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Cash flow growth and stock returns

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Abstract

I extend the financial economic literature by presenting and testing a model that expresses a firm's expected stock return as a function of its expected free cash flow growth. Results suggest that cash flow growth is positively associated with stock returns. Furthermore, additional information is reflected through cash flow growth relative to cash flow, profits, and dividends. Evidence additionally suggests that operating activities explain more than investment activities of the firm. I find that \$1 invested in the long–short cash flow growth portfolio grows to \$15.30 over the sample period, whereas \$1 invested in the stock market grows to \$9.85.

JEL CLASSIFICATION
G12, G32

1 | INTRODUCTION

The most that owners in aggregate can earn between now and Judgment Day is what their businesses in aggregate earn.

(Warren Buffett, Chairman's Letter, February 2006)

How does a firm's activities affect its stock price? Historically, the dividend growth model has been used to connect a firm's value-generating capabilities to its share price. This model has also been used to show that a firm's profits are a measure of its value through the accounting association with dividends and profits. However, there are serious problems with using either dividends or profits as the variable proxying for a firm's value, and I propose that cash flow growth (CFG) is a better measure of how a firm creates value. I extend the financial economic literature by proposing and empirically testing a model in which expected returns are driven by the expected CFG (ECFG) of a firm.

Research on asset pricing has focused on the consumption, or demand, side of the economy, as noted by Hou et al. (2015). The theoretical and empirical models, such as the capital asset pricing model and the Fama–French factor model, offer evidence of the consumption factors embedded in security prices. The consumption side of security pricing generally takes the risk preferences of investors, those "consuming" the security, and links these preferences to the riskiness of the security to estimate the risk premium needed to price the security. However, for something to be consumed, it must first be produced. Therefore, it is important to also study the production factors embedded in security prices.

Research on the production side of security prices usually focuses on how firm characteristics affect value in stock returns using the level of dividends or profits. However, there are issues with using dividend and profits to capture value added to shareholders. Although correlated to adding value, dividends do not necessarily reflect value being generated by the firm. Harris et al. (2020) find evidence that firms pay dividends even when the firms are not generating cash flows to support the dividends. Dividends may be funded through raising external capital or selling assets. Alternatively, dividends may be cut to internally fund value-adding projects. Therefore, an increase (decrease) in dividends may not reflect value created (destroyed) in a given period. For example, Olson and McFarlane (2019) report that despite a fall in profits and lower future oil demand, firms in the oil industry have been relying on asset sales to fund payouts to shareholders. These payouts do not reflect management's strong belief in the firm's future cash flow prospects but rather management's capacity to sell assets in place. In his 2006 letter to shareholders, Warren Buffett defines intrinsic value as "the discounted value of cash that can be taken out of a business in its remaining life." Value is not how much a firm pays out to its shareholders in a given period; it is how much cash shareholders may claim as their own over time that matters. This further demonstrates the limitations of dividends as a proxy for shareholder value creation. Additionally, increasingly fewer firms pay dividends (DeAngelo et al., 2004; Fama & French, 2001; Hoberg & Prabhala, 2009); therefore, dividend-reliant valuation models are increasingly inapplicable.

Profits are another measure that the financial literature has used as a proxy of shareholder value. However, profits are a pure accounting measure that do not entirely capture value added to shareholders and are prone to manipulation (Bernstein, 1993; Markham, 2006; Novy-Marx, 2013; Sloan, 1996). Fama and French (2008) note that the factors prevalent in stock pricing are all rough proxies for expected cash flows of a firm, which indicates that direct measures of cash flow may be more appropriate than using proxies. Evidence presented by Foerster et al. (2017) additionally suggests that cash flows offer empirically better explanatory power in stock returns relative to profits. In contrast to Foerster et al., who focus on cash flow levels, I focus on CFG.[1] As discussed later, I study the association between CFG and returns because CFG offers information beyond that offered by the level of cash flows, which has been examined in the literature.

In addition to the problems associated with using dividends and profits to predict returns, there is a problem in interpreting the relation between these variables and returns. Using the level of a variable ignores the scale in the differences between firms. This is why returns, rather than the price level, are typically used in economic settings so that variables may be better compared and analyzed. Furthermore, as shown in this article, it is the growth in expected cash flows that generates the change in expected returns. However, research studying the relation between stock returns and profitability or dividends typically uses the profit or dividend level, often scaled by sales, assets, or stock price, to capture profitability.[2] Although scaling by sales or assets may make the profit or dividend measure more comparable, these scalars introduce another dimension of variability in the empirical proxy of profitability. Therefore, these scaled variables capture information not necessarily related to a firm's cash production. Furthermore, firms may have comparable cash flows relative to their size; however, this does not mean that these firms will generate similar levels of CFG. Consider the growth potential of large versus small firms.

[1]In this case, CFG refers to all types of cash flow growth: realized, expected, and unexpected.

[2]Several other studies have examined the relation between a variable's growth and stock returns, such as sales growth (Lakonishok et al., 1994) and capital expenditure growth (Anderson & Garcia-Feijóo, 2006) and stock returns.

Large and small firms may have similar cash flows controlling for size; however, controlling for size does not change the fact that small and large firms have different investment opportunities, which translates into the potential CFG a firm may earn.

Although research has not studied the association between CFG and stock returns, several studies have investigated how profitability and cash flow levels are associated with stock returns. Fama and French (2006, 2016), Novy-Marx (2013), and Hou et al. (2015) find that profitability is significantly related to stock returns. Bernstein (1993) notes that cash flows, rather than profits, are a more direct measure of value added to shareholders and are therefore more relevant to shareholder consideration. Lakonishok et al. (1994) and Hou et al. (2011) present evidence suggesting that cash flow to price explains a significant amount of return variation. However, they find that negative cash flows do not earn commensurately negative returns. Similarly, Fama and French (2008) find that unprofitable firms do not earn lower returns. Additionally, Foerster et al. (2017) find evidence suggesting there is more information in free cash flow (FCF) than in profits and operating cash flow (OCF). I extend their research by investigating the association between CFG and returns by developing a model that shows that ECFG is positively related to expected stock returns, and I find that the model is empirically supported. Additionally, contrary to Hou et al. (2011) and Fama and French (2008), I find that firms with negative cash flows earn lower returns when controlling for factors that studies have found to explain stock returns. Furthermore, the results I present extend the findings of Foerster et al. by suggesting that the reason for FCF providing explanatory power above profits is that FCF reflects both the operating performance and investing activities of the firm.

The contribution of this article is threefold. First, by focusing on the production side of the firm, I develop a model that shows ECFG is a significant factor in determining stock returns. The intuition of the model I develop—that expected stock returns are positively related to the firm's ECFG—is conceptually similar to the dividend growth model. Based on the arguments presented earlier, my model is an alternative that is principally sounder than a dividend-reliant model because it relies on FCF rather than dividends. This model supports previously established financial theory stating that a stock's price should reflect the value generated by the firm and extends this theory to show that growth in expected cash flow streams generated by the firm lead to changes in the stock price. My model additionally supports the findings of prior studies, which find a positive association between stock returns and profitability and cash flow measures. My article extends these empirical studies by testing the growth in FCF rather than the level of FCF. As shown later, although the level of FCF is correlated to the growth of FCF, there are differences between the two variables, which suggests they capture different information.

Second, cross-sectional and time-series regressions suggest that monthly and annual stock returns are significantly and positively related to a firm's CFG. These results are robust over time, between size classifications, across industries, and to the inclusion of other value measures that other studies have found to be significant in explaining stock returns. Furthermore, I find that when jointly controlling for ECFG and unexpected CFG (UCFG), ECFG has an economically and statistically higher association to stock returns. Fama–French regressions further confirm the cross-sectional results, and I find that alpha increases across CFG quintile sorts. Additionally, I find evidence that the significance of CFG lies in CFG reflecting both operating CFG (OCFG) and investing CFG (ICFG). The literature (Beneish et al., 2001; Foerster et al., 2017; Novy-Marx, 2013; Richardson et al., 2005) has separately suggested OCF and investing cash flow (ICF) have information pertaining to stock returns because these variables reflect the firm's operating performance and the exercise of real options, respectively. I find evidence that both OCFG and ICFG are significant factors in determining stock returns, and both of these measures are components of CFG, but OCFG is relatively more significant than ICFG.

Third, results suggest that investors can earn significantly higher returns by investing in firms with high CFG and shorting firms with low CFG. Equal- (value-) weighted Fama–French three-factor portfolios suggest the top quintile of realized CFG (RCFG) firms earn 0.95% (0.38%) per month. However, equal- (value-) weighted Fama–French three-factor portfolios suggest the bottom quintile of RCFG firms earn –0.06% (–0.43%) per month. This suggests portfolios that are long in the highest RCFG quintile and short in the lowest quintile may earn an alpha of 1.01% per month when estimated with equal-weighted returns and 0.81% per month when estimated with value-weighted returns. Over the 1988–2019 sample period, $1 invested in a value-weighted stock market portfolio grows to $9.85, whereas $1 in a value-weighted long–short RCFG portfolio grows to $15.30. Although the long–short RCFG portfolio earns higher returns and has lower volatility than the broader market, investing solely in the high RCFG portfolio results in growing $1–$42.29 over the sample period. However, the long RCFG portfolio is more volatile than the long–short RCFG portfolio.

2 | PRIOR RESEARCH

Although most of the research studying returns focuses on the investor side of the return process, as noted by Hou et al. (2015), the supply-side contribution to the firm's return dates to the nascent era of finance being established as its own field of study. Williams (1938) suggests that the price of an asset reflects its intrinsic value. Graham (1949) famously notes that the stock market is a voting machine in the short run but a weighing machine in the long run, where the weight is the intrinsic value of the firm. Gordon and Shapiro (1956) and Gordon (1959) express the stock price through the dividend discount model. Campbell and Shiller (1988a, 1988b) find that dividends and the dividend–price ratio can partially explain stock returns. In addition, they find that the long-run averages of real earnings can forecast future dividends, which allows for an estimate of a stock's price.

However, there are several issues with using dividends to capture firm value. Black (1976) discusses how the nature of dividends is elusive. It is not clear why firms pay dividends and why investors should demand dividends when there are other channels through which firms may distribute value to shareholders and other ways for shareholders to capitalize on their investment. Fama and French (2001), DeAngelo et al. (2004), and Hoberg and Prabhala (2009) find a significant reduction in the number of firms that pay dividends, although each study cites a different reason for the reduction. This suggests that between the unclear nature of dividends and the reduction in the number of firms paying dividends, models that rely on dividends as the source of value may not be capturing an accurate value of the firm and are increasingly inapplicable to publicly listed firms. Additionally, Harris et al. (2020) find evidence that firms pay dividends even when they do not have enough cash flow to pay for the dividends.

There is much debate between the accounting and finance literatures on the appropriate way to measure value to shareholders. The accounting literature typically argues that accrual measures of earnings best reflect shareholder value (Beneish et al., 2001; Dechow, 1994; Ohlson & Bilinski, 2014; Richardson et al., 2005, 2010). In contrast, the finance literature typically argues that cash flow measures of earnings best reflect shareholder value (Bernstein, 1993; Bowen et al., 1987; Foerster et al., 2017). Cash flow measures actual cash receipts and expenses at the time the change in cash takes place. In other words, cash flow reflects tangible changes in firm value. This is important to avoid dealing with manipulated earnings estimates in financial statements and earnings recorded on an accrual basis as opposed to a realized basis. Although there is mixed empirical evidence over the informational content of cash flows versus accruals, I use cash flows because of the theoretical soundness of cash flows over accrual methods of measuring earnings as argued throughout the financial economic literature.

Novy-Marx (2013) finds evidence that gross profitability, proxying for value, is a highly significant factor of monthly stock returns. He contends that “gross profits is the cleanest accounting measure of true economic profitability. The farther down the income statement one goes, the more polluted profitability measures become, and the less related they are to true economic profitability” (p. 2). Fama and French (2006, 2016) and Hou et al. (2015) also find that profitability is significantly related to stock returns. However, Bernstein (1993) notes that profits are an accounting item and are more prone to manipulation. Furthermore, he finds that although earnings disseminate some information to shareholders, they do not fully reflect the financial standing of the company. The veracity of earnings depends on how much of the earnings are based on cash flows or accruals. Cash flows are a better indicator of financial standing and are not as easily manipulated as accruals.

Several papers have evaluated the role of a firm's cash flows in a firm's stock returns. Sloan (1996) finds that stock markets underreact to the cash flow component of earnings and that investors can earn returns using the underreaction to cash flow. Vuolteenaho (2002) finds that firm-level stock returns are primarily driven by a positive relation with cash flow news, proxied by return on equity. Celiker et al. (2016) similarly find that cash flow news is positively associated with price momentum. Cohen et al. (2003) find that the dispersion of the "value spread" in the book-to-market ratio is largely driven by expected 15-year profitability. Hou et al. (2011) find that cash flow to price explains a significant amount of the return variation in an international setting. However, they capture cash flow using only non-negative values of cash flow levels in the time-series tests and include positive cash flows as a continuous variable. They designate negative cash flows as an indicator variable in cross-sectional tests. Contrary to Hou et al.'s (2011) finding, Eisdorfer (2007) finds evidence that cash flow news is the most important driver of stock returns in financially distressed firms. Similar to the conclusions of Eisdorfer, I find that negative CFG is informative and yields a commensurate negative return as would be expected with poor CFG when controlling for other factors. Foerster et al. (2017) show that cash flow measures are more informative and are better predictors of stock returns than profit measures and that FCF is more informative than OCF, although they do not provide evidence as to why.

Although research agrees that value is pertinent to a firm's stock price, how exactly that value is measured is debatable. Research has shown that (1) dividends are a decreasingly used method to distribute earnings to shareholders and dividends are therefore a decreasingly useful valuation metric; (2) profit is an inferior value metric relative to cash flow; (3) although studies have found FCF has incremental explanatory power over profits in explaining stock returns, they have not found why this is the case; and (4) scaling matters when determining what valuation metric to use to estimate a firm's stock return. Studies have not examined how CFG, rather than the level of FCF, is associated with stock returns. I extend the literature by examining how CFG is related to stock returns. Additionally, I present empirical evidence that the reason there is more information in FCF than in profits is that FCF captures the information contained in both OCF and ICF, each of which has been found to reflect significant components of firm value.

3 | THE MODEL

3.1 | Model motivation

Research has focused on inferring the expected return of a security by tying the risk preferences of investors to the riskiness of the security. A problem with models developed using this method is that they usually ignore the production aspects of a firm. I correct for this by focusing on how a change in the firm's expected cash flows affects the firm's stock price, rather than focusing on how investors' risk profiles affect the price.

The market value of a firm is based on the discounted expected future cash flows generated by the firm. If the price is based on expected cash flows, it stands to reason that changes in price, or returns, should be based on changes in expected cash flow streams. To provide an example that helps motivate the need for the model expressed later, I assume that the discount factor is fixed. A firm's stock price is observed at three periods: P_t, P_{t+1}, and P_{t+2}. Additionally, there is a positive change in the firm's expected cash flow stream growth observed at each period. Given this assumption, it necessarily follows from the growth in expected cash flow streams that $P_t < P_{t+1} < P_{t+2}$. This reflects that there is a positive stock return over these periods stemming from the growth in the expected cash flow streams of the firm. This relation necessitates a model that reflects the relation between a firm's stock return and its growth in the cash flow generated by the firm.

By relying on the principle of market efficiency and rearranging the basic asset pricing identity—that the price of any asset is the expected discounted future payoff—I can express a simple relation between ECFG and expected return. I assume that the required return to shareholders and expected stock return are in equilibrium and are used interchangeably. Hence, if a firm is expected to generate more (less) value for its shareholders and the current price remains the same, the rate at which the future value is discounted has to increase (decrease) to keep the stock price at time t equal to the future payoff at time t+1. Holding the discount rate constant, the stock price increases (decreases) as cash flows increase (decrease).

3.2 | Propositions

The price of an asset at time t (P_t) is the expected discounted future cash flow, $P_t = E_t(m_{t+1}P_{t+1})$, where m_{t+1} is the discount factor and P_{t+1} is the price at time t+1. The price at each time reflects the discounted future cash flow stream at that time, that is, $P_t = DCFS_t$ and $P_{t+1} = DCFS_{t+1}$. Adjusting the fundamental pricing equation by dividing by price at time t in the right-hand side (RHS) and left-hand side (LHS) and substituting the cash flow stream for the respective price gives the expected change of value generated by the firm:

$$1 = E_t(m_{t+1}R_{cf,t+1}), \tag{1}$$

where

$$R_{cf,t+1} = \frac{DCFS_{t+1}}{DCFS_t}.$$

Expectations built in the current period are based on the expected cash flow generated in the current period. It is through these expectations that the future cash flow estimations are built on. The prices at t and t+1 are determined by the expected future cash flow stream at the respective period; therefore, the return observed between times t and t+1 is the result of the observed and expected growth in the cash flow generated by the firm at time t.

Next, I separate the expectation and rearrange the equation to express return with regard to value created, and because $m_{t+1} = \frac{1}{R_{r,t+1}}$, the equation becomes

$$1 = E_t\left(\frac{1}{R_{r,t+1}}\right)E_t(R_{cf,t+1}) + \mathrm{cov}(m_{t+1}, R_{cf,t+1}). \tag{2}$$

This equation may be rearranged to be expressed in a stochastic framework and continuing value. Although each derivation results in a similar direct association between firm-generated CFG and stock return, the additional value in expressing the continuing value model lies in its general simplicity.

3.3 | Proposition 1: Stochastic expression

Carrying the discount factor out of the expectation in the RHS of Equation (2) evokes Jensen's inequality in the expression of the rearrangement. Therefore, by bringing m_{t+1} to the LHS, Equation (2) may be expressed as:

$$E_t(R_{r,t+1}) \geq \frac{E_t(R_{cf,t+1})}{(1\text{-}\mathrm{cov}(m_{t+1}, R_{cf,t+1}))}. \tag{3}$$

Equation (3) shows that the expected return of shareholders is at least as high as the growth in expected cash flows, scaled by 1 minus the variance of the discount factor and growth in value term. This suggests that investors may expect to earn a return on their equity holdings at least as high as the growth in the expected cash flow of the firm.

Another adjustment may be made to Equation (3) to arrive at a strict equality between stock return and firm-generated value. $R_{r,t+1}$ is (1+$r_{r,t+1}$), where $r_{r,t+1}$ is the stochastic return and $R_{r,t+1}$ may be interpreted as an approximation of $e^{r_{r,t+1}}$. $E\left(\frac{1}{R_{r,t+1}}\right)$ is therefore approximately equivalent to $E\left(e^{-r_{r,t+1}}\right)$, which may be expressed as $e^{E(-r_{r,t+1})+\frac{1}{2}\sigma^2(-r_{r,t+1})}$, through a second-order Taylor approximation. The last term may be rearranged to be expressed as $E\left(e^{r_{r,t+1}}\right)^{-1} \times e^{\sigma^2(r_{r,t+1})}$, which implies $E\left(\frac{1}{R_{r,t+1}}\right)$ is equal to $\left(\frac{1}{E\left(R_{r,t+1}\right)}\right)e^{\sigma^2(r_{r,t+1})}$, where $e^{\sigma^2(r_{r,t+1})} \geq 1$, consistent with Jensen's inequality. Under these conditions, Equation (3) may be rearranged as:

$$E_t(R_{r,t+1}) = \frac{E_t(R_{cf,t+1})e^{\sigma^2(r_{r,t+1})}}{(1 - \mathrm{cov}(m_{t+1}, R_{cf,t+1}))}. \tag{4}$$

The model shows that the expected stock return ($E_t(R_{r,t+1})$) equals the growth of the expected cash flow streams ($E_t(R_{cf,t+1})$) multiplied by the exponential of the return variance ($e^{\sigma^2(r_{r,t+1})}$), divided by 1 minus the covariance of the discount factor and the growth of the expected cash flow streams ($cov(m_{t+1}, R_{cf,t+1})$). The variance term indicates that the return is scaled in magnitude to the expected growth in cash flows, commensurate with the idiosyncratic volatility of returns. The idiosyncratic variance term is in line with the theoretical and empirical findings linking expected returns to idiosyncratic volatility shown by Levy (1978), Merton (1987), Jiang and Lee (2006), Fu (2009), and Feunou et al. (2014).

3.4 | Proposition 2: Terminal growth expression

I now assume that the firm has reached terminal growth and therefore cash flows grow at a constant rate. Because of the constant growth, the CFG variance becomes 0 and therefore the covariance of cash flow and return becomes 0, and it is shown that the required return of shareholders is based on the value created by the firm through growing FCF:

$$E_t(R_{r,t+1}) = E_t(R_{cf,t+1}). \tag{5}$$

Equation (5) explicitly shows that the expected return of shareholders equals the ECFG generated by the firm and that it is the primary driver of stock returns. This pricing identity is significant because much of the research in relation to asset pricing looks at pricing risk components or interpreting risks that drive demand behavior. However, Equation (5) directly links the expected return with the intrinsic value supplied by a firm through its cash flow generation. Because the value of the firm reflects the discounted expected future cash flows the firm generates, $E_t(R_{cf,t+1})$ expresses shareholder return through expected value created by expected cash flow stream growth, which may be translated into capital appreciation and dividends. This relation shows that ceteris paribus, if a firm increases cash flows, the value created increases, which increases the return to shareholders.

If I assume that cash flows are growing at a continuous rate—that is, the continuing value of the firm is reached—and the firm is not paying dividends, Equation (5) can be expressed through the terminal value of a constantly growing cash flow stream:

$$E_t(R_{r,t+1}) = E_t\left(\frac{G * CF_{t+2}/(r_r - g)}{G * CF_{t+1}/(r_r - g)}\right) \tag{6}$$

where

$G = 1 + g$.

r_r = required return, and

g = cash flow growth.

Equation (6) is simplified to

$$E_t(R_{r,t+1}) = E_t\left(\frac{CF_{t+2}}{CF_{t+1}}\right). \tag{7}$$

Because cash flow is growing at a steady rate, cash flow at each period is the previous period's cash flow multiplied by the CFG rate. Therefore, Equation (7) can be expressed as

$$E_t(R_{r,t+1}) = E_t\left(\frac{G * CF_{t+1}}{CF_{t+1}}\right), \tag{8}$$

which simplifies to

$$E_t(R_{r,t+1}) = E_t(G). \tag{9}$$

Finally, taking the unconditional expectation of the conditional expected return and CFG:

$$E(R_{r,t+1}) = E(G), \tag{10}$$

where

$E(G)$ = expected cash flow growth.

With the continuous growth rate assumption, Equation (10) shows that the expected stock return is equal to the value generated to shareholders, or the growth of cash flows. This is important because it shows that expected stock return is primarily driven by the value generated by the firm, measured as CFG. The model expressed in Equations (4) and (10) may be thought of analogously to the Gordon growth model; however, rather than relying on dividends paid by the firm, this model relies on the cash flows generated by the firm. This is a significant improvement on the dividend-centered pricing literature because not all firms pay dividends, and there is evidence suggesting that firms are increasingly unlikely to initiate dividends (DeAngelo et al., 2004; Denis & Osobov, 2008; Fama & French, 2001; Grullon & Michaely, 2002), which leads to a decline in the applicability of dividend-reliant pricing models.

The stochastic model in Equation (4) and the terminal value model in Equation (10) both suggest the hypothesis that stock returns are positively and significantly related to ECFG. One potential issue with using CFG to proxy for value generation is that CFG may not reflect all the value being generated, such as by investing in intangible assets. However, to create value, intangible assets have to eventually generate cash flows and this cash flow is captured by CFG when the value is realized.

3.5 | Hypotheses

The literature has examined the association of stock returns with dividends, profitability, and FCF. However, studies have not taken the next step of examining the association of stock returns with free CFG. Although the preceding model predicts expected returns are predicated on ECFG, investors and empirical asset pricing tests often use realized variables as the basis to estimate their expectations. Therefore, I use both RCFG and ECFG as a proxy for ECFG:

H1: *Stock returns are positively related to RCFG and ECFG.*

However, any realized variable is the sum of its expected and unexpected components. In this case, RCFG is the sum of ECFG and UCFG. The model presented in Equation (10) suggests that ECFG should explain expected stock returns. Because RCFG reflects ECFG and UCFG, there may still be explanatory power in UCFG. Therefore, an extension of the first hypothesis is to additionally analyze ECFG and UCFG:

$$E(R_{r,t+1}) = E(G) + U(G), \tag{11}$$

where

$U(G)$ = unexpected cash flow growth.

Because the model suggests ECFG should be the cash flow component, which is associated with returns, I hypothesize that ECFG is more economically and statistically significant in stock returns than UCFG:

H2: *ECFG is more economically and statistically significant than UCFG.*

Additionally, Berk et al. (1999), Anderson and Garcia-Feijóo (2006), Cooper et al. (2008), and Watanabe et al. (2013) suggest that asset growth reflects a firm's exercise of the real options it holds. Furthermore, Foerster et al. (2017) find there is more information contained in FCF than in profitability and OCF. However, Foerster et al. do not provide evidence showing why FCF has more explanatory power than profitability or OCF. I hypothesize that FCF explains more than profitability or OCF because FCF has the additional information contained in capital expenditures (CAPX), as measured by ICF. ICF reflects a firm's decision to exercise its real options and is included in FCF but not in profitability or OCF. Additionally, separating CFG into its operating and investment components shows where the explanatory power of FCF in stock returns lie (i.e., FCF $=$ OCF $-$ICF). OCFG is positively related to returns, whereas asset growth, captured through ICFG, is negatively related to returns. Therefore, CFG jointly captures the information of OCFG and ICFG (i.e., $E(G) = E(\text{OCFG}) - E(\text{ICFG})$), and Equation (10) may be separated into CFG's components of OCFG and ICFG:

$$E(R_{r,t+1}) = E(\text{OCFG}) - E(\text{ICFG}). \tag{12}$$

Because FCF captures both the operating and investing activities of the firm, CFG jointly reflects the operating and investment activities of the firm. Which component of CFG, OCFG or ICFG, explains relatively more of the stock returns is a matter of empirical investigation. Therefore:

H3a1: *Stock returns are positively related to OCFG.*

H3b1: *Stock returns are negatively related to ICFG.*

H3a2: *OCFG explains stock returns more than does ICFG.*

H3b2: *ICFG explains stock returns more than does OCFG.*

4 | DATA AND DESCRIPTIVE ANALYSIS

4.1 | Data

All financial statement and stock data are gathered from June 1988 to December 2019. Monthly stock return information is collected from the Center for Research in Security Prices (CRSP) for stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and Nasdaq. Annual financial statement information is collected from Compustat. The monthly risk-free rate and Fama–French factors are gathered from Kenneth French's website.[3] In line with previous research, all financial firms are dropped from the sample to avoid the idiosyncratic effect of highly regulated firms. All independent variables are trimmed at the 1st and 99th percentiles.[4]

[3]I thank Kenneth French for making these data available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[4]Results are sensitive to outliers in CFG measures. As seen in the summary statistics, even with the 1% trim at the top and bottom of the distribution, there are still relatively high levels of CFG in the tails. However, as shown in the following tests, controlling for changes in the firm's asset base partially explains the effects of CFG outliers. Additionally, in tests not shown, I use lower cut points in the data to trim out the high CFG data, and results remain similar.

The dependent variable is the holding period return (R) of common stocks, including dividends, measured both monthly and annually. Following the literature, I assume that R is an approximate proxy of the expected return and use realized accounting variables lagged back to last June. The independent variable of focus is CFG: RCFG, ECFG, and UCFG. RCFG is the growth of FCF, $(\text{FCF}_t - \text{FCF}_{t-1})/(\text{FCF}_{t-1})$. Following Foerster et al. (2017), FCF is calculated as operating activities net cash flow (OANCF from Compustat) net of CAPX. Because growth rates yield uninterpretable inferences when a value crosses 0, CFG is measured when FCF is either consecutively positive for at least 2 years or consecutively negative[5] for at least 2 years and then stacked together. I additionally test for RCFG using strictly positive or strictly negative cash flows.[6] Although empirical tests of stock return factors generally use lagged measures of the independent variable, the preceding model suggests a contemporaneous association. Therefore, I test both lagged to last June and contemporaneous values of RCFG.[7]

Following Kahl et al. (2019), I empirically measure ex ante expectations of FCF using the geometric growth rate of positive FCF from the previous 2 years:

$$E(\text{FCF}_{i,t}) = \text{FCF}_{i,t-1}\sqrt{\left(\frac{\text{FCF}_{i,t-1}}{\text{FCF}_{i,t-3}}\right)}, \tag{13}$$

where $\text{FCF}_{i,t}$ is firm i's FCF in time t. ECFG is then measured as:

$$E(\text{CFG}_{i,t}) = \frac{(E(\text{FCF}_{i,t}) - \text{FCF}_{i,t-1})}{\text{FCF}_{i,t-1}}. \tag{14}$$

As suggested by the second hypothesis, it follows from RCFG and ECFG that there is the remaining unexpected portion of CFG. Therefore, I additionally measure UCFG as:[8]

$$U(\text{CFG}_{i,t}) = \text{RCFG}_t - E(\text{CFG}_{i,t}) = \frac{(\text{FCF}_{i,t} - \text{FCF}_{i,t-1})}{\text{FCF}_{i,t-1}} - \frac{(E(\text{FCF}_{i,t}) - \text{FCF}_{i,t-1})}{\text{FCF}_{i,t-1}} = \frac{(\text{FCF}_{i,t} - E(\text{FCF}_{i,t}))}{\text{FCF}_{i,t-1}}. \tag{15}$$

I use several sets of control variables throughout the empirical tests. Consistent with the literature, I follow Novy-Marx (2013), Fama and French (2016), and Foerster et al. (2017) in measuring control variables, which are year-end Beta estimates from CRSP (Beta); the natural log of firm size measured by total market value (SIZE), measured in the prior June; the natural log of book-to-market-equity ratio (BM), with the book value taken from the prior June and market value taken from the prior December; the previous month's return (LR); and the previous 11 months' return (MOM) taken from $t-2$ to $t-12$.[9] These studies find evidence that operating profits and investment are significantly related to stock returns. I additionally control for the level of FCF, operating profitability, and firm investment to test whether CFG has explanatory power above these variable levels examined in previous studies. Although Fama and French (2016) present evidence of a firm's operating performance and investment activities being separately related to a firm's return, I argue that the combination of OCF and ICF in FCF is the reason why cash flows are better estimates of a firm's value and therefore are more closely related to the firm's stock return.

[5]Because negative values are inversely grown without adjustment, growth rates for negative cash flows are multiplied by –1. For example, if a firm's cash flow goes from –\$10 million to –\$20 million, its unadjusted growth rate is (–20 – (–10))/–10 = 100%.

[6]I do not tabulate the results for RCFG tests using the strictly positive or negative FCF samples. Results for the positive FCF sample are economically and statistically stronger. Although results for the negative FCF sample are statistically weaker, the results for the negative FCF sample are statistically significant after controlling for changes in the firm's asset base.

[7]I tabulate only the lagged to last June RCFG; contemporaneous RCFG results are available upon request.

[8]Because FCF and E(FCF) values cross 0 at different times and these variables cannot cross over 0 within the same 2 consecutive years, the number of observations decreases from RCFG, ECFG, and UCFG.

[9]Berk et al. (1999), Anderson and Garcia-Feijóo (2006), Cooper et al. (2008), Watanabe et al. (2013), and Chowdhury et al. (2018) find evidence of asset growth and market share growth having explanatory power in stock returns. Because these growth variables may be associated with CFG, I additionally control for market share growth and asset growth in untabulated results. Results for the association between CFG and returns are robust to the inclusion of these related growth variables.

4.2 | Descriptive analysis

Panel A of Table 1 reports the averages of all measures of CFG. After trimming CFG at the top and bottom 1%, around 20% of CFG are greater than |100%| growth, as shown in the first and fifth quintile sorts. Results discussed later are similar when I use higher cutoffs, such as trimming at the 5% level or dropping observations greater than |100%|, though results are generally more statistically and economically significant when the larger cutoffs are used. Because the high CFG rates may stem from structural changes in the firm (such as restructuring through mergers and acquisitions), I control for this in RCFG measures later in robustness tests. Finally, the negative median UCFG suggests that firms generally have lower RCFG than expected.

Panel B of Table 1 reports the averages of the respective CFG, cash-flow-to-assets (CFA), market value (MKTV[10]), and BM across respective CFG quintile sorts. CFA is highest in the top RCFG quintile and lowest in the bottom RCFG quintile; however, CFA is flat across the second to fourth RCFG quintiles. CFA is concavely associated with both ECFG and UCFG. The association between CFA and CFG suggests that FCF levels may yield different inferences from CFG. I find that BM is convexly associated with all three CFG measures and MKTV is concavely associated with all three CFG measures. These results suggest that the typical scalars used in previous studies may not directly reflect a firm's CFG because of the nonlinear association of these variables with CFG. In other words, CFG may capture information that is not necessarily reflected in CFA or a similarly constructed scaled variable.

Panel C of Table 1 reports the average ECFG across independent bivariate quintile sorts of ECFG and UCFG. This table shows that ECFG is relatively constant across UCFG quintile sorts. Panel D reports the average UCFG across independent bivariate quintile sorts of ECFG and UCFG. This table shows that UCFG is not significantly different across the 2–4 ECFG quintiles; however, there is a decrease in UCFG across ECFG quintiles in the lowest UCFG quintile and a convex association of UCFG across ECFG quintiles in the highest UCFG quintile. This suggests that the higher the CFG expectations are, the lower the propensity for unexpected cash flow shocks. In untabulated results, as well as inferred by the construction of the variables, ECFG and UCFG are negatively related. Therefore, although not always the case, firms that have higher ECFG may have lower UCFG. However, as shown in Panel D, there are relatively few firms that are in the intersection of the highest ECFG and UCFG quintiles.

Panel E of Table 1 reports the average number of firm-year observations per ECFG and UCFG quintile intersections. Because of the general negative relation between ECFG and UCFG, there are relatively fewer firms in the top and bottom quintile intersections than there are around the middle quintile intersections. This sorting biases against finding significant results in their intersection in the following tests.

Table 2 reports the monthly return sorted into CFG portfolios, sorted from low (1) to high (5) quintiles. The returns observed in Panel A increase from the lowest to highest CFG portfolio in RCFG and UCFG. However, returns are flat across ECFG quintiles. This suggests that RCFG, particularly the UCFG component of RCFG, is positively and significantly associated with monthly stock returns. This is contrary to the second hypothesis, which posits that ECFG should be relatively more associated with returns. However, because ECFG and UCFG are components of RCFG, there may be omitted variable bias when controlling only for either ECFG or UCFG. Therefore, I additionally control for both ECFG and UCFG. Panel B presents the independent bivariate quintile sorts of ECFG and UCFG. When controlling for both ECFG and UCFG, the increase in monthly stock returns across quintiles is more economically and statistically significant, with the return difference across ECFG quintiles becoming statistically significant. The intersection of the fifth quintile for ECFG and UCFG sorts results in an average monthly return of 2.88% for equal-weighted returns and 2.04% for value-weighted returns. The average monthly return in the S&P 500 over the sample period is 0.71% and the average monthly return of the CRSP sample in the

[10]I also look at total book assets and stock price, two other common scalars, across CFG quintiles, and results are similar to the convexity of CFG's association to MKTV.

TABLE 1 Summary statistics

Panel A: Summary statistics								
Variable	Obs.	Mean	*SD*	1	2	3	4	5
RCFG	573,030	0.2644	2.0600	−1.5116	−0.2902	0.0593	0.4498	2.6178
ECFG	325,031	0.2491	0.7025	−0.4046	−0.0870	0.1032	0.3426	1.2934
UCFG	283,047	0.2726	2.1549	−1.4543	−0.4828	−0.0952	0.3651	3.0385

Panel B: Averages across CFG portfolios			
	Average		
	CFA	BM	MKTV
RCFG quintile			
1	−0.0524	0.5541	2,400
2	0.0190	0.4898	5,100
3	0.0366	0.4387	8,830
4	0.0323	0.4749	6,110
5	0.0761	0.5414	3,940
ECFG quintile			
1	0.0414	0.5999	4,370
2	0.0657	0.4867	8,890
3	0.0776	0.4285	11,800
4	0.0772	0.4310	8,610
5	0.0641	0.4894	5,500
UCFG quintile			
1	0.0577	0.5045	4,880
2	0.0741	0.4509	8,350
3	0.0909	0.4047	13,600
4	0.0959	0.4385	10,900
5	0.0893	0.5316	5,520

Panel C: Average ECFG in independent bivariate ECFG and UCFG quintile sorts					
	UCFG quintile				
ECFG quintile	1	2	3	4	5
1	−0.2295	−0.3116	−0.3435	−0.3396	−0.4356
2	−0.0496	−0.0817	−0.0803	−0.0931	−0.1103
3	0.1199	0.1143	0.1114	0.0926	0.0948
4	0.3949	0.3607	0.3238	0.3396	0.3544
5	1.4929	0.8392	0.9098	0.9050	1.0178

Panel D: Average UCFG in independent bivariate ECFG and UCFG quintile sorts					
	UCFG quintile				
ECFG quintile	1	2	3	4	5
1	−0.6827	−0.4625	−0.0729	0.4630	3.9079
2	−0.8268	−0.4929	−0.0765	0.4059	2.0331

TABLE 1 (Continued)

Panel D: Average UCFG in independent bivariate ECFG and UCFG quintile sorts					
	UCFG quintile				
ECFG quintile	1	2	3	4	5
3	−0.9131	−0.4899	−0.0967	0.3572	2.0355
4	−1.0119	−0.5132	−0.1188	0.3650	2.3423
5	−1.7376	−0.5525	−0.1172	0.3851	2.5045

Panel E: Average number of firms per year in independent bivariate ECFG and UCFG quintile sorts						
	UCFG quintile					
ECFG quintile	1	2	3	4	5	Total
1	39.27	154.26	166.87	391.28	1,195.07	856.37
2	90.55	324.70	504.12	795.94	487.44	569.97
3	178.94	510.20	781.01	586.35	203.64	570.34
4	435.70	806.67	565.29	288.03	146.76	566.25
5	1,429.30	357.78	132.98	92.39	86.65	1,059.44
Total	1,072.25	547.44	572.09	569.88	822.51	716.36

Note: This table presents summary statistics of realized cash flow growth (RCFG), expected cash flow growth (ECFG), and unrealized cash flow growth (UCFG), where RCFG = ECFG + UCFG. Panel A presents summary statistics and average cash flow growth (CFG) across respective quintile sorts. Panel B presents the average cash flow to assets (CFA), book-to-market equity (BM), and market value of the firm (MKTV) across respective CFG quintiles. Panel C presents average values of ECFG across independent quintile sorts of ECFG and UCFG. Panel D presents average values of UCFG across independent quintile sorts of ECFG and UCFG. Panel E presents the average number of firm-month observations within independent quintile sorts of ECFG and UCFG. The sample spans 1988–2019 and excludes financial firms.

sample period is 1.3%. This suggests that investing in a portfolio of firms that are expected to generate high CFG outperforms the market by around 1 percentage point per month.

5 | CROSS-SECTIONAL RESULTS

5.1 | Fama–MacBeth regressions

Table 3 reports the results of Fama–MacBeth regressions of stock returns on CFG and controls for OCF to assets (OCFA), investment cash flow to assets (ICFA), cash flow to assets (CFA), Beta, BM, SIZE, LR, and MOM.[11] Panel A presents results using monthly stock returns, Panel B controls for CFA, and Panel C presents results using annual stock returns. Results suggest that CFG is significantly related to both monthly and annual stock returns. The association of CFG and returns is similar with or without the controls. Results support the first hypothesis: RCFG is positively and significantly associated with stock returns. ECFG is statistically insignificant when UCFG is not controlled for;[12] however, ECFG is significant when UCFG is controlled for. Additionally, the coefficient estimate of UCFG roughly doubles when controlling for ECFG. However, the ECFG coefficient is around 100% larger than the UCFG coefficient when both ECFG and UCFG

[11]LR and MOM are not controlled for in the annual return regressions because of the time mismatch with LR and MOM.

[12]Even though it is standard practice to lag accounting-based variables to the previous June, contemporaneous ECFG is more consistent with the model in Equation (10). ECFG is more statistically significant when I use the contemporaneous estimation of ECFG.

TABLE 2 CFG portfolio sorts

Panel A: Average monthly stock returns in univariate CFG quintile sorts						
	Equal weighted			Value weighted		
Portfolio	RCFG	ECFG	UCFG	RCFG	ECFG	UCFG
1	0.0099	0.0138	0.0114	0.0035	0.0071	0.0051
2	0.0119	0.0134	0.0121	0.0066	0.0074	0.0062
3	0.0139	0.0137	0.0134	0.0074	0.0085	0.0096
4	0.0175	0.0136	0.0163	0.0096	0.0089	0.0098
5	0.0198	0.0136	0.0188	0.0111	0.0088	0.0099
High − low	0.0099	−0.0002	0.0074	0.0076	0.0017	0.0048
t-stat.	(3.42)	(−0.09)	(2.85)	(3.05)	(0.66)	(1.64)

Panel B: Average monthly stock returns in independent bivariate ECFG and UCFG quintile sorts						
Equal weighted						
	UCFG quintile					
ECFG quintile	1	2	3	4	5	High − low
1	0.0080	0.0066	0.0110	0.0112	0.0170	0.0090
						(3.44)
2	0.0003	0.0096	0.0111	0.0156	0.0188	0.0185
						(6.88)
3	0.0072	0.0114	0.0130	0.0170	0.0223	0.0152
						(5.29)
4	0.0090	0.0118	0.0147	0.0212	0.0238	0.0148
						(3.69)
5	0.0126	0.0182	0.0246	0.0215	0.0262	0.0136
						(2.88)
High − low	0.0046	0.0116	0.0136	0.0103	0.0092	0.0182
t-stat.	(1.79)	(3.87)	(3.51)	(2.42)	(1.95)	(3.86)
Value weighted						
	UCFG quintile					
ECFG quintile	1	2	3	4	5	High − low
1	0.0065	0.0079	0.0051	0.0082	0.0093	0.0029
						(0.96)
2	−0.0012	0.0050	0.0073	0.0086	0.0106	0.0118
						(4.16)
3	0.0006	0.0074	0.0087	0.0110	0.0130	0.0124
						(3.78)
4	0.0025	0.0075	0.0114	0.0136	0.0129	0.0104
						(2.72)

TABLE 2 (Continued)

Value weighted						
	UCFG quintile					
ECFG quintile	1	2	3	4	5	High – low
5	0.0076	0.0066	0.0196	0.0155	0.0170	0.0094
						(1.86)
High – low	0.0011	−0.0013	0.0145	0.0074	0.0077	0.0105
t-stat.	(0.38)	0.38	(3.43)	(1.54)	(1.52)	(2.08)

Note: This table presents average monthly stock returns across realized cash flow growth (RCFG), expected cash flow growth (ECFG), and unrealized cash flow growth (UCFG) quintiles, where RCFG = ECFG + UCFG. The lowest CFG quintile is represented by 1 and the largest by 5. Panel A presents univariate quintile sorts. Panel B presents independent variate quintile sorts of ECFG and UCFG. The sample spans 1988–2019 and excludes financial firms.

are controlled for, which supports the second hypothesis. This suggests that ECFG explains more of a firm's stock returns than does UCFG. However, the change from insignificance to significance when jointly estimating returns using ECFG and UCFG suggests an omitted variable bias when estimating either ECFG or UCFG without controlling for the other respective RCFG component. I use various empirical models to alleviate concerns for this omitted variable bias, and the CFG results are consistent across all models.[13]

When ECFG and UCFG are not jointly controlled for, results suggest a rejection of the second hypothesis. However, when jointly controlling ECFG and UCFG, results support the second hypothesis. Why do the estimated coefficients for ECFG and UCFG increase so much when jointly controlled for? First and foremost, ECFG and UCFG are negatively related to each other, but each is positively related to stock returns. Therefore, excluding one introduces omitted variable bias in the coefficient estimate. Second, as the cash flows are realized, the stock price impounds that information and these cash flows are then used to estimate the next period's cash flows.

Panel B of Table 3 controls for CFA to test whether there is marginal information in CFG relative to the FCF level. Results suggest that CFG has explanatory power in stock returns above that in the FCF level, which previous studies have examined. All CFG proxies remain statistically and economically significant when controlling for CFA. This further suggests that CFG contains pertinent information to a firm's value above that reflected in the level of cash flows, profitability, or dividends, which previous studies have examined.

Fama and French (2008) find that many variables shown to explain stock returns are primarily significant in micro-cap stocks. Therefore, I replicate Table 3 across size quintiles and use subsamples of NYSE-, AMEX-, and NASDAQ-listed firms separately.[14] The positive and significant relation between CFG and stock returns is present in each size quintile, suggesting that the result is not driven by firm size. Results using only firms listed on each exchange are similar to the aggregate sample, further suggesting that results are not being driven by the small firm effect.

Table 4 presents the results of Fama–MacBeth regressions of firms' monthly stock returns regressed on RCFG, separated into OCFG and ICFG, reflecting operating performance and asset growth, respectively. Following Anderson and Garcia-Feijóo (2006), Cooper et al. (2008), and Watanabe et al. (2013), ICFG is measured from years $t-1$ and $t-2$. The results support the third hypothesis: When CFG is separated into its operating and investing

[13]To alleviate omitted variable bias concerns, I test the association between stock returns and CFG while controlling for Beta, SIZE, BM, LR, and MOM to reflect factors that studies have found to be consistently associated with stock returns. I additionally control for cash flow levels, OCF, investing cash flow, net income, gross profitability, revenue, asset growth, market share growth, and dividends to control for variables that have been found to be associated with stock returns and that may be related to CFG.

[14]Results for robustness tests are not tabulated and are available upon request.

TABLE 3 Fama–MacBeth regressions of stock return on CFG

Panel A: Fama–MacBeth regressions of monthly stock return on CFG												
	R											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
RCFG	0.0013***	0.0009***							0.0009***			
	(10.82)	(8.14)							(9.27)			
ECFG			0.0001	0.0000			0.0030***	0.0019***		−0.0002		0.0020***
			(0.32)	(−0.02)			(5.10)	(3.59)		(−0.58)		(3.68)
UCFG					0.0009***	0.0005***	0.0015***	0.0009***			0.0006***	0.0011***
					(6.88)	(3.95)	(8.83)	(5.95)			(4.86)	(6.79)
Beta		0.0050**		0.0039		0.0042*		0.0039	0.0028	0.0021	0.0027	0.0024
		(1.99)		(1.50)		(1.66)		(1.52)	(1.25)	(0.92)	(1.15)	(1.01)
SIZE		−0.0024***		−0.0013***		−0.0013***		−0.0013***	−0.0020***	−0.0011**	−0.0011***	−0.0011**
		(−4.94)		(−2.91)		(−2.93)		(−2.83)	(−4.59)	(−2.56)	(−2.66)	(−2.56)
BM		0.0022***		0.0050***		0.0047***		0.0047***	0.0022***	0.0052***	0.0050***	0.0050***
		(3.12)		(6.86)		(6.58)		(6.56)	(3.74)	(8.10)	(7.88)	(7.85)
OCFA		0.0256***		0.0766***		0.0761***		0.0727***	0.0286***	0.0795***	0.0765***	0.0731***
		(6.17)		(16.90)		(14.60)		(13.78)	(7.93)	(17.48)	(15.95)	(14.99)
ICFA		−0.0221***		−0.0509***		−0.0594***		−0.0563***	−0.0240***	−0.0538***	−0.0585***	−0.0556***
		(−3.18)		(−6.75)		(−6.38)		(−6.01)	(−3.77)	(−7.43)	(−6.52)	(−6.14)
LR									−0.0428***	−0.0519***	−0.0534***	−0.0537***
									(−9.46)	(−10.46)	(−10.51)	(−10.57)
MOM									0.0023	0.0006	−0.0002	−0.0004
									(1.47)	(0.33)	(−0.12)	(−0.23)

TABLE 3 (Continued)

Panel A: Fama–MacBeth regressions of monthly stock return on CFG

	R (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.0143***	0.0588***	0.0136***	0.0347***	0.0142***	0.0342***	0.0133***	0.0333***	0.0504***	0.0296***	0.0301***	0.0293***
	(5.42)	(5.81)	(5.57)	(3.66)	(5.94)	(3.70)	(5.65)	(3.61)	(5.51)	(3.35)	(3.49)	(3.39)
N	569,179	533,107	323,658	303,225	282,072	264,098	281,032	263,082	514,195	298,007	260,197	259,203
R^2	0.002	0.056	0.002	0.06	0.003	0.062	0.006	0.065	0.067	0.077	0.08	0.083

Panel B: Fama–MacBeth regressions of monthly stock return on CFG, controlling for CFA

	R (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RCFG	0.0011***	0.0009***						
	(9.01)	(8.80)						
ECFG			−0.0001	−0.0001			0.0021***	0.0016***
			(−0.13)	(−0.32)			(3.46)	(2.85)
UCFG					0.0007***	0.0004***	0.0011***	0.0009***
					(5.13)	(3.66)	(6.59)	(5.29)
CFA	0.0037	0.0200***	0.0493***	0.0760***	0.0563***	0.0817***	0.0510***	0.0775***
	(0.56)	(4.43)	(8.95)	(16.84)	(7.61)	(13.41)	(6.63)	(11.81)
Beta		0.0023		0.0019		0.0023		0.002
		(1.04)		(0.80)		(0.97)		(0.86)
SIZE		−0.0017***		−0.0010**		−0.0009**		−0.0009**
		(−3.91)		(−2.46)		(−2.23)		(−2.15)
BM		0.0024***		0.0047***		0.0047***		0.0046***
		(4.26)		(7.54)		(7.51)		(7.41)

(Continues)

TABLE 3 (Continued)

Panel B: Fama–MacBeth regressions of monthly stock return on CFG, controlling for CFA								
	R							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LR		−0.0413***		−0.0516***		−0.0529***		−0.0528***
		(−9.11)		(−10.31)		(−10.47)		(−10.48)
MOM		0.0031*		0.0005		−0.0004		−0.0005
		(1.92)		(0.24)		(−0.21)		(−0.29)
Intercept	0.0142***	0.0455***	0.0105***	0.0303***	0.0096***	0.0271***	0.0094***	0.0266***
	(5.31)	(5.07)	(4.02)	(3.49)	(3.81)	(3.18)	(3.75)	(3.13)
N	556,123	506,037	319,343	295,417	277,984	257,180	276,975	256,216
R^2	0.012	0.063	0.008	0.074	0.008	0.076	0.012	0.08
Panel C: Fama–MacBeth regressions of annual stock return on CFG								
	AR							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RCFG	0.0171***	0.0141***						
	(10.02)	(7.16)						
ECFG			−0.0029	−0.0039			0.0357***	0.0222**
			(−0.47)	(−0.77)			(3.63)	(2.68)
UCFG					0.0111***	0.0053***	0.0180***	0.0106***
					(5.17)	(2.84)	(6.52)	(4.28)
Beta		0.042		0.0363		0.0438		0.0386
		(1.16)		(1.07)		(1.22)		(1.09)
SIZE		−0.0302***		−0.0177**		−0.0167**		−0.0163**
		(−4.18)		(−2.74)		(−2.75)		(−2.65)

TABLE 3 (Continued)

Panel C: Fama–MacBeth regressions of annual stock return on CFG	*AR*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BM		0.0123		0.0510***		0.0511***		0.0493***
		(1.01)		(4.07)		(4.10)		(3.86)
OCFA		0.1404		0.8294***		0.8166***		0.7527***
		(1.33)		(11.17)		(9.10)		(8.66)
ICFA		−0.1844*		−0.6617***		−0.7419***		−0.6893***
		(−1.87)		(−7.48)		(−4.48)		(−4.07)
Intercept	0.1717***	0.7430***	0.1631***	0.4607***	0.1709***	0.4400***	0.1604***	0.4346***
	(−6.05)	(−4.91)	(−6.29)	(−3.62)	(−6.65)	(−3.64)	(−6.33)	(−3.57)
N	44,003	41,466	25,275	23,769	22,060	20,722	21,979	20,643
R^2	0.007	0.062	0.002	0.079	0.006	0.079	0.011	0.082

Note: This table presents Fama–MacBeth regressions of monthly returns (R) and compounded annual return (AR) on realized cash flow growth (RCFG), expected cash flow growth (ECFG), and unrealized cash flow growth (UCFG), where RCFG = ECFG + UCFG. Panel A presents monthly returns, Panel B controls for free cash flow to assets (CFA), and Panel C presents annual returns. Controls include Beta, ln(market equity) (SIZE), ln(book equity/market equity) (BM), operating cash flow scaled by assets (OCFA), investing cash flow scaled by assets (ICFA), 1-month lag of monthly stock return (LR), and prior 11-month momentum taken from t−1 to t−12 (MOM). The sample spans 1988–2019 and excludes financial firms. The t-statistics are reported in parentheses.

*p < 0.10; **p < 0.05; ***p < 0.01.

TABLE 4 Fama–MacBeth regressions of return on OCFG and ICFG

	R (1)	(2)	(3)	(4)	(5)	(6)
OCFG	0.0065***	0.0068***			0.0069***	0.0072***
	(11.79)	(15.66)			(12.48)	(16.00)
ICFG			−0.0026***	−0.0017***	−0.0023***	−0.0017***
			(−5.75)	(−4.73)	(−4.31)	(−3.90)
Beta		0.0014		0.0022		0.0014
		(0.64)		(1.12)		(0.65)
SIZE		−0.0012***		−0.0013***		−0.0012***
		(−2.95)		(−3.31)		(−2.85)
BM		0.0032***		0.0041***		0.0031***
		(6.05)		(7.73)		(5.81)
LR		−0.0431***		−0.0468***		−0.0433***
		(−10.07)		(−12.24)		(−10.07)
MOM		0.0039**		0.0051***		0.0035**
		(2.53)		(3.79)		(2.19)
Intercept	0.0136***	0.0367***	0.0152***	0.0395***	0.0137***	0.0360***
	(5.44)	(4.32)	(6.33)	(4.86)	(5.61)	(4.27)
N	639,035	587,752	816,426	745,242	579,498	534,385
R^2	0.003	0.059	0.002	0.057	0.006	0.062

Note: This table presents Fama–MacBeth regressions of monthly return (*R*) on operating cash flow growth (OCFG) and investing cash flow growth (ICFG) lagged 1 additional year. Controls include Beta, ln(market equity) (SIZE), ln(book equity/market equity) (BM), 1-month lag of monthly stock return (LR), and prior 11-month momentum taken from t−1 to t−12 (MOM). The sample spans 1988–2019 and excludes financial firms. The t-statistics are reported in parentheses.
$^{**}p < 0.05$; $^{***}p < 0.01$.

elements, they have significant positive and negative estimated coefficients, respectively. However, OCFG has a much higher economic and statistical significance relative to ICFG, which supports Hypothesis H3a2. This suggests that the significance of CFG stems from its joint capture of operating performance through OCFG and investing activities through ICFG but that operating performance is more important than investment performance.

Why does operating performance explain more in stock returns than does investment performance? I think this has an intuitive economic explanation. Because the value of an asset is tied to the expected cash flows of that asset, it follows that over the long run, it is the operating performance of a firm that maintains that firm's operations. Although it is necessary for firms to make investments to generate future value, it does not matter what investments a firm makes if those investments are not generating cash flows. Therefore, we should expect to see that the operating performance of the firm is more closely related to the firm's stock returns than its investment activities.

5.2 | Changes in the asset base

A significant concern of the RCFG measure used is whether the large RCFG rates reflect significant changes in the firm's asset base. Although results are stronger using more conservative growth cutoff criteria, these high growth rates may be the result of changes within the firm, such as significant growth periods early on in the firm or acquiring another firm, and therefore may not represent outliers in the sample. In periods such as these, the prior year's FCF may be much smaller than the preceding or following year's cash flow, which is grown by the firm's expanding or contracting asset base. To control for these large growth changes, I rerun regressions using only firms with asset growth less than 25%. Results are presented in Panel A of Table 5 and are similar to those presented in Table 3. RCFG is positively and significantly related to monthly stock returns.[15]

Another way to control for RCFG reflecting changes in the firm's asset base, and therefore the changes in the magnitude of the cash flows it is capable of generating, is to scale FCF by the firm's size. This provides a relative measure of CFG. Additionally, RCFG is positively related to SIZE, and this relation may affect both RCFG's and SIZE's relation to stock returns. To additionally control for changes in the firm's size, which may affect its cash flow levels and the interrelation between RCFG and SIZE, I scale FCF by the firm's total assets that year[16] and estimate RCFG using the asset scaled measure of FCF. Results for this test are presented in Panel B of Table 5 and remain similar to those presented in Table 3. CFG is positively related to stock returns.

5.3 | Test across periods and industries

It is possible that the association between CFG and stock returns declines across time. Therefore, I examine the association between CFG and returns across my sample period by dividing the sample into three roughly equal periods: 1988–1999, 2000–2009, and 2010–2019. Additionally, it is possible that results are industry specific. Therefore, I also split my sample into industry groups based on the first-digit Standard Industrial Classification (SIC) code.[17]

Table 6 reports time subsample estimations of the Fama–MacBeth regressions of monthly stock returns on CFG in Panel A and industry subsamples in Panel B.[18] The results offer the same conclusions obtained earlier: RCFG is a highly significant factor of monthly stock returns in each period. Consistent with the results of Wahal (2019), who finds evidence suggesting that profitability is significant in stock returns before 1963, the persistence of the relation between stock returns and CFG suggests that the relation between a firm's CFG and its stock return is not the result of a temporary anomaly.

Results in the industry subsample are similar to those presented earlier; there is a positive and significant relation between RCFG and monthly stock returns. Although RCFG and control variables are statistically insignificant or negative in the agriculture, acquisition firm, and mining industries, these industries make up around 6% of the observations of the sample and each industry has a small number of observations to test statistical significance. Additionally, acquisition firms are not oriented toward generating cash flows, but rather their sole purpose is acquiring other firms. However, CFG is statistically insignificant in the transportation and utilities industry, which has a relatively high number of sampled observations. As discussed in the descriptive section, results are sensitive to extreme CFG values. In untabulated results, I find an overrepresentation of highly negative RCFG observations in both the transportation and utilities and mining industries. When I trim these extreme

[15] I additionally test the CFG and return relation for firms with asset growth under 5%, 10%, and 50% in untabulated regressions, and results remain similar.

[16] I do not use market value of equity to proxy for size because both SIZE and BM already use that measure and using assets rather than equity avoids introducing multicollinearity.

[17] I reinclude financial firms in the sample for the cross-industry tests.

[18] I do not tabulate results for ECFG and UCFG in the subsample tests because results are similar. Results are available upon request.

TABLE 5 Fama–MacBeth regressions of stock return on RCFG controlling for asset growth effects on FCF and SIZE in FCF

Panel A: Fama–MacBeth regressions of monthly stock return on RCFG for firms with less than 25% asset growth			Panel B: Fama–MacBeth regressions of monthly stock return on CFGA, where FCF Is scaled by total assets		
	R			*R*	
	(1)	(2)		(1)	(2)
RCFG	0.0012***	0.0013***	CFGA	0.0014***	0.0014***
	(9.74)	(11.54)		(10.13)	(11.96)
Beta		−0.0006	Beta		0.0017
		(−0.28)			(0.76)
SIZE		−0.0005	SIZE		−0.0014***
		(−1.19)			(−2.88)
BM		0.0035***	BM		0.0026***
		(6.14)			(4.18)
LR		−0.0513***	LR		−0.0406***
		(−11.39)			(−8.77)
MOM		−0.0008	MOM		0.0039**
		(−0.50)			(2.45)
Intercept	0.0117***	0.0237**	Intercept	0.0143***	0.0398***
	(4.74)	(2.58)		(5.43)	(4.08)
N	449,739	412,734	*N*	566,144	514,155
R^2	0.002	0.059	R^2	0.002	0.057

Note: This table presents Fama–MacBeth regressions of monthly returns (*R*) regressed on realized cash flow growth (RCFG) when asset growth is less than |25%| in Panel A and regressed on realized growth of free cash flow scaled by total assets (CFGA) in Panel B. Controls include Beta, ln(market equity) (SIZE), ln(book equity/market equity) (BM), 1-month lag of monthly stock return (LR), and prior 11-month momentum taken from $t-1$ to $t-12$ (MOM). The sample spans 1988–2019 and excludes financial firms. The *t*-statistics are reported in parentheses.

$^{**}p < 0.05$; $^{***}p < 0.01$.

values, the estimated RCFG coefficient is statistically significant in these industries. This suggests that the relation between the firm's cash flow generation and its stock return is not constrained to a given industry.

6 | FAMA–FRENCH REGRESSIONS AND PORTFOLIOS

6.1 | Fama–French regressions

Table 7 presents the alphas from the Fama–French three- and five-factor time-series regression results of CFG quintile-sorted portfolios. Portfolios are formed in June of each year. Panel A presents the univariate sorts, and Panel B presents the bivariate ECFG and UCFG sorts. Results for the three- and five-factor models are similar, except where noted next, so I refer to the three-factor model throughout the discussion of alpha estimates.

TABLE 6 Time and industry subsample Fama–MacBeth regressions of returns on RCFG

Panel A: Fama–MacBeth regressions of monthly stock return on CFG across sample periods

	1990s		2000s		Postcrisis	
	R		*R*		*R*	
	(1)	(2)	(1)	(2)	(1)	(2)
RCFG	0.0011***	0.0011***	0.0013***	0.0014***	0.0014***	0.0014***
	(5.74)	(6.98)	(5.90)	(7.80)	(7.11)	(7.44)
SIZE		−0.0014*		−0.0019**		−0.0009*
		(−1.80)		(−2.31)		(−1.89)
BM		0.0027**		0.0057***		0.0002
		(2.06)		(4.57)		(0.28)
LR		−0.0439***		−0.0429***		−0.0254***
		(−5.58)		(−4.18)		(−2.92)
MOM		0.0107***		−0.0025		−0.0006
		(4.46)		(−0.61)		(−0.24)
Intercept	0.0161***	0.0432**	0.0140**	0.0517***	0.0125***	0.0292***
	(3.79)	(2.57)	(2.44)	(2.88)	(3.03)	(2.79)
N	152,757	144,956	194,135	174,960	213,497	195,636
R^2	0.002	0.033	0.002	0.041	0.002	0.027

Panel B: Fama–MacBeth regressions of monthly stock return on CFG across sample industries

Industry	Manufacturing	Services	Financials	Transportation and utilities	Trade	Mining and construction	Agriculture	Acquisition
RCFG	0.0014***	0.0019***	0.0017**	0.0004	0.0013***	−0.0002	−0.074	−0.0087**
	(9.74)	(7.11)	(2.13)	(1.43)	(4.16)	(−0.31)	(−1.25)	(−2.13)
SIZE	−0.0015***	−0.0014**	−0.0004	−0.0006	0.0006	−0.0009	−0.0128	−0.0099**
	(−3.27)	(−2.49)	(−0.95)	(−1.59)	(1.26)	(−1.27)	(−1.38)	(−2.25)

(Continues)

TABLE 6 (Continued)

Panel B: Fama–MacBeth regressions of monthly stock return on CFG across sample industries								
Industry	Manufacturing	Services	Financials	Transportation and utilities	Trade	Mining and construction	Agriculture	Acquisition
BM	0.0030***	0.0027***	0.0005	0.0026***	0.0047***	0.0044***	0.0506	−0.0163
	(3.93)	(2.69)	(0.65)	(2.72)	(4.15)	(3.31)	(1.37)	(−0.88)
LR	−0.0440***	−0.0367***	−0.0615***	−0.0478***	−0.0388***	−0.0298**	0.6277	0.1225
	(−7.83)	(−5.32)	(−7.06)	(−5.25)	(−5.10)	(−2.06)	(1.28)	(0.95)
MOM	0.0015	0.0042**	0.0113***	0.0042	0.0033	0.0055	0.0553	0.0153
	(0.75)	(2.01)	(3.72)	(1.25)	(1.26)	(1.07)	(0.66)	(0.47)
Intercept	0.0436***	0.0416***	0.0191**	0.0228***	0.0015	0.0299*	0.2918	0.2068**
	(4.57)	(3.75)	(2.13)	(2.71)	(0.15)	(1.94)	(1.55)	(2.35)
N	276,081	105,088	55,728	55,180	53,385	31,149	2,306	912
R^2	0.041	0.06	0.101	0.097	0.081	0.158	0.894	0.999

Note: This table presents subsample Fama–MacBeth regressions of monthly return (R) on realized cash flow growth (RCFG), ln(market equity) (SIZE), ln(book equity/market equity) (BM), 1-month lag of monthly stock return (LR), and prior 11-month momentum taken from $t-1$ to $t-12$ (MOM). Panel A presents period subsamples, and Panel B presents industry subsamples. The 1990s cover 1990–1999, 2000s cover 2000–2009, and postcrisis covers 2010–2019. The sample spans 1988–2019 and excludes financial firms. The t-statistics are reported in parentheses.

$^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE 7 Excess returns of portfolios sorted on CFG

Panel A: Alphas across univariate CFG portfolio sorts								
	Fama–French three-factor model				Fama–French five-factor model			
	EW		VW		EW		VW	
	α	*t*-stat.	α	*t*-stat.	α	*t*-stat.	α	*t*-stat.
RCFG portfolio								
Low	−0.0006	(−0.69)	−0.0043***	(−3.30)	−0.0001	(−0.13)	−0.0042***	(−3.06)
2	0.0020***	(2.92)	−0.0003	(−0.30)	0.0012*	(1.75)	−0.0009	(−0.82)
3	0.0041***	(5.87)	0.0012	(1.54)	0.0040***	(5.43)	0.0001	(0.08)
4	0.0074***	(9.06)	0.0034***	(3.21)	0.0075***	(8.91)	0.0036***	(3.27)
High	0.0095***	(13.30)	0.0038***	(3.86)	0.0090***	(12.15)	0.0034***	(3.31)
ECFG portfolio								
Low	0.0037***	(4.13)	0.0001	(0.04)	0.0027***	(2.94)	−0.0019	(−1.37)
2	0.0039***	(5.43)	0.0015	(1.44)	0.0025***	(3.61)	−0.0001	(−0.06)
3	0.0045***	(6.26)	0.0027***	(2.76)	0.0030***	(4.42)	0.0015	(1.52)
4	0.0042***	(5.93)	0.0024*	(1.93)	0.0032***	(4.53)	0.0026**	(2.07)
High	0.0038***	(4.84)	0.0015	(1.05)	0.0032***	(3.89)	0.0017	(1.16)
UCFG portfolio								
Low	0.0015*	(1.73)	−0.0024	(−1.48)	0.0002	(0.18)	−0.0037**	(−2.31)
2	0.0026***	(3.44)	−0.0006	(−0.45)	0.0013*	(1.79)	−0.0003	(−0.25)
3	0.0045***	(6.53)	0.0039***	(4.02)	0.0030***	(4.61)	0.0027***	(2.78)
4	0.0070***	(9.37)	0.0043***	(4.05)	0.0057***	(7.75)	0.0027**	(2.54)
High	0.0090***	(11.04)	0.0031**	(2.29)	0.0077***	(9.63)	0.002	(1.45)

(Continues)

TABLE 7 (Continued)

Panel B: Alphas across independent bivariate ECFG and UCFG portfolio sorts											
	Fama–French three-factor model						Fama–French five-factor model				
	EW						EW				
	UCFG quintile						UCFG quintile				
ECFG quintile	1	2	3	4	5	ECFG quintile	1	2	3	4	5
1	−0.0013	−0.0045*	0.0015	0.0013	0.0071***	1	−0.0018	−0.0048*	0.0006	0.0000	0.0057***
	(−0.17)	(−1.91)	(0.72)	(1.02)	(6.91)		(−0.23)	(−1.93)	(0.26)	(−0.03)	(5.55)
2	−0.0089***	−0.0007	0.0019*	0.0065***	0.0092***	2	−0.0105***	−0.002	0.0004	0.0051***	0.0081***
	(−2.86)	(−0.41)	(1.94)	(6.38)	(7.31)		(−3.23)	(−1.07)	(0.39)	(4.97)	(6.30)
3	−0.0036	0.0018	0.0045***	0.0089***	0.0131***	3	−0.0048**	0.0003	0.0025***	0.0073***	0.0115***
	(−1.61)	(1.43)	(4.98)	(8.07)	(7.38)		(−2.07)	(0.24)	(3.00)	(6.68)	(6.37)
4	−0.0008	0.0027***	0.0062***	0.0115***	0.0143***	4	−0.0024*	0.0012	0.0047***	0.0109***	0.0134***
	(−0.56)	(2.88)	(5.58)	(6.86)	(5.24)		(−1.79)	(1.33)	(4.27)	(6.25)	(4.80)
5	0.0029***	0.0086***	0.0148***	0.0117***	0.0171***	5	0.0017*	0.0081***	0.0154***	0.0102***	0.0182***
	(3.05)	(5.88)	(5.64)	(3.67)	(4.26)		(1.79)	(5.32)	(5.68)	(3.08)	(4.43)
	Fama–French three-factor model						Fama–French five-factor model				
	VW						VW				
	UCFG quintile						UCFG quintile				
ECFG quintile	1	2	3	4	5	ECFG quintile	1	2	3	4	5
1	−0.0048	−0.0004	−0.0028	0.0015	0.0019	1	−0.0048	−0.0024	−0.0047*	−0.0019	0.0001
	(−0.56)	(−0.13)	(−1.01)	(0.71)	(1.03)		(−0.55)	(−0.81)	(−1.65)	(−0.93)	(0.05)
2	−0.0084**	−0.0025	0.0007	0.0033**	0.0040**	2	−0.0105***	−0.0036	−0.0011	0.0017	0.002
	(−2.30)	(−1.17)	(0.44)	(2.20)	(2.05)		(−2.75)	(−1.62)	(−0.63)	(1.13)	(1.02)

TABLE 7 (Continued)

	Fama–French three-factor model						Fama–French five-factor model				
	VW						VW				
	UCFG quintile						UCFG quintile				
ECFG quintile	1	2	3	4	5	ECFG quintile	1	2	3	4	5
3	−0.0080***	0.0005	0.0031**	0.0064***	0.0062**	3	−0.0107***	0.0015	0.0008	0.0045***	0.0058**
	(−2.61)	(0.21)	(2.22)	(3.92)	(2.50)		(−3.39)	(0.63)	(0.57)	(2.69)	(2.28)
4	−0.0054**	0.0009	0.0059***	0.0064**	0.0073**	4	−0.0070***	0.0008	0.0058***	0.0068**	0.0055*
	(−2.28)	−0.57	(3.15)	(2.53)	(2.27)		(−2.84)	(0.49)	(2.99)	(2.54)	(1.72)
5	0.0001	−0.0002	0.0126***	0.0082**	0.0101**	5	−0.0013	−0.0001	0.0117***	0.0062	0.0133***
	(0.08)	(−0.11)	(3.65)	(2.03)	(2.28)		(−0.74)	(−0.04)	(3.27)	(1.49)	(2.92)

Note: This table presents alphas from time-series regressions of equal-weighted (EW) and value-weighted (VW) monthly portfolio returns sorted on realized cash flow growth (RCFG), expected cash flow growth (ECFG), or unrealized cash flow growth (UCFG) quintile portfolios each June, where RCFG = ECFG + UCFG. Panel A presents the univariate portfolio sorts, and Panel B presents the bivariate ECFG and UCFG sorts. Portfolio returns are regressed in the market return above the risk-free rate (MKT), small stock returns above large stock returns (SMB), and high BM returns above low BM returns (HML). The sample spans 1988–2019 and excludes financial firms. The *t*-statistics are reported in parentheses.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

The portfolio alpha increases across CFG sorts, after controlling for the market return, size, value, profitability, and investment factors. The highest equal-weighted RCFG portfolio earns a significant monthly excess return of 0.95%, whereas the lowest earns a significant −0.06% per month. The highest value-weighted RCFG portfolio earns a significant monthly excess return of 0.38%, whereas the lowest earns a significant −0.43% per month. The negative alpha in the lower RCFG quintiles suggests that firms that have low RCFG earn negative market returns for their underperformance. This result is contrary to Hou et al. (2011) and Fama and French (2008) who find that negative earnings are not commensurately related to negative returns. Given these estimated alphas and assuming no transaction frictions, an investor can earn an average costless monthly excess return of 1.01% per month under the equal-weighted estimates and 0.81% per month under the value-weighted estimates by investing in the high RCFG portfolio and shorting the low RCFG portfolio. This translates into averages of 12.81% and 10.16% compounded annual excess returns per year for the equal- and value-weighted portfolios, respectively.

Similar to the univariate and cross-sectional results, the univariate time-series portfolios of ECFG and UCFG reflect the omitted variable bias from not controlling for the counterpart to RCFG. The highest equal-weighted ECFG portfolio earns a significant monthly excess return of 0.38%, and the lowest earns a significant 0.37% per month. The highest value-weighted ECFG portfolio earns a significant monthly excess return of 0.15%, and the lowest earns an insignificant 0.01% per month. The highest equal-weighted UCFG portfolio earns a significant monthly excess return of 0.90%, and the lowest earns an insignificant 0.15% per month. The highest value-weighted UCFG portfolio earns a significant monthly excess return of 0.31%, and the lowest earns an insignificant −0.24% per month. One stark difference between the time-series alphas and the univariate results presented earlier is the nonmonotonic alpha increase across value-weighted ECFG and UCFG portfolios. This might suggest a nonlinear association of returns with ECFG and UCFG; however, results in Panel B of Table 7 suggest a more linear association between portfolio alphas with ECFG and UCFG sorts.

Results in Panel B of Table 7 suggest alpha increases across the ECFG and UCFG quintiles for both equal- and value-weighted returns. However, the intersection of the ECFG and UCFG portfolios results in a higher alpha increase across portfolios going from low to high. The highest equal-weighted return is observed in the intersection of the top quintiles of ECFG and UCFG with an alpha of 1.71%. Similarly, the highest value-weighted return is observed in the intersection of the ECFG and UCFG top quintiles with an alpha of 1.01%. Although the increase in excess portfolio returns across CFG portfolios is consistent across the proxies of CFG, alpha remains negative in the untabulated strictly negative FCF value-weighted cash flow portfolios. This further suggests that firms that have negative cash flows and negative CFG are discounted for their poor performance.

6.2 | Alphas across periods

Table 8 presents the estimated portfolio alphas of the time-series regressions sorted across RCFG quintiles for three periods: 1988–1999, 2000–2009, and 2010–2019. Similar to the cross-sectional results, the positive alpha across portfolio sorts is higher in the 2000s and postcrisis period. Although there is some variation in the sign and significance of the inner portfolios, the results in each period show increases in alpha across the cash flow sorts. This further suggests that the relation is not driven by any one of the sample periods from which the data are collected, and future out-of-sample tests are likely to arrive at similar conclusions.

6.3 | CFG cumulative return

One of the benefits of investment research is providing investors with profitable investment strategies. The typical strategy stemming from findings presented here is to take a long position in firms that have relatively high CFG and a short position in firms that have relatively low CFG with the long-short composition affording a costless investment strategy. Stocks are sorted into quintiles based on their CFG, and portfolios are rebalanced each June. The average

TABLE 8 Time-series alphas of portfolios sorted on RCFG across periods

	Equal-weighted returns					
	Fama–French three-factor model					
	1990s		2000s		Postcrisis	
CFG portfolio	α	t-stat.	α	t-stat.	α	t-stat.
Low	−0.0004	(−0.32)	0.0032	(1.64)	−0.0030***	(−2.65)
2	0.0014	(1.39)	0.0058***	(3.75)	−0.001	(−1.03)
3	0.0034***	(3.21)	0.0095***	(5.97)	0.0021**	(2.58)
4	0.0063***	(5.39)	0.0147***	(8.42)	0.0042***	(4.55)
High	0.0085***	(7.89)	0.0157***	(9.97)	0.0059***	(6.35)
	Fama–French five-factor model					
	1990s		2000s		Postcrisis	
CFG portfolio	α	t-stat.	α	t-stat.	α	t-stat.
Low	−0.0004	(−0.30)	0.0037*	(1.78)	−0.0027**	(−2.46)
2	0.001	(0.99)	0.0044***	(2.82)	−0.0009	(−0.94)
3	0.0029***	(2.70)	0.0094***	(5.61)	0.0023***	(2.67)
4	0.0059***	(4.98)	0.0150***	(8.46)	0.0044***	(4.67)
High	0.0077***	(7.29)	0.0148***	(9.06)	0.0059***	(6.27)
	Value-weighted returns					
	Fama–French three-factor model					
	1990s		2000s		Postcrisis	
CFG portfolio	α	t-stat.	α	t-stat.	α	t-stat.
Low	−0.0050***	(−3.08)	0.0009	(0.28)	−0.0054***	(−3.45)
2	−0.0008	(−0.46)	0.0035	(1.31)	−0.0021*	(−1.90)
3	0	(0.02)	0.0030*	(1.84)	0.0011	(1.25)
4	0.0069***	(3.91)	0.0077***	(2.99)	−0.0002	(−0.22)
High	0.0025	(1.51)	0.0079***	(3.39)	0.0027**	(2.36)
	Fama–French five-factor model					
	1990s		2000s		Postcrisis	
CFG portfolio	α	t-stat.	α	t-stat.	α	t-stat.
Low	−0.0057***	(−3.44)	0.0013	(0.38)	−0.0058***	(−3.65)
2	−0.0017	(−0.98)	0.0023	(0.83)	−0.0023**	(−2.08)
3	−0.0013	(−0.96)	0.002	(1.23)	0.0006	(0.72)
4	0.0068***	(3.73)	0.0072***	(2.74)	−0.0005	(−0.46)
High	0.0021	(1.26)	0.0073***	(3.03)	0.0025**	(2.19)

Note: This table presents alphas from time-series regressions of equal- and value-weighted monthly return sorted by realized cash flow growth (RCFG). Returns are regressed on the monthly stock market return above the risk-free rate (MKT), small stock returns above large stock returns (SMB), and high BM returns above low BM returns (HML). The 1990s cover 1990–1999, 2000s cover 2000–2009, and postcrisis covers 2010–2019. The sample spans 1988–2019 and excludes financial firms. The *t*-statistics are reported in parentheses.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

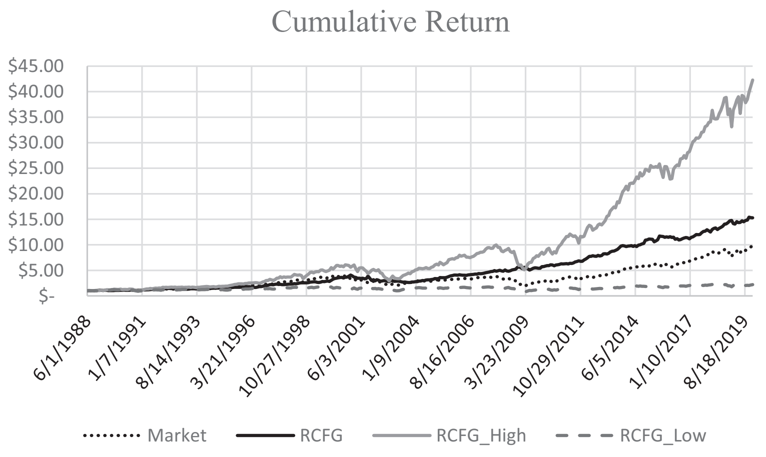

FIGURE 1 Cash-flow portfolio cumulative return. This figure presents the value-weighted cumulative return of investing in a portfolio of the top fifth of realized cash flow generating firms (RCFG_High), the bottom fifth of firms (RCFG_Low), a neutral cost strategy of long in the top fifth and short the bottom fifth (RCFG), and the cumulative return of investing in the excess market return (MKT). Portfolios are rebalanced June of each year. Data are from 1988 through 2019

monthly value-weighted return for that portfolio is then estimated.[19] Figure 1 presents the value-weighted cumulative return on a $1 investment from May 1988 through December 2019 of the zero-cost strategy, shown in RCFG. Additionally, the cumulative value-weighted excess return of the Fama–French market factor (MKT), the return to the high RCFG (RCFG_High) portfolio, and the return to the low RCFG (RCFG_Low) portfolio are depicted in the figure.

This analysis implies that the return of the zero-cost investment strategy outperforms the market and is less volatile than the market. Ignoring trading frictions, $1 invested in May 1988 in the RCFG portfolio grows into $15.30 in December 2019, compared to $9.85 for the MKT portfolio. There are no significant drawdowns over the sample period for the RCFG strategy, including during the 2008 financial crisis. In addition, these results suggest that investors focusing their investments in firms that generate relatively high CFG and short firms with relatively low CFG may earn high and stable returns on their investments without being exposed to significant drawdown risk. In fact, the RCFG portfolio did not experience the same negative shock that the overall stock market experienced in the financial crisis. However, if an investor placed $1 solely into the top RCFG quintile in May 1988, that investment would be worth $42.29 in December 2019. Even though investing in the highest CFG firms earns higher returns, it does not offer the same low volatility as the long–short investment. Finally, $1 invested in the bottom quintile of RCFG in May 1988 grows to $2.20 in 2019. This is significantly less than the stock market returned over this period. Overall, the results suggest that firms generating high CFG consistently outperform firms generating low CFG.

7 | CONCLUSION

In this article I develop a model that shows that expected changes in cash flows are the primary driver of stock returns. Empirical evidence supports the fundamental implication of the model, that stock returns are positively associated with CFG. CFG is found to be highly economically and statistically significant. From a practical standpoint, the results suggest that investors may be able to earn substantial returns by focusing their investment in companies that can create value for shareholders by growing cash flows.

[19]The equal-weighted RCFG portfolio earns higher average returns than the value-weighted portfolio and results in a terminal portfolio value of $40.29.

Daniel and Titman (1997) and Cochrane (2011) describe the findings of Fama and French (1993) as not being based on the covariation of the factors but rather on the "characteristics" of the factors. It may not be the risk component of these factors that is propelling returns but rather the characteristics of the associated factors. These characteristics may reflect properties associated with companies' proficiency in generating value for shareholders, which is then reflected in the stock price. There may always be some factors outside the standard framework (e.g., behavioral aspects, temporary correlations, or observable variables capturing unobservable effects) that have an impact on a market-driven asset. However, much research in stock values has not assigned the significance that is due to the value supplied by a firm to the value of its securities, proxied by CFG in this article. Ultimately, it is the cash flow a firm generates that sustains its stock price, and over the long run, it is the growth in the firm's cash flows that causes the firm's stock price to grow.

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