	(1.87)	(3.02)
SMB	0.074	0.074	0.136	0.152	0.163	0.107	0.099	0.110	0.131
	(3.40)	(3.46)	(6.53)	(7.58)	(8.44)	(6.76)	(4.34)	(5.35)	(6.22)
HML	0.690	0.711	0.511	0.288	0.213	0.080	0.426	0.276	0.305
	(31.13)	(31.22)	(18.85)	(7.66)	(5.86)	(2.88)	(12.27)	(7.09)	(7.77)
UMD		0.055							
		(3.51)							
RMW			0.255	0.082	0.088	−0.182	0.180	0.065	0.012
			(8.94)	(2.39)	(2.91)	(−6.33)	(5.29)	(1.76)	(0.32)
CMA			0.397	0.406	0.317	0.204	0.368	0.299	0.284
			(9.46)	(10.11)	(8.07)	(6.19)	(8.72)	(6.54)	(3.81)
E/P factor				0.292					
				(8.21)					
CF/P factor					0.382				
					(11.31)				
IEM factor						0.718			
						(22.86)			
S/P factor							0.134		
							(12.27)		
RE/P factor								0.294	0.314
								(7.31)	(7.81)
COP/AT factor									0.154
									(3.81)
R^2	.601	.608	.668	.697	.720	.811	.675	.673	.680

(continued)

Table 6
Spanning regressions

D. Spanning regressions (dependent variables are the monthly returns of the other factors)

	(1) HML	(2) RMW	(3) CMA	(4) UMD	(5) E/P	(6) CF/P	(7) IEM	(8) S/P	(9) RE/P	(10) COP/AT
Alpha	−0.123	0.265	0.087	0.821	0.018	−0.144	−0.026	−0.064	−0.026	0.614
	(−1.71)	(3.37)	(1.47)	(5.10)	(0.23)	(−1.99)	(−0.46)	(−0.78)	(−0.33)	(9.28)
COP/P	0.843	0.166	0.475	−0.186	0.832	0.967	0.936	0.780	0.920	−0.112
	(31.13)	(5.60)	(20.48)	(−3.05)	(27.71)	(35.40)	(44.12)	(24.96)	(29.00)	(−4.48)
MktRf	−0.036	−0.029	−0.107	−0.170	−0.151	−0.117	−0.066	0.044	−0.110	−0.110
	(−2.16)	(−1.57)	(−7.87)	(−4.55)	(−8.16)	(−6.96)	(−5.03)	(2.30)	(−5.88)	(−7.19)
SMB	−0.044	−0.252	−0.025	−0.008	−0.245	−0.237	−0.170	0.098	−0.158	−0.214
	(−1.84)	(−9.53)	(−1.24)	(−0.14)	(−9.18)	(−9.77)	(−9.01)	(3.51)	(−6.00)	(−9.65)
R^2	.601	.169	.488	.039	.608	.693	.762	.488	.629	.238

In this table we report the results of the information content analysis of the *COP/P* factor. The *COP/P* factor and other factors are constructed following the six-portfolio methodology of Fama and French (1993, 2015). In panel A we report monthly average returns (in percentages), standard deviations, and *t*-values of the factor returns. Panel B displays the Pearson correlations. For panel C we measure the information content of the *COP/P* factor by reporting estimates from spanning regressions. For panel C, the left-hand-side variable is monthly *COP/P* factor returns. For panel D, the left-hand-side variables are the monthly returns on other factors, that is, the market return minus the risk-free rate, MktRf; size, SMB; book-to-market, HML; momentum, UMD; robust-minus-weak profitability, RMW; conservative-minus-aggressive investment, CMA; earnings-to-price, E/P; cash flow-to-price, CF/P; inverse enterprise multiple, IEM; sales to price, S/P; retained earnings-to-price, RE/P; and cash-based operating profitability to the book value of total assets, COP/AT. The sample period starts in July 1963 and ends in December 2021, except for the RE/P factor sample period, which starts in July 1964.

factors except the *E/P* and *IEM* factors, where the correlations are weakly positive. Second, the *COP/P* factor and other value factors are also positively correlated with the CMA factor. This result is consistent with the finding that the HML and CMA factors are related to each other (Fama and French 2015). Third, the *COP/P* and *COP/AT* factors are negatively correlated, with a correlation coefficient of −0.123. On the one hand, this assures that these two factors are fundamentally distinct. On the other hand, the negative correlation is somewhat surprising, especially given that *COP/P* and *COP/AT* are positively correlated (see Table 1). We further examine their relation in Sections 3.7 and 3.9.

In panels C and D of Table 6, we use spanning regressions to determine whether other factors explain the *COP/P* factor (panel C). We also check, for the opposite, whether the *COP/P* factor explains the other factors (panel D). Each candidate factor is regressed on other factors of a model. If the intercept in a spanning regression is nonzero, that factor adds to the model's explanation of average returns (Fama 1998a; Barillas and Shanken 2017). We consider the Fama-French three-factor model, the Fama-French-Carhart four-factor model, and the Fama-French five-factor model. We also consider five augmented Fama-French five-factor models in which we add the *E/P*, *CF/P*, *IEM*, *S/P*, or the *RE/P* factor. The model with the *RE/P* factor is of particular interest since Ball et al. (2020) find that the *RE/P* factor dominates the HML factor. Ball et al. (2016) and Fama and French (2018) find that the *COP/AT* factor better captures average returns than the RMW factor. We, therefore, also consider factor models with the *COP/AT* factor and the *RE/P* factor.

Panel C of Table 6 shows that all the factor models leave sizable alphas for the *COP/P* factor. The alpha from the Fama-French three-factor model is 0.320% ($t = 5.00$). The alpha from the Fama-French five-factor model is 0.146% ($t = 2.42$). Adding the *E/P*, *CF/P*, *IEM*, *S/P*, or *RE/P* factors has little impact on the estimated alphas. These statistically significant alphas indicate that, relative to other models, the *COP/P* factor contains useful information about average returns.

Panel C of Table 6 also reveals that, as expected, the *COP/P* factor has high loadings on other value factors and CMA, but not other factors. This is consistent with the high correlations between the *COP/P* factor, other value factors, and CMA in panel B. The weak loading of the *COP/AT* factor in column 9 reassures that *COP/P* and *COP/AT* are distinct.

In panel D of Table 6, we regress other factors on the *COP/P* factor and the market and size factors. The market and size factors are from the Fama-French three-factor model. The results in panel D are insensitive to the inclusion of the market and size factors. As the table shows, the loadings of these two factors are mostly negative. The alphas of all the value factors become either indistinguishable from zero (HML, *E/P*, *IEM*, *S/P*, and *RE/P*) or negative (*CF/P*). These results are consistent with the Fama-MacBeth regressions in Table 4. The alpha of the CMA factor also becomes indistinguishable from zero. The *COP/P* factor has little impact on the alpha of the *COP/AT* factor.

Overall, these results suggest that the *COP/P* factor contains useful information about expected returns, even after other widely used factors are considered. Moreover, the *COP/P* factor captures valuable information in the existing value factors, including the book-to-market factor, the *E/P* factor, the *CF/P* factor, the *IEM* factor, the *S/P* factor, and the *RE/P* factor, as well as the investment factor of Fama and French (2015).[18]

2.8 *COP/P* and the book-to-market ratio

In this section, we examine why *COP/P* performs better than the book-to-market ratio in predicting future stock returns and why the difference in predictability is stronger after 1990 than before 1990. One conjecture is that *COP* is a more accurate measure of firm fundamentals than the book value of equity. Measuring firm fundamentals requires forecasting payouts into the distant future, which is difficult. Instead of measuring firm fundamentals directly, we examine two important determinants: total cash-flow distributions to stock investors

[18] Golubov and Konstantinidi (2019) decompose book-to-market into a market-to-value component and a value-to-book component, following Rhodes-Kropf, Robinson, and Viswanathan (2005), and find that the market-to-value component drives all of the value strategy return. We obtain data on the market-to-value factor (constructed in the usual way) from Golubov and Konstantinidi (2019). We use the authors' original data from July 1975 to June 2013. Their market-to-value factor has a mean monthly return of 0.376% ($t = 3.30$). In untabulated results, we also examine the relation between our *COP/P* factor and their market-to-value factor. Its correlation with the *COP/P* factor is 0.571. In spanning regressions, the *COP/P* factor explains the market-to-value factor, but not the other way around. The *COP/P* factor return has an alpha of 0.202% ($t = 2.46$) for a Fama-French five-factor model augmented with the market-to-value factor and the *COP/AT* factor. The market-to-value factor has an alpha of 0.027% ($t = 0.27$) for a model with the market factor, the size factor, and the *COP/P* factor.

(i.e., payouts) and the payout growth rate. In the Gordon growth model, payouts (PO), the payout growth rate (g), and current stock value (P) are sufficient statistics for calculating the discount rate (r):

$$\frac{Fundamental_{i,t}}{P_{i,t}} = \frac{PO_{i,t+1}}{P_{i,t}} \frac{1}{r-g}.$$

A more accurate value measure should be more positively correlated with *PO/P* and g. Following Boudoukh et al. (2007), we measure *PO* as dividends plus repurchases minus issuances.[19] The payout growth rate is calculated as $g_t = (PO_{t+5} - PO_t)/|PO_t|$. We find similar results when measuring payout growth over a 3-year window. Panel A of Figure 6 presents the annual cross-sectional correlation coefficients between *COP/P* (or book-to-market) and *PO/P*. Panel B of Figure 6 reports the correlation coefficients between *COP/P* (or book-to-market) and g_t. The analysis starts with 1971 data because earlier data on net equity purchases are not available.

As Figure 6 shows, relative to book-to-market, *COP/P* is more positively correlated with *PO/P* and g_t, and the difference is greater in the second half of the sample period than in the first half. Averaging across all sample years, Corr(*COP/P*, *PO/P*) is 0.204 (t = 15.63) and Corr(*COP/P*, book-to-market) is 0.035 (t = 2.65), and the difference is 0.169 (t = 7.58). Corr(*COP/P*, *PO/P*) is 0.151 (t = 9.71) and 0.235 (t = 14.33) before and after 1990, respectively. Corr(*COP/P*, book-to-market) is 0.100 (t = 4.49) and −0.003 (t = −0.23) before and after 1990, respectively. Before 1990, Corr(*COP/P*, *PO/P*) is marginally higher than Corr(*COP/P*, book-to-market), with a difference of 0.051 (t = 2.02). After 1990, the difference between Corr(*COP/P*, *PO/P*) and Corr(*COP/P*, book-to-market) increases to 0.238 (t = 9.50).

These findings are consistent with the conjecture that *COP* is a more accurate measure of fundamentals than the book value of equity. They also help to explain why the return-predictive power difference between *COP/P* and book-to-market is stronger in the second half of the sample period than in the first half. We also note that the correlation between book-to-market and *PO/P* is positive in the first half of the sample period but falls to zero afterward, potentially explaining why book-to-market fails to predict the cross-section of post-1990 stock returns.

2.9 Further analyses on *COP/P* and *COP/AT*

COP/P and *COP/AT* are positively correlated (see Table 1), but the *COP/P* and *COP/AT* factor returns are slightly negatively correlated (see Table 6). No theory predicts that factor returns constructed by correlated characteristics must be similarly correlated. As discussed by Christie (1987) and Ball et al. (2015), the

[19] *PO* = DVC + PRSTKC- SSTK + ΔPreferredStock. DVC is cash dividends; PRSTKC is purchase of common and preferred Stock; and SSTK is sale of common and preferred stock. ΔPreferredStock is the net issuance of preferred stocks. ΔPreferredStock is calculated as the increase in the book value of preferred stock. We calculate the book value of preferred stock following Fama and French (2008).

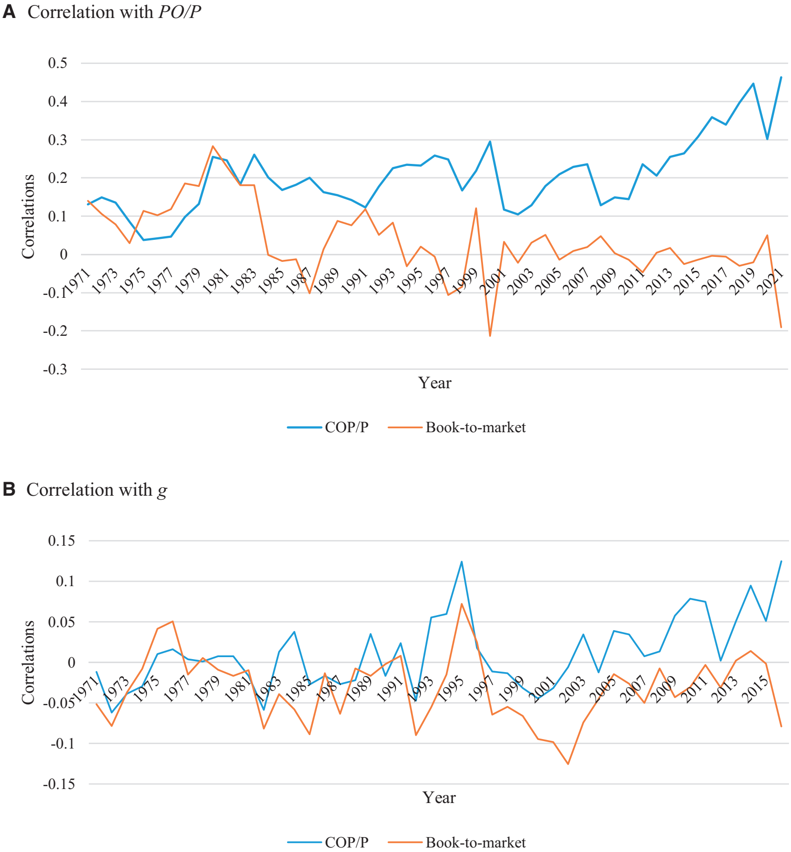


Figure 6
***COP/P* and book-to-market**
This figure plots the annual cross-sectional correlations between *COP/P* (book-to-market) and *PO/P* (panel A) and between *COP/P* (book-to-market) and *g* (panel B). *PO/P* is payouts divided by market capitalization. *g* is payout growth from year *t* to year *t* + 5.

economics of a return regression change when switching from one profit deflator to another. After all, *COP/P* is a value measure and *COP/AT* is a profitability measure. Nevertheless, we conduct analyses further to understand the relation between *COP/P* and *COP/AT*.

Our first test follows Ball et al. (2015). Specifically, we can rewrite *COP/P* as the product as *COP/AT* and *AT/ME*. It is possible that the return predictive power of *COP/P* can emanate from its individual components, *COP/AT* and *AT/ME*, and not from their product, per se. We use the Fama-MacBeth regression methodology to conduct this test. Table 4 shows that when included in the same regression, both *COP/AT* and *log*(*COP/P*) have independent return predictive power. However, in

Table 4, *COP/P* is measured as a natural logarithm, and *COP/AT* as a ratio. We treat both variables as ratios in the following tests to ensure that the different variable transformation does not drive the results.

Panel A of Table 7 reports the test results. Column 1 includes *COP/P*, *COP/AT*, and *AT/ME*, but no control variables. In columns 2 and 3, we add the control variables. In all three specifications, the coefficients of both *COP/P* and *COP/AT* are positive and statistically significant. The return predictive power of *COP/P* is at least comparable with *COP/AT*. In column 1, *COP/P* has a slightly higher coefficient. Even in the other two columns, when *COP/P* has a lower coefficient than *COP/AT*, one standard deviation change in *COP/P* is associated with a bigger change in expected returns than one standard deviation change in *COP/AT*, as *COP/P* is more than twice as volatile as *COP/AT* (see Table 1). These results show that the return predictive power of *COP/P* does not emanate from its two individual components, *COP/AT* and *AT/ME*. The product has additional return predictive power. If anything, *AT/ME* predicts returns with a negative sign. The finding that *COP/P* predicts returns after controlling for *COP/AT* and *AT/ME* can be interpreted as *COP/AT* and *AT/ME* having an interesting interactive effect on returns: the marginal effect of *COP/AT* on returns is an increasing function of *AT/ME*.

We conduct two additional tests to shed light on why *COP/P* and *COP/AT* are positively correlated, but the *COP/P* and *COP/AT* factor returns are negatively correlated. Panel B of Table 7 reports the average *COP/P* and *COP/AT* values for the six *COP/P*-size portfolios used to construct the *COP/P* factor. Among small firms, *COP/AT* increases from −0.009 to 0.193 as *COP/P* increases. However, among big firms, *COP/AT* changes little from the low-*COP/P* group to the high-*COP/P* group. This finding suggests that the correlation between *COP/P* and *COP/AT* depends on firm size.

In light of the findings from panel B of Table 7, in panel C, we report the correlations between the *COP/P* and *COP/AT* factor portfolios. The *COP/P* factor is the equal-weighted average of the high-*COP/P* minus low-*COP/P* portfolio for small stocks and the high-*COP/P* minus low-*COP/P* portfolio for big stocks. The *COP/P* portfolios are similarly defined. The results show that the two high-minus-low *COP/P* portfolios are strongly positively correlated, as are the two high-minus-low *COP/AT* portfolios. Among small stocks, the high-minus-low *COP/P* portfolio and the high-minus-low *COP/AT* portfolio are positively correlated, consistent with their positive correlation in panel A. However, among big stocks, when *COP/P* and *COP/AT* are uncorrelated, the high-minus-low *COP/P* portfolio and the high-minus-low *COP/AT* portfolio are negatively correlated. The cross correlations (between small firms' high-minus-low *COP/P* portfolio and big firms' high-minus-low *COP/AT* portfolio, and between big firms' high-minus-low *COP/P* portfolio and small firms' high-minus-low *COP/AT* portfolio) are also negative. These negative correlations contribute to the negative correlation between the *COP/P* and *COP/AT* factors that we see in Table 6.

Table 7
Further analyses of *COP/P* and *COP/AT*

A. Fama-MacBeth regressions

	(1)	(2)	(3)
COP/P	0.878	0.543	0.479
	(2.86)	(2.31)	(2.21)
COP/AT	0.870	1.030	0.855
	(3.41)	(4.46)	(3.81)
AT/ME	−0.038	−0.017	−0.004
	(−2.26)	(−1.16)	(−0.22)
Beta		−0.000	0.022
		(−0.00)	(0.25)
log(*ME*)		−0.078	−0.122
		(−2.42)	(−4.18)
log(*BM*)		0.072	0.068
		(1.26)	(1.28)
$R_{1,1}$			−3.137
			(−8.50)
$R_{12,2}$			0.710
			(5.63)
$R_{60,13}$			−0.041
			(−2.08)
ILLIQ			0.090
			(0.19)
IVOL			−0.192
			(−5.23)
Average R^2	.021	.057	.092

B. Characteristics of the six COP/P-size portfolios

Size groups	*COP/P* groups	*COP/P*	*COP/AT*
Small	Low	−0.028	−0.009
	Intermediate	0.183	0.184
	High	0.506	0.193
Big	Low	0.063	0.192
	Intermediate	0.179	0.212
	High	0.399	0.204

C. Correlations between the COP/P and COP/AT factor portfolios

	(1)	(2)	(3)	(4)	(5)	(6)
	Small *COP/P*	Big *COP/P*	*COP/P* factor	Small *COP/AT*	Big *COP/AT*	*COP/AT* factor
	Small firms' high-minus-low *COP/P* portfolio	Big firms' high-minus-low *COP/P* portfolio	= 0.5*(1) + 0.5*(2)	Small firms' high-minus-low *COP/AT* portfolio	Big firms' high-minus-low *COP/AT* portfolio	= 0.5*(4) + 0.5*(5)
Small *COP/P*	1					
Big *COP/P*	0.438	1				
COP/P factor	0.814	0.878	1			

(continued)

Table 7
Continued

C. Correlations between the COP/P and COP/AT factor portfolios

	(1)	(2)	(3)	(4)	(5)	(6)
Small *COP/AT*	0.099	−0.119	−0.024	1		
Big *COP/AT*	−0.049	−0.210	−0.162	0.407	1	
COP/AT factor	0.015	−0.204	−0.123	0.777	0.891	1

In this table we report the results of further analyses in which we compare *COP/P* and *COP/AT*. In panel A we report the average Fama-MacBeth regression slopes and their *t*-values from cross-sectional regressions that predict monthly returns (in percentages). *t*-statistics are reported in parentheses. The regressions are estimated monthly, using data running from July 1963 through December 2021. The sample consists of all but microcap firms with a positive book value of equity, nonmissing *COP/P*, and nonmissing *COP/AT*. *COP/P* is cash-based operating profitability divided by market capitalization, *COP/AT* is cash-based operating profitability divided by the book value of total assets, and *AT/ME* is the book value of total assets divided by the market value of equity. All accounting variables, including *COP/P* and *COP/AT*, are winsorized month by month at the 1% level in both tails. Table A1 of the appendix defines the variables. Panel B reports the average *COP/P* and *COP/AT* values of the six *COP/P*-size portfolios, and panel C reports the correlations between the *COP/P* and *COP/AT* factor portfolio returns. At the end of June in each sample year, stocks are allocated to one of two size groups (small or big) using NYSE market capitalization breakpoints. We then perform an independent sort of stocks into high (i.e., above the 70th NYSE percentile breakpoint), low (i.e., below the 30th NYSE percentile breakpoint), and intermediate portfolios based on *COP/P*. Small *COP/P* is the high-*COP/P* minus low-*COP/P* portfolio for the small-size group, and Big *COP/P* is the high-*COP/P* minus low-*COP/P* portfolio for the large-size group. The *COP/P* factor is the average of Small *COP/P* and Big *COP/P*, and Small *COP/AT*, Big *COP/AT*, and the *COP/AT* factor are constructed similarly. The sample period runs from July 1963 to December 2021.

Overall, the return predictive power of *COP/P* cannot be explained by its two individual components, *COP/AT* and *AT/ME*. The measure *COP/P* itself, as the product of these two individual components, has additional return predictive power. We also find that *COP/P* and *COP/AT* are almost uncorrelated among large-capitalization firms. The returns of portfolios constructed based on *COP/P* and *COP/AT* are not as strongly correlated as *COP/P* and *COP/AT* are correlated themselves, especially among large-capitalization firms. These results provide further evidence that *COP/P* and *COP/AT* are distinct return predictors.

3. Is the *COP/P* Effect Due to Risk or Mispricing?

3.1 Tests of risk-based explanations

The results so far show that standard models of risk have difficulty explaining the variation in the returns associated with the *COP/P* effect. We now examine whether the high-minus-low *COP/P* portfolio return is correlated with other macroeconomic factors and whether a conditional CAPM model can explain its return spread.

In panel A of Table 8, we regress the high-*COP/P* minus low-*COP/P* portfolio return on the five macroeconomic variables analyzed by Chen, Roll, and Ross (1986): the growth rate of industrial production (*MP*), unexpected inflation (*UI*), change in expected inflation (*DEI*), the default premium (*DEF*), and the term premium (*TERM*). The variables *MP*, *UI*, and *DEI* are defined following Liu and Zhang (2018) and the data are downloaded from Laura Liu's website

Table 8
Tests of risk-based explanations

A. Chen, Roll, and Ross (1986) test

	Equal-weighted		Value-weighted	
Intercept	1.391	1.032	1.177	0.751
	(3.55)	(3.19)	(2.45)	(1.93)
MP	0.125	0.104	0.154	0.092
	(0.60)	(0.61)	(0.61)	(0.45)
UI	−1.259	−0.857	0.565	0.315
	(−1.58)	(−1.29)	(0.58)	(0.39)
DEI	−0.756	−0.606	−2.653	−1.204
	(−0.37)	(−0.36)	(−1.07)	(−0.59)
DEF	−0.005	−0.005	−0.003	−0.002
	(−1.50)	(−1.64)	(−0.69)	(−0.67)
TERM	0.128	0.075	−0.000	0.048
	(1.07)	(0.76)	(−0.03)	(0.40)
MktRf		0.085		−0.027
		(2.79)		(−0.72)
SMB		−0.116		−0.318
		(−2.75)		(−6.28)
HML		0.351		0.336
		(5.98)		(4.75)
RMW		0.581		0.333
		(9.78)		(4.67)
CMA		0.396		0.672
		(4.52)		(6.37)
Adj. R^2	.007	.330	−.004	.348

B. Conditional CAPM

	Equal-weighted		Value-weighted	
Intercept	1.085	0.658	0.905	0.549
	(7.64)	(5.90)	(5.30)	(3.61)
MktRf	−0.393	0.243	−0.397	−0.016
	(−5.08)	(3.73)	(−3.47)	(−0.15)
*DY*MktRf*	24.554	−6.650	17.191	1.403
	(7.14)	(−1.23)	(3.34)	(0.29)
*DEF*MktRf*	−0.026	0.021	−0.272	−0.285
	(−0.48)	(0.51)	(−3.22)	(−3.88)
*TERM*MktRf*	−0.034	0.007	0.069	0.079
	(−1.51)	(0.42)	(2.04)	(2.68)
*TB*MktRf*	−0.098	0.000	−0.044	0.027
	(−7.58)	(0.00)	(−2.33)	(1.56)
SMB		−0.301		−0.319
		(−6.67)		(−5.97)
HML		0.477		0.521
		(8.01)		(7.30)
RMW		0.742		0.306
		(12.42)		(3.97)
CMA		0.119		0.450
		(1.37)		(4.20)
Adj. R^2	.165	.528	.106	.346

In this table we report the results of tests of risk-based explanations. Panel A reports results using the Chen, Roll, and Ross (1986) test, and panel B reports the results obtained with a conditional CAPM model. For panel A, we regress the high-*COP*/*P* minus low-*COP*/*P* portfolio returns (both equal-weighted and value-weighted) on the five macroeconomic variables analyzed by Chen, Roll, and Ross (1986): the growth rate of industrial production (*MP*), unexpected inflation (*UI*), change in expected inflation (*DEI*), the default premium (*DEF*), and the term premium (*TERM*). *MP*, *UI*, *and DEI* are defined following Liu and Zhang (2018) and data are downloaded from Laura Liu's website (http://lauraxiaoleiliu.gsm.pku.edu.cn/en-home.html). *DEF* is the yield spread between Baa- and Aaa-rated corporate bonds, and *TERM* is the yield spread between 10-year Treasury bonds and 3-month Treasury bills. For panel B, we estimate and report the results of the conditional CAPM model,

$$r_{t+1} = \alpha + (b_0 + b_1 DY_t + b_2 DEF_t + b_3 TERM_t + b_4 TB_t) r_{mkt,t+1} + b_{SMB} SMB_{t+1} + b_{HML} HML_{t+1} + b_{RMW} RMW_{t+1} + b_{CMA} CMA_{t+1} + \varepsilon_{t+1},$$

where r_{t+1} is the monthly high-*COP*/*P* minus low-*COP*/*P* portfolio return; $r_{mkt,t+1}$ is the excess return on the value-weighted CRSP market index; SMB_{t+1}, HML_{t+1}, RMW_{t+1}, and CMA_{t+1} are the other four Fama-French five factors; DY_t and TB_t are the dividend yield of the S&P 500 index and the yield of a Treasury bill with 3 months to maturity, respectively; and ε_t is an error term. The sample period runs from July 1963 to December 2021.

(http://lauraxiaoleiliu.gsm.pku.edu.cn/en-home.html). *DEF* is the yield spread between Baa- and Aaa-rated corporate bonds, and *TERM* is the yield spread between 10-year Treasury bonds and 3-month Treasury bills. The data for calculating *DEF* and *TERM* are obtained from the Federal Reserve. The results show that none of the coefficients for these five macroeconomic variables is statistically different from zero.[20]

In panel B of Table 8, we estimate and report the results of a conditional CAPM model:

$$\begin{aligned} r_{t+1} = \alpha &+ (b_0 + b_1 DY_t + b_2 DEF_t + b_3 TERM_t + b_4 TB_t) r_{mkt,t+1} \\ &+ b_{SMB} SMB_{t+1} + b_{HML} HML_{t+1} + b_{RMW} RMW_{t+1} + b_{CMA} CMA_{t+1} \\ &+ \varepsilon_{t+1}, \end{aligned} \tag{1}$$

where r_{t+1} is the monthly high-*COP*/*P* minus low-*COP*/*P* portfolio return; $r_{mkt,t+1}$ is the excess return of the value-weighted CRSP market index; SMB_{t+1}, HML_{t+1}, RMW_{t+1}, and CMA_{t+1} are the other four factors in the Fama-French five-factor model; DY_t and TB_t are the dividend yields of the S&P 500 index and of a Treasury bill with 3 months to maturity; ε_t is an error term; and α, b_1, b_2, b_3, and b_4 are parameters that we estimate. The data for *DY* are from Robert Shiller's website (http://www.econ.yale.edu/~shiller/). If the conditional CAPM can explain the *COP*/*P* effect, then the estimated alpha should be indistinguishable from zero.

We report the results for four model specifications. Specifically, we estimate Equation (1) with and without the other four Fama-French factors and separately for the equal-weighted and value-weighted high-*COP*/*P* minus low-*COP*/*P* portfolio. We find that the alphas from the regressions are all significantly positive. The lowest *t*-value is 3.61. The parameter b_1 is significantly positive in columns 1 and 3, suggesting that the high-minus-low *COP*/*P* portfolio return is more sensitive to the market return when the beginning period dividend yield is higher. The parameter b_4 is significantly negative in columns 1 and 3, suggesting that the high-minus-low portfolio return is less sensitive to the market return when the beginning period 3-month Treasury rate is higher. However, both become insignificant in columns 2 and 4. The parameter b_2 is significantly negative for the value-weighted portfolio, suggesting that the high-minus-low portfolio return is less sensitive to the market return when the beginning period term spread is higher. The parameter b_2 becomes insignificant for the equal-weighted portfolios. These results suggest that time-varying risk from a conditional CAPM model does not explain the *COP*/*P* effect.

3.2 Tests of mispricing-based explanations

We examine whether our results are consistent with the mispricing arguments. Investors could harbor mistaken beliefs about firms whose valuations differ (Lakonishok, Shleifer, and Vishny 1994) and be surprised by the subsequent earnings realizations (La Porta et al. 1997).

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[20] The intercept from the regressions in panel A of Table 8 cannot be explained as abnormal returns because the macroeconomic factors are not traded factors.

To test the relationship between subsequent earnings performance and stock return reactions, we examine earnings surprises and stock returns around earnings announcements following portfolio formation. This is a common method with which to examine whether anomalies result from biased expectations (Chopra, Lakonishok, and Ritter 1992; Sloan 1996; La Porta et al. 1997; Engelberg, McLean, and Pontiff 2018; Wang, 2019). If the COP/P effect is driven by biased expectations, we expect high-*COP/P* firms to experience larger earnings surprises than low-*COP/P* firms. If the *COP/P* effect is explained by risk, we predict that the mean returns on earnings announcement days (EADs) should be similar to the mean returns on non-EADs. If mispricing is the explanation, the prediction is that, for high-*COP*/*P* (low-*COP*/*P*) firms, the EAD returns will tend to be higher (lower) than the non-EAD returns because investors are surprised by the subsequent unanticipated good (bad) news.

We define earnings surprises (SUE) following Livnat and Mendenhall (2006). Specifically, SUE is calculated as the difference between actual earnings per share (EPS) and analysts' EPS forecasts divided by lagged quarter-end stock prices. Considering only the most recent forecast for each analyst, our measure of analysts' EPS forecasts is the median of forecasts reported to the Institutional Brokers' Estimation System (I/B/E/S) in the 90 days prior to an earnings announcement. To reduce noise caused by small SUE deflators, we exclude stocks priced below \$5 as of the end of the preceding quarter.

We define cumulative abnormal returns (CARs) as size decile-adjusted returns in the three days around an announcement ($t-1$, $t+1$). The size decile portfolio returns are taken directly from CRSP. We obtain EADs from quarterly Compustat and I/B/E/S. Following DellaVigna and Pollet (2009), we keep the earlier of the two dates when the dates from Compustat and I/B/E/S are not in accordance. We show results for the entire sample period from 1983 through 2021.

Figure 7 presents the average SUE (panel A) and CARs (panel B) for each *COP*/*P* decile. The solid lines represent the averages and the dotted lines track 95% confidence intervals. We first calculate the mean SUE (CARs) for each *COP*/*P* decile for each of the 154 quarters in our sample and then calculate the quarterly means' averages and t-values (hence also the confidence intervals). We follow the same convention in matching CARs with accounting data (Fama and French 1992). It is obvious that earnings surprises and announcement returns are higher for deciles with higher *COP*/*P* stocks. The average SUE is -0.292% ($t=-5.31$) for the lowest *COP*/*P* decile and -0.098% ($t=-2.47$) for the highest *COP*/*P* decile. The difference is 0.194% ($t=4.19$). Such a difference is economically sizable. For example, for a stock priced at \$30, a 0.194% difference in SUE translates to a \$0.058 difference in EPS.

The average CAR is -0.257% ($t=-2.18$) for the lowest *COP*/*P* decile and 0.963% ($t=7.09$) for the highest *COP*/*P* decile, with a difference of

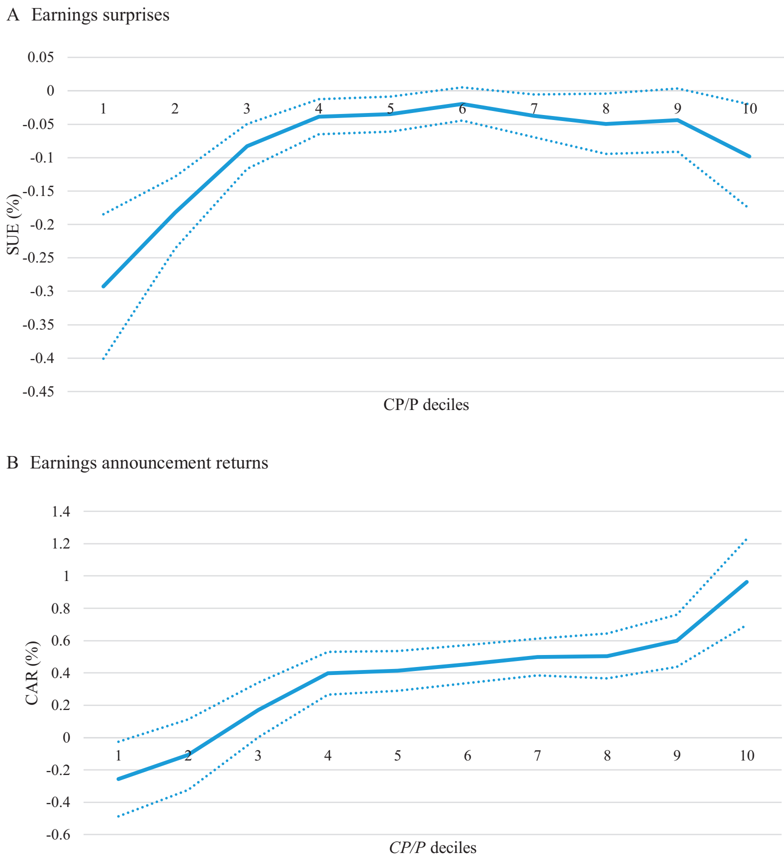

Figure 7
Earnings surprises and earnings announcement returns
This figure plots standardized earnings surprises (SUE) and the three-day size decile portfolio–adjusted cumulative abnormal returns (CARs) around earnings announcement days for stocks in *COP/P* decile portfolios. *COP/P* is cash-based operating profitability divided by market capitalization. The *x*-axis represents *COP/P* decile portfolios, and the *y*-axis represents SUE or CARs in percentages. SUE and CARs are first calculated for each quarter and then averaged across quarters. The sample period runs from July 1983 through December 2021.

1.220% (t = 9.11).[21] The return spread between the lowest and highest *COP/P* deciles, as reported in Table 2, is about 1% per month. On average, earnings announcements occur four times a year. This indicates that roughly 30%–40% of the abnormal returns on the long-short trading strategy are realized around EADs. This result is consistent with Engelberg, McLean, and Pontiff (2018),

[21] For most deciles, earnings surprises are negative, and earnings announcement returns are positive. The former is consistent with the widely documented finding that analysts tend to give optimistic forecasts. The latter is consistent with the earnings announcement premium in the literature (Beaver 1968; Ball and Kothari 1991; Barber et al. 2013).

who study 97 stock market anomalies and find that, relative to returns around non-EADs, daily anomaly returns are much higher around EADs. These results are consistent with the mispricing explanation, according to which investors' expectations of future earnings are systematically biased.

3.3 Limits to arbitrage

The evidence shows that the *COP/P* effect is mostly consistent with mispricing. Thus, we should expect the return spread to be the largest (mispricing to be the greatest) for those stocks that are the most difficult to arbitrage (Pontiff 1996; Shleifer and Vishny 1997). Evidence consistent with limits to arbitrage has been documented for the book-to-market effect (Griffin and Lemmon 2002; Ali, Hwang, and Trombley 2003; Nagel 2005). The findings in Table 5 show that the *COP/P* effect is stronger for small firms than for large firms, consistent with the limits to arbitrage. We now explore how the *COP/P* effect varies with other measures of limits to arbitrage.

We investigate two additional limits to arbitrage measures: idiosyncratic volatility (*IVOL*) and illiquidity (*ILLIQ*). Both are widely used limits to arbitrage proxies (e.g., Barberis, Mukherjee, and Wang, 2016). We first sort all the stocks into five quintiles based on a limits-to-arbitrage measure, and then, within each quintile, we further sort stocks into *COP/P* quintiles. We calculate the Fama-French three-factor alphas for each of these 25 portfolios, and for each *IVOL* (or *ILLIQ*) quintile, the alpha of the high-*COP/P* minus low-*COP/P* portfolio. We also calculate the alpha of the difference in the high-*COP/P* minus low-*COP/P* portfolios between the more arbitrage-constrained (high-*ILLIQ* or high-*IVOL*) and less arbitrage-constrained (low-*ILLIQ* or low-*IVOL*) quintiles.

The results in Table 9 show that the alphas of the high-*COP/P* minus low-*COP/P* portfolio are always positive and statistically significant, except in the lowest *IVOL* quintile. This confirms the finding in Table 5 that the *COP/P* effect exists among the largest and most liquid firms. The alpha of the high-*COP/P* minus low-*COP/P* portfolio also increases when *IVOL* (or *ILLIQ*) increases. The differences in the high-*COP/P* minus low-*COP/P* portfolio alphas between the lowest and highest *IVOL* quintiles are 0.514% ($t = 2.48$) and 1.452% ($t = 4.73$) for the equal-weighted and value-weighted portfolios, respectively. The differences between the lowest and highest *ILLIQ* quintiles are 0.656% ($t = 3.26$) and 0.883% ($t = 4.58$) for the equal-weighted and value-weighted portfolios, respectively. Overall, the results in Table 9 strongly support limits to arbitrage.

3.4 Discussion

The results show that the high-*COP/P* firms' earnings announcements are associated with significantly higher returns than those of the low-*COP/P* firms. The *COP/P* effect is also stronger among stocks that are smaller, less liquid, or more volatile, consistent with limits to arbitrage. These two tests are consistent with a mispricing interpretation of the *COP/P* effect. We also find that the *COP/P* effect

Table 9
Limits to arbitrage

	IVOL						ILLIQ					
	Low 1	2	3	4	High 5	High-minus-Low	Low 1	2	3	4	High 5	High-minus-Low
A. Equal-weighted alphas												
Low *IVOL*	−0.086	0.207	0.236	0.198	0.206	0.291	0.010	0.275	0.152	0.194	0.116	0.106
/*ILLIQ*	(−1.08)	(3.23)	(3.78)	(3.15)	(3.05)	(3.64)	(0.10)	(4.66)	(2.63)	(3.35)	(1.49)	(0.92)
2	−0.020	0.252	0.300	0.309	0.354	0.374	−0.326	0.121	0.249	0.173	0.228	0.554
	(−0.29)	(4.06)	(4.65)	(4.87)	(5.10)	(4.32)	(−3.38)	(1.61)	(3.35)	(2.28)	(2.41)	(4.71)
3	−0.187	0.167	0.271	0.274	0.384	0.571	−0.617	−0.135	0.017	0.130	−0.007	0.610
	(−2.45)	(2.42)	(3.95)	(3.79)	(4.97)	(5.63)	(−5.87)	(−1.51)	(0.22)	(1.67)	(−0.07)	(4.70)
4	−0.433	−0.219	0.029	0.110	0.275	0.709	−0.961	−0.393	0.009	0.071	0.006	0.966
	(−4.44)	(−2.50)	(0.36)	(1.45)	(3.01)	(5.76)	(−7.58)	(−3.98)	(0.11)	(0.88)	(0.06)	(6.63)
High *IVOL*	−0.978	−0.825	−0.485	−0.252	−0.220	0.758	−0.383	−0.093	−0.053	0.190	0.379	0.762
/*ILLIQ*	(−5.41)	(−5.45)	(−3.90)	(−2.00)	(−1.50)	(3.96)	(−2.33)	(−0.69)	(−0.54)	(1.92)	(3.26)	(4.49)
High − Low						0.514						0.656
						(2.48)						(3.26)
B. Value-weighted alphas												
Low *IVOL*	0.071	0.201	0.154	0.164	0.122	0.051	−0.110	0.153	0.061	0.163	0.102	0.212
/*ILLIQ*	(0.78)	(2.79)	(2.06)	(1.99)	(1.34)	(0.38)	(−1.35)	(2.56)	(1.10)	(2.46)	(1.25)	(1.68)
2	−0.154	0.089	0.151	0.149	0.158	0.313	−0.633	−0.132	0.014	0.106	0.117	0.750
	(−1.45)	(1.02)	(1.78)	(1.59)	(1.53)	(2.14)	(−6.13)	(−1.83)	(0.21)	(1.57)	(1.49)	(5.96)
3	−0.372	−0.043	0.043	0.121	0.187	0.559	−0.808	−0.384	−0.066	0.062	0.006	0.815
	(−2.45)	(−0.35)	(0.41)	(1.00)	(1.42)	(2.86)	(−6.67)	(−3.91)	(−0.87)	(0.93)	(0.07)	(6.00)
4	−0.719	−0.677	−0.216	−0.225	0.139	0.858	−1.052	−0.584	−0.034	0.017	0.119	1.172
	(−4.38)	(−4.28)	(−1.57)	(−1.73)	(0.85)	(4.16)	(−7.02)	(−4.92)	(−0.40)	(0.19)	(1.17)	(7.78)
High *IVOL*	−1.719	−1.533	−1.129	−0.734	−0.216	1.503	−0.975	−0.693	−0.270	−0.037	0.121	1.096
/*ILLIQ*	(−6.73)	(−6.50)	(−5.36)	(−3.97)	(−0.83)	(5.37)	(−5.26)	(−4.25)	(−2.09)	(−0.32)	(0.90)	(6.82)
High − Low						1.452						0.883
						(4.73)						(4.58)

In this table we report the results for limits to arbitrage. Based on each limits-to-arbitrage measure (*IVOL* or *ILLIQ*), we sort all the stocks into five quintiles. Then, within each quintile, we further sort stocks into quintiles based on *COP/P*, where *COP/P* is cash-based operating profitability divided by market capitalization. We calculate the Fama-French three-factor alphas (monthly percentage) on both an equal-weighted and value-weighted basis for each of the 25 portfolios, and the alphas of the high-*COP/P* minus low-*COP/P* portfolio for each *IVOL* (*ILLIQ*) quintile. We also report the differences in the high-minus-low portfolio between the two extreme *IVOL* (*ILLIQ*) quintiles. The sample period runs from July 1963 to December 2021.

predicts returns for at least 5 years after the data of the portfolio formation (Figure 4). Although this result is not necessarily inconsistent with mispricing, as argued by Ball et al. (2015), it is difficult to explain by mispricing because the effects of limits to arbitrage and other trading frictions are unlikely to persist for this long. Although we do not find direct evidence to support the risk-based interpretation, the results do not rule out the possibility that some risks can also contribute to the *COP*/*P* return spread. We acknowledge that differentiating between rational and irrational pricing explanations is notoriously difficult (Fama 1998b). Therefore, we caution that these results do not conclusively exclude one interpretation or the other.

4. Conclusions

Motivated by the finding of Ball et al. (2016) that cash-based operating profitability (*COP*)—operating profitability adjusted by the noncash component of earnings—is a better profitability measure than other common profitability measures for predicting stock returns, this paper investigates the asset pricing implications of a new value measure, the ratio of *COP*-to-price, or *COP*/*P*. If *COP* is a better measure of economic profitability than others, we expect *COP*/*P* to work better than existing value measures. We find that high-*COP*/*P* firms earn higher returns than low-*COP*/*P* firms do. A long-short portfolio that buys the stocks in the highest *COP*/*P* decile and shorts the stocks in the lowest *COP*/*P* decile earns monthly returns of 1.043% on an equal-weighted basis and 0.779% on a value-weighted basis. Standard asset pricing models cannot explain the return spread, and *COP*/*P* is distinct from other known return predictors, including *COP* deflated by the book value of total assets.

Book-to-market fails to predict returns in the post-1990 period (Asness et al. 2015; Lev and Srivastava 2019). The same conclusion holds for most of the existing value measures. Our evidence shows that the value strategy based on *COP*/*P* is alive and well even in recent decades.

The value strategy has been widely discussed by academicians and industry practitioners (Graham and Dodd 1934; Fama and French 1992, 1993). Several value measures have been analyzed (Basu 1977; Jaffe, Keim, and Westerfield 1989; Chan, Hamao, and Lakonishok 1991; Fama and French 1992; Ball et al. 2020; Golubov and Konstantinidi 2019). In both Fama-MacBeth regressions and portfolio analysis, *COP*/*P* subsumes several widely used value measures, including the book-to-market ratio of Fama and French (1992) and the retained earnings-to-market ratio of Ball et al. (2020). The *COP/P* factor also subsumes the investment factor of Fama and French (2015). Fama and French (2015) find the HML factor is redundant in their five-factor model. We find that our *COP*/*P* factor subsumes both their value factor and investment factor. Hence, value is not "redundant."

Appendix

Table A1
Variable definitions

Variable	Description
COP/P	Cash-based operating profitability (*COP*) divided by year-end market capitalization: *COP* = REVT − COGS − (XSGA − XRD) − ΔRECT − ΔINVT − ΔXPP + Δ(DRC + DRLT) + ΔAP + ΔXACC, following Ball et al. (2016). REVT is revenue; COGS is cos of goods sold; XSGA is sales, general, and administrative expenses; XRD is research and development expenses; RECT is accounts receivable; INVT is inventories; XPP is prepaid expenses; DRC is current deferred revenue; DRLT is long-term deferred revenue; AP is accounts payable; and XACC is accrued expenses
Beta	Following Fama and French (1992), we estimate betas from the past 5 years of monthly data, with the requirement that at least 24 months of data be available
log(*BM*)	The ratio of the total book value of equity to total market capitalization, as a natural logarithm. Book value is measured following Fama and French (2008)
log(*ME*)	Market capitalization at the end of last month, measured as a natural logarithm.
$R_{1,1}$	Short-term reversal, returns in month $t-1$
$R_{12,2}$	Buy-and-hold returns from month $t-12$ to month $t-2$
$R_{60,13}$	Long-term reversal, buy-and-hold returns from month $t-60$ to month $t-13$
ILLIQ	Illiquidity measure of Amihud (2002), based on daily data over month $t-1$
IVOL	Idiosyncratic volatility of Ang et al. (2006)
AG	$(AT_t - AT_{t-1})/AT_{t-1}$, following Cooper, Gulen, and Schill (2008). AT is total value of book assets.
D/P	Total dividends paid from July of year $t-1$ to June of year t per dollar of equity in June of year t.
E/P	Earnings divided by market capitalization, where earnings = IB. IB is income before extraordinary items
CF/P	Cash flow divided by market capitalization, where cash flow = IB + DP + TXDB. IB is income before extraordinary items; DP is depreciation and amortization; and TXDB is deferred taxes
IEM	Inverse enterprise multiple = (OIBDP/(ME + DLC + DLTT + PSTKRV − CHE)), where OIBDP is operating income before depreciation; ME is market value of equity; DLC is debt in current liabilities – total; DLTT is long-term debt – total; PSTKRV is preferred stock value; and CHE is cash and short-term investments
S/P	Sales-to-price ratio = REVT/ME. REVT is total sales; ME is market capitalization
RE/P	Retained earnings divided by market capitalization, where retained earnings = RE − ACOMINC. RE is retained earnings; ACOMINC is accumulated other comprehensive income (loss)
COP/AT	Cash-based operating profitability divided by the lagged book value of total assets
PO	*PO* = DVC + PRSTKC − SSTK + ΔPreferredStock. DVC is cash dividends; PRSTKC is purchase of common and preferred Stock; SSTK is sale of common and preferred stock. ΔPreferredStock is the net issuance of preferred stocks. ΔPreferredStock is calculated as the increase in the book value of preferred stock. We calculate the book value of preferred stock following Fama and French (2008)

This table defines the main variables used in the paper, along with their Compustat acronyms.

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